Pami Dua *Editor*

Macroeconometric Methods

Applications to the Indian Economy

Springer

Macroeconometric Methods

Pami Dua
Editor

Macroeconometric Methods

Applications to the Indian Economy

Springer

Editor
Pami Dua
Delhi School of Economics
University of Delhi
Delhi, India

ISBN 978-981-19-7591-2 ISBN 978-981-19-7592-9 (eBook)
https://doi.org/10.1007/978-981-19-7592-9

This Springer imprint is published by the registered company Springer Nature Singapore Pte Ltd.
The registered company address is: 152 Beach Road, #21-01/04 Gateway East, Singapore 189721, Singapore

Foreword

Edited by Prof. Pami Dua, this volume of 13 chapters on selected aspects of the fast-growing Indian macroeconomy along with an introduction is a highly valuable contribution to the literature on macroeconomic policy and analyses in India. Professor Dua is the sole author of the first three chapters and a co-author of the remaining ten chapters. Among her collaborators are two senior researchers in RBI, namely Dr. Rajiv Ranjan and Dr. Nishita Raje, Dr. Anirvan Banerji of the Economic Cycle Research Institute (ECRI), New York, and her former research scholars, Deepika Goel, Ritu Suri, Niti Khandelwal Garg, Hema Kapur, Divya Tuteja, Vineeta Sharma and Anshuman Tuteja, most of them teaching in Delhi University colleges.

The "Introduction" is a very good account of the Indian economy. The second chapter in the volume draws heavily from Prof. Dua's Presidential Address at the 52nd Annual Conference of the Indian Econometric Society (TIES) at IIM, Kozhikode, in 2016, published later in the *Journal of Quantitative Economics (JQE).* The chapter traces the evolution of macroeconometric modelling in India and presents some new applications of the Bayesian vector autoregression (BVAR) method to the Indian economy. The reader of the essay is amply rewarded, thanks to the comprehensive coverage of the theme.

The third chapter "Monetary Policy Framework in India" reviews the evolution of monetary policy framework in India beginning with Prof. Sukhamoy Chakravarty Committee Report, "Review of the Working of the Monetary System", 1985, and the recent Dr. Urjit Patel Committee Report of 2014, leading to amendment in 2016 of the RBI Act 1934. Professor Dua's chapter describes the monetary policy transmission process in detail and refers to its limitations in terms of lags and rigidities. Her discussion of the functioning of the newly constituted Monetary Policy Committee of the RBI is in international perspective, covering both developed and emerging economies. The analysis in this chapter is highly enlightening.

The 13 chapters are classified into three parts as indicated in Sect. 3 of Chap. 1.

Part I: "Macroeconomic Modelling and Policy" consists of Chaps. 2–7

Part II: "Forecasting the Indian Economy" consists of Chaps. 8–10

Part III: "Business Cycles and Global Crises" consists of Chaps. 11–13.

Table 1 in Chap. 1 gives the techniques covered in the volume and is a good guide to the entire volume. It lists the chapters and authors in column 1 and techniques in column 2. The classification of chapters under Parts I, II and III is also shown in column 1.

A wide range of methodologies (techniques) including Bayesian methods, cointegration, structural VAR, panel GMM-IV, GMM, VAR, BVAR, ARIMA-GARCH, VECM, FAVAR, simultaneous equations model, 2SLS, policy simulations, spectral methods, Markov-switching models, multivariate GARCH models, GARCH-CCC, GARCH-DCC and GARCH-EWMA and statistical measures of synchronization of recessions across countries have been used in the different chapters.

Weekly data, monthly data, annual data or panel data have also been exploited in the different chapters. The empirical results of the econometric analyses have been interpreted with due care.

Economics students at the master's level and researchers in applied econometrics will find the volume very educative and useful. Policy analysts will benefit a great deal by a careful study of the volume.

Professor Dua and all her collaborators deserve to be profusely complimented for the invaluable contributions and for producing the monumental volume.

Delhi, India

K. L. Krishna
Centre for Development Economics
Delhi School of Economics and Former
Director, Delhi School of Economics

Acknowledgments

I have no words to express my deepest regards and infinite gratitude to Revered Prof. P. S. Satsangi Sahab, Chairman, Advisory Committee on Education for Dayalbagh Educational Institutions (a non-statutory body constituted to serve as a think-tank to suggest inter-alia steps necessary for achieving highest levels of excellence), for intuitive guidance, blessings and inspiration in writing this book.

I am greatly indebted to Prof. K. L. Krishna for his invaluable contribution in writing the Foreword of this book.

I am grateful to all my co-authors who contributed their research work towards this book. These include my collaborators from the Reserve Bank of India (Rajiv Ranjan and Nishita Raje) as well as the Economic Cycle Research Institute (Anirvan Banerji) and my former Research Scholars (Deepika Goel, Ritu Suri, Niti Khandelwal Garg, Hema Kapur, Vineeta Sharma, Divya Tuteja and Anshumaan Tuteja).

I am especially thankful to Divya Tuteja for being associated with this book ever since its conceptualization. I also extend my sincere thanks to Rajiv Ranjan and Deepika Goel for their constructive inputs and suggestions. Special thanks are due to Naina Prasad for competent and diligent research assistance.

I greatly appreciate support from Springer for making this collection of papers accessible in book form to students and researchers working in various fields such as macroeconometrics, applied econometrics, time series econometrics, financial econometrics, forecasting methods and contemporary issues of the Indian economy. I am thankful to Nupoor Singh, Senior Editor, Springer Nature, for her constant support in this endeavour. I would also like to acknowledge the support I received from the Production team of Springer Nature—Ashok Kumar, Radhakrishnan Madhavamani, and Umamagesh Perumal.

I am also much obliged to my husband, Harish, son, Agam, and daughter-in-law, Alex, for their continuous support.

The views expressed in the book are attributed to the authors and do not necessarily reflect those of the institutions they represent.

Contents

Editor and Contributors

About the Editor

Dr. Pami Dua is Director of the Delhi School of Economics and Senior Professor of Economics. She has served the University of Delhi in various capacities including Dean of Academic Activities and Projects; Chairperson, Research Council; Dean Research of Humanities and Social Sciences and Coordinator, Internal Quality Assurance Cell of the University of Delhi.

She was a Member of the first Monetary Policy Committee of the Reserve Bank of India from 2016 to 2020. She is currently Co-Chair of the Task Force on Macroeconomics, Trade and Livelihoods under Think20 (T20) India / G20 India. She is also an Honorary Distinguished Fellow (non-resident) of the Indira Gandhi Institute of Development Research (IGIDR), Mumbai, and Member of the Governing Council of the Centre for Advanced Financial Research and Learning (CAFRAL). She is a member of the Governing Body and Academic Council of the Dayalbagh Educational Institute. She is also a member of the Governing Council of the Madras Institute of Development Studies (MIDS) and is affiliated with the Economic Cycle Research Institute (ECRI) in New York. She earlier served as President of the Indian Econometric Society and has been Editor of the *Indian Economic Review*, a reputed journal of the Delhi School of Economics, for almost two decades.

She has published numerous research papers in renowned international journals as well as books and chapters in her fields of study, viz. time series econometrics, forecasting, macroeconometrics, monetary policy and business cycle analysis. She has over three and a half decades of experience in teaching of macroeconomics, econometrics and forecasting. She earlier taught at the University of Connecticut, USA, and Wayne State University, Michigan, USA, and has also been affiliated with Yale University as well as Columbia University.

She completed her B.A. (Hons.) in Economics from Lady Shri Ram College, University of Delhi and obtained her Masters (with distinction) and Doctorate in Economics from London School of Economics. She has been conferred the highest honour of the University of Delhi, *Nishtha Dhriti Satyam Samman*, given to a person of eminence who has made an extraordinary contribution to the development of the University. She has also been conferred the *National Systems Gold Medal* by the Systems Society of India for her outstanding contributions in the area of Economics and Social Sciences.

Contributors

Anirvan Banerji Economic Cycle Research Institute, New York, NY, USA

Pami Dua Department of Economics, Delhi School of Economics, University of Delhi, Delhi, India

Niti Khandelwal Garg Department of Economics, Kirori Mal College, University of Delhi, Delhi, India

Deepika Goel Department of Economics, Aryabhatta College, University of Delhi, New Delhi, India

Hema Kapur Department of Economics, Hansraj College, University of Delhi, Delhi, India

Nishita Raje Department of Regulation, Reserve Bank of India, Mumbai, India

Rajiv Ranjan Monetary Policy Department, Reserve Bank of India, Mumbai, India

Vineeta Sharma Department of Economics, Kirori Mal College, University of Delhi, Delhi, India

Ritu Suri Department of Economics, Lakshmibai College, University of Delhi, Delhi, India

Anshumaan Tuteja Department of Economics, University of Warwick, Warwick, UK

Divya Tuteja Economics Division, Indian Institute of Foreign Trade, New Delhi, India

Chapter 1
Introduction

Pami Dua

Abstract This chapter discusses the broad scope and tools of macroeconometric methods. It illustrates the applications of macroeconometric methods to contemporary issues of the Indian economy. The chapter also describes the significance of the Indian economy in the current global economic order. It summarizes the contents of the three broad areas of applications of macroeconometric methods covered in the edited volume, Macroeconometric Methods: Applications to the Indian Economy, viz. macroeconomic modelling and policy; forecasting the Indian economy; business cycles and global crises.

The purpose of the edited volume "***Macroeconometric Methods: Applications to the Indian Economy***" is to illustrate applications of macroeconometric methods to contemporary issues for the Indian economy. Each chapter delves into an issue of macroeconomic relevance which is analysed using the appropriate econometric method. The techniques employed are applicable to a wide variety of economic and financial areas and are also suitable for the analysis of other emerging as well as developed economies.

This Introduction is divided into four sections. The first section briefly dwells on macroeconometrics. The subsequent section brings to the fore the significance of the Indian economy in the current economic order. The third section elucidates the themes explored in the volume. The final section concludes.

1 Macroeconometrics

Macroeconometrics refers to the application of computational tools based on mathematics, statistics and probability and econometrics to macroeconomics. The key issue underlying the development of macroeconometrics has been the need to provide a

P. Dua (✉)
Department of Economics, Delhi School of Economics, University of Delhi, Delhi, India
e-mail: dua@econdse.org

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_1

quantitative assessment of the impact of policy actions on the macroeconomy. The definition and scope of macroeconometrics have evolved substantially alongside the development in the tools, especially econometrics, over the past century. The broad definition of macroeconometrics includes methods which have been employed to study the issues at the centre of macroeconomics such as economic growth, business cycle fluctuations, transmission of policy shocks, forecasting economic aggregates and analysing impact of policy decisions. The rapid developments in tools available to the researchers have substantially altered the manner in which researchers have investigated the validity of theory by testing them using the data available.

The tools of macroeconometrics encompass estimation and inferential techniques such as structural econometric models, time series models, dynamic stochastic general equilibrium (DSGE) models and panel data methods.[1] These methods are described in Dua (2017) and also Dua (2023), Chap. 2 of this volume.

Structural econometric models are generally estimated by ordinary least squares (OLS), two-stage least squares (2SLS), three-stage least squares (3SLS), limited information maximum likelihood (LIML), full information maximum likelihood (FIML) and seemingly unrelated regression equation (SURE) methods.

Time series models can be further classified into the following categories: univariate models; co-integrated VAR/VECM and ARDL models; vector autoregression (VAR) and its variants; factor/dynamic factor model (FMs/DFMs); nonlinear models and Bayesian methods.

Univariate models for modelling of the mean equation include moving average, exponential smoothing, decomposition, Fourier transformations and ARIMA (Box–Jenkins) methods. The univariate techniques used for modelling the variance are ARCH/GARCH models.

The presence of non-stationarity in macroeconomic variables led to co-integration analysis and estimation of models such as vector error correction model (VECM) and the autoregressive distributed lag (ARDL) model.

The VAR methodology included several extensions such as unrestricted VAR, structural VAR, time-varying parameter VAR, factor-augmented VAR, Markov-switching VAR, threshold VAR, spatial VAR, VAR-X (with exogenous regressors) and global VAR.[2]

Another interesting class of time series models is factor/dynamic factor models (DFMs) that have become increasingly popular because they can utilize large data sets in an effective manner.

Some of the popular nonlinear time series models include spectral models, threshold VARs, threshold VECMs, Qual VARs, artificial neural networks, Markov-switching model and state space models.

---

[1] Other relevant work on macroeconometrics include Canova (2011), Durlauf and Blume (2016), Favero (2001) and Hoover (2012).

[2] It noteworthy that the VAR specifications and time series models also have extensions which involve modelling second moments such as GARCH or stochastic volatility. These include VAR-GARCH BEKK, VAR-GARCH-DCC and other similar extensions.

Apart from these pure time series models, novel methods such as instrumental variables, generalized method of moments (GMM), simulation and computational algorithms have been routinely utilized by macroeconometricians.

The estimation of DSGE models can be based on historical data calibration or Bayesian methods. Hybrid models such as DSGE-VAR and DSGE-DFM have also been implemented by researchers.

Another important advancement is the use of panel data methods in macroeconometrics. These models allow incorporation of variations at the cross-section level with the time series characteristics and, therefore, lead to gains in efficiency. The techniques in this domain include dynamic panel data models, panel VAR, large heterogenous panel data models, panel co-integration/ARDL, spatial panel models and global VAR.

The Bayesian counterparts for all these techniques are available and give more efficient estimates. For a detailed treatment[3] of macro-modelling and econometric techniques, refer to Dua (2017) which is the author's 2016 Presidential Address to the Indian Econometric Society, and Dua (2023), Chap. 2 of this volume.

2 Significance of the Indian Economy in the Current Economic Order

The research presented in the current volume focuses on various aspects of the Indian economy. Therefore, in this section, we discuss the importance of the Indian economy in the global context.

The Indian economy has gained prominence in the world and emerged as one of the fastest-growing economies over the last two decades. It is notable that while the US economy experienced a severe recession from December 2007 to June 2009, which was accompanied by a highly concerted global recession (Banerji and Dua, 2010), India escaped almost unscathed. Instead, it experienced a milder counterpart of a recession, a slowdown, meaning a downshift in the pace of positive growth in economic activity.[4] The drivers of the recent, most synchronized global recession on record, however, are simultaneous shocks from the global pandemic. As a result, India fell prey to it in 2020, with the redeeming factor being that the recession in India (February–April 2020) was sharp but short (Banerji and Dua, 2023). These two global recessions reflect the long-term potential of the Indian economy.

In recent times, various initiatives and structural reforms have been implemented in different areas including taxation, banking and finance, the monetary policy framework, infrastructure development, labour market, disinvestment, manufacturing, innovation and entrepreneurship, agriculture and capital flows. These have

[3] A detailed discussion on the history and evolution of econometrics is given in Krishna (2019).

[4] A recession, on the other hand, would have been more severe, involving a vicious cycle of pronounced, pervasive and persistent cascading *declines* in output, income, employment and sales.

greatly strengthened India's macroeconomic fundamentals and bolstered economic resilience.

Today, the Indian economy stands favourably vis-à-vis its peers in terms of economic growth, trade, ease of doing business, foreign direct investment flows, labour resources, opportunities to integrate with global value chains, etc. Already known as the pharmacy of the world, India proved its strength by supplying vaccines to many countries during the COVID-19 pandemic. The increased participation in various international initiatives such as climate change and green economy and steps taken towards fulfilment of the United Nations Sustainable Development Goals reflect India's rising strategic importance in the world.

India's role has thus become paramount in addressing new challenges faced by the world economy. In this backdrop, India' rising importance in different spheres of the world economy is discussed below.[5]

2.1 Economic Growth

India has emerged as the fastest-growing major economy over the last several years on the back of continuous structural reforms, conducive business environment and demographic dividends. It is progressing well towards achieving the GDP target of US$5 trillion and has already attained over US$3.17 trillion in 2021–22. On this basis, India has been placed at sixth position in world ranking just marginally lower than UK.

Even during the COVID-19 pandemic that hit the economies all over the world, the Indian economy contracted by 6.6% in 2020–21 which is much lower compared to several large economies. At the same time, it rebounded sharply and posted strong growth at 8.7% in 2021–22. According to the IMF World Economic Outlook (April, 2022), global growth is predicted to fall from 6.1% in 2021 to 3.6% in 2022. While the projections of Indian growth for the fiscal year 2022–23 have been revised downward to 8.2% in April 2022 from 9.0% in January 2022, it is still expected to remain the fastest-growing major economy in the world (Chart 1).

As per IMF's estimates, India's share in global GDP (on purchasing power parity basis) has increased from 5.0% in 2007 to 7.0% in 2021 and is further expected to reach 8.6 per cent by 2027 (Chart 2).

Investment remains one of the key drivers of economic growth across countries. Despite some moderation, investment activity in India remains resilient as its share of GDP continues to remain significantly higher than other countries (Chart 3).

[5] For details of research on the Indian economy, refer to related works such as Agrawal (2018), Basu and Maertens (2012), Krishna (2022), Krishna et al. (2017).

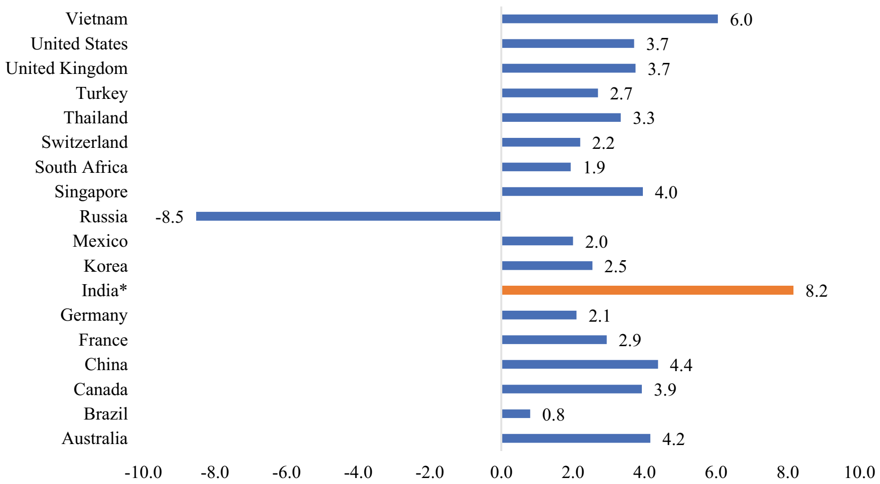


Chart 1 GDP growth rates 2022. *Source* IMF

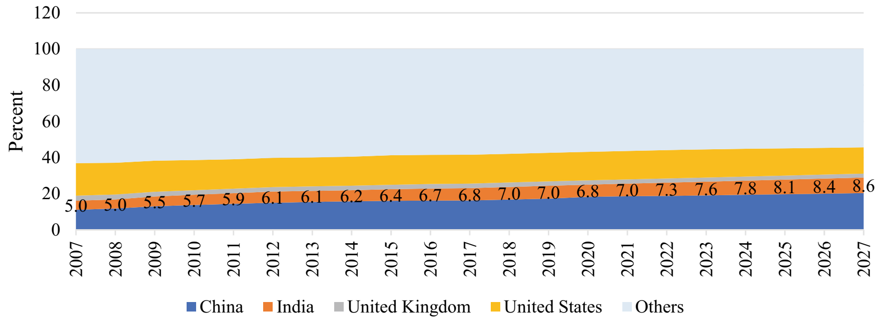


Chart 2 Gross domestic product based on purchasing-power-parity (PPP) share. *Source* IMF

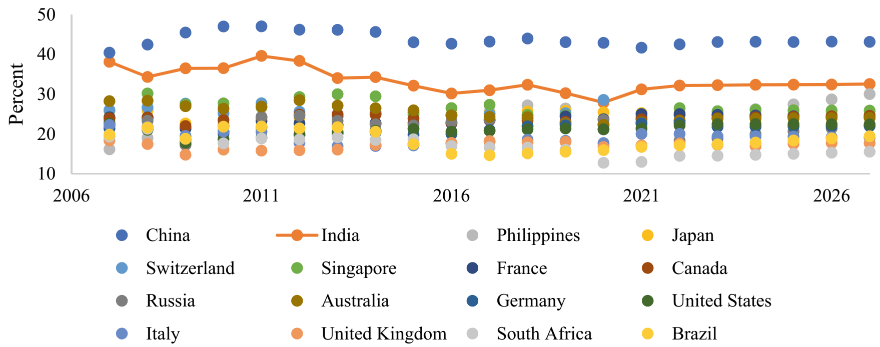


Chart 3 Total investment (as percent of GDP). *Source* IMF

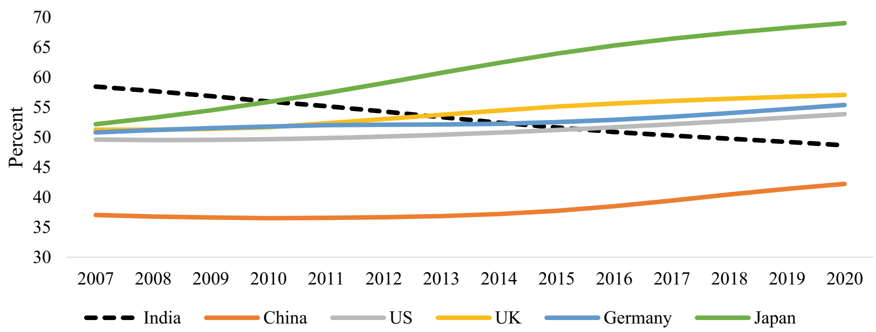


Chart 4 Dependency ratio. *Source* World Bank

2.2 Demographic Dividends

As alluded to earlier, the favourable demographics—a young working-age population—have been one of the key drivers of India's higher growth potential. A comparison of India's age dependency ratio[6] with other countries, viz. China, USA and Japan, shows that India stands in an advantageous position as the age dependency ratio for those countries has started rising while it continues to fall for India (Chart 4).

2.3 International Trade

India has made rapid strides in openness and globalization since the economic reforms initiated in 1991 following a balance of payments (BoP) crisis. The opening up of international trade in goods and services and increased integration with the global economy acted as a catalyst and contributed to India's higher growth trajectory. India's share in global trade has been continuously rising reflecting its improved competitiveness and increased integration in the global supply chain. Its share in global merchandise exports surged from 0.9% in 2005 to 1.7% in 2019 (pre-pandemic) and further accelerated to 1.8% in 2021 (Chart 5). India's share in services exports rose from 1.9% in 2005 to 3.4% in 2019 and further to 3.9% during 2021.

The COVID-19 pandemic disrupted global economic activity including trade which in volume terms (goods and services) declined by 7.9% in 2020. As the pandemic receded and vaccination expanded, world trade experienced a robust recovery. India's external trade registered a record performance in 2021–22 with both merchandise and services exports surpassing their targets.

India achieved an all-time high annual merchandise export of USD 419.7 billion in FY 2021–22, an increase of 43.8% over FY 2020–21 and 33.9% over FY2019–20,

[6] Age dependency ratio is the ratio of dependents—people younger than 15 or older than 64—to the working-age population, i.e. those aged 15–64.

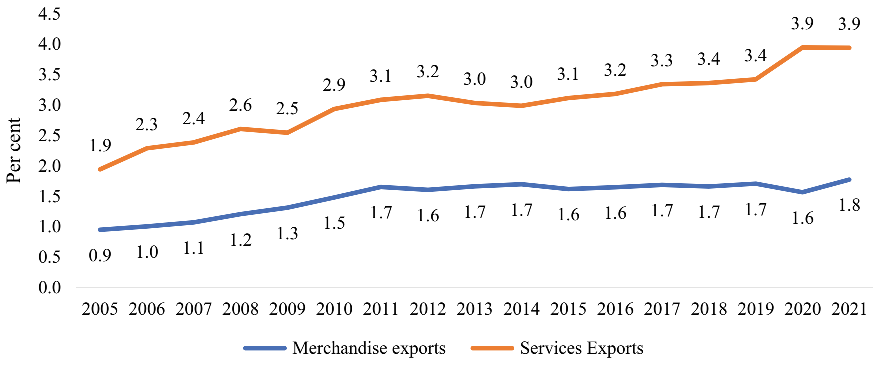


Chart 5 India's exports share (percent). *Source* UNCTAD

overshooting the annual target of US$400 billion. Services exports were also at a record high (USD 254.4 billion) during FY 2021–22 underpinned by robust demand for IT services, albeit exports of travel and transport services are yet to catch up to their pre-pandemic levels. Merchandise imports too rebounded strongly in 2021–22 on the back of buoyant and durable domestic demand. According to UNCTAD, India was the 18th largest exporter of goods in 2021.

2.4 Foreign Direct Investment

India has emerged as a favourite destination for foreign investors and, accordingly, has been receiving large foreign direct investment (FDI) inflows over the years. In fact, FDI has been a stable source of India's external financing requirements. The reform measures undertaken by the government, targeted at increased participation of foreign investors, investment facilitation and ease of doing business, have resulted in increased FDI inflows into the country (Chart 6).

As India's share in global inward FDI increased from 2.1% in 2011–15 to 3.4% in 2016–20, India's ranking in terms of inward FDI has improved from rank 12 in 2015 to 5 in 2020 (Chart 7). India's score on FDI Regulatory Restrictiveness Index[7] has improved in recent years reflecting various reform measures undertaken to ease foreign investment norms over the years.

[7] The OECD FDI Regulatory Restrictiveness Index (FDI Index) measures statutory restrictions on foreign direct investment in over 20 economic sectors across several countries. Restrictions are evaluated on a 0 (open) to 1 (closed) scale.

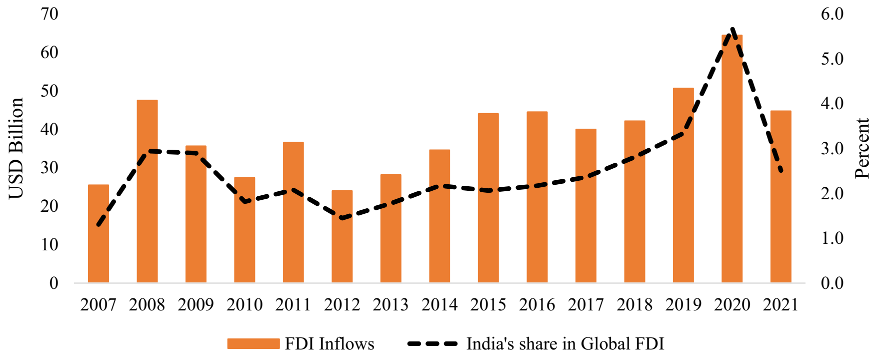


Chart 6 FDI inflows India. *Source* OECD

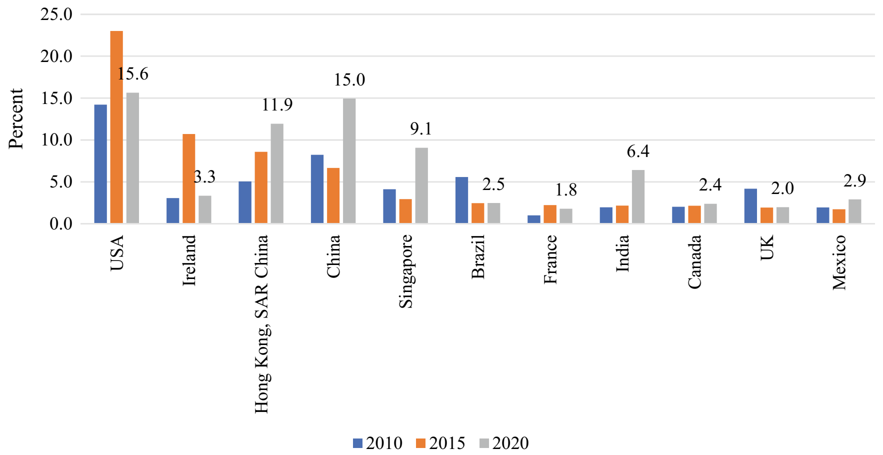


Chart 7 Country-wise share in global FDI (inward). *Source* OECD

2.5 Remittances

India, the world's largest recipient of remittances, received USD 87 billion in 2021 with the USA being the biggest source, accounting for over 20% of these funds. With the higher integration of the Indian labour force into the global economy, remittances are an important source of social security for Indian households. Continued resilience of remittance flows into India during 2020–2021 provided a cushion to households against economic hardship due to the pandemic. India is followed by China, Mexico, the Philippines and Egypt as the recipients of remittance inflows (Chart 8).

Thus, India's position in the world economy has strengthened in recent times and is expected to be a major driver of growth in the world economy. India is also expected to play a critical role in various new initiatives like climate change, ensuring environmental and wildlife protection, as well as transitioning to cleaner fuels and

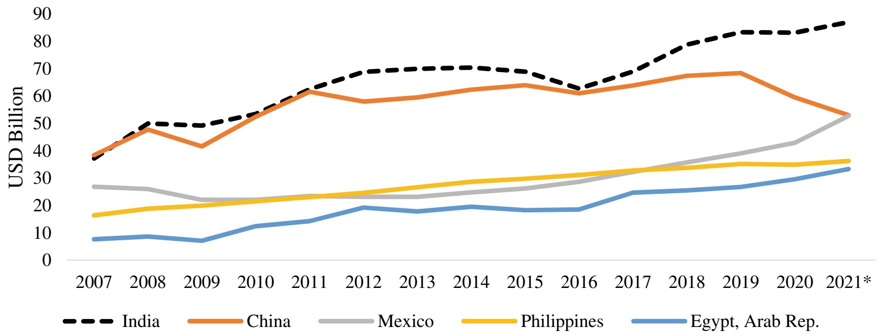


Chart 8 Remittance inflows. *Source* World Bank

renewable energy. It has pledged to become a net zero emitter of carbon by 2070 at the COP 26 United Nations Climate Change Conference in Glasgow.

Moreover, India has been making strides towards achieving social, economic and environmental goals covered under 17 United Nations Sustainable Development Goals (SDGs). India's progress in attaining the SDGs is captured by the NITI Aayog SDG India Overall Index[8] that improved to 66 in 2020–21 from 60 in 2019–20 and 57 in 2018–19, showing progress in India's journey towards achieving the SDGs (Economic Survey, 2021–22).

In this context, Dua, Narayan and Allamraju (2023) illustrate a holistic approach towards attaining SDGs using a case study of Dayalbagh, headquarters of the Radhasoami Faith, a colony located in Agra in the state of Uttar Pradesh, India. The study uses the SDG Index developed by Sachs et al. (2022) for regions and countries (including India) across the globe as well as the index developed by NITI Aayog (2018) for India to measure the progress towards achieving the UN Sustainable Development Goals. It notes that sustainable development encompassing three interconnecting dimensions—environmental, economic and social, is difficult to achieve in practice which may be due to the underlying challenges, constraints and trade-offs. There is thus a need for a fundamental shift in approach towards sustainable development by integrating people's consciousness and conscientiousness that are based on people's values, beliefs, attitudes and spiritual consciousness. The study defines this as the inner dimension of sustainability and develops the concept of holistic sustainability as encompassing both inner and external dimensions (environmental, social and economic). The paper suggests that the inner dimension of sustainability is likely to enhance the impact of the external dimensions to yield more lasting strategies and solutions and serves as the foundation for sustainable development. It is the key to protecting people and planet and fostering prosperity.

[8] To monitor progress towards attainment of SDGs, the NITI Aayog (National Institution for Transforming India (Commission)) developed the NITI Aayog SDG India Index which is the world's first government-led sub-national measure of SDG progress. It captures the progress of all states and union territories in their journey towards achieving the SDGs and also provides an overall nationwide index computed across all goals (NITI Aayog, 2018).

The paper shows that based on this holistic approach, the Dayalbagh Model with inner and external dimensions of sustainability, goes beyond the 2030 United Nations agenda of Sustainable Development. The lifestyle of Dayalbagh, in harmony with nature, is based on the *Sigma Six Quality, Values & Attributes Model* that covers—agriculture (agroecology-cum-precision farming) and dairy; education and healthcare; air quality; water quality; human values; and innovation in all spheres such as renewable energy and use of state-of-the-art technology. There is an emphasis on: trinity of physical, mental and spiritual development from maternity to eternity; creation of a sustainable healthcare and eco-habitat; women empowerment; rendering selfless service and extending benefits particularly to *the last, the least, the lowest and the lost*. The way of life is based on the ideal of Fatherhood of God and Brotherhood of Man; the principle of Better Worldliness and the motto of Service to Mankind. The lifestyle also advocates lacto-vegetarianism. As pointed out by Satsangi (2022), lacto-vegetarianism practiced by approximately 1 billion population, holds the capacity of feeding requisite healthy diet to 11 billion people on planet earth.

Thus, such a model with holistic sustainability as the foundation for sustainable development nurtures prosperity and well-being of people and planet through an ecosystem enriched with values, beliefs, attitudes, spiritual consciousness and conscientiousness. It is indeed remarkable that this model is already prevalent in India and has universal appeal and applicability.

Turning specifically to Sustainable Development Goal 4 on Quality Education, it is commendable that India has implemented the National Education Policy 2020 that provides an equitable platform for education with an impetus for lifelong learning. The National Education Policy is a major step forward and embraces Education 5.0 that integrates ideas from Industry 5.0 on personalized education assisted with state-of-the-art technologies such as immersive experiences (Dua, 2022). This further underscores India's growing stature in the global economy.

3 Themes in the Volume

This volume emphasizes the methodological aspects along with coverage of contemporary policy issues relevant for the Indian economy. The central issues under macroeconometrics relate to economic growth, business cycle fluctuations, transmission of policy shocks, forecasting economic aggregates and analysing impact of policy decisions. Accordingly, the twelve papers included in the volume are classified under three broad areas, namely

(1) Macroeconomic modelling and policy,
(2) Forecasting the Indian economy, and
(3) Business cycles and global crises.

The book, thus, focuses on critical macro aspects of the Indian economy and has wide applications both in terms of techniques and macroeconomic issues. The techniques covered in this volume are given chapter-wise in Table 1.

The first section contains six chapters. The first chapter "**Macroeconomic Modelling and Bayesian Methods**" discusses the evolution of macroeconomic modelling. In particular, it focuses on Bayesian methods and provides some applications of the Bayesian vector autoregression methods to the Indian economy. This chapter is based on Pami Dua's Presidential Address to the 52nd Annual Conference of the Indian Econometric Society.

Chapter 3 titled "**Monetary Policy Framework in India**" reviews the evolution of monetary policy frameworks in India since the mid-1980s. It also describes the monetary policy transmission process and its limitations in terms of lags and rigidities. It highlights the importance of unconventional monetary policy measures in supplementing conventional tools especially during the easing cycle. Further, it examines the voting pattern of the MPC in India and compares this with that of various developed and emerging economies. The synchronization of cuts in the policy rate by MPCs of various countries during the global slowdown in 2019 and the COVID-19 pandemic in the early 2020s is also analysed.

The following chapter on "**Determinants of Yields on Government Securities in India**" examines the determinants of government yields in India using weekly data from April 2001 through June 2012. The analysis covers treasury bills with residual maturity of 15–91 days and government securities of residual maturity 1, 5 and 10 years. The empirical estimates show that a long-run relationship exists between each of these interest rates and the policy rate, rate of growth of money supply, inflation, interest rate spread, foreign interest rate and forward premium. At the same time, the empirical results show that the relative importance of the determinants varies across the maturity spectrum.

The next chapter "**Monetary Transmission in the Indian Economy**" examines monetary transmission channels of India during the period 1998–2015. In a structural VAR framework, the authors use a non-recursive strategy to identify monetary policy shocks using monthly data while controlling for international factors like global interest rates and oil prices affecting the Indian economy. The results confirm that a contractionary shock lowers inflation as well as long-term expectations on inflation and output, while output response is low and insignificant. The study also finds the presence of the exchange rate channel and evidence of a weak asset price channel in the Indian economy.

Chapter 6 entitled "**India's Bi-lateral Export Growth and Exchange Rate Volatility: A Panel GMM Approach**" empirically examines the effect of real exchange rate volatility on India's bilateral export growth. Additionally, the paper examines impact of exchange rate volatility on growth in India's exports to developed and developing countries. For this purpose, the study utilizes panel data of India's twelve export trading partners, six developed (USA, Hong Kong, Singapore, EZ, UK and Japan) and six developing countries (China, Indonesia, Brazil, South Africa, Malaysia and Thailand) from 2005 Q2 to 2019 Q2. It utilizes panel GMM-IV technique to estimate a "hybrid model" for India's export growth. The findings

Table 1 Techniques covered in the volume

Chapter	Technique
Part I: Macroeconomic Modelling and Policy	
Chapter 2: Macroeconomic Modelling and Bayesian Methods—based on presidential address to the 52nd annual conference of the Indian econometric society, 2016 (Author: Pami Dua)	Macroeconomic modelling; Bayesian methods; time series
Chapter 3: Monetary Policy Framework in India, Reprint, ***India Economic Review***, 2020, 55, 117–154. (Author: Pami Dua)	Schematic representation of a monetary policy framework; analysis of MPC voting patterns in various countries; synchronization of interest rates in India and of policy rates across the globe
Chapter 4: Determinants of Yields on Government Securities in India, Reprint, ***Margin—The Journal of Applied Economic Research***, 2014, 8, 375–400) (Authors: Pami Dua and Nishita Raje)	Co-integration
Chapter 5: Monetary Transmission in the Indian Economy (Authors: Pami Dua and Anshumaan Tuteja)	Structural VAR
Chapter 6: India's Bi-lateral Export Growth and Exchange Rate Volatility: A Panel GMM Approach (Authors: Pami Dua and Ritu Suri)	Panel GMM-IV
Chapter 7: Aggregate and Sectoral Productivity in the Indian Economy: Analysis and Determinants (Authors: Pami Dua and Niti Khandelwal)	GMM
Part II: Forecasting the Indian Economy	
Chapter 8: Forecasting the INR/USD Exchange Rate: A BVAR Framework (Authors: Pami Dua, Rajiv Ranjan and Deepika Goel)	VAR, BVAR
Chapter 9: Forecasting India's Inflation in a Data Rich Environment: A FAVAR Study (Authors: Pami Dua and Deepika Goel)	ARIMA-GARCH, VECM, FAVAR
Chapter 10: A Structural Macroeconometric Model for India (Authors: Pami Dua and Hema Kapur)	Simultaneous equations model, 2SLS, policy simulation
Part III: Business Cycles and Global Crises	
Chapter 11: International Synchronization of Growth Rate Cycles: An Analysis in Frequency Domain (Authors: Pami Dua and Vineeta Sharma)	Spectral methods
Chapter 12: Inter-linkages between Asian and US Stock Market Returns: A Multivariate GARCH Analysis (Authors: Pami Dua and Divya Tuteja)	Markov-switching models; multivariate GARCH models—GARCH-CCC, GARCH-DCC and GARCH-EWMA

(continued)

Table 1 (continued)

Part III: Business Cycles and Global Crises	
Chapter 13: The Increasing Synchronization of International Recessions (Authors: Anirvan Banerji and Pami Dua)	Statistical measures of synchronization of recessions across countries

suggest that while real exchange rate volatility significantly decreases growth in India's exports to developing countries, it has an insignificant impact on growth in India's exports to developed countries. Further, while the authors find that the growth in India's exports to both developed and developing economies is positively affected by growth in real exchange rate, foreign income, domestic income, and infrastructure, it is negatively influenced by domestic demand.

The last chapter in this section "**Aggregate and Sectoral Productivity in the Indian Economy: Analysis and Determinants**" analyses and compares estimates of labour productivity growth and total factor productivity growth for the Indian economy as provided by four databases, viz. India KLEMS (IKLEMS), Asian Productivity Organization (APO), Penn World Tables (PWT9.1) and The Conference Board's Total Economy Database (TED) over the period 1981–2015. It investigates determinants of productivity growth of the Indian economy based on measures of productivity growth from the four data sets using GMM method. It also examines the trends and determinants of productivity growth of the major components of industry and services sectors. The study finds that while there are differences in the estimates of productivity growth across various data sets that may be attributed to differences in the definitions, methods of measurement and revisions of databases, the trends are broadly similar. Further, the econometric results of the study are robust across all databases.

Section 2 on forecasting the Indian economy consists of three chapters. The first chapter in this section "**Forecasting the INR/USD Exchange Rate: A BVAR Framework**" uses VAR and Bayesian VAR techniques to forecast the Indian Re/US dollar exchange rate. It extends the Dua and Ranjan (2010) model by including the domestic–foreign differential of the rate of return in stock prices as well as global oil prices as determinants of the exchange rate in addition to monetary model fundamentals (i.e. differential in money supply, interest rate and inflation), forward premium, volatility of capital flows, order flows and central bank intervention. The estimation period is from July 1996 to January 2017, while an analysis of the out-of-sample forecasting performance is undertaken from February 2017 to January 2019. The key findings are as follows: (i) forecast accuracy of the extended model that includes stock market information and global oil prices is somewhat better than the Dua and Ranjan (2010) model, especially at the longer end. (ii) Bayesian VAR models generally outperform their corresponding VAR variants.

The following chapter "**Forecasting India's Inflation in a Data Rich Environment: A FAVAR Study**" develops a multivariate factor-augmented VAR (FAVAR) model of inflation for India to forecast India's inflation. The analysis covers both WPI and CPI measures of inflation. Factors are extracted for determinants of inflation such as output, monetary and credit indicators, interest rate, fiscal indicators, exchange rate, minimum support prices, food inflation, rainfall and foreign inflation using 117 economic time series. The study further evaluates the forecasting performance of the FAVAR model vis-à-vis the VECM model and univariate ARIMA/ARIMA-GARCH models. The models are estimated using monthly data covering the period 2001:05 to 2016:06, and out-of-sample forecasts are generated for the period 2016:07 to 2018:01. The forecasting exercise suggests that FAVAR emerges as the best model in terms of various forecast accuracy measures.

The third chapter "**A Structural Macroeconometric Model for India**" builds a small empirical structural macroeconometric model using quarterly data for India. The model has five sectors: real, fiscal, monetary, price and external sector and 14 behavioural equations (and five identities) which are estimated using two-stage least squares from 1996 Q2 to 2010 Q4. The observations from 2011 Q1 to 2013 Q2 are used for out-of-sample forecasting performance. The model is a modified and extended version of the SMEM developed by Haque et al. (1990) and also accommodates sectoral shifts, real and financial sector linkages and open macroeconomy linkages. The paper also quantifies the economic impact of the following six alternative scenarios on key macroeconomic variables: tight monetary policy; fiscal profligacy; mixed liberal policy; weather shock; external price shock (hike) and a global shock. Policy shocks/measures such as fiscal policy in the form of higher government borrowings and spending and/or monetary policy in the form of a decline in repo or CRR positively impact output growth.

Section three includes three chapters on business cycles and global crises. The first study "**International Synchronization of Growth Rate Cycles: An Analysis in Frequency Domain**" examines international synchronization of growth rate cycles using spectral techniques in the frequency domain. In particular, the paper looks at synchronization of growth rate cycles between bilateral country pairs USA, UK, Germany, Japan and India over the period January 1974 to December 2018. The authors examine two aspects of the synchronization process—one, strength of comovement across countries' growth rate cycles, and two, sequencing in terms of leads and lags of these cycles vis-à-vis each other. Based on the growth rate of the coincident index obtained from ECRI, we infer the sequencing of growth rate cycles in one country vis-à-vis the other in terms of the relative timing of their peaks and troughs. The leads/lags obtained from the spectral phase shift estimates are found to be in line with those inferred from Economic Indicator Analysis (EIA).

The following chapter on "**Inter-linkages between Asian and US Stock Market Returns: A Multivariate GARCH Analysis**" investigates interlinkages of the Asian stock markets, viz. China, Hong Kong, India, Japan and Singapore, with the US stock market. The objective is to discern the impact of the global financial crisis and the Eurozone debt crisis on the linkages across these equity markets. In order to identify the crisis periods, the paper utilizes the timeline given by the respective US and Eurozone specific Markov-switching vector autoregressive models. The study employs multivariate generalized autoregressive conditional heteroscedasticity (GARCH) models to estimate the time-varying conditional correlation among the stock market pairs. The results suggest that there were significant contagion effects among the stock markets at play during the crisis episodes.

The last chapter of the volume titled "**The Increasing Synchronization of International Recessions**" examines various measures of synchronization of recessions, including clustering of the onset of and exit from recession across economies, the proportion of economies in expansion and the diffusion index of international coincident indexes. It shows that the recent COVID recession and recovery were the most concerted in the post-world war period. Factors that contributed to the synchronization and severity of the recession, such as common shocks, trade and supply chain dynamics and financial linkages, are analysed.

4 Conclusions

The present volume is an endeavour towards familiarizing the reader with econometric techniques which are not only explained in depth but also applied in the context of macroeconomic issues for India. It may be noted that the techniques presented in the volume are applicable to a wide range of contemporary issues in macroeconomics. The methods discussed in the book can also be applied to study issues in the context of developed, emerging and developing economies. The macroeconomic problems pertaining to India that have been covered in the book may also be analysed further using other techniques and data methods.

References

Agrawal, P. (2018). *Sustaining high growth in India.* Cambridge University Press.

Banerji, A., & Dua, P. (2010). The synchronization of recessions in major developed and emerging economies. *Margin: The Journal of Applied Economic Research, 4*, 197–223.

Banerji, A., & Dua, P. (2023). The increasing synchronization of international recessions. In P. Dua (Ed.), *Macroeconometric methods: Applications to the Indian Economy, Chapter 13.* Springer Nature, Singapore.

Basu, K., & Maertens, A. (2012). *The new Oxford companion to economics in India.* Oxford University Press.

Canova, F. (2011). *Methods for applied macroeconomic research.* Princeton University Press.

Dua, P. (2022). "Industry 5.0 and Education 5.0", Convocation Address, Indira Gandhi Institute of Development Research, Mumbai, May 13, 2022, http://www.igidr.ac.in/convocation/

Dua, P. (2023). Macroeconomic modelling and bayesian methods. In P. Dua (Ed.), *Macroeconometric methods: Applications to the Indian Economy, Chapter 2.* Springer Nature, Singapore.

Dua, P. (2017). Macroeconomic modelling and bayesian methods. *Journal of Quantitative Economics, 15,* 209–226.

Dua, P., & Ranjan, R. (2010). Exchange rate policy and modelling in India, DRG Study No. 33, Reserve Bank of India.

Dua, P., Narayan, A., & Allamraju, A. S. (2023). A Holistic Approach to Achieving SDGs: A Case Study from Dayalbagh, India. http://hdl.handle.net/10012/19181

Durlauf, S. N., & Blume, L. E. (2016). *Macroeconometrics and time series analysis*. Palgrave Macmillan UK.

Favero, C. A. (2001). *Applied macroeconometrics*. Oxford University Press.

Government of India. (2022). *Economic survey 2021–22, Ministry of Finance*.

Haque, N. U., Lahiri, K., & Montiel, P. J. (1990). A macroeconometric model for developing countries. *IMF Staff Papers, 37*, 537–559.

Hoover, K. D. (2012). *Macroeconometrics: Developments, tensions, and prospects*. Springer.

International Monetary Fund. (2022). *World economic outlook*. Washington D.C.

Krishna, K. L. (2022). Progress in applied econometrics in India: A selective review. In S. R. Hashim, R. Mukherji, B. Mishra (Eds.), *Perspectives on inclusive policies for development in India. India studies in business and economics*. Springer.

Krishna, K. L. (2019). Historical perspective of econometrics. In A. Sinha, A. M. Thomas (Eds.), *Pluralistic economics and its history*. Routledge.

Krishna, K. L., Pandit, V., Sundaram, K., & Dua, P. (2017). Perspectives on economic development and policy in India: In *Honour of Suresh D. Tendulkar*. Springer.

NITI Aayog. (2018). *SDG India index: Baseline report 2018*. http://niti.gov.in/content/sdg-india-index-baseline-report-2018

Sachs, J., Kroll, C., Lafortune, G., Fuller, G., & Woelm, F. (2022). *Sustainable Development Report 2022*. Cambridge University Press.

Satsangi, P. S. (2022). Comments from the Editor on the Two Articles Published in Scientific American, July 2022. In P. S. Satsangi, Horatschek, A. M., Srivastav, A (Eds.), *Consciousness Studies in Sciences and Humanities: Eastern and Western Perspectives*. Springer Nature, Switzerland.

Part I
Macroeconomic Modelling and Policy

Chapter 2
Macroeconomic Modelling and Bayesian Methods

Pami Dua

Abstract This paper discusses the evolution of macroeconomic modelling. In particular, it focuses on Bayesian methods and provides some applications of the Bayesian vector autoregression methods to the Indian economy. This paper is based on my Presidential Address to the 52nd Annual Conference of the Indian Econometric Society.

Keywords Macroeconomic modelling · Bayesian methods · Time series

JEL Classification C11 · C2 · C3

1 Introduction

> Macro models are never static. They constantly evolve. 'Survival of the fittest' is a good description of the history of models...
>
> —Hall et al. (2013)

Research on macroeconomic modelling, the world over, has been driven by constantly evolving economic theory and advancements in econometric methodology in a dynamic macroeconomic environment. The focus has been on striking a balance between internal consistency, empirical adherence and adequacy for policy analysis. In this paper, I describe the evolution of macroeconomic modelling and specifically focus on Bayesian methods. Additionally, I present some applications of Bayesian vector autoregression (BVAR) methods to the Indian economy. The paper is organized as follows. In Section 2, I first briefly outline the evolution of macroeconomic models. Thereafter, Section 3 discusses the tenets of Bayesian methodology.

This chapter draws largely from Dua (2017) published in Journal of Quantitative Economics, 2017, 15, 209–226.

P. Dua (✉)
Department of Economics, Delhi School of Economics, University of Delhi, Delhi, India
e-mail: dua@econdse.org

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_2

Section 4 presents some applications of the BVAR methods to the Indian economy. The final section concludes.

2 Evolution of Macroeconomic Models

The methods for macroeconomic modelling can be described under four heads:

1. Structural econometric models,
2. Time series models,
3. Dynamic stochastic general equilibrium (DSGE) models and
4. Panel data models.

These four approaches to macroeconomic modelling are discussed in brief below. I begin with the structural econometric models.

The genesis of macroeconomic modelling can be traced back to pioneering work by Tinbergen (1939), Klein (1950), Klein and Goldberger (1955) and subsequent developments regarding structural econometric models at the Cowles Commission.[1] A structural econometric model may be employed to examine inter-linkages between various sectors of an economy and produce forecasts and/or simulations of the endogenous variables based on the evolution of the exogenous variables (which may be known or assumed or forecasted).[2]

Lucas (1976) raised doubts on the usefulness of structural econometric models as a guide to policy formulation. He argued that structural econometric models are not useful for policy simulations because their coefficients are not invariant to the policy rule under the rational expectations hypothesis (REH).

At the same time, Sims (1980) questioned the traditional Cowles Commission approach to identify behavioural relations, which had been based on what Sims termed as 'incredible' restrictions on the short-run dynamics of the model which include non-justifiable exclusion and identification restrictions. Sims introduced the 'a theoretical' VAR model which does not require specification of the projected values of the exogenous variables as standard in structural econometric models.

The presence of non-stationarity in macroeconomic variables also had an indelible impact on macroeconomic modelling. This followed from the seminal work of Nelson

[1] A structural econometric model comprises a simultaneous equation system specifying causal relationships between the variables based (either formally or informally) on economic theory where all the variables are classified as endogenous or exogenous variables.

[2] These models are generally estimated by Ordinary Least Squares (OLS), Two-stage Least Squares (2SLS), Three-stage Least Squares (3SLS), Limited Information Maximum Likelihood (LIML), Full Information Maximum Likelihood (FIML) and Seemingly Unrelated Regression Equation (SURE) methods. Econometric models for the Indian economy include Krishnamurty et al. (2002, 2004, 2008; OLS), Bhanumurthy and Kumawat (2009; OLS and ARDL), Sachdeva and Ghosh (2009; SURE), Narayana and Ghosh (2009; VAR/VEC), Kumar and Panda (2009; calibration and social accounting matrix (SAM), Kar and Pradhan (2009; OLS), Bhide and Parida (2013; OLS), Srivastava (2013; 2SLS and 3SLS) and Dua and Kapur (2023; 2SLS).

and Plosser (1982) for the USA where they show that the null hypothesis of non-stationarity could not be rejected for a wide range of macroeconomic time series.[3] Subsequently, the significant work of Engle and Granger (1987), Johansen (1991), Phillips (1991) on cointegration showed possible ways to deal with unit roots in macro time series, with important consequences for macroeconomic modelling including the vector error correction model (VECM) and the autoregressive distributed lag (ARDL)[4] model.

The Lucas critique also provoked considerable scepticism concerning the use of large-scale structural econometric models in policy analysis leading to the utilization of VAR initially. It ushered in a new generation of econometric models later on which were explicitly based on the dynamic intertemporal optimisation decisions by firms and households, the so-called Dynamic Stochastic General Equilibrium (DSGE) approach.[5] Panel data macroeconometric models also evolved adding a cross-sectional dimension to time series analysis.

I now turn to, time series models which can be further classified into the following categories:

- Vector autoregression (VAR) and its more sophisticated variants,
- Cointegrated VAR/VECM and ARDL models,
- Factor/dynamic factor model (FMs/DFMS),
- Nonlinear models and
- Bayesian methods.

VAR and its various incarnations range from unrestricted VAR, structural VAR (SVAR), time-varying parameter VAR (TVP-VAR), factor/factor augmented VAR (FVAR/FAVAR), Markov switching VAR (MSVAR), threshold VAR (TVAR), spatial VAR (SPVAR) and global VAR (GVAR).[6]

Sims (1980) introduced the unrestricted VAR which is data-driven, and each variable is treated as endogenous and depends on lagged values of all the variables in the system.

Although the VAR approach is ‘a theoretical’, Zellner and Palm (1974), Zellner (1979) show that a VAR model approximates the reduced form of a structural system of simultaneous equations.[7]

---

[3] This resurrected the spectre of spurious regression as noted by Yule (1926), Champernowne (1960), Granger and Newbold (1974).

[4] See Pesaran and Shin (1999), Pesaran, Shin and Smith (2001, 2002).

[5] See Kydland and Prescott (1982), Long and Plosser (1983).

[6] It noteworthy that the VAR specifications and time series models also have extensions which involve modelling second moments such as GARCH or stochastic volatility. See Dua and Suri (2019), Dua and Tuteja (2016a) for applications of VAR-multivariate GARCH BEKK and Dua and Tuteja (2016b, 2023) for applications of DCC-GARCH models. For instance, a BVAR with stochastic volatility has been estimated by Uhlig (1997), while Clark and Ravazzolo (2012) compared macroeconomic forecasting performance of AR models with alternative specifications of time-varying macroeconomic volatility. However, we do not discuss these here for the sake of brevity.

[7] Thus, a VAR model is similar to a large-scale structural model and given the ‘correct’ restrictions on the parameters of the VAR model, they reflect mirror images of each other. As shown by Zellner and

Sims (1980) and others such as Doan (1992) recommend estimating the VAR in levels even if the variables contain a unit root.[8] The standard practice in the presence of a cointegrating relationship between the variables in a VAR is to estimate the VAR in levels or to estimate its error correction representation, the VECM. However, if the variables are non-stationary but not cointegrated, the VAR can be estimated in first differences. Finally, if there is a mix of stationary and non-stationary variables, then an ARDL model can be estimated.

The structural VAR (SVAR) model builds on Sims' approach[9] and imposes restrictions on the covariance structure of different types of innovations in a VAR framework. Sims proposed these models to resolve criticisms levelled by Cooley and LeRoy (1985) that VARs lack the structural assumptions that are essential for reasonable identification of shocks and meaningful interpretation of the impulse response functions.[10]

Another variant is the time-varying parameter VAR (TVP-VAR) model.[11] These models allow for variation of parameters overtime and also accommodate structural changes.

More recently, factor augmented VAR (FAVAR)[12] models have evolved for the estimation of large-scale dynamic econometric models in the VAR framework. These extract information contained in a large number of economic variables and condense them into a small number of factors and then employ them for estimation in a VAR model.[13]

The VAR framework is also used for global and regional modelling referred to as global VAR (GVAR) and spatial VAR (SPVAR) models.

The GVAR approach, originally proposed in Pesaran et al. (2004), provides a relatively simple yet effective way of modelling complex high-dimensional systems. It is a two-step approach. In the first step, small-scale country-specific models are estimated conditional on the rest of the world.[14] In the second step, individual country

Palm (1974), Zellner (1979), any linear structural model theoretically reduces to a VAR moving average (VARMA) model, whose coefficients combine the structural coefficients. Under some conditions, a VARMA model can be expressed as a VAR model and as a Vector Moving Average (VMA) model. A VAR model can also approximate the reduced form of a simultaneous structural model.

[8] The argument against differencing is that it discards crucial information related to co-movements amongst the variables such as cointegrating relationships.

[9] See Bernanke (1986), Blanchard and Watson (1986), Sims (1986).

[10] However, this approach does not attempt to model the structure of the economy in the form of specific behavioural cause and effect relationships. These are relatively small sized models compared to structural macroeconometric models.

[11] See Cogley and Sargent (2002), Del Negro and Otrok (2008).

[12] See Dua and Goel (2023) for an application of FAVAR to the Indian economy.

[13] Thus, adding a few common factors to a macroeconomic VAR system controls for a variety of omitted variables within a typical low-dimensional VAR analysis.

[14] These models are represented as augmented VAR models, denoted as VARX* and feature domestic variables and weighted cross-section averages of foreign variables, also referred to as "star variables", which are treated as weakly exogenous (or long-run forcing).

VARX* models are stacked and solved simultaneously as one large global VAR model.[15] Therefore, it is like a panel model.

On the other hand, SPVAR models are macromodels that explicitly account for spatial or regional influences. Various modelling techniques that correspond to different spatial locations (spatial time series) are employed in order to examine the spatiotemporal evolution of a single variable.

Yet another interesting class of pure time series models are factor/dynamic factor models[16] (DFMs) that have become increasingly popular because they can utilize large data sets in an effective manner.[17]

A proliferating set of nonlinear models including spectral models,[18] regime switching models, (e.g. Markov switching VARs,[19] threshold VARs, smooth transition VARs, etc.), threshold error correction/cointegration models, artificial neural network (ANN) models and state space models (SSMs) have also been progressively and increasingly applied in macroeconometric modelling.

The final category under time series modelling is 'Bayesian methods' which are discussed in detail in Sect. 3.

In contrast to time series models, the DSGE approach is a micro-founded approach, originally applied to real business cycles and are based on the studies by Kydland and Prescott (1982), Long and Plosser (1983). The broad class of DSGE models includes dynamic macroeconomic models that span the standard neoclassical growth model discussed in King et al. (1988)[20] as well as the monetary model with numerous real and nominal frictions developed by Christiano et al. (2005). Decision rules of economic agents are derived from assumptions regarding preferences and technologies by solving the intertemporal optimization problems. These models are immune to Lucas' critique because they involve forward looking and optimizing

---

[15] The solution can be used for shock-scenario analysis and forecasting as is usually done with standard low-dimensional VAR models. See Pesaran et al. (2004), Dees et al. (2005).

[16] The alternative assumptions of the Factor models include the Strict Factor models, Approximate Factor models and Dynamic Factor models.

[17] The most popular estimation methods include the principal components approach (Breitung and Tenhofen, 2011), ML-type estimators (Doz et al., 2011), time-domain approach (Stock and Watson, 1989, 2002a, 2002b) and the frequency-domain approach (Forni and Reichlin, 1998; Forni et al., 2001, 2005). They have been widely used for various purposes such as to construct economic indicators, to forecast real and nominal economic variables and for instrumental variable estimation. Factor models have also been used for monetary policy analysis in combination with a vector autoregressive (VAR) system as in Bernanke et al. (2005). In many cases, only five to ten factors are constructed to capture more than a half of the total variation within a large data set of more than three hundred macroeconomic variables. Thus, adding a few common factors to a macroeconomic VAR system is supposed to control for a variety of omitted variables within a typical low-dimensional VAR analysis and circumvents the curse of dimensionality.

[18] See Dua and Sharma (2023) for an application of spectral models to examine the synchronization of international growth rate cycles.

[19] For example, Dua and Tuteja (2015, 2016b) Dua and Sharma (2016) utilize MS-VAR models to study the common regimes across international economies and financial markets.

[20] The New Keynesian DSGE framework was later proposed by Rotemberg and Woodford (1997).

economic agents and can be, thus, used for policy analysis.[21] These are generally estimated using calibration, Bayesian MLE technique or a hybrid approach. The hybrid approach involves the combination of DSGE models with time series econometric models like VAR, FAVAR, DFM, BVAR. The hybrid models are expected to better capture the dynamic properties of the DSGE models.

Finally, the panel models[22] may be broadly classified into dynamic panel data models, panel VAR, panel VECM/ARDL models, spatial panel models, GVAR and panel factor models.

Dynamic panel data models include the dynamic macroeconomic relationships for which the data generating process is a panel containing lagged dependent variables.[23] Panel cointegration models, on the other hand, represent the panel counterpart of the pure time series cointegration models. As such, a panel VECM is a general model to accommodate cointegration across panel units (or cross sections) and dynamic links between the panel units.[24] Spatial panel models, on the other hand, represent an extension of spatial models to panel data by considering a panel VAR model with a particular class of dependence structure in the disturbances. Furthermore, factor models have also been used in panel regressions as a way of modelling cross-sectional correlations.[25]

3 Bayesian Methods

I now discuss Bayesian methods. There is a Bayesian counterpart for most of the techniques discussed so far. In fact, most classical methods can be cast in a Bayesian framework including simultaneous equation models, time series models, DSGE and panel data models. The appealing feature of the Bayesian inference is the beliefs that are imposed on the parameters in the form of priors. This also helps to deal with small samples and the so-called curse of dimensionality. Furthermore, with the advent of powerful and inexpensive computing, numerically complex and intensive methods can be applied such as the Markov chain Monte Carlo (MCMC) simulation method

---

[21] Large-scale DSGE models with a sophisticated structure are being utilized by Central Banks as the papers by Smets and Wouter (2003, 2007) advanced evidence that these models fit the US macroeconomic data aptly.

[22] Refer to Dua and Kapur (2017), Dua and Suri (2023) for applications of panel VAR models.

[23] In such a case, the MLE or the within estimator under the fixed-effects specification is no longer consistent with large N (number of cross-section units) and small T (number of time periods) due to the presence of incidental parameters problem. Thus, instrumental variables (IVs) and generalized methods of moments (GMM) estimation methods have been generally used to obtain consistent estimates.

[24] However, in panel data models, the analysis of co-integration is further complicated in the presence of heterogeneity, unbalanced panels, cross-sectional dependence, and cross-unit co-integration. Further, the asymptotic theory is contingent on the sizes of N and T and lacks coherence.

[25] See Bai and Ng (2004), Bai (2009), Moon and Perron (2004), Pesaran (2006), Phillips and Sul (2003).

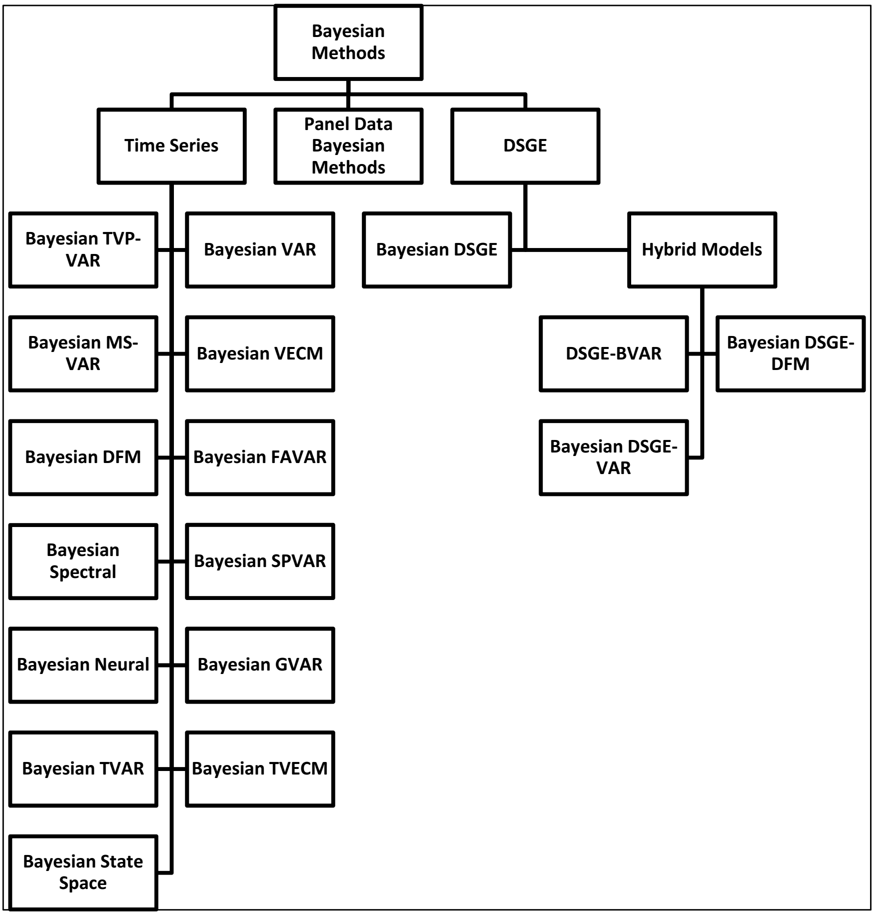


Fig. 1 Bayesian models

for sampling which involves, e.g. the Gibbs sampler. The Bayesian paradigm thus provides a rich framework for inference and forecasting based on macroeconomic models such as VAR and its variants and DSGE. Some of the Bayesian models[26] are given in Fig. 1.

[26] See the seminal work by Litterman (1981, 1982), Doan, Litterman and Sims (1984), Todd (1984), Litterman (1986), Blanchard and Quah (1989), Spencer (1993).

3.1 Why Bayesian?

Bayesian methods use Bayes' Theorem to combine prior information about the models and their parameters with sample information in a logical and cohesive manner. While Classical estimation treats population parameters as constant, Bayesian methods assume that these are random variables. Bayesian econometrics allows the incorporation of beliefs about parameters (that researchers may have) in the form of priors imposed on the parameters. These priors are imposed as distributions of the parameters that are considered to be random variables. Classical estimation, on the other hand, does not incorporate prior beliefs since it is based purely on the data.

Thus, a Bayesian statistician is not interested in a single estimate but rather in a distribution, the posterior distribution of the parameters. At the same time, the posterior distribution depends not only on the prior but also on the data. Further, in the Bayesian approach, the likelihood is not maximized to arrive at point estimates, rather the whole information in the likelihood function is used.

The cornerstone of Bayesian methods, the Bayes' theorem, states that the probability of an event a conditional on an event B equals the product of the probability that B has occurred given A and the probability of A divided by the probability that event B occurs.

$$P(A|B) = \frac{P(A\Omega B)}{P(B)} = \frac{P(B|A) \cdot P(A)}{P(B)}$$

If we replace the events A and B with data y and parameters θ and the probabilities with probability density functions (p(.)) to denote a density function (pdf), we get

$$P(\theta|y) = \frac{P(\theta\Omega y)}{P(y)} = \frac{P(y|\theta) \cdot P(\theta)}{P(y)}$$

Here, $p(\theta)$ is the pdf that represents prior beliefs on the parameters, $p(y|\theta)$ represents the likelihood and $p(\theta|y)$ is the posterior distribution of the parameters. This is of primary interest to the researcher as it provides information on the parameters, given the data. Since, $p(y)$ has no information on θ, it is more useful to express the relationship above as:

$$P(\theta|y) = \frac{P(\theta\Omega y)}{P(y)} \propto (P(y|\theta) \cdot P(\theta))$$

This can be rewritten as:

$$\begin{aligned}&\text{Posterior Density of the Parameters(given current data)}\\&\propto \text{Likelihood function} \times \text{Prior Density}\end{aligned}$$

The left-hand side gives the revised beliefs about the distribution of the parameters after observing the data.

The first term on the right is the joint distribution of the observed random variables **y**, given the parameters. The second term gives the **prior beliefs** of the analyst. Bayesian inference relies on this product where the role of the prior density is to integrate the researcher's "knowledge" about the parameters into the estimation. Note that the posterior density can become the prior density in future. This aspect of continuous upgradation of information on the priors is absent in the Classical school.

According to Sims (2007),

> Bayesian inference is a Way of Thinking....................
>
> Bayesian inference should be the starting point for discussing implications of data analysis with decision makers. The Bayesian approach to inference should be the starting point also of our education of econometricians.

We now turn to forecasting using Bayesian models. Two major competitors in the forecasting arena are DSGE and BVAR models. Forecasting studies in the 1990s and early 2000s suggest that out-of-sample macroeconomic forecasts from DSGE models are more accurate than Bayesian VAR forecasts, even if both are estimated by Bayesian methods. In fact, Del Negro and Schorfeide (2013) recommend that the DSGE model should be the benchmark for forecasting horse races. However, Gurkaynak et al. (2013) find mixed evidence on comparing the real time forecasting accuracy of the Smets and Wouters (2007) DSGE model with time series models. Therefore, although the winner of the forecasting horse race is yet to be decided, we examine the forecasting ability of the Bayesian VAR model, which seems to be a reasonable choice as a benchmark model.

3.2 Forecasting Using Bayesian Models

What can we say about forecasting with Bayesian models? Quoting from Granger (1986),

> ......in terms of forecasting ability, ...a good Bayesian will beat a non-Bayesian, who will do better than a bad Bayesian.

The Bayesian approach to forecasting provides a scientific way of imposing prior or judgmental beliefs on a statistical model. Selection of the Bayesian prior, of course, depends on the expertise of the forecaster. Bayesian forecasting, thus, is as much an art as it is a science.

One serious drawback of the unrestricted VAR model is over parameterization which produces multicollinearity and loss of degrees of freedom that can lead to inefficient estimates and large out-of-sample forecasting errors. One possible solution is to exclude insignificant variables/lags based on statistical tests. However, such *hard* restrictions rule out the possibility of spillover effects which may not be desirable.

The Bayesian approach integrates *soft* restrictions through probability distributions for coefficients that are centred at the desired restriction but have a nonzero variance.

Thus, instead of eliminating longer lags and/or less important variables, the Bayesian technique imposes restrictions on these coefficients based on the assumption that these are more likely to be near zero than the coefficients on shorter lags and/or more important variables. If, however, strong effects do occur from longer lags and/or less important variables, the data can override this assumption. The blend of prior information and sample data can be controlled through *loose* or *tight* imposition of the prior where a loose prior would produce coefficients close to those from a non-Bayesian VAR model while a tight prior would produce estimates close to the prior restrictions.

The Bayesian model, therefore, imposes prior beliefs on the relationships between different variables as well as between own lags of a particular variable. If these beliefs (or restrictions) are appropriate, the forecasting ability of the model should improve. Several prior beliefs can be imposed so that the set of beliefs that produces the best forecasts is selected for making forecasts. The role of prior distributions is to reduce the dimensionality of the parameter space to avoid overfitting.

The most standard prior utilized for the BVAR model is the Minnesota prior. Details are given in the Appendix. A number of extensions on the Minnesota prior have been developed. Some of these are the Normal Wishart prior; Normal Diffuse prior (Kadiyala & Karlsson, 1997) and Hierarchical priors for the hyperparameters (Giannone et al., 2012).

4 Applications of Bayesian VAR Methods

I now describe some applications of forecasting with BVAR models with respect to the Indian economy.

4.1 Forecasting the INR/USD Exchange Rate: A BVAR Framework (Dua et al. 2023)

This paper extends the Dua and Ranjan (2010, 2012) model by including the domestic-foreign differential of the rate of return in stock prices as well as global oil prices as determinants of the exchange rate in addition to monetary model fundamentals (i.e. differential in money supply, interest rate and inflation), forward premium, volatility of capital flows, order flows and central bank intervention. The estimation period is July 1996 to January 2017, while an analysis of the out-of-sample forecasting performance is undertaken from February 2017 to January 2019. The main findings of the study suggest that the exchange rate is granger caused by all the determinants considered, including differential of the rate of return of stock prices and global oil prices. Forecast accuracy of the model can be improved by including stock market information and global oil prices in the model, especially on the longer end. Bayesian vector autoregressive models outperform their corresponding VAR variants. However, the turning points are difficult to predict. These results are similar to those reported in Dua and Ranjan (2010, 2012).

4.2 Forecasting Indian Macroeconomic Variables using Medium-Scale VAR Models: Aye et al. (2015)

This paper employs VAR, BVAR and FAVAR models to forecast output, inflation, interest rates and the exchange rate in the Indian economy over the out-of-sample period—January, 2007 to October, 2011. The estimation period extends from April 1997 to December 2006. The results indicate that in general, the Bayesian VARs and Bayesian Factor Augmented VARs outperform the classical VARs. We also provide an ex-ante forecast using the selected ‘best’ models and find that these models do not perfectly capture the turning points in each of the series, which may point to the importance of conducting future research in a nonlinear framework.

4.3 Forecasting Interest Rates in India: Dua et al. (2008)

This paper develops univariate (ARIMA and ARCH/GARCH) and multivariate models (VAR, VECM and Bayesian VAR) to forecast short- and long-term rates, viz. call money rate, 15–91 days Treasury Bill rates and interest rates on government securities with (residual) maturities of one year, five years and ten years. Multivariate models consider factors such as liquidity, repo rate, yield spread, inflation rate, foreign interest rates and forward premium. The models are estimated from April 1997 through December 2001 and out-of-sample forecasts are generated from January 2002 through June 2004. The paper finds that multivariate models generally outperform univariate ones over longer forecast horizons. Overall, the paper concludes that the forecasting performance of Bayesian VAR models is satisfactory for most interest rates and their superiority in performance is marked at longer forecast horizons. Furthermore, the Pesaran–Timmerman test shows that the performance of multivariate models (in most cases BVAR) in correctly predicting the direction of the various interest rates is generally better than that of univariate models.

Some of the limitations of BVAR forecasts merit mention at this point. The search for an optimal prior requires an objective function (e.g. RMSE, Theil U-statistic) that is optimized over the out-of-sample forecasts. The chosen prior, therefore, may not be optimal beyond the period for which it was selected. In other words, the selected specification may not produce the ‘best’ forecasts outside the sample for which the selection was made.

Nevertheless, the applications discussed above show that in general, the BVAR model outperforms alternative models.

5 Concluding Remarks

> Macroeconometric modelling is multi-dimensional and both a science and an art…. to achieve three objectives, viz. structural analysis, forecasting and policy evaluation…—Intriligator et al. (1996)

Thus far, we have reviewed the different and expanding building blocks of modern macroeconomic modelling. Given the inherent complexity and challenges that macromodelling entails, this is an ever-evolving field. For instance, the cutting-edge research now focuses on nowcasting[27] and utilizing mixed frequency models which involve combination of high-frequency data with low-frequency data in order to produce forecasts for say, GDP.[28] Of course, it is evident that a good researcher cannot rely merely on the knowledge of econometric methodology but must depend on his/her judgement as well. It is in this very aspect that Bayesian techniques contribute greatly as they facilitate the researcher to exercise his/her acumen in a scientific manner. Thus, we can conclude:

> It pays to go Bayes—Zellner (2000)

Questions to Think About

1. What are ‘incredible restrictions’? Suggest an alternative approach.
   Hint: See Sect. 2 and Sims (1980)
2. According to Zellner (2000), “It pays to go Bayes.” What are the advantages of the Bayesian approach?
   Hint: See Sect. 3
3. What is the difference between priors and posteriors?
   Hint: See Sect. 3

Acknowledgements An earlier version of this paper was delivered as the Presidential Address to the 52nd Annual Conference of the Indian Econometric Society at IIM, Kozhikode in January, 2016.

[27] Forecasting not the future but the present as well the near past is termed as ‘nowcast’.

[28] See Marcellino and Schumacher (2008), Camacho et al., (2011, 2012), Angelini et al. (2011), Giannone and Reichlin (2012).

Appendix: A Note on Priors

The Minnesota prior (and its variants) used in Bayesian VAR is due to Litterman (1981), Doan et al. (1984), Todd (1984), Litterman (1986), Spencer (1993). The restrictions on the coefficients specify normal prior distributions with means zero and small standard deviations for all coefficients with decreasing standard deviations on increasing lags, except for the coefficient on the first own lag of a variable that is given a mean of unity.

$$\beta_i = N\left(1, \sigma_{\beta_i}^2\right) \text{and} \beta_j = N(0, \sigma_{\beta_j}^2)$$

where β_i denote the coefficients associated with the lagged dependent variables in each equation and β_j denote all other coefficients. The prior variances $\sigma_{\beta_i}^2$ and $\sigma_{\beta_j}^2$ denote uncertainity about the prior means in each equation.

The standard deviation of the prior distribution for lag m of variable j in equation i for all i, j, and m, σ_{ijm} is specified as follows:

$$\begin{aligned} \sigma_{ijm} &= \{wg(m)f(i, j)\}si/sj; \\ f(i, j) &= 1, \text{if } i = j; \\ &= k \text{ otherwise}(0 < k < 1); \text{ and} \\ g(m) &= m - d, d > 0. \end{aligned}$$

The term s_i equals the standard error of a univariate autoregression for variable i. The ratio s_i/s_j scales the variables to account for differences in units of measurement and allows the specification of the prior without consideration of the magnitudes of the variables. The parameter w measures the standard deviation on the first own lag and describes the overall tightness of the prior. The tightness on lag m relative to lag 1 equals the function $g(m)$, assumed to have a harmonic shape with decay factor d. The tightness of variable j relative to variable i in equation i equals the function $f(i, j)$.

The value of $f(i, j)$ determines the importance of variable j relative to variable i in the equation for variable i, higher values implying greater interaction. For instance, $f(i, j) = 0.5$ implies that relative to variable i, variable j has a weight of 50%. Further, this value (k) may differ across js highlighting the flexibility imparted by the Bayesian approach. A tighter prior occurs by decreasing w, increasing d, and/or decreasing k. Examples of selection of hyperparameters are given in Dua and Ray (1995), Dua and Smyth (1995), Dua and Miller (1996), Dua et al. (1999), Dua et al. (2003, 2008), Dua and Ranjan (2010, 2012), Dua et al. (2023).

The BVAR method uses Theil's (1971) mixed estimation technique that supplements data with prior information on the distributions of the coefficients. With each restriction, the number of observations and degrees of freedom artificially increase by one. Thus, the loss of degrees of freedom due to over parameterization does not affect the BVAR model as severely.

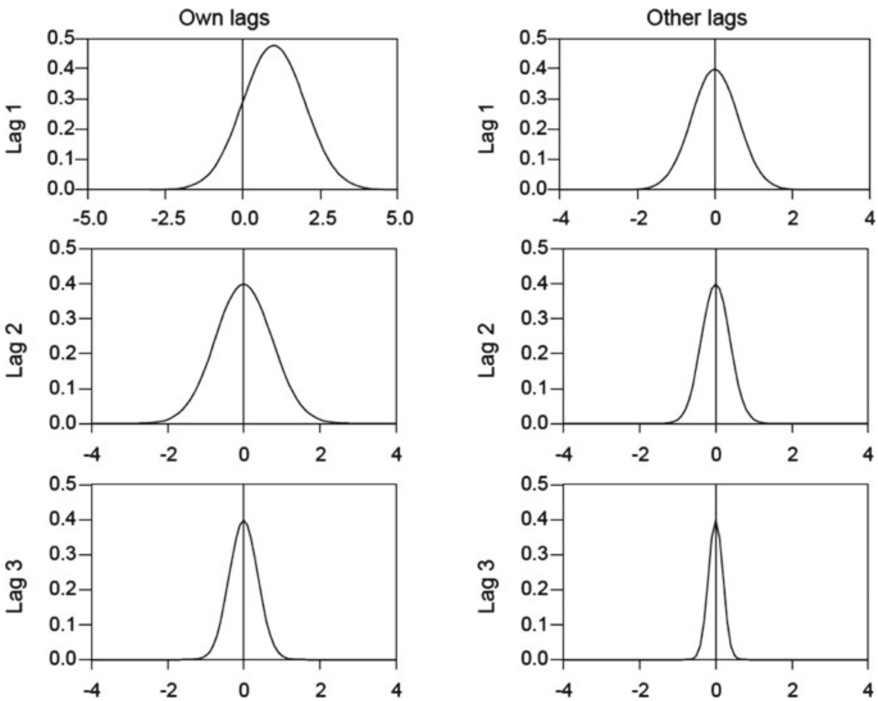


Fig. 2 Minnesota prior (*source* Blake & Mumtaz, 2012, p. 5)

Figure 2 provides a graphical representation of the Minnesota prior where all coefficients have zero prior mean, apart from the first own lag. Moreover, it is observed that the prior distributions tend to become more concentrated for coefficients on longer lags. Further, the prior distributions of the lags of the other variables are more concentrated than those of the variable's own lags

In Fig. 3, we provide an example of a tight and a loose prior. In both the cases, the mean of the Normal distribution is 1 but the variance for the tight prior is 2 and that for the loose prior is 4.

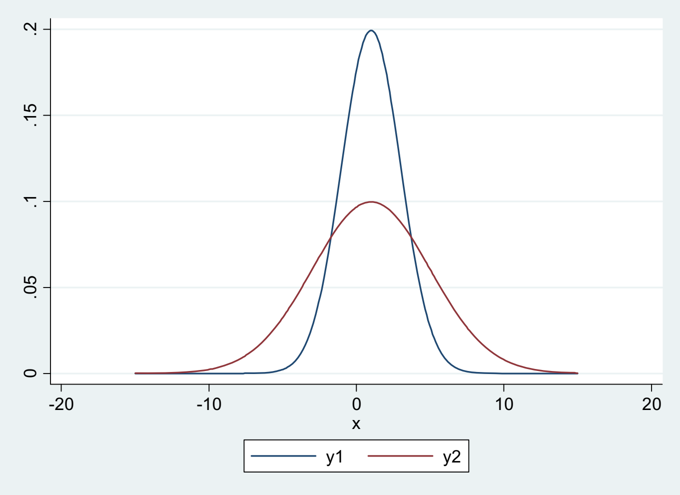


Fig. 3 Tight ($y1 \sim N(\mu, \sigma_1)$) versus loose prior ($y2 \sim N(\mu, \sigma_2)$) with $\mu = 1, \sigma_1 = 2, \sigma_2 = 4$, and$\sigma_1 < \sigma_2$

References

Angelini, E., Camba-Mendez, G., Giannone, D., Reichlin, L., & Rünstler, G. (2011). Short-term forecasts of euro area GDP growth. *Royal Econometric Society Econometrics Journal, 14*, C25–C44.

Aye, G. C., Dua, P., & Gupta, R. (2015). Forecasting Indian macroeconomic variables using medium scale VAR models. *Current Trends in Bayesian Methodology with Applications.*

Bai, J. (2009). Panel data models with interactive fixed effects. *Econometrica, 77*, 1229–1279.

Bai, J., & Ng, S. (2004). A PANIC attack on unit roots and cointegration. *Econometrica, 72*, 1127–1177.

Bernanke, B. (1986). Alternative exploration of the money-income correlation. *Carnegie-Rochester Conference Series on Public Policy, 25*, 49–100.

Bernanke, B., Boivin, S., & Eliasz, P. (2005). Measuring the effects of monetary policy. *Quarterly Journal of Economics, 120*, 387–422.

Bhanumurthy, N. R., & Kumawat, L. (2009). *External shocks and the Indian economy: Analyzing through a small, structural quarterly macroeconometric model* (No. 19776). Munich Personal RePEc Archive.

Blake, A., & Mumtaz, H. (2012). Technical handbook-No. 4 applied Bayesian econometrics for central bankers. *Bank of England Handbook in Central Banking.*

Blanchard, O. J., & Quah, D. (1989). The dynamic effects of aggregate demand and supply disturbances. *American Economic Review, 79*, 655–673.

Blanchard, O. J., & Watson, M. W. (1986). Are business cycles all alike? *The American Business Cycle: Continuity and Change*, 123–180.

Breitung, J., & Tenhofen, J. (2011). GLS estimation of dynamic factors models. *Journal of American Statistical Association, 106*, 1150–1166.

Camacho, M., Perez-Quiros, G., & Poncela. (2011). Green shoots in the euro area: A real time measure, WP 1026. The Central Bank of Spain Working Papers.

Camacho, M., Perez-Quiros, G., & Poncela. (2012). Markov-switching dynamic factor models in real time, WP 1205. Bank of Spain Working Paper Series.

Champernowne, D. G. (1960). An experimental investigation of the robustness of certain procedures for estimating means and regressions coefficients. *Journal of the Royal Statistical Society Series A, 123*, 398–412.

Christiano, L., Eichenbaum, M., & Evans, C. L. (2005). Nominal rigidities and the dynamic effects of a shock to monetary policy. *Journal of Political Economy, 113*, 1–45.

Clark, T. E., & Ravazzolo, F. (2012). The macroeconomic forecasting performance of autoregressive models with alternative specifications of time-varying volatility, WP 9/2012. Norges Bank Research Working Paper Series.

Cogley, T., & Sargent, T. J. (2002). Evolving post-world war II U.S. *Inflation Dynamics, NBER Macroeconomics Annual, 16*, 331–388.

Cooley, T., & LeRoy, S. (1985). A theoretical macroeconomics: A critique. *Journal of Monetary Economics, 16*, 283–308.

Dees, S., di Mauro, F., Pesaran, M. H., & Smith, L. V. (2005). Exploring the international linkages of the euro area: A global VAR analysis, WP 1425. CESifo Area Conference on Macro, Money and International Finance.

Del Negro, M., & Otrok, C. (2008). *Dynamic factor models with time-varying parameters. Measuring changes in international business cycles* (p. 325). Federal Reserve Bank of New York Staff Report.

Del Negro, M., & Schorfheide, F. (2013). DSGE model-based forecasting. *Handbook of Economic Forecasting, 2*, 57–140.

Doan, T. (1992). RATS user's manual. *Estima, 3.*

Doan, T., Litterman, R., & Sims, C. (1984). Forecasting and conditional projection using realistic prior distributions. *Econometric Reviews, 3*, 1–100.

Doz, C., Giannone, D., & Reichlin, L. (2011). A quasi maximum likelihood approach for large approximate dynamic factor models. *The Review of Economics and Statistics, 82*, 540–554.

Dua, P., & Goel, D. (2023). Forecasting India's inflation in a data rich environment: A FAVAR study. In P. Dua (Ed.), *Macroeconometric methods: Applications to the Indian economy*, Chapter 9, Springer Nature, Singapore

Dua, P., & Kapur, H. (2017). Macro stress testing of Indian Bank groups. *Margin—The Journal of Applied Economic Research, 11*, 375–403.

Dua, P. (2017). Macroeconomic modelling and Bayesian methods. *Journal of Quantitative Economics, 15*, 209–226.

Dua, P., & Kapur, H. (2023). A structural macroeconometric model for India. In P.Dua (Ed.), *Macroeconometric methods: Applications to the Indian Economy,*Chapter 10, Springer Nature, Singapore

Dua, P., & Miller, S. M. (1996). Forecasting Connecticut home sales in a BVAR framework using coincident and leading indexes. *The Journal of Real Estate Finance and Economics, 13*, 219–235.

Dua, P., Miller, S. M., & Smyth, D. J. (1999). Using leading indicators to forecast US home sales in a Bayesian VAR framework. *Journal of Real Estate Finance and Economics, 18*, 191–205.

Dua, P., Raje, N., & Sahoo, S. (2003). Interest rate modelling and forecasting in India, Study No. 24. Reserve Bank of India Development Research Group.

Dua, P., Raje, N., & Sahoo, S. (2008). Forecasting interest rates in India. *Margin—The Journal of Applied Economic Research, 2*, 1–41.

Dua, P., & Ranjan, R. (2010). Exchange rate policy and modelling in India, Study No. 33. Reserve Bank of India Development Research Group.

Dua, P., & Ranjan, R. (2012). *Exchange rate policy and modelling in India.* Oxford University Press.

Dua, P., Ranjan, R., & Goel, D. (2023). Forecasting the INR/USD exchange rate: A BVAR framework. In P. Dua (Ed.), *Macroeconometric methods: Applications to the Indian Economy*, Chapter 8, Springer Nature, Singapore.

Dua, P., & Ray, S. C. (1995). A BVAR model for the Connecticut economy. *Journal of Forecasting, 14*, 217–227.

Dua, P., & Sharma, V. (2016). A comparison of economic indicator analysis and Markov switching methods concerning the cycle phase dynamics. *OECD Journal: Journal of Business Cycle Measurement and Analysis*, 1–27.

Dua, P., & Sharma, V. (2023). International synchronization of growth rate cycles: An analysis in frequency domain. In P. Dua (Ed.), *Macroeconometric methods: Applications to the Indian Economy*, Chapter 11, Springer Nature, Singapore.

Dua, P., & Smyth, D. J. (1995). Forecasting US home sales using BVAR models and survey data on households' buying attitudes for homes. *Journal of Forecasting, 14*, 217–227.

Dua, P., & Suri, R. (2019). Inter-linkages between USD-INR, EUR-INR, GBP-INR and JPY-INR exchange rate markets and the impact of RBI Intervention. *Journal of Emerging Market Finance, 2019*(18), S102–S136.

Dua, P., & Suri, R. (2023). India's bi-lateral export growth and exchange rate volatility: A panel GMM approach. In P. Dua (Ed.), *Macroeconometric methods: Applications to the Indian Economy*, Chapter 6, Springer Nature, Singapore.

Dua, P., & Tuteja, D. (2015). Impact of Eurozone sovereign debt crisis on China and India. *Singapore Economic Review, 62*, 1137–1164.

Dua, P., & Tuteja, D. (2016a). Linkages between Indian and US financial markets: Impact of global financial crisis and Eurozone debt crisis. *Macroeconomics and Finance in Emerging Market Economies, 9*, 217–240.

Dua, P., & Tuteja, D. (2016b). Financial crises and dynamic linkages across international stock and currency markets. *Economic Modelling, 59*, 249–261.

Dua, P., Tuteja, D. (2023). Inter-linkages between Asian and U.S. stock markets: A multivariate GARCH analysis. In P. Dua (Ed.), *Macroeconometric methods: Applications to the Indian Economy*, Chapter 12, Springer Nature, Singapore.

Engle, R., & Granger, G. (1987). Cointegration and error-correction: Representation. *Estimation and Testing, Econometrica, 55*, 251–276.

Forni, M., & Reichlin, L. (1998). Let's get real: A factor analytical approach to disaggregated business cycle dynamics. *The Review of Economic Studies, 65*, 453–473.

Forni, M., Hallin, M., Lippi, M., & Reichlin, L. (2005). The generalized dynamic factor model. *Journal of the American Statistical Association, 100*, 830–840.

Forni, M., Hallin, M., Lippi, M., & Reichlin, L. (2001). Coincident and leading indicators for the euro area. *The Economic Journal, 111*, 62–85.

Giannone, D., Lenza, M., Pill, H., & Reichlin, L. (2012). The ECB and the interbank market. *The Economic Journal, 122*, F467–F486.

Giannone, D., & Reichlin, L. (2012). Nowcasting. *Handbook of Economic Forecasting*, *2*, Forthcoming.

Granger, C. W. J. (1986). Developments in the study of co-integrated economic variables. *Oxford Bulletin of Economics and Statistics, 48*, 213–228.

Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics, 2*, 111–120.

Gurkaynak, R. S., Kisacikoglu, B., & Rossi, B. (2013). Do DSGE models forecast more accurately out-of-sample than VAR models? *Advances in Econometrics, 32*.

Hall, T., Jacobs, J. P., & Pagan, A. (2013). Macro-econometric system modelling@ 75, paper presented at the Ken@75 conference in honour of Ken Wallis' 75th birthday, University of Warwick, July 2013.

Intriligator, MD., Bodkin, RG., & Hsia, C. (1996). Econometric Models, Techniques and Applications, New York: Prentice-Hall.

Johansen, S. (1991). Estimation and hypothesis testing of cointegrating vector in Gaussian vector autoregressive models. *Econometrica, 59*, 1551–1580.

Kadiyala, K. R., & Karlsson, S. (1997). Numerical methods for estimation and inference in Bayesian VAR-models. *Journal of Applied Econometrics, 12*, 99–132.

Kar, S., & Pradhan, B. K. (2009). Shocks, meltdowns, policy responses and feasibility of high growth in the Indian Economy: A macroeconometric approach. *Macro-modelling for the Eleventh Five Year Plan of India.*

King, R. G., Plosser, C. I., & Rebelo, S. T. (1988). Production, growth and business cycles: I. The basic neoclassical model. *Journal of Monetary Economics, 21*, 195–232.

Klein, L. R. (1950). Economic fluctuations in the United States, 1921–1941. *Cowles Commision for Research in Economics, 11*, 1–169.

Klein, L. R., & Goldberger, A. S. (1955). *An econometric model of the United States 1929–1952.* North-Holland Co.

Krishnamurthy, K. (2008). Macroeconometric models for India: Past, present and future. *Theory, Measurement and Policy: Evolving Themes in Quantitative Economics.*

Krishnamurthy, K. (2002). Macroeconomic models for India: Past, present and prospects. *Economic and Political Weekly, 37*, 4295–4308.

Krishnamurthy, K., Pandit, V., & Mahanty, G. (2004). Policies for stability and growth experiments with a large and comprehensive structural model for India. *Economic Policy Modelling for India.*

Kumar, A. G., & Panda, M. (2009). Global economic shocks and Indian policy response: An analysis using a CGE model. *Macro-Modelling for the Eleventh Five Year Plan of India.*

Kydland, F., & Prescott, E. (1982). Time to build and aggregate fluctuations. *Econometrica, 50*, 1345–1370.

Litterman, R. (1986). Forecasting with Bayesian vector autoregressions—Five years of experience. *Journal of Business and Economic Statistics, 4*, 25–38.

Litterman, R. B. (1982). Forecasting and policy analysis with Bayesian vector autoregression models. *Federal Reserve Bank of Minneapolis Quarterly Review, 4*, 30–41.

Litterman, R. B. (1981). A Bayesian procedure for forecasting with vector autoregressions. Federal Reserve Bank of Minneapolis Working Paper.

Long, J. B., & Plosser, C. (1983). Real business cycles. *Journal of Political Economy, 91*, 39–69.

Lucas, R. E. (1976). Econometric policy evaluation: A critique. *Carnegie-Rochester Series on Public Policy, 1*, 19–46.

Marcellino, M., & Schumacher, C. (2008). Factor-MIDAS for now- and forecasting with ragged-edge data: A model comparison for German GDP, No. 6708. CEPR Discussion Papers.

Moon, H. R., & Perron, B. (2004). Testing for a unit root in panels with dynamic factors. *Journal of Econometrics, 122*, 81–126.

Narayana, N. S. S., & Ghosh, P. P. (2009). Macroeconomic simulations based on VEC models. *Macro-modelling for the Eleventh Five Year Plan of India.*

Nelson, C. R., & Plosser, C. I. (1982). Trends and random walks in macro-economic time series. *Journal of Monetary Economics, 10*, 139–162.

Parida, P. C., & S. Bhide. (2013). Economic modelling of emerging scenarios for India's twelfth five year plan. *Margin: The Journal of Applied Economic Research, 8*, 495–565.

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica, 74*, 967–1012.

Pesaran, M. H., & Shin, Y. (1999). An autoregressive distributed-lag modelling approach to cointegration analysis. *Econometric Society Monographs, 31*, 371–413.

Pesaran, M. H., & Shin, Y. (2002). Long-run structural modelling. *Econometric Reviews, 21*, 49–87.

Pesaran, M. H., Schuermann, T., & Weiner, S. M. (2004). Modelling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business & Economic Statistics, 22*, 129–162.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics, 16*, 289–326.

Phillips, P. C. B. (1991). Optimal inference in cointegrated systems. *Econometrica, 59*, 283–306.

Phillips, P. C. B., & Sul, D. (2003). Dynamic panel estimation and homogeneity testing under cross section dependence. *The Econometrics Journal, 6*, 217–259.

Rotemberg, J., & Woodford, M. (1997). An optimization-based econometric framework for the evaluation of monetary policy. *NBER Macroeconomics Annual, 12*, 297–346.

Sachdeva, A. S., & Ghosh, P. P. (2009). A macro consistency planning model. *Macro-modelling for the Eleventh Five Year Plan of India.*
Sims, C. (2007). Bayesian methods in applied econometrics, or, why econometrics should always and everywhere be Bayesian. *Hotelling Lecture.*
Sims, C. (1986). Are forecasting models usable for policy analysis? *Quarterly Review Federal Reserve Bank of Minneapolis, 10*, 2–16.
Sims, C. (1980). Macroeconomics and reality. *Econometrica, 4*, 1–48.
Smets, F., & Wouters, R. (2003). An estimated dynamic stochastic general equilibrium model of the euro area. *Journal of the European Economic Association, 1*, 1123–1175.
Smets, F., & Wouters, R. (2007). Shocks and frictions in US business cycles: A Bayesian DSGE approach. *American Economic Review, 97*, 586–606.
Spencer, D. E. (1993). Developing a Bayesian vector autoregression forecasting model. *International Journal of Forecasting, 9*, 407–421.
Srivastava, D. K. (2013). Macro-econometric model of the Indian economy based on quarterly data. *RBI-MSE Macro-Modelling Project.*
Stock, J. H., & Watson, M. W. (1989). New indices of coincident and leading economic indicators. *NBER Macroeconomics Annual, 4*, 351–394.
Stock, J. H., & Watson, M. W. (2002a). Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association, 97*, 1167–1179.
Stock, J. H., & Watson, M. W. (2002b). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics, 20*, 147–162.
Theil, H. (1971). *Principles of econometrics.* North-Holland Co.
Tinbergen, J. (1939). *Statistical testing of business cycle theories* (p. 244). League of Nations Economic Intelligence Service.
Todd, R. M. (1984). Improving economic forecasting with Bayesian vector autoregression. *Quarterly Review Federal Reserve Bank of Minneapolis*, 18–29 (Fall).
Uhlig, H. (1997). Bayesian vector autoregressions with stochastic volatility. *Econometrica, 65*, 59–73.
Yule, G. U. (1926). Why do we sometimes get nonsense-correlations between time-series? *A Study in Sampling and the Nature of Time Series, Journal of the Royal Statistical Society, 89*, 1–64.
Zellner, A. (1979). Statistical analysis of econometric models. *Journal of the American Statistical Association, 74*, 628–643.
Zellner, A. (2000). *Bayesian and Non-Bayesian approaches to scientific modeling and inference in economics and econometrics,* Econometric Society World Congress 2000 Contributed Papers 1206, Econometric Society.
Zellner, A., & Palm, F. (1974). Time series analysis and simultaneous equation econometric models. *Journal of Econometrics, 2*, 17–54.

Chapter 3
Monetary Policy Framework in India

Pami Dua

Abstract In 2016, the monetary policy framework moved towards flexible inflation targeting and a six-member Monetary Policy Committee (MPC) was constituted for setting the policy rate. With this step towards modernization of the monetary policy process, India joined the set of countries that have adopted inflation targeting as their monetary policy framework. The Consumer Price Index (CPI combined) inflation target was set by the Government of India at 4% with ± 2% tolerance band for the period from August 5, 2016, to March 31, 2021. In this backdrop, the paper reviews the evolution of monetary policy frameworks in India since the mid-1980s. It also describes the monetary policy transmission process and its limitations in terms of lags and rigidities. It highlights the importance of unconventional monetary policy measures in supplementing conventional tools, especially during the easing cycle. Further, it examines the voting pattern of the MPC in India and compares this with that of various developed and emerging economies. The synchronization of cuts in the policy rate by MPCs of various countries during the global slowdown in 2019 and the COVID-19 pandemic in the early 2020s is also analysed.

Keywords Inflation targeting · Monetary policy committee · Monetary transmission process · Unconventional monetary policy measures

JEL Classification E4 · E5

1 Introduction

The monetary policy framework in India has evolved over the past few decades in response to financial developments and changing macroeconomic conditions. The operational framework of monetary policy has also gone through significant changes with respect to instruments and targeting mechanisms. The preamble of the Reserve

Reprinted from Indian Economic Review, Vol. 55, 117–154.

P. Dua (✉)
Department of Economics, Delhi School of Economics, University of Delhi, Delhi, India
e-mail: dua@econdse.org

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_3

Bank of India (RBI) Act, 1934 was also amended in 2016, which now clearly provides the mandate of the RBI. It reads as follows:

> To regulate the issue of Bank notes and keeping of reserves with a view to securing monetary stability in India and generally to operate the currency and credit system of the country to its advantage; to have a modern monetary policy framework to meet the challenge of an increasingly complex economy; to maintain price stability while keeping in mind the objective of growth.

The aim of monetary policy in the initial years of inception of RBI was mainly to maintain the sterling parity, with exchange rate being the nominal anchor of monetary policy. Liquidity was regulated through open market operations (OMOs), bank rate and cash reserve ratio (CRR). Soon after independence and through the late 1960s, the role of the central bank was aligned with the planned development process of the nation in accordance with the 5-year plans. Thus, it played a major role in regulating credit availability, employing OMOs, bank rate, and reserve requirement towards this end.

With the nationalization of major banks in 1969, the main objective of monetary policy through the 1970s till the mid-1980s was the regulation of credit in accordance with the developmental needs of the country. This period was marked by monetization of fiscal deficit while inflationary consequences of high public expenditure necessitated frequent recourse to CRR.

In 1985, on the recommendation of the Committee set up to Review the Working of the Monetary System (Chairman: Dr. Sukhamoy Chakravarty), a new monetary policy framework, monetary targeting with feedback was implemented based on empirical evidence of a stable demand for money function. However, financial innovations in the 1990s implied that demand for money may be affected by factors other than income. Further, interest rates were deregulated in the mid-1990s and the Indian economy was getting increasingly integrated with the global economy. Therefore, the RBI began to deemphasize the role of monetary aggregates and implemented a multiple indicator approach (MIA) to monetary policy in 1998 encompassing all economic and financial variables that influence the major objectives outlined in the Preamble of the RBI Act. This was done in two phases—initially MIA and later augmented MIA (AMIA) which included forward looking variables and time series models.

Based on RBI's Report of the Expert Committee to Revise and Strengthen the Monetary Policy Framework (2014, Chairman: Dr. Urjit R Patel), a formal transition was made in 2016 towards flexible inflation targeting and a six-member Monetary Policy Committee (MPC) was constituted for setting the policy repo rate. The Monetary Policy Framework Agreement (MPFA) was signed between the Government of India and the RBI in February 2015 to formally adopt the flexible inflation targeting (FIT) framework. This was followed up with the amendment to the RBI Act, 1934 in May 2016 to provide a statutory basis for the implementation of the FIT framework. With this step towards modernization of the monetary policy process, India joined the set of countries that adopted inflation targeting, starting from 1990 by New Zealand, as their monetary policy framework. The Central Government notified in the Official

Gazette dated August 5, 2016, that the Consumer Price Index (CPI) inflation target would be 4% with $\pm$ 2% tolerance band for the period from August 5, 2016, to March 31, 2021. At the time of writing (April 2020), this period is drawing to a close in less than a year. In this backdrop, this paper discusses the evolution of the monetary policy framework in India and describes the workings of the current framework.

The paper is divided into the following sections. Section 2 presents a schematic representation of the main components of a general monetary policy framework and describes its key features. Section 3 describes the genesis of the monetary policy framework in India since 1985 covering the monetary targeting framework, multiple indicator approach and flexible inflation targeting. The main recommendations of RBI's Report of the Expert Committee to Revise and Strengthen the Monetary Policy Framework (2014, Chairman: Dr. Urjit R. Patel) are also discussed. Composition, workings and voting pattern of the Monetary Policy Committee from October 2016 to March 2020 are also provided. Further, a comparison of voting patterns with various countries across the globe is undertaken.

Section 4 discusses a general framework for monetary policy transmission and applies the framework to India. It also describes interest rate linkages at the global level. Section 5 examines unconventional monetary policy measures adopted in late 2019 and early 2020. Section 6 concludes the paper.

2 Schematic Representation of a Monetary Policy Framework

The specification of the monetary policy framework facilitates the conduct of monetary policy. The general framework comprises well-defined objectives/goals of monetary policy along with instruments, operating targets and intermediate targets that aid in the implementation of monetary policy and achievement of the ultimate objectives. A schematic representation of a monetary policy framework is shown in Fig. 1 (Laurens et al., 2015; Mishkin, 2016).

Instruments are tools that the central bank has control over and are used to achieve the operational target. Examples of instruments include open market operations, reserve requirements, discount policy, lending to banks, policy rate. Operational targets are the financial variables that can be controlled by the central bank to a large extent through the monetary policy instruments and guide the day-to-day operations of the central bank. These can impact the intermediate target and thus help in the delivery of the final goal of monetary policy. Examples of operational targets include reserve money and short-term money market interest rates.

Instruments → Operating Targets → Intermediate Targets → Goals of Monetary Policy

Fig. 1 Key components of a monetary policy framework

Intermediate targets are variables that are closely related with the final goals of monetary policy and can be affected by monetary policy. Intermediate targets may include monetary aggregates and short-term and long-term interest rates. Goals refer to the final policy objectives. These may include price stability, economic growth, financial stability and exchange rate stability.

This general framework is applied to the monetary targeting framework with feedback that prevailed from 1985 to 1998 and to the inflation targeting framework that exists from 2016 onwards. The multiple indicator approach that was operational from 1998 to 2016 was based on a number of financial and economic variables and was not exactly specified on the basis of this framework although broad money was treated as an intermediate target and the goals of monetary policy are the same across the various frameworks.

3 Genesis of Monetary Policy in India Since 1985

3.1 Monetary Targeting with Feedback: 1985–1998

In the 1970s through the mid-1980s, monetization of the fiscal deficit exerted a dominant influence on monetary policy with inflationary consequences of high public expenditure necessitating frequent recourse to CRR. Against this backdrop, in 1985, on the recommendation of the Committee set up to Review the Working of the Monetary System (RBI, 1985; Chairman: Dr. Sukhamoy Chakravarty), a new monetary policy framework, monetary targeting with feedback was implemented based on empirical evidence of a stable demand for money function. The recommendation of the committee was to control inflation within acceptable levels with desired output growth. Further, instead of following a fixed target for money supply growth, a range was followed which was subject to mid-year adjustments. This framework was termed 'Monetary Targeting with Feedback' as it was flexible enough to accommodate changes in output growth.

This operational framework is depicted in Fig. 2. (Definitions of variables shown in Fig. 2 are given in Annexure 1). The main instruments in this framework were cash reserve ratio (CRR), open market operations (OMOs), refinance facilities and foreign exchange operations. Broad money (M3) was chosen as the intermediate target while reserve money (M0) was the main operating target. However, an analysis of money growth outcomes during the monetary targeting framework reveals that targets were rarely met (RBI, 2009–12). Even with increases in CRR, money supply growth remained high and fuelled inflation.

Further, financial innovations in the 1990s implied that demand for money may be affected by factors other than income. Since the mid-1990s, with global integration, factors such as swings in capital flows, volatility in the exchange rate and global growth also impacted the economy. Moreover, interest rates were deregulated

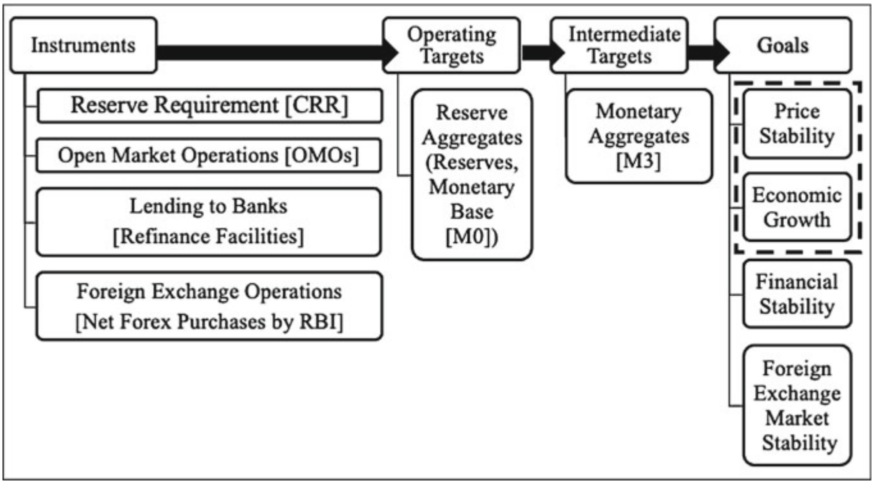


Fig. 2 Monetary policy linkages—monetary targeting in India operating framework: 1985–1998
Notes (1) Primary objective of monetary policy in India is to maintain price stability, while keeping in mind the objective of growth (2) Definitions of variables are given in Annexure 1. *Source* Author

allowing for changing interest rates and a market determined management system of exchange rates was also adopted.

3.2 Multiple Indicator Approach: 1998–2016

Against the backdrop of changing domestic and global dynamics, RBI implemented a multiple indicator approach (MIA) to monetary policy in 1998 encompassing various economic and financial variables based on the recommendations of RBI's Working Group on Money Supply (RBI, 1998; Chairman: Dr. Y. V. Reddy). These variables included several quantity variables such as money, credit, output, trade, capital flows, fiscal indicators as well as rate variables such as interest rates, inflation rate and the exchange rate. The information on these variables provided a broad-based monetary policy formulation, which not only encompassed a diverse set of information but also accorded flexibility to the conduct of monetary management.

The MIA was conceptualized when Dr. Bimal Jalan was Governor and was implemented in two stages—MIA and later Augmented MIA, by including forward looking variables and a panel of time series models, in addition to the economic and financial variables (Mohanty, 2010; Reddy, 1999). Forward-looking indicators were drawn from RBI's industrial outlook survey, capacity utilization survey, inflation expectations survey and professional forecasters' survey. All the variables together with time series models provided the projection of growth and inflation while RBI provided the projection for broad money (M3) and treated this as the intermediate target.

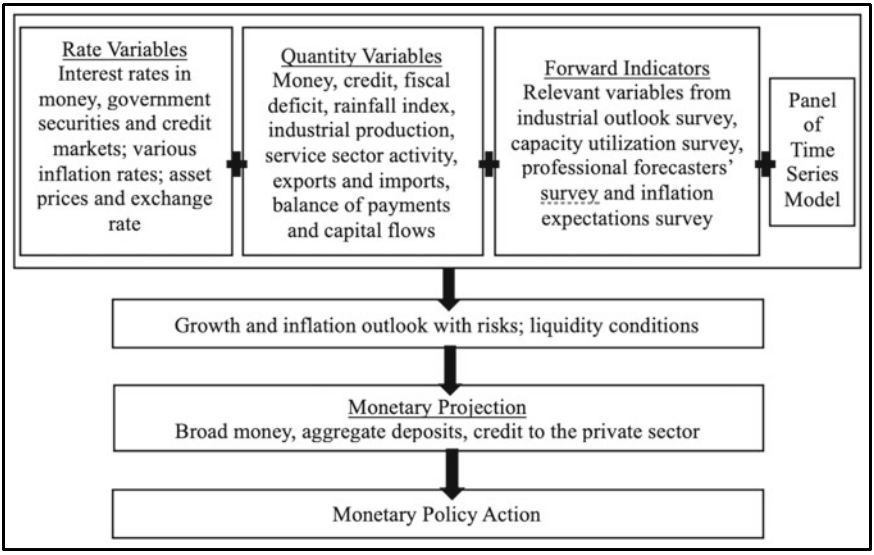


Fig. 3 Augmented multiple indicator approach (AMIA) operating framework: 1998–2016. Notes: (1) *Source* RBI Bulletin, December 2011

The operational framework of AMIA is illustrated in Fig. 3. Compared to the Monetary Targeting Framework, the goals of monetary policy remained the same and broad money continued to serve as the intermediate target while the underlying operating mechanism of MIA evolved over time. In May 2011, the weighted average call money rate (WACR) was explicitly recognized as the operating target of monetary policy while the repo rate was made the only one independently varying policy rate. These measures improved the implementation and transmission of monetary policy along with enhancing the accuracy of signalling of monetary policy stance (Mohanty, 2011).

3.2.1 Shift Towards Inflation Targeting

The importance of focusing on inflation was first highlighted in the Report of the Committee on Financial Sector Reforms (Government of India, 2009; Chairman: Dr. Raghuram Rajan) constituted by the Government of India. The report recommended that RBI can best serve the cause of growth by focusing on controlling inflation and intervening in currency markets only to limit excessive volatility. The report pointed out that the cause of inclusion can also be best served by maintaining this focus because the poorer sections are least hedged against inflation. Further, the report recommended that there should be a single objective of staying close to a low inflation number, or within a range, in the medium term, moving steadily to a single instrument, the short-term interest rate to achieve it.

Former RBI Governor, Dr. Raghuram Rajan set up an Expert Committee in 2013 to Review and Strengthen the Monetary Policy Framework (RBI, 2014; Chairman: Dr Urjit R. Patel). The mandate of the Committee, amongst others, was to review the objectives and conduct of monetary policy in a globalized and highly inter-connected environment. The committee was also required to review the organizational structure, operating framework and instruments of monetary policy, liquidity management framework, to ensure compatibility with macroeconomic and financial stability, as well as market development. The impediments to monetary policy transmission were to be identified and measures along with institutional pre-conditions to improve transmission across financial markets and real economy were to be suggested.

Some issues central to the report were selecting the nominal anchor for monetary policy, defining the inflation metric and specifying the inflation target. A nominal anchor is central to a credible monetary policy framework as it ties down the price level or the change in the price level to attain the final goal of monetary policy. It is a numerical objective that is defined for a nominal variable to signal the commitment of monetary policy towards price stability.

Generally, five types of nominal anchors have been used, namely, monetary aggregates, exchange rate, inflation rate, national income and price level. The Expert Committee recommended inflation to be the nominal anchor of the monetary policy framework in India as flexible inflation targeting recognizes the existence of growth-inflation trade-off in the short-run and stabilizing and anchoring inflation expectations is critical for ensuring price stability on an enduring basis. Further, low and stable inflation is a necessary precondition for sustainable high growth and inflation is also easily understood by the public.

Regarding the inflation metric, the Committee recommended that RBI should adopt the all India CPI (combined) inflation as the measure of the nominal anchor. This is to be defined in terms of headline CPI inflation, which closely reflects the cost of living and influences inflation expectations relative to other available metrics. CPI is also easily understood as it is used as a reference in wage contracts and negotiations. Headline inflation was preferred against core inflation (headline inflation excluding food and fuel inflation) since food and fuel comprise more than 50% of the consumption basket and cannot be discarded.

The Committee recommended the target level of inflation at 4% with a band of ± 2% around it. The tolerance band was formulated in the light of the vulnerability of the Indian economy to supply and external shocks and the relatively large weight of the food in the CPI basket.

The Expert Committee also recommended that decision-making should be vested in a Monetary Policy Committee (MPC).

3.3 Flexible Inflation Targeting: 2016 Onwards

With the signing of the Monetary Policy Framework Agreement (MPFA) between the Government of India and the RBI on Feb. 20, 2015, Flexible Inflation Targeting

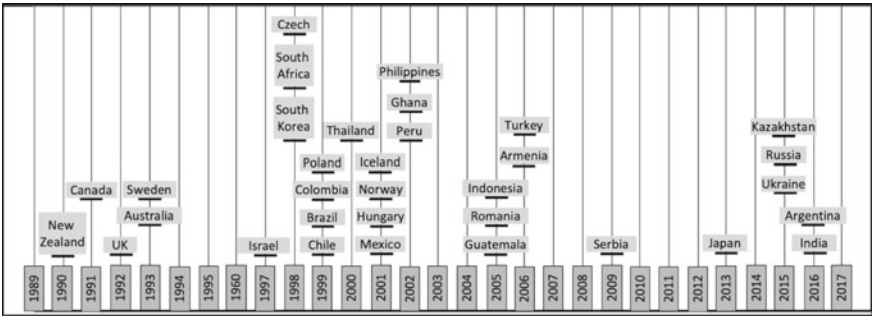


Fig. 4 Inflation targeting regime adoption. Notes: (1) *Source* Hammond (2012), Hattori and Yetman (2017), Korhonen and Nuutilainen (2017), The Economist (2016), Central Bank Websites of Kazakhstan and Ukraine

(FIT) was formally adopted in India. In May 2016, the Reserve Bank of India (RBI) Act, 1934 was amended to provide a statutory basis for the implementation of the FIT framework. The amended RBI Act, 1934 also provided that the Central Government shall, in consultation with the Bank, determine the inflation target in terms of the Consumer Price Index, once in every 5 years.

Accordingly, the Central Government has notified in the Official Gazette 4% Consumer Price Index (CPI) inflation as the target for the period from August 5, 2016, to March 31, 2021, with the upper tolerance limit of 6% and the lower tolerance limit of 2%. The amended RBI Act, 1934 also provides that RBI shall be seen to have failed to meet the target if inflation remains above 6% or below 2% for three consecutive quarters. In such circumstances, RBI is required to provide the reasons for the failure and propose remedial measures and the expected time to return inflation to the target.

In 2016, India thus joined several developed and emerging market economies that have implemented inflation targeting. Figure 4 shows the timeline for implementation of inflation targeting for countries in this category, starting in 1990.

3.3.1 Monetary Policy Committee: Composition, Monetary Policy Framework and Voting Patterns

The amended RBI Act, 1934 provides for a statutory and institutionalized framework for a six-member Monetary Policy Committee (MPC) to be constituted by the Central Government by notification in the Official Gazette. The Central Government in September 2016 thus constituted the MPC with three members from RBI including the Governor as Chairperson and three external members as per Gazette Notification dated September 29, 2016. (Details of the composition of MPC are given in Annexure 3). The Committee is required to meet at least four times a year although it has been meeting on a bi-monthly basis since October 2016. Each member of the MPC has one vote, and in the event of equality of votes, the Governor has a second or casting vote. The resolution adopted by the MPC is published after conclusion of every meeting of the MPC. On the fourteenth day, the minutes of the proceedings of the MPC are published which includes the resolution adopted by the MPC, the vote of each member on the resolution, and the statement of each member on the resolution.

It may be noted that before the constitution of the MPC, a Technical Advisory Committee (TAC) on Monetary Policy was set up in 2005 which consisted of external experts from monetary economics, central banking, financial markets and public finance. The role of this committee was to enhance the consultative process of monetary policy by reviewing the macroeconomic and monetary developments in the economy and advising RBI on the stance of monetary policy. With the formation of MPC, the TAC on Monetary Policy ceased to exist.

The MPC is entrusted with the task of fixing the benchmark policy rate (repo rate) required to contain inflation within the specified tolerance band. The framework entails setting the policy rate on the basis of current and evolving macroeconomic conditions. Once the repo rate is announced, the operating framework looks at liquidity management on a day-to-day basis with the aim to anchor the operating target—the weighted average call rate (WACR)—around the repo rate. This is illustrated in Fig. 5, where the intermediate targets are the short-term and long-term interest rates and the goals of price stability and economic growth are aligned with the primary objective of monetary policy to maintain price stability, keeping in mind the objective of growth. In addition to the repo rate, the instruments include liquidity facility, CRR, OMOs, lending to banks and foreign exchange operations (RBI, 2018).

It is imperative here to note some of the key elements of the revised framework for liquidity management (RBI, 2019) that are particularly relevant for the operating framework shown in Fig. 5. As noted in the RBI Monetary Policy Report, 2020:

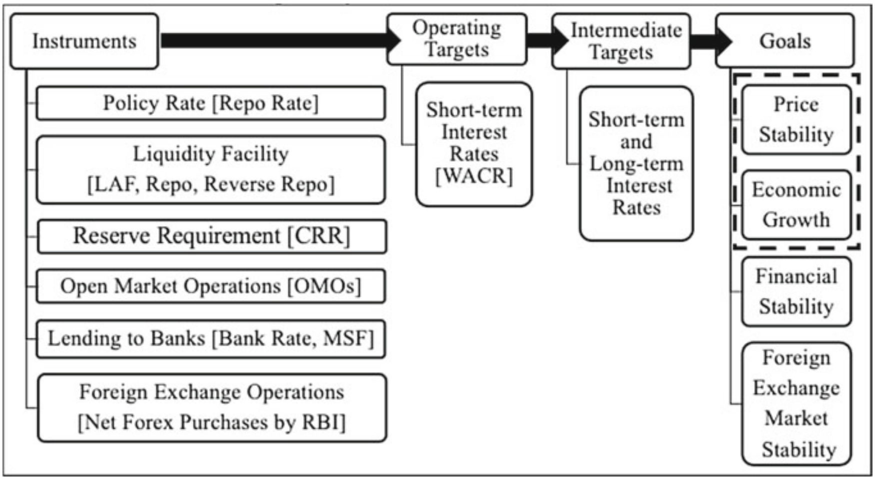


Fig. 5 Monetary policy linkages—interest rate targeting in India operating framework: 2016 onwards. *Notes* (1) Primary objective of monetary policy in India is to maintain price stability, while keeping in mind the objective of growth (2) Definitions of variables are given in Annexure 1

- Liquidity management remains the operating procedure of monetary policy; the weighted average call rate (WACR) continues to be its operating target.
- The liquidity management corridor is retained, with the marginal standing facility (MSF) rate as its upper bound (ceiling) and the fixed reverse repo rate as the lower bound (floor), with the policy repo rate in the middle of the corridor.
- The width of the corridor is retained at 50 basis points—the reverse repo rate being 25 basis points below the repo rate and the MSF rate 25 basis points above the repo rate. (The corridor width was asymmetrically widened on March 27, and April 17, 2020.)
- Instruments of liquidity management continue to include fixed and variable rate repo/reverse repo auctions, outright open market operations, forex swaps and other instruments as may be deployed from time to time to ensure that the system has adequate liquidity at all times.
- The current requirement of maintaining a minimum of 90% of the prescribed CRR on a daily basis will continue. (This was reduced to 80% on March 27, 2020.)

The first meeting of the MPC was held in October 2016. Between October 2016 and March 2020, the MPC has met 22 times. Table 1 shows the voting patterns for each meeting with respect to the direction of change in the policy rate, magnitude of change and the stance of monetary policy. Table 2, on the other hand, provides an overall summary of the voting of all the meetings. It is interesting to note in Table 2, that with respect to direction of change/status quo of the policy rate, consensus was achieved in 12 meetings out of 22. Of these 12 meetings, there were 3 meetings where there were differences in the magnitude of the change voted for although there was consensus regarding the direction of change. The diversity in voting of the MPC members reflects the differences in the assessment and expectations of individual members as well as their policy preferences.

To examine if this diversity exists in MPCs of other countries as well, we analyse the voting patterns of 18 countries across the globe during October 2018 to March 2020 in Table 3. For many countries, we find dissents in some of the meetings, similar to the lack of consensus in some of the meetings of the Indian MPC.

It merits mention that the committee approach towards the conduct of monetary policy has gained prominence across globe. The advantages of this approach include confluence of specialized knowledge and expertise on the subject domain, bringing together different stakeholders and diverse opinions, improving representativeness and collective wisdom, thus making the whole greater than the sum of parts (Blinder and Morgan, 2005; Maier, 2010). Further, Rajan (2017) notes that MPC would bring more minds to bear on policy setting, preserve continuity in case a member has to quit or retire, and be less subject to political pressures.

Table 1 RBI MPC policy repo rates (October 2016–March 2020)

Date	Policy repo rate voting and decision	Stance decision and voting
October 2016	Reduce 25 bps [6–0] 6.50–**6.25**	Accommodative 6–0
December 2016	Maintain **6.25** bps [6–0]	Maintain accommodative 6–0
February 2017	Maintain **6.25** bps [6–0]	<u>Change to neutral</u> 6–0
April 2017	Maintain **6.25** bps [6–0]	Maintain neutral 6–0
June 2017	Maintain **6.25** bps [5–1] *Reduce 50 bps [1]*	Maintain neutral 6–0
August 2017	Reduce 25 bps [4–2] 6.25 to **6.00 bps** *Reduce 50 bps [1]* *Maintain 6.25 bps [1]*	Maintain neutral 6–0
October 2017	Maintain **6.00** bps [5–1] *Reduce 25 bps [1]*	Maintain neutral 6–0
December 2017	Maintain **6.00** bps [5–1] *Reduce 25 bps [1]*	Maintain neutral 6–0
February 2018	Maintain **6.00** bps [5–1] *Increase 25 bps [1]*	Maintain neutral 6–0
April 2018	Maintain **6.00** bps [5–1] *Increase 25 bps [1]*	Maintain neutral 6–0
June 2018	Increase 25 bps [6–0] 6.00 to **6.25** bps	Maintain neutral 6–0
August 2018	Increase 25 bps [5–1] 6.25 to **6.5** *Maintain 6.25 bps [1]*	Maintain neutral 6–0
October 2018	Maintain **6.50** bps [5–1] *Increase 25 bps [1]*	<u>Change to calibrated tightening</u> 5–1
December 2018	Maintain **6.50** bps [6–0]	Maintain calibrated tightening 5–1

(continued)

Table 1 (continued)

Date	Policy repo rate voting and decision	Stance decision and voting
February 2019	Reduce 25 bps [4–2] 6.5 to **6.25** bps *Maintain 6.5 bps [2]*	<u>Change to neutral</u> 6–0
April 2019	Reduce 25 bps [4–2] 6.25 to **6.0** bps *Maintain 6.25 bps [2]*	Maintain neutral 5–1
June 2019	Reduce 25 bps [6–0] 6.0–**5.75** bps	<u>Change to accommodative</u> 6–0
August 2019	Reduce [6–0] Reduce 35 bps [4] 5.75 to **5.40** bps *Reduce 25 bps [2]*	Maintain accommodative 6–0
October 2019	Reduce [6–0] Reduce 25 bps [5] 5.40–**5.15** *Reduce 40 bps [1]*	Maintain accommodative 6–0
December 2019	Maintain **5.15** bps [6–0]	Maintain accommodative 6–0
February 2020	Maintain **5.15** bps [6–0]	Maintain accommodative 6–0
March 2020	Reduce [6–0] Reduce 75 bps [4] 5.15–**4.40** bps *Reduce 50 bps [2]*	Maintain accommodative 6–0

Notes: (1) *Source* Reserve Bank of India Monetary Policy Committee Meeting Press Releases and Minutes.
(2) The decided rates are in bold, the minority votes are italicized, the meetings with changes in stance are underlined

4 Monetary Policy Transmission Framework

This section presents a stylized representation of a framework for monetary policy transmission and also applies this framework to India.

Monetary policy transmission is the process through which changes in monetary policy affect economic activity in general as well as the price level. With developments in financial systems, the world over and growing sophistication of financial markets, most central banks use the short-term interest rate as the policy instrument for the conduct of monetary policy. Monetary policy transmission is thus the process through which a change in the policy rate is transmitted first to the short-term money market rate and then to the entire maturity spectrum of interest rates covering the

Table 2 RBI MPC voting summary (October 2016–March 2020)

Total meetings	Meetings with decision to *increase* rates	Meetings with decision to *decrease* rates	Meetings with decision to *maintain* rates	Meetings with consensus regarding direction of change/status quo
22	2	8	12	12
	June 2018 Aug. 2018	Oct. 2016 Aug. 2017 Feb. 2019 April 2019 June 2019 Aug. 2019 [35 bps vs. 25 bps]: 4–2 Oct. 2019 [25 bps vs 40 bps]: 5–1 March 2020 [75 bps vs 50 bps]: 4–2	Dec. 2016 Feb. 2017 April 2017 June 2017 Oct. 2017 Dec. 2017 Feb. 2018 April. 2018 Oct. 2018 Dec. 2018 Dec. 2019 Feb 2020	Oct. 2016 Dec. 2016 Feb. 2017 April 2017 June 2018 Dec. 2018 June 2019 Aug. 2019 [35 bps vs. 25 bps]: 4–2 Oct. 2019 [25 bps vs 40 bps]: 5–1 Dec 2019 Feb. 2020 March 2020 [75 bps vs. 50 bps]: 4–2

Notes: (1) *Source* Reserve Bank of India Monetary Policy Committee Meeting Press Releases and Minutes.
(2) The meetings without consensus on magnitude of rate change are underlined

money and bond markets as well as banks' deposit and lending rates. These impulses, in turn, impact consumption (private and government), investment and net exports, which affect aggregate demand and hence output and inflation.

There are five channels of monetary transmission—interest rate channel; exchange rate channel; asset price channel; credit channel and expectations channel. The *interest rate channel* is described above. Monetary transmission takes place through the *exchange rate channel* when changes in monetary policy impact the interest rate differential between domestic and foreign rates leading to capital flows (inflow or outflow) which in turn affects the exchange rate and hence the relative demand for exports and imports. Transmission through the *asset price channel* occurs when changes in monetary policy influence the price of assets such as equity and real estate that lead to changes in consumption and investment. A change in prices of assets can lead to a change in consumption spending due to the associated wealth effect. For example, if interest rates fall, people may consider purchasing assets that are non-interest bearing such as real estate and equity. A rise in demand for these assets may result in higher prices, a positive wealth effect and thus higher consumption. Further, if equity prices rise, firms may increase investment spending. Transmission through the *credit channel* happens if monetary policy influences the quantity of available credit. This may happen if the willingness of financial institutions to lend

Table 3 Monetary policy committees: voting patterns in various countries (October 2018–March 2020)

Continent	Country	Meetings statistics				
		Total	Consensus	Dissent	Meetings with rate cuts	
Africa	South Africa	10	6	4	4	July 18, 2019, Jan. 6, 2020, Mar. 19, 2020, Apr 14, 2020
Asia	China	8	N/A	N/A	4	Aug. 21, 2019, Sept. 20, 2019, Nov. 20, 2019, Feb. 20, 2020
	India	10	7	3	7	Feb. 21, 2019, Apr. 18, 2019, June 20 2019, Aug. 9, 2019, Oct. 4, 2019, Feb. 6, 2020, Mar. 27, 2020
	Japan	11	0	11	0	Maintain Status Quo
	Thailand	13	8	5	4	Aug. 7, 2019, Nov. 6, 2019, Feb. 5, 2020, Mar. 20, 2020
Europe	Czech Republic	13	4	9	2	Mar. 16, 2020, Mar. 26, 2020
	ECB	12	N/A	N/A	1	Sep. 12, 2019
	Hungary	18	18	0	0	Maintain Status Quo
	Sweden	9	5	4	0	Maintain Status Quo
	UK	13	10	3	2	Mar. 10, 2020, Mar. 26, 2020
Europe/Asia	Russia	11	N/A	N/A	5	June 14, 2019, July 26, 2019, Sep. 6, 2019, Oct. 25, 2019, Dec. 13, 2019, Feb. 7, 2020
Middle East	Israel	12	3	9	1	April 6, 2020
North America	Canada	15	N/A	N/A	3	Mar. 4, 2020, Mar. 16, 2020, Mar. 27, 2020

(continued)

Table 3 (continued)

Continent	Country	Meetings statistics				
		Total	Consensus	Dissent	Meetings with rate cuts	
	US	14	9	5	5	July 31 2019, Sep. 18, 2019, Oct. 30, 2019, Mar. 3, 2020, Mar. 15, 2020
Oceania	Australia	17	N/A	N/A	5	June 4, 2019, July 2, 2019, Oct. 1, 2019, Mar. 3, 2020, Mar. 18, 2020
South America	Brazil	12	12	0	6	July 30, 2019, Sep. 17, 2019, Oct. 29, 2019, Dec. 10, 2019, Feb. 4, 2020, Mar. 18, 2020
	Chile	13	11	2	5	June 7, 2019, Sep. 3, 2019, Oct. 23, 2019, Mar. 16, 2020, Mar. 31, 2020
	Colombia	11	11	0	1	Mar. 27, 2020

Source Central Bank Websites, Press Releases and Minutes of the Meetings

changes due to a change in monetary policy. Further, debt obligations of businesses may also change due to a change in the interest rate. For instance, if the policy rate falls, debt obligations of firms may decrease, strengthening their balance sheets. As a result, financial institutions may be more willing to lend to businesses, thus increasing investment spending. Monetary policy changes can impact public's expectations of output and inflation and accordingly, aggregate demand can be impacted via the *expectations channel.* For instance, expected future changes in the policy rate can impact medium-term and long-term expected interest rates through market expectations and thus affect aggregate demand. Further, if inflation expectations are firmly anchored by the central bank, this would imply price stability.

A stylized representation of the monetary policy transmission framework of a change in the policy rate is shown in Fig. 6. Figure 7 depicts the monetary transmission through the interest rate channel with specific reference to India. (Definitions of all variables shown in Fig. 6 are given in Annexure 2). This shows that a change in the policy rate (repo rate) first impacts the call money rate (weighted average call money rate—WACR) and in turn all other money market rates as well as bond market rates including the repo market, certificates of deposit (CD) and commercial paper (CP) markets, Treasury Bill (T-Bill) market, Government Securities (G-Sec) market and

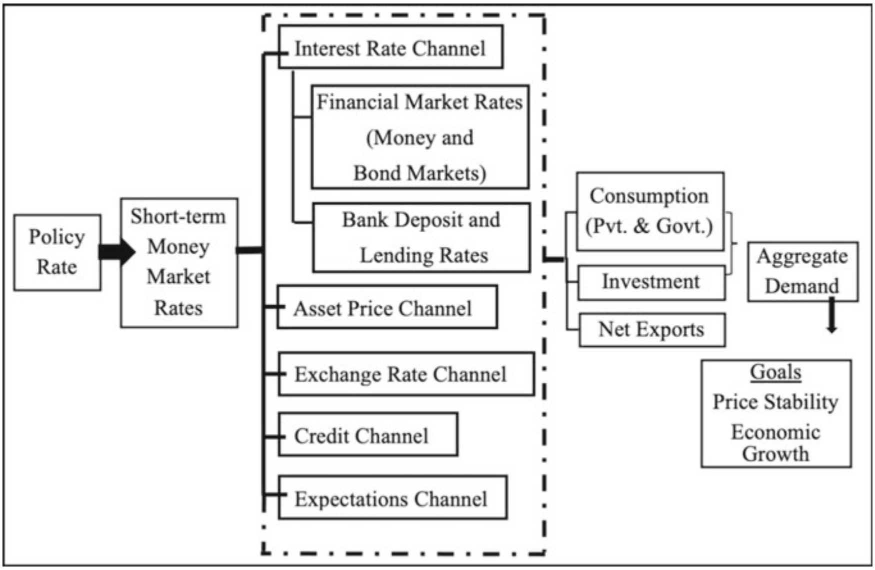


Fig. 6 Monetary policy transmission framework.
Source Author

the Bond Market. The lending rate of banks also changes as depicted by the marginal cost of fund-based lending rate (MCLR). This further impacts consumption and investment decisions as well as net exports and through these, aggregate demand and ultimately the goals of monetary policy. Details of the monetary transmission process are given in RBI (2020c).

The transmission mechanism is beset with lags. As explained in simple terms in Rangarajan (2020), there are two components of the transmission mechanism. The first is how far the signals sent out by the central bank are picked by the banks, and the second is how far the signals sent out by the banking system impact the real economy. Rangarajan (2020) labels the first component as 'inner leg' and the second as 'outer leg'.

To illustrate monetary transmission of the first kind, we examine the impact of a cumulative reduction in the policy repo rate by 135 basis points between February 2019 and January 2020. During this period, transmission to various money and bond markets ranged from 146 basis points in the overnight call money market to 73 basis points in the market for 5-year government securities to 76 basis points in the market for 10-year government securities. Transmission to the credit market was also modest with the 1-year median marginal cost of funds based lending rate (MCLR) declining by 55 basis points during February 2019 and January 2020. The weighted average lending rate (WALR) on fresh rupee loans sanctioned by banks fell by 69 basis points, while the WALR on outstanding rupee loans declined by 13 basis points during February to December 2019.

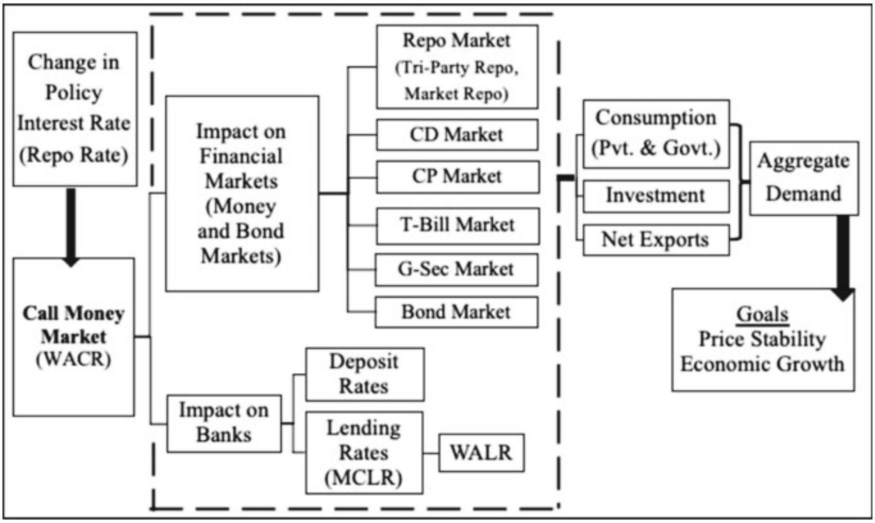


Fig. 7 Monetary policy transmission in India—interest rate channel. *Notes* (1) Definitions of variables are given in Annexure 2. *Source* Author

Monetary transmission increased somewhat after the introduction of the external benchmark system in October 2019, whereby most banks have linked their lending rates to the policy repo rate of the Reserve Bank. During October to December 2019, the WALRs of domestic banks on fresh rupee loans fell by 18 basis points for housing loans, 87 basis points for vehicle loans and 23 basis points for loans to micro, small and medium enterprises (MSMEs).

Monetary transmission in various markets is depicted in Figs. 8, 9 and 10. Figure 8 shows the policy corridor with the MSF rate as the ceiling and the reverse repo rate as the floor for the daily movement in the weighted average call money rate. The figure shows that the WACR moved closely in tandem with the policy rate (repo rate). Figure 9 shows that the G-Sec market rates followed the movements in the policy rate. Figure 10 shows that the direction of change of MCLR was more or less in synchronization with that of the repo rate. The WALR for fresh rupee loans tracked the repo rate much more than the WALR on outstanding loans.

Figure 11 shows the 4% target inflation rate with the ± 2% tolerance band along with the headline inflation rate. This shows that the headline inflation generally stayed within the band. The average inflation rate from August 2016 to March 2020 was 3.93%, and up to December 2019, it was 3.72%, i.e. close to 4%. The average GDP growth between Q2: 2016–17 and Q3: 2019–20 was 6.6% (Fig. 12).

An interesting phenomenon, worldwide, is the synchronization in the movements in interest rates across the globe. Table 4 shows that MPCs in various countries have voted for a cut in their policy rate in 2019 at a time when many countries were simultaneously experiencing a slowdown. Due to COVID-19 pandemic, in early 2020, some countries have cut the policy rate sharply.

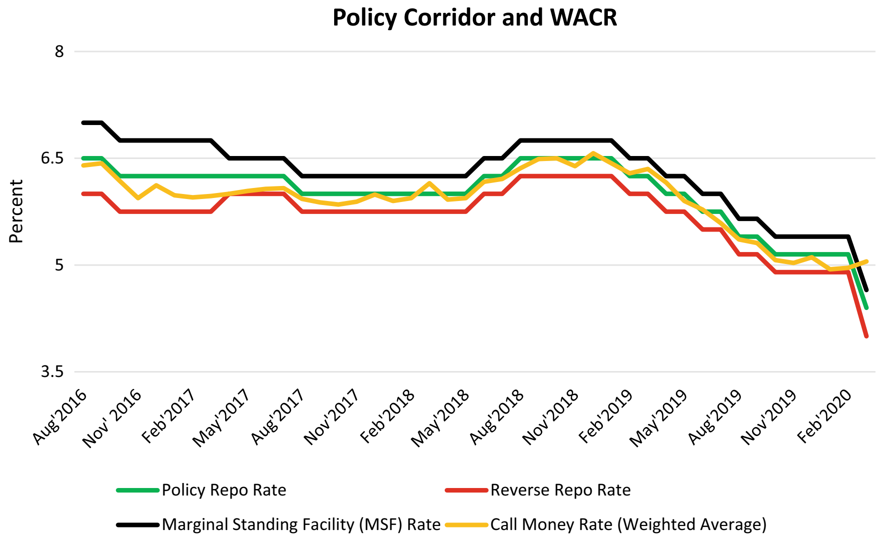


Fig. 8 Policy corridor and WACR. Notes: (1) *Source* RBI Database on Indian Economy, RBI Weekly Statistical Supplement

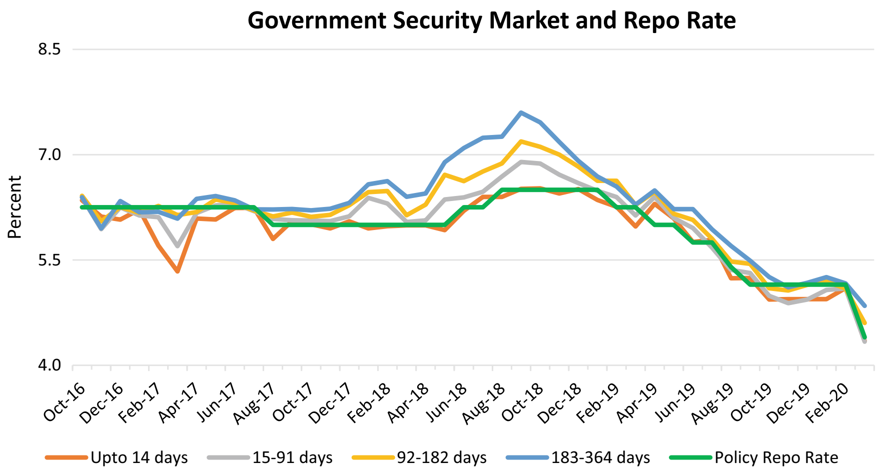


Fig. 9 Government security market and repo rate. Notes: (1) *Source* RBI Database on Indian Economy

This pattern of rate cuts in 2019 up to March 2020 is almost perfectly aligned with the movements in the repo rate (policy rate) in India. These global patterns are illustrated in Figs. 13 and 14. Figure 13 shows that the policy rates for the BRICS nations moved in tandem from 2017 to 2020. Figure 14 indicates a similar pattern amongst policy rates of USA, ECB, UK and Japan.

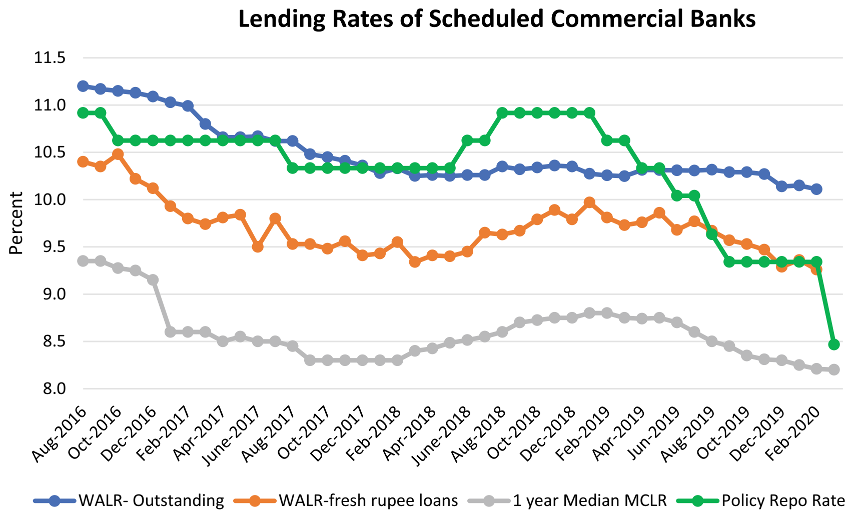


Fig. 10 Lending rates of scheduled commercial banks. Notes: (1) *Source* RBI Website

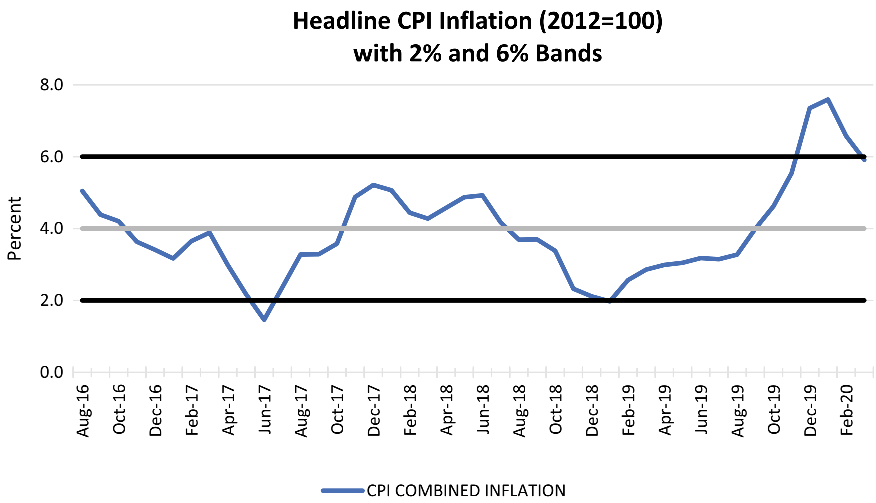


Fig. 11 Headline CPI inflation (2012 = 100) with 2 and 6% bands. Notes: (1) *Source* Ministry of Statistics and Programme Implementation, GOI

5 Unconventional Monetary Policy Measures

We have so far discussed conventional monetary policy. As already described, monetary transmission of conventional monetary policy entails a change in the policy rate impacting financial markets from short-term interest rates to longer-term bonds and

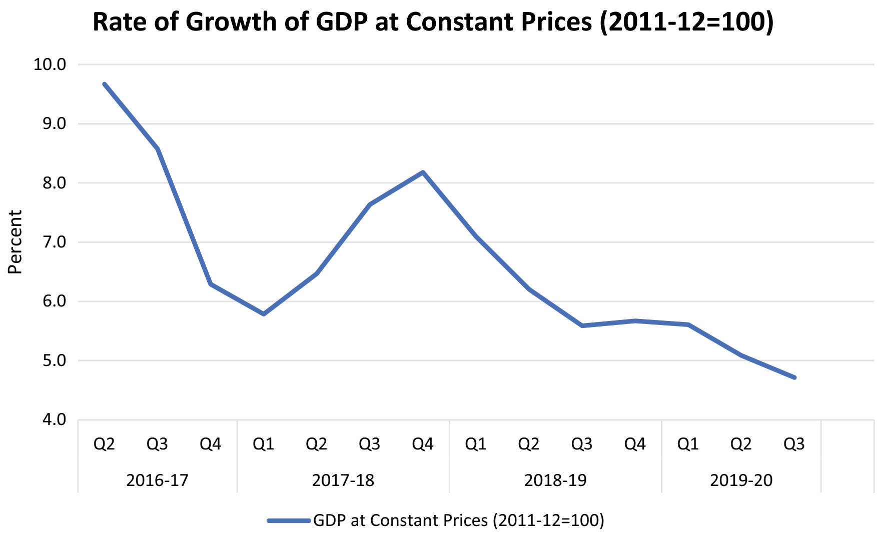


Fig. 12 Rate of growth of GDP at constant prices (2011–12 = 100). Notes: (1) *Source* Ministry of Statistics and Programme Implementation, GOI

Table 4 Monetary policy committees: change in policy rate in various countries (October 2018–March 2020)

Continent	Country	Policy rate as of March 31, 2020	Total rate cuts (bps)
Africa	South Africa	4.25	– 250
Asia	China	4.05	– 20
	India	4.40	– 210
	Japan	– 0.10	0
	Thailand	0.75	– 100
Europe	Czech Republic	1.00	– 125
	ECB	– 0.50	– 10
	Hungary	0.90	0
	Sweden	0.00	0
	UK	0.10	– 65
Europe/Asia	Russia	6.00	– 175
Middle East	Israel	0.10	– 15
North America	Canada	0.25	– 150
	US	0.00–0.25	– 225
Oceania	Australia	0.25	– 125
South America	Brazil	3.75	– 275
	Chile	0.50	– 225
	Colombia	3.75	– 50

Source Central Bank Websites, Press Releases and Minutes of the Meetings

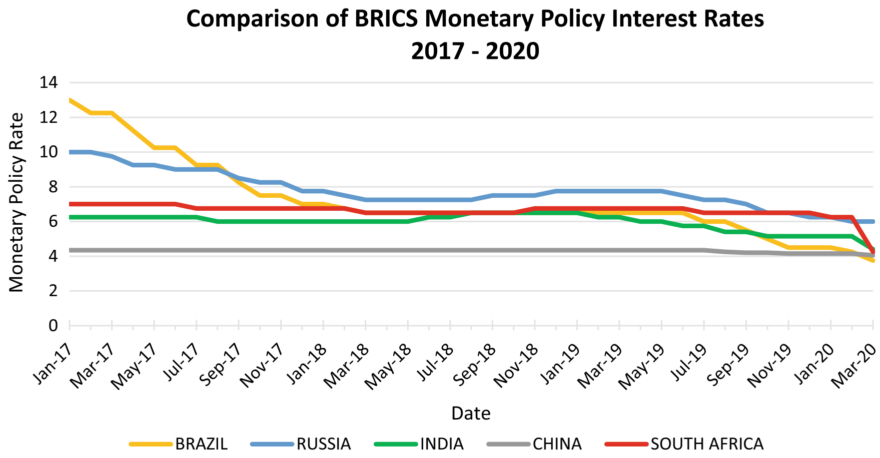


Fig. 13 Comparison of BRICS monetary policy interest rates 2017–2020. Notes: (1) *Source* Central Bank Websites (2) *Brazil*: Selic Rate; *Russia*: Key Rate; *India*: Repo Rate; *China*: Interest Rate; *South Africa*: Repo Rate

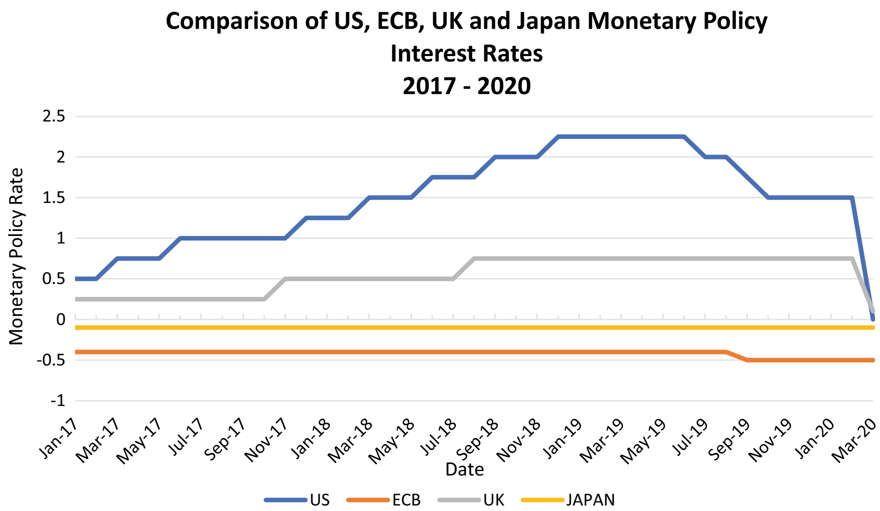


Fig. 14 Comparison of US, ECB, UK and Japan Monetary Policy Interest Rates 2017–2020. Notes: (1) *Source* Central Bank Websites (2) *USA*: Fed Funds Rate; *ECB*: Interest Rate on the Deposit Facility; *UK*: Bank Rate; *Japan*: Policy Interest Rate

bank funding and lending rates. A change in the policy rate is thus expected to permeate through the entire spectrum of rates that further translates into affecting interest sensitive spending and thus economic activity. However, if there are problems in the monetary policy transmission mechanism or if additional monetary stimulus is required in the circumstances that the policy rate cannot be reduced further (or in addition to a change in the policy rate), then the central banks may employ unconventional monetary policy tools. Unconventional monetary measures target financial variables other than the short-term interest rate such as term spreads (e.g. interest rates on risk-free bonds), liquidity, credit spreads (e.g. interest rates on risky assets) and asset prices. The objective of unconventional tools is to supplement the conventional monetary policy tools especially in the easing cycle to boost economic growth.

In the recent past, RBI has utilized various unconventional tools in addition to conventional monetary policy measures. To better understand the use of unconventional tools in the Indian economy, examples of unconventional monetary policy tools are first analysed and their applications to the Indian scenario are described. Broadly, unconventional measures can be classified into four categories, large-scale asset purchases, lending operations, forward guidance and negative interest rates (BIS, 2019). The key features of the measures and their applications in India are described in Table 5.

- Large-scale asset purchases (also referred to as quantitative easing) by a central bank involve purchase of long-term government securities financed by crediting reserve accounts that commercial banks hold at the central bank. This purchase would lower government bond yields and serve as a signal that the policy rate will stay at a lower level for a longer period. Sellers of government bonds may, in turn, change their investment portfolios and invest in more risky assets (e.g. corporate bonds) leading to a decrease in the relevant interest rate and higher asset price and thus boost economic growth. Central banks can also purchase assets from the private sector.
- Lending operations entail provision of liquidity to financial institutions by the central bank through the creation of new or extension of existing lending facilities. This mechanism is different from conventional lending since this is undertaken at looser or specific conditions, e.g. expanding the set of eligible collateral, extending maturity of the loan, providing funding at lower cost and channel/target lending to desired areas or activities with explicit conditions on loans. This lending increases the credit flows to the private sector and helps to restart flow of credit to credit-starved sectors. It can also lead to lower borrowing costs for the financial and real economy sectors.
- Forward guidance involves central banks communicating future policy intentions and commitments regarding the policy rate in order to influence policy expectations. Forward guidance is given routinely by most central banks. Its use as an unconventional tool implies that a central bank uses this to signal that it is open to undertaking extraordinary policy actions for a longer duration. Forward guidance can be ‘time specific’ or ‘state specific’. Under the former, the central bank makes a commitment to keep interest rates low for a specified period. Under the latter, the central bank maintains low rates until specific economic conditions are met.
- The rationale of a negative interest rate is that if an interest rate is charged on the reserves that commercial banks hold at the central bank, the banks may be induced to reduce their excess reserves by increasing lending.

Table 5 Unconventional policy measures

UMP measure	Financial indicators	Mechanism	Intermediate goals	Application for India
Large-scale asset purchases	• Long-term yields • Asset prices • Financial system liquidity	• Purchase of long-term government securities financed by crediting reserve accounts that commercial banks hold at the central bank, lowering government bond yields • Induce sellers of government bonds to purchase riskier assets (e.g., corporate bonds), leading to lower cost of debt, i.e. reduction in relevant interest rates and higher asset prices • Central banks can also purchase assets from the private sector • Purchases lead to large increases in central banks' balance sheets	• Lower interest rates on risk-free assets (e.g., government securities) across different terms to maturity • Lower interest rates across various markets • Signalling device that policy rate will stay lower for longer and thus, stabilize interest rate expectations • Easing financial conditions	Simultaneous buying and selling of long-term and short-term G-Secs have been used to 'twist' and flatten the yield curve (Operation Twist) in December 2019, January and April 2020[1]

(continued)

Table 5 (continued)

UMP measure	Financial indicators	Mechanism	Intermediate goals	Application for India
Lending operations	• Credit growth • Corporate yield spreads • Financial system liquidity	• Provision of liquidity to financial institutions through creation of new or extension of existing lending facilities • Different from conventional lending due to looser or specific conditions, e.g., expanding set of eligible collateral, extending maturity of loan, provide funding at lower cost, channel lending to desired areas or activities with explicit conditions on loans	• Increase credit flows to private sector • Restart flow of credit to credit-starved sectors • Lower borrowing costs for financial and real economy sectors • Stabilize interest rate expectations • Easing financial conditions	• To augment credit flows to productive sectors at reasonable cost, RBI announced LTROs on Feb 6, 2020[2] • TLTRO and TLTRO 2.0 were announced on Mar 27 and April 17, 2020 respectively to stimulate targeted lending wherein banks access liquidity at lower costs from RBI to be lent to targeted sectors[3] • Provision of special refinance facilities to NABARD, SIDB and NHB were announced on April 17, 2020 to enable them to meet sectoral credit needs[4]

(continued)

Table 5 (continued)

UMP measure	Financial indicators	Mechanism	Intermediate goals	Application for India
Forward guidance	• Policy Rate • Stance of monetary policy • Policy space	• State central banks' intentions and commitment regarding policy rate • Typically, can be 'time specific' or 'state specific' • Under time specific, central bank makes a commitment not to increase interest rates for a specified time period • Under state specific, central bank maintains low rates until specific economic conditions are met	• Signalling device that policy rate will stay lower for longer	• RBI Governor and MPC resolution regularly offer forward guidance on the trajectory of policy direction, policy stance[5] (accommodative, neutral and tightening) and policy space As an unconventional tool, RBI signals extraordinary policy actions for a longer duration

(continued)

Table 5 (continued)

UMP measure	Financial indicators	Mechanism	Intermediate goals	Application for India
Negative Interest Rate	• Policy Rate • Long-term yields • Financial conditions	• Banks reduce their excess reserves by increasing lending and purchasing other financial assets	• Adjustment of long-term yields downwards in line with expectations of future short-term rates • Easing financial conditions	NA

Notes
The final goals of unconventional monetary policy are to boost economic growth and supplement conventional monetary policy tools, especially during the easing cycle

1. See RBI Monetary Policy Report (MPR), April 2020 (RBI, 2020d)
2. Long-Term Repo Operations, RBI Governor's Statement, February 6, 2020; RBI MPR, April 2020 (RBI, 2020a, 2020d)
3. Targeted Long-Term Repo Operations, RBI Governor's Statement, March 27, and April, 17, 2020; RBI MPR, April 2020 (RBI, 2020b, 2020d, 2020e)
4. National Bank for Agriculture and Rural Development (NABARD), Small Industries Development Bank of India (SIDBI) and National Housing Bank (NHB), RBI Governor's Statement, April 17, 2020 (RBI, 2020e)
5. Accommodative: interest rates stay the same or decrease; tightening: interest rates stay the same or increase: neutral: interest rates can decrease, increase or stay the same. *Source* Author

The first three of these have been applied to India and are reported in Table 4. These include Operations Twist in December 2019 and January as well as April 2020, long-term repo operation (LTRO) in February 2020, targeted long-term repo operations (TLTRO) in March and April 2020, and special refinance facilities to National Bank for Agriculture and Rural Development (NABARD), Small Industries Development Bank of India (SIDBI) and National Housing Bank (NHB) in April 2020.

The application of these unconventional monetary tools was necessitated, first by the slowdown in the Indian economy in 2019, and second, by the impact of COVID-19 pandemic due to which economic activity and financial markets, the world over, came under severe stress. It was thus necessary for the Reserve Bank to employ measures to mitigate the impact of COVID-19, revive growth and preserve financial stability. Thus, the unconventional monetary policy tools supplemented the conventional monetary policy measures to stimulate growth in the economy.

6 Conclusion

This paper reviews the evolution of monetary policy frameworks in India since the mid-1980s. It also describes the monetary policy transmission process and its limitations in terms of lags in transmission as well as the rigidities in the process. It also highlights the importance of unconventional monetary policy measures in supplementing conventional tools especially during the easing cycle.

At the time of writing (April 2020), three and a half years have passed since the implementation of the Flexible Inflation Targeting Framework and the constitution of the Monetary Policy Committee. With the implementation of FIT, India joined the group of various developed, emerging and developing countries that have implemented inflation targeting since 1990.

The inflation target specified by the Central Government was 4% for the Consumer Price Index (CPI) inflation for the period from August 5, 2016, to March 31, 2021, with the upper tolerance limit of 6% and the lower tolerance bound of 2%. As shown in Fig. 11, from August 2016 through March 2020, the headline inflation generally stayed within the tolerance band with the average inflation rate slightly less than 4% during this period. There were episodes of high/unusual inflation due to supply shocks (food inflation, oil prices), but these were suitably integrated in the policy decisions.

The Monetary Policy Committee has also been in existence since October 2016. The mandate of the MPC is to set the policy repo rate while taking cognizance of the primary objective of monetary policy—to maintain price stability while keeping in mind the objective of growth—as well as the target inflation rate within the tolerance band. Once the policy repo rate is set, the monetary transmission process facilitates the percolation of the change in the policy rate to all financial markets (money and bond markets) as well as the banking sector which further impacts interest sensitive spending in the economy and eventually increases aggregate demand and output growth.

In practice, however, there are rigidities as well as lags in the transmission process that impede the speed and magnitude of the transmission and thus question the efficacy of monetary policy with respect to the policy repo rate. Nevertheless, the external benchmarking system introduced by RBI from October 1, 2019, whereby all new floating rate personal or retail loans (housing, auto, etc.) and floating rate loans to micro and small enterprises extended by banks were benchmarked to an external rate, strengthened the monetary transmission process with several banks benchmarking their lending rate to the policy repo rate. This requirement of an external benchmark system was further expanded to cover new floating loans to medium enterprises extended by banks with effect from April 1, 2020. This is expected to further improve the transmission process.

Of course, the policy repo rate is not a panacea for all ills but serves well as a signaling rate. The RBI routinely brings out the Statement on Developmental and Regulatory Policies[1] that is released simultaneously with the resolution of the MPC. RBI has also taken recourse to unconventional measures to supplement the conventional tools to boost economic growth. More recently, with the slowdown in 2019 followed by the extraordinary slump in economic activity due to COVID-19 pandemic, RBI has been compelled to use rather innovative and unconventional tools starting in December 2019 as discussed in Table 5.

Needless to say, in the unprecedented times of the global pandemic (and, in general, in periods of severe crises), a multi-pronged approach comprising monetary, fiscal and other policy measures is required to protect economic activity and minimize the negative impact of the pandemic (crisis) on economic growth. The importance of monetary-fiscal coordination is highlighted in the resolution of the Monetary Policy Committee dated March 27, 2020 (available on the RBI Website) that states the following: ‘Strong fiscal measures are critical to deal with the situation’. Thus, in addition to monetary policy, fiscal policy has a major role in combating the economic effects of the COVID-19 pandemic. In response to the need of the hour, the Government of India has implemented various fiscal measures to provide a boost to the economy. In fact, while central banks across the globe have responded to the global pandemic with monetary and regulatory measures, various governments have reinforced the monetary measures by deploying massive fiscal measures to shield economic activity from the effect of the COVID-19 pandemic.

A few words about the workings of the MPC are also warranted. As discussed in the paper, the voting pattern of the Indian MPC is comparable to international standards, reflecting the healthy diversity in the assessment of the members. The workings of the MPC are transparent with the resolution being made available soon after the end of the meetings. Furthermore, each member of the Committee has to submit a statement that is made available in the public domain on the 14th day after the meeting. Thus, each member is individually accountable, making the process perhaps more stringent than that of MPCs in other countries.

[1] Statement on Developmental and Regulatory Policies sets out various developmental and regulatory policy measures and macroprudential policies for strengthening financial markets and systems, regulation and supervision, banking sector etc. from time to time.

Questions to Think About

1. Describe the various unconventional monetary policy measures applied in the Indian economy.
2. To what extent has the flexible inflation targeting framework been successful in India?
3. Collect and plot monthly data on interest rates of various emerging and developed economies. Analyse the trends in the series over the years 2019–2022.

Acknowledgements I am grateful to Michael Patra and Janak Raj, Deputy Governor and Executive Director respectively, Reserve Bank of India for useful and constructive suggestions. I also gratefully acknowledge help and support from Hema Kapur, Deepika Goel and Neha Verma, who are teachers in colleges of the University of Delhi and motivated me to write in a student-friendly manner. Special thanks are due to Naina Prasad for competent and diligent research assistance. I am grateful to the Editors of the *Indian Economic Review* for inviting me to contribute to the newly instituted section on Policy Corner. Earlier versions of this paper were presented as a Public Lecture at the Delhi School of Economics in March 2020 and as a Keynote Address at the Annual Conference of the Indian Econometric Society at Madurai Kamaraj University in January 2020. I am grateful to the participants of these events for their feedback.

Disclaimer The views expressed in this paper are of the author and not of the Monetary Policy Committee (MPC), of which she was a member from 2016 to 2020.

Annexure 1

Glossary—Figs. 2 and 5.

Repo rate is the (fixed) interest rate at which the RBI provides overnight liquidity to banks against the collateral of government and other approved securities under the liquidity adjustment facility (LAF)
Reverse repo rate is the (fixed) interest rate at which the RBI absorbs liquidity, on an overnight basis, from banks against the collateral of eligible government securities under the LAF
Liquidity Adjustment Facility (LAF) enables the RBI to modulate short-term liquidity under varied financial market conditions in order to ensure stable conditions in the overnight (call) money market. The LAF operates through daily repo and reverse repo auctions, thereby setting a corridor for the short-term interest rate consistent with policy objectives
Corridor is determined by the MSF rate as ceiling and reverse repo rate as the floor of the corridor for the daily movement in the weighted average call money rate
Marginal Standing Facility (MSF) is the facility under which scheduled commercial banks can borrow additional amount of overnight money from the RBI at a penal rate against eligible securities. Banks are allowed to dip into their Statutory Liquidity Ratio (SLR) portfolio to borrow funds under this facility up to a limit decided by the RBI. This provides a safety valve against unanticipated liquidity shocks to the banking system
Bank rate is the standard rate at which the RBI is prepared to buy or rediscount bills of exchange or other commercial papers eligible for purchase under the Reserve Bank of India Act, 1934
Cash Reserve Ratio (CRR) is the minimum cash balance that a scheduled commercial bank is required to maintain with the RBI as a certain percentage of its net demand and time liabilities (NDTL) relating to the second preceding fortnight. It is prescribed by RBI from time to time

(continued)

(continued)

Statutory Liquidity Ratio (SLR) is the share of NDTL that the scheduled commercial banks are required to maintain on a daily basis in safe and liquid assets, such as unencumbered government securities and other approved securities, cash and gold
Open market operations (OMOs) are conducted by the RBI by way of sale/purchase of Government securities to/from the market with an objective to adjust the rupee liquidity conditions in the market on a durable basis
Market Stabilization Scheme (MSS) was introduced as an instrument for monetary management in April 2004. Surplus liquidity of a more enduring nature arising from large capital inflows is absorbed through sale of short-dated government securities and treasury bills. The cash so mobilized is held in a separate government account with the RBI
Monetary Base (Reserve Money/M0) = Currency in circulation + Bankers' deposits with the RBI + 'Other' deposits with the RBI
M1 = Currency with the public + Demand deposits with the banking system + 'Other' deposits with the RBI
M2 $= M1$ + Saving deposits of post office saving banks
M3 $= M1$ + Time deposits with the banking system
Call money rate is the rate at which overnight money are lent and borrowed in the money market
Weighted average call money rate (WACR) is volume weighted average of rates at which overnight money or money at short notice (up to a period of 14 days) are lent and borrowed in the money market. This weighted average rate can be computed for any period such as, daily, weekly, yearly
Refinance facility under Monetary Targeting Framework was provided by RBI as an additional source of reserves. The two types of refinance facility provided to banks include export credit refinance (extended against bank's outstanding export credit eligible for refinance) and general refinance (provided to banks to tide over their temporary liquidity shortages)

Source Handbook on RBI's Weekly Statistical Supplement; Reserve Bank of India Website

Annexure 2

Glossary—Fig. 8.

Marginal Cost of Funds based Lending Rate (MCLR): An internal benchmark rate for determining the interest rate on all floating rate rupee loans.[2] It was introduced on April 1, 2016, after replacing the base rate system. MCLR comprises of marginal costs of funds (92% share of Marginal Cost of Deposits and Other Borrowings + 8% share of return on net worth)[3] + negative carry-on account of CRR + operating costs + tenor premium

(continued)

[2] Interest rates on fixed rate loans of tenor below 3 years shall not be less than the benchmark rate for similar tenor.

[3] In case of newly set up banks (either domestic or foreign banks operating as branches in India) where lending operations are mainly financed by capital, the weightage for this component may be higher in proportion to the extent of capital deployed for lending. This dispensation will be available for a period of three years from the date of commencing operations.

(continued)

Weighted Average Lending Rate (WALR): The weighted average of the lending rates of all SCBs (excluding RRBs, payment banks and small finance banks) on the outstanding rupee loans and fresh rupee loans sanctioned by the banks. It is based on lending rates to different sectors with weights based on credit extended to different sectors
Money Market: Market for lending and borrowing of short-term funds which are highly liquid. It covers money and financial assets that are close substitutes for money including call money, repo, Tri-party repo, T-bills, Cash Management Bills, Commercial Paper and Certificate of Deposit
Call Money Market **Instrument**: Overnight money and money at short notice (up to a period of 14 days) is lent and borrowed without collateral. Call money is liquid and can be turned into money quickly at low cost and provides an avenue for equilibrating the short-term surplus funds of lenders and the requirements of borrowers **Borrowers**: Scheduled Commercial Banks (excluding RRBs), Co-operative Banks (other than Land Development Banks), and Primary Dealers (PDs) **Lenders**: Same as borrowers
Market Repo: **Instruments:** Repurchase agreement (Repo) which is used for borrowing funds by selling securities with an agreement to repurchase the said securities on a mutually agreed future date at an agreed price which includes interest for the funds borrowed. Government securities, CPs, CDs, Units of Debt ETFs, listed corporate bonds and debentures are eligible securities for repo. Repo against corporate bonds is called repo in corporate bond **Participants**: Banks, PDs, mutual funds, listed corporates, All India Financial Institutions, any other entity approved by the RBI
Tri-Party Repo Market **Instrument**: Tri-party repo, a repo contract where a third entity (apart from the borrower and lender), called a Tri-Party Agent, acts as an intermediary between the two parties to the repo to facilitate services like collateral selection, payment and settlement, custody and management during the life of the transaction **Participants**: Scheduled commercial banks, recognized stock exchanges and clearing corporations of stock exchanges or clearing corporations authorized under PSS Act and any other entity regulated by RBI or SEBI are eligible subject to certain criterion. All the repo market eligible entities are permitted to participate in Tri-party repo market
Treasury Bills Market **Instrument**: Short-term debt instruments issued by the GOI and sold by RBI on an auction basis. Treasury bills are zero coupon securities that pay no interest, issued at a discount and redeemed at the face value at maturity. They are currently issued in three tenors, namely 91, 182 and 364 day. They are also traded in the secondary market **Investors**: Any person resident of India, including firms, companies, corporate bodies, institutions and Trusts along with Non-Resident Indians and Foreign Investors (subject to approval by Government) can invest through a competitive route
Certificate of Deposits Market **Instrument**: A negotiable money market instrument issued in dematerialized form or as a usance promissory note against funds deposited at a bank or other eligible financial institution for a specified time period. Maturity ranges from 7 days to three years. CDs can be traded in the secondary market **Issuers**: Banks and Financial Institutions **Investors**: Individuals, corporations, companies (including banks and PDs), trusts, funds, associations and non-resident Indians (but only on non-repatriable basis)

(continued)

(continued)

Commercial Paper Market
Instrument: An unsecured money market instrument issued in the form of a promissory note. They are issued for the maturities between a minimum of 7 days and a maximum of up to one year from the date of issue (given that the credit rating of the issuer is valid in the period). CPs can be traded in the secondary market
Issuers: Corporates, PDs and All India Financial Institutions (FIs)
Investors: Individuals, banks, other corporate bodies (registered and incorporated in India), non-resident Indians,

---

Bond Market
Instrument: A debt instrument whereby an investor loans money to an entity (typically corporate or government) which borrows the funds for a defined period of time at a variable or fixed interest rate. Bonds are used by companies, municipalities, states and sovereign governments to raise money to finance a variety of projects and activities
Issuers: Government or Corporates
Investors: Banks, Mutual Funds, Foreign Institutional Investors, Provident Funds, Pension Funds

---

Government Securities Market
Instrument: A tradeable instrument issued by the Central or the State Governments. It acknowledges the Government's debt obligation. Securities issued by State Governments in India are known as State Development Loan (SDL). The short-term G-Secs (Treasury Bills) have original maturities of less than one year while long-term G-Secs (Government Bonds or dated securities) have original maturity of one year or more. There is an active secondary market in G-Secs
Participants: Commercial banks, PDs, institutional investors like insurance companies, other banks including cooperative banks, regional rural banks, mutual funds, provident and pension funds, foreign portfolio investors (allowed with quantitative limits prescribed from time to time) and corporates

---

Corporate Bond Market
Instrument: Debt securities issued by private and public corporations. Companies issue corporate bonds to raise money for a variety of purposes, such as building a new plant, purchasing equipment, or growing the business. The stock exchanges have a dedicated debt segment in their trading platforms to facilitate the needs of retail investors. A corporate bond is generally priced on the basis of price of G-sec of comparable tenure with a spread added to it. They are also traded in secondary market
Participants: Corporates, banks, retail investors and institutional investors including insurance companies and mutual funds, foreign investors

---

Source Handbook on RBI's Weekly Statistical Supplement; Reserve Bank of India Website

Annexure 3: Constitution of the Monetary Policy Committee

The Gazette Notification of the Ministry of Finance dated September 29, 2016, notes the following: "In exercise of the powers conferred by section 45ZB of the Reserve Bank of India Act, 1934 (2 of 1934), the Central Government hereby constitutes the Monetary Policy Committee of the Reserve Bank of India, consisting of the following, namely: i. The Governor of the Bank—Chairperson, ex officio; ii. Deputy Governor of the Bank, in charge of Monetary Policy—Member, ex officio; iii. One officer of the Bank to be nominated by the Central Board—Member, ex officio; iv. Shri Chetan Ghate, Professor, Indian Statistical Institute (ISI)—Member; v. Professor Pami Dua, Director, Delhi School of Economics (DSE)—Member; and vi. Dr. Ravindra H. Dholakia, Professor, Indian Institute of Management, Ahmedabad, Member."
The three external members have served on the Committee since its inception and continue to serve. There have been some changes in the RBI members as follows: • Former Governor, Dr. Urjit Patel chaired the Committee from October 2016 to December 2018. Governor, Shri Shaktikanta Das presided from the February 2019 meeting onwards • Shri R. Gandhi, Former Deputy Governor, attended the October and December meetings in 2016 • Dr. Viral Acharya, Former Deputy Governor in charge of Monetary Policy attended the meetings from February 2017 to June 2019 • Shri Bibhu Prasad Kanungo, Deputy Governor, attended the meetings from August to December 2019 • Dr. Michael Patra attended all the meetings, first as Executive Director till December 2019 and continues to attend meetings as Deputy Governor in charge of Monetary Policy • Dr. Janak Raj has attended meetings since February 2020 as Executive Director

References

Bank for International Settlements. (2019). *Unconventional monetary policy tools: A cross-country analysis*. Report by Working Group, Committee on the Global Financial System.

Blinder, A., & Morgan, J. (2005). Are two heads better than one? An experimental analysis of group versus individual decision-making. *Journal of Money, Credit and Banking, 35*(5), 789–811.

Government of India. (2009). *A hundred small steps: Report of the committee on financial sector reforms*. In R. Rajan (Chair.). Planning Commission.

Hammond, G. (2012). State of the art of inflation targeting. *Handbooks, Centre for Central Banking Studies*, 29(4).

Hattori, M., & Yetman, J. (2017). The evolution of inflation expectations in Japan, WP 647. Bank of International Settlements.

Korhonen, L., & Nuutilainen, R. (2017). Breaking monetary policy rules in Russia. *Russian Journal of Economics, 3*(4), 366–378.

Laurens, B. J., Eckhold, K., King, D., Maehle, N., Naseer, A., & Durré, A. (2015). The journey of inflation targeting: Easier said than done—the case for transitional arrangements along the road, WP 136. International Monetary Fund.

Maier, P. (2010). How central banks take decisions: An analysis of monetary policy meetings. In P. L. Siklos, M. T. Bohl, & M. E. Woher (Eds.), *Challenges in central banking: The current institutional environment and forces affecting monetary policy*. Cambridge University Press.

Mishkin, F. S. (2016). *The economics of money, banking, and financial markets*. Pearson.

Mohanty, D. (2010). Monetary policy framework in India: Experience with multiple-indicators approach. In *Speech delivered at the conference of the Orissa Economic Association in Baripada, Orissa on 21st February 2010.*

Mohanty, D. (2011). Changing contours of monetary policy in India. *Reserve Bank of India Bulletin.*

Rajan, R. (2017). *I do what I do*. Harper Collins.

Rangarajan, C. (2020). The new monetary policy framework—What it means. In *Prof. Sukhamoy Chakravarty Memorial Lecture*, delivered at annual conference of the Indian Econometric Society at Madurai Kamaraj University in January 2020. https://www.nipfp.org.in/media/medialibrary/2020/02/WP_297_2020.pdf

Reddy, Y. V. (1999). Monetary policy operating procedures in India, in monetary policy operating procedures in emerging market economies. *Bank for International Settlement, 5*, 99–109.

Reserve Bank of India. (1985). *Report of the committee to review the working of the monetary system.* In S. Chakravarty (Chair.).

Reserve Bank of India. (1998). *Report of the working group on money supply: Analytics and methodology of compilation.* In Y. V. Reddy (Chair.).

Reserve Bank of India. (2013), *Report on currency and finance 2009–2012: Fiscal-monetary co-ordination.*

Reserve Bank of India. (2014). *Report of the expert committee to revise and strengthen the monetary policy framework.* In U. Patel (Chair.).

Reserve Bank of India. (2017). *Report of the internal study group to review the working of the marginal cost of funds based lending rate system.* In J. Raj (Chair.).

Reserve Bank of India. (2018). *Forex market operations and liquidity management*. In J. Raj, S. Pattanaik, I. Bhattacharya, & Abhilasha (Eds.).

Reserve Bank of India. (2019). *Report of the internal working group to review the liquidity management framework*.

Reserve Bank of India. (2020a). *Governor's statement, sixth bi-monthly monetary policy statement*.

Reserve Bank of India. (2020b). *Governor's statement, seventh bi-monthly monetary policy statement*.

Reserve Bank of India. (2020c). *Monetary policy transmission in India—Recent trends and impediments.* In A. K. Mitra & S. K. Chattopadhyay (Eds.).

Reserve Bank of India. (2020d). *Monetary policy report*.

Reserve Bank of India. (2020e). *Governor's statement*.

The Economist Intelligence Unit. (2016). *Argentine central bank adopts inflation-targeting regime.* Argentina Financial Services.

Vasudevan, A. (2017). Reflections on analytical issues in monetary policy: The Indian economic realities. *Economic and Political Weekly, 52*(12), 45–52.

Chapter 4
Determinants of Yields on Government Securities in India

Pami Dua and Nishita Raje

Abstract This article examines the determinants of government yields in India using weekly data from April 2001 through June 2012. The analysis covers treasury bills with residual maturity of 15–91 days and government securities of residual maturity 1, 5 and 10 years. The empirical estimates show that a long-run relationship exists between each of these interest rates and the policy rate, rate of growth of money supply, inflation, interest rate spread, foreign interest rate and forward premium. At the same time, the empirical results show that the relative importance of the determinants varies across the maturity spectrum. The normalised generalised variance decompositions suggest that the policy rate and the rate of growth of high-powered money are more important in explaining the proportion of variation in shorter-term interest rates than the longer-term rates. The weight of the forward premium also diminishes as we move towards higher maturity interest rates. The inflation rate becomes relatively less important in explaining variations in the yields as the maturity of the security increases. The yield spread, on the other hand, is more important in explaining the longer-term rates. The results also show that a large proportion of the variation in the rates on the 5-year and 10-year government securities is attributed to the interest rate itself, suggesting that the unexplained variation may be a result of cyclical factors that are relatively more important for longer-term rates but are not captured by the yield spread and are omitted from the estimations in this article due to the high frequency of data employed here.

Keywords Yields on government securities · Determination of interest rates · Term structure

JEL Classification C5 · E43

Reprinted from Margin—The Journal of Applied Economic Research, Vol. 8, 375–400.

P. Dua (✉)
Department of Economics, Delhi School of Economics, University of Delhi, Delhi, India
e-mail: dua@econdse.org

N. Raje
Department of Regulation, Reserve Bank of India, Mumbai, India
e-mail: nbraje@rbi.org.in

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_4

1 Introduction

Interest rates are the focal point of attention of both financial market participants and policymakers, and understanding their determinants is crucial for academicians and practitioners alike. This is especially true in the case of an economy such as India, with an evolving financial sector and increasing integration with the global economy. After two decades of financial liberalisation, financial markets in India are now fairly developed and its monetary policy is also comparable to some extent to that of developed countries. Prior to economic reforms in India, interest rates were administered, and yields on government securities were kept artificially low.

As a result, the market for these securities was essentially captive. With liberalisation, various segments of the financial market have been gradually deregulated. Indian financial markets have integrated and become more responsive to market forces as well as to monetary policy signals. Government securities have also started paying market determined interest rates as they coevolved with other segments of the financial markets, leading to better transmission of monetary policy. In this scenario, the relevance of the present study cannot be overstated.

The objective of the study is to examine the impact of domestic market forces and external factors on yields on government securities in India across the maturity spectrum. The government securities (G-Sec) market serves as a benchmark for the entire fixed income segment. The focus of this study is on secondary market yields on government securities. Limiting the analysis to zero-default risk government paper enables us to examine a uniform set of securities across the maturity spectrum. This article examines the relative influence of various monetary and financial factors on the short- and long-term yields on government securities from April 2001 through March 2012. The maturity of securities is taken on a residual maturity basis, while the frequency of the data used is weekly. The determinants that are considered include the policy rate (repo rate), money supply growth, inflation rate, interest rate spread, liquidity, forward premium and foreign interest rates.

The rest of the article proceeds as follows: Section 2 describes the salient features of the Indian economy with respect to interest rate determination. Section 3 outlines the model for interest rate determination. Section 4 covers the data, Section 5 explains the methodology and Section 6 reports the empirical results. Section 7 provides the conclusions.

2 Interest Rates and Monetary Policy in India: Some Stylised Facts

The Indian financial system till the early 1990s was characterised by an administered structure of interest rates and restrictions on various market players, namely banks, financial institutions, mutual funds and corporate entities. Under the erstwhile administered interest rate regime, the Reserve Bank of India (RBI) fixed interest rates on both the assets and liabilities of commercial banks to ensure they had a reasonable spread. Government securities had artificially low yields and were dependent mainly on a captive market resulting from the statutory liquidity requirement (SLR, applicable to banks and insurance companies). Such an arrangement facilitated the floatation of debt at relatively low interest rates. Since lending and borrowing operations did not involve any interest rate risk, there was no real incentive for market players to actively manage their assets and liabilities. Moreover, during that era, the public sector banks were not driven by the profit motive. There were also restrictions on portfolio allocations in the form of specified targets. All these factors culminated in the lack of adequate volumes in the government bond market, as a result of which the market lacked depth and liquidity.

In the early 1990s, the country embarked on structural reforms that encompassed the external sector, industry, investment and the financial sector. Reforms in the financial sector were initiated along the lines of the recommendations of a high-powered Committee on the Financial System (Chairman: Mr. M. Narasimham). These reforms were aimed at imparting efficiency and dynamism to the financial sector. The report highlighted that one of the major factors that affected banks' profitability was high pre-emption of their resources in the SLR and the cash reserve ratio (CRR). From April 1992, the central government borrowing programme started being conducted through auctions, which enabled market-based price discovery. This was followed by phased reductions in the SLR and CRR stipulations in January 1993 and April 1993, respectively.[1] There was also a sharp reduction in the central government's fiscal deficit in the initial years of reforms.[2] Gradually, the need to use the banking sector as a captive source of funds declined. In this context, the phasing-out of automatic monetisation of fiscal deficits through ad hoc treasury bills, from April 1997, turned out to be valuable in many respects. It further increased the costs of borrowing, imparted greater fiscal discipline and reduced crowding out. It also freed monetary policy from the straitjacket of the fiscal deficit and allowed the interest rate to reflect the opportunity cost of holding money among financial and other assets so as to improve its allocative efficiency (Jalan, 2002; Report on Currency and Finance, 2008).

The reform process in government securities was followed by various measures to facilitate the evolution and smooth functioning of the G-Sec market. Developments like the setting up of Clearing Corporation of India Limited (CCIL) as a Central Counterparty for guaranteed settlement and a strong legal framework through amendments to existing laws (the SCRA, Reserve Bank Act, 1934, etc.) and passing of new laws (FRBM Act 2003, GS Act 2006) provided a solid foundation for the development of the G-Sec market. The G-Sec market gathered depth and breadth with a number of institutional and technological measures introduced by the RBI. The foremost of

[1] Along with these developments, the external sector dynamics were changing fast: exchange rates were first made flexible and then left to market forces so as to increase the role of the exchange rate channel with increasing global integration.

[2] The process of fiscal consolidation was more or less on track till the period of the global economic crisis when the FRBM had to be paused.

these were the setting up of the Discount and Finance House of India (DFHI), Securities Trading Corporation of India (STCI) and the introduction of the primary dealers system in 1996. These measures enhanced the liquidity and depth in the markets. The primary dealers ensured maximum participation in the primary auctions and provided two-way quotes. Computerisation of the Statutory General Ledger (SGL) operations and dissemination of information on secondary market trading imparted considerable transparency in the trading and settlement system for the G-Sec market. Recognising the importance of the payment systems, several initiatives were undertaken to bring about efficiency in the payment and settlement systems. These included implementation of real-time gross settlement (RTGS) and introduction of the Negotiated Dealing System (NDS) in February 2002 to facilitate electronic bidding and secondary market trading and settlement, and to disseminate information on trades on a real-time basis. In India, the spread of the RTGS system was very rapid in comparison with other countries. Effective funds movements through the RTGS platform also greatly helped cash management by banks and the G-Sec market.

These developments enabled the G-Sec market to leapfrog on technology. Both in terms of volume and value, the transactions in the G-Sec market have increased significantly in recent years, and today are vibrant and have acquired significant depth and liquidity. During the last two decades, the size of the G-Sec market has grown from ₹76,908 crore (in 1991–92) to ₹6,588,036 crore (2012–13)—an almost 86-fold increase—recording a phenomenal compounded annual growth of almost 20%. Significant activity in the secondary market has helped the development of the yield curve and term structure of interest rates. The average maturity of outstanding G-Secs has risen from 5.5 years (in 1996–97) to 14 years (2012–13) with issuances ranging from 2 years to up to 30 years in maturity. Consequently, we have a sovereign yield curve that stretches up to 30 years, thereby providing a benchmark for issuances by non-sovereign issuers.[3]

In conjunction with these developments, commercial banks were also given the freedom to fix their own deposit and lending rates depending on commercial judgement, subject to the approval of their boards. The process of deregulation of interest rates, that took place between 1994 and 1997, ushered in a greater role for market forces and enabled a shift from direct to indirect instruments of monetary policy. The prominence of the interest rate channel increased after financial sector liberalisation, as a greater role was assigned to the policy rates and bank rate and later to the repo rate. The RBI's Working Group on Money Supply (1998) underscored the significance of the interest rate channel for monetary transmission in a deregulated environment. The increasing role of interest rates was, in fact, the underlying principle of the multiple indicator approach that was adopted by the central bank, the RBI during 1998–99, whereby a set of economic variables (including interest rates) were to be monitored along with the growth in broad money, for monetary policy purposes. After 5 June 2000, moving to a full-fledged LAF, the repo rate and liquidity

[3] RBI (2012), *Report of the Working Group on Enhancing Liquidity in the Government Securities and Interest Rate Derivatives Markets*, Chairman R. Gandhi.

management have continued to be the fulcrum of monetary policy. Financial liberalisation has made it possible for the monetary authority to shift to indirect instruments to conduct monetary policy. The process of monetary policy making also underwent a change.[4]

The operating procedures of monetary policy were revised in May 2011, and the 'weighted call rate' was explicitly recognised as the operating target. This rate has continued to move within the corridor specified by the reverse repo rate and the Marginal Standing Facility (MSF) rate. While the money market segment has seen fairly well-aligned rates with almost immediate transmission of monetary policy rate changes, we need to examine whether the signals also flow across the rest of the maturities of the sovereign curve. Such a transmission has increased with the interest rates across various financial markets that have been progressively rationalised and deregulated. The reforms were aimed at easing quantitative restrictions, removal of barriers to entry, wider participation, an increase in the number of instruments and improvements in trading, clearing and settlement practices as well as informational flows. Once the G-Sec market was freed, the dynamics changed with respect to public sector banks which were the major holders of government bonds and were required to handle interest rate risk and market risk by managing their assets and liabilities appropriately.

This fostered greater emphasis on treasury management in banks across the board. Consequently, an element of competitive pricing and substitutability in response to interest rate movements gradually entered the operations of banks and institutions leading to market integration. Along the maturity continuum, the G-Sec market has also become active. A typical feature of this market is the concentration of volume around the 10-year bucket and limited liquidity at other points of this curve. With a view to enhancing liquidity in the G-Sec market, the RBI in 2012 set up a working group under the chairmanship of R. Gandhi. The report of the working group on enhancing liquidity in the government securities and interest rate derivatives markets is now in the public domain and its recommendations are currently being implemented.

With the initiation of the process of financial liberalisation, financial markets have become progressively integrated as is evident from the closer alignment of interest rates across markets strengthening the interest rate channel of monetary transmission in recent years. Now, the market repo and interbank market are both geared to take care of short-term liquidity in the system. There is also a close correspondence between changes in the monetary policy stance and movements in the yields of money market securities, treasury bills and government dated securities.

There are various factors that influence the movement of interest rates in India. Determinants of interest rates can be enumerated as factors affecting demand and supply of liquidity that are key determinants of the market determined rates. The RBI conducts its day-to-day operations by maintaining adequate liquidity in the system. It has put in place a liquidity management framework to manage daily liquidity,

[4] See Nachane and Raje (2007) for details on how monetary policy changed in India with liberalisation.

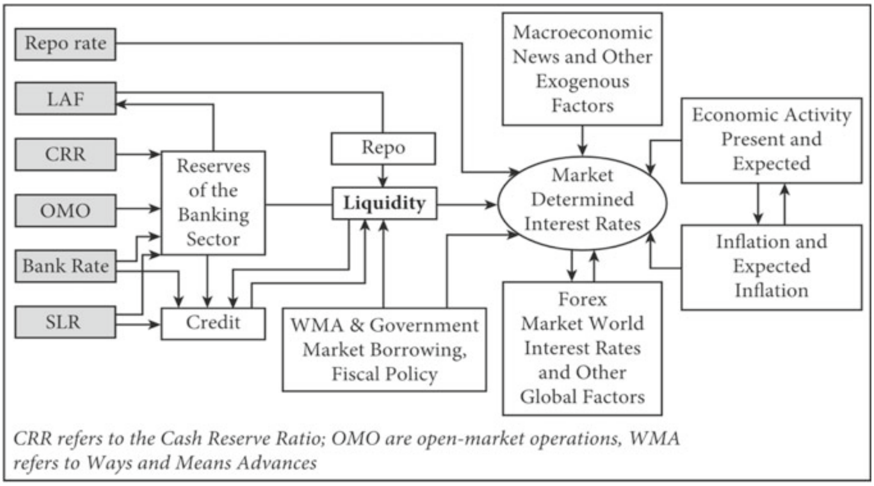


Fig. 1 Determinants of interest rates

taking into account country-specific features. The market interest rates are affected by a series of factors, like the RBI's decisions to alter the quantum of liquidity in the system; or changes it may make in the required reserve ratios; changes in the level of government balances with the RBI and its use of the Ways and Means Advance (WMA) facility. The LAF window is used to modulate liquidity according to the system requirement.[5] Summing up, the RBI has a multipronged impact on the market through the repo rate/reverse repo rate, LAF auctions, open market operations, the term repo auctions and direct changes in the CRR, all of which impact market interest rates through liquidity in the system as illustrated through the boxes on the left-hand side of Fig. 1.

The present article focuses on the yields on G-Secs in the secondary market on a residual maturity basis so as to eliminate the differential impact of various risks. As far as the government bond market is concerned, the shorter rates are again influenced by similar near-term factors while the longer rates are driven by fundamentals. In the Indian context, we use the repo rate as the policy rate. In recent years, the repo rate has emerged as a reference rate as well as a signalling mechanism for monetary policy actions, while the LAF has been effective both as a tool for liquidity management as well as a signal for interest rates in the overnight market. The liquidity in the system is also influenced by 'autonomous' factors like the WMA to the government, and interest rates are also affected by developments in the foreign exchange markets, macroeconomic activity, actual and expected inflation and 'news'.

[5] The MSF window is taken as a part of the LAF. While the MSF rate was above the repo rate, in recent months the MSF rate was hiked independent of the repo rate to take care of the exchange rate. The study ends in 2012.

3 Determinants of Interest Rates

Interest rates are determined by a number of macroeconomic variables, and their impacts may differ depending upon the maturity spectrum of the interest rates. For instance, for short-term/medium-term rates, factors that might impact interest rates include monetary policy, liquidity, demand and supply of credit, actual and expected inflation and external factors such as foreign interest rates. For long-term interest rates, the demand and supply of funds, economic activity and expectations about government policy might be relatively more important.

Some of these factors also emerge from the stylised model developed by Dua and Pandit (2002) under the covered interest parity condition. The equation for the real interest rate derived from their model can be expressed as a function of expected inflation, the foreign interest rate, forward premium and variables to denote fiscal and monetary effects. They estimate the cointegrating relationship using monthly data for India from March 1993 to May 2000 for three interest rates, the 3-month and 12-month treasury bill rates and the commercial paper rate. The cointegrating relationship for each of the interest rates suggests that while real money supply is negatively related to the real interest rate, real government expenditure, forward premium and the foreign interest rate have positive signs. Furthermore, real money supply, real government expenditure, foreign interest rate, forward premium and the domestic inflation rate Granger cause the domestic real interest rate.

Dua et al. (2008) develop vector autoregressive (VAR), vector error correction (VEC) and Bayesian vector autoregressive (BVAR) models to forecast short-term and long-term Indian rates, namely the call money rate, 15–91 days treasury bill rate and rates on 1-year, 5-year and 10-year government securities. Since weekly data are used to estimate the multivariate models over the period April 1997 to December 2001 (with the out-of-sample forecast period as January 2002 to June 2004), financial and monetary factors available at this high frequency such as the inflation rate, policy rate, yield spread, liquidity, foreign interest rates and forward premium are considered. The study reports that all the variables significantly Granger cause the various interest rates, thus justifying their inclusion in the model.

The use of weekly data obviously restricted the selection of variables for inclusion in the models. Variables such as measures of current and future economic activity and fiscal policy could not be included due to unavailability of data at the weekly frequency. Nevertheless, some of these effects can be captured in financial spreads that are measured by differences in the yields on financial assets. These spreads exist due to differences in liquidity, risk and maturity that can also be influenced by factors such as taxes and portfolio regulations. Cyclical changes in any of these factors can arise from monetary policy shifts leading to changes in financial spreads. The most commonly used financial spread is the yield spread whose role in predicting future changes in interest rates is documented in several articles including Campbell and Shiller (1991), Froot (1989), Sarantis and Lin (1999).

The slope of the yield curve—the difference between the long-term interest rate and the short-term interest rate—measures the yield spread. According to the expectations hypothesis of the term structure, this yield differential provides an indication of the expected future inflation rate, (Mishkin, 1988). Furthermore, it provides a signal about growth in future output. For instance, tight monetary policy and high short-term interest rates can imply a declining yield curve, and thus a slowdown in future output growth (Dua et al., 2008). The specification employed in Dua et al. (2008) is applied in this study.

Following Dua et al. (2008), the variables of interest are as below:

$$i = f(\text{policy rate, liquidity}, \pi, \text{yield spread}, i*, \text{fp})$$

So far, the discussion has used the nomenclature of yield and interest rates interchangeably. We now need to make the distinction between the two, specifically that what is being used here is the yield to maturity. The simple definition of yield to maturity is the discount rate at which the sum of all future cash flows from the bond (coupons and principal) is equal to the price of the bond.

In the foregoing specification, the policy rate and the quantum of liquidity capture the impact of monetary policy. Monetary policy plays an important role in the determination of interest rates although the extent of influence and the transmission effect depends on whether interest rates are regulated, or market determined and on the degree of development of the financial markets. Other factors that affect the yield on G-Secs are the change in the size of the government borrowing programme, changes in policy variables by the RBI such as changes in the CRR, changes in the policy rate (repo/MSF) or expectations of this change, and the announcement of outright purchase/sales of government securities, that is, open market operations (OMO). The operating procedures of monetary policy vary a great deal across countries. Nevertheless, one common feature across countries in recent years is that shorter-term interest rates have emerged as key indicators of monetary policy stance across the globe. Central banks can influence interest rates either directly through a policy rate change or indirectly by changing the quantum of liquidity in the system, through various other instruments, such as OMO. It is expected that the more developed the financial market, the greater is the adjustment by the market in response to a cue from the central bank regarding expected movements in the policy rate. In the case of developed countries, mere announcements by the monetary authority are adequate to align the markets. Thornton (2000) had discussed how by just announcing the desired level of the interest rate, central banks can align market players to new levels of interest rates. In this scenario, 'open mouth operations' may be enough and OMO may not be required.[6] Central banks of developing countries may, however, face some constraints on the transmission of their monetary policy impulses. This often

[6] The extent of intervention required is purely a reaction to the kind of channels of transmission in the system as illustrated by Bernanke and Blinder (1992). In recent times communication or merely talking about monetary policy has become very important in the transmission process of monetary policy and in this context, Blinder (2009) has illustrated the virtues (and vices) of central bank communication.

occurs due to the existence of segmentation in markets and/or administered interest rates.

In an attempt to gauge the impact of a change in the policy rate on the market interest rate, Cook and Hahn (1989) show that the changes in the federal funds rate target influence shorter-term rates more than longer-term rates. These results are reinforced by a study by Piazzesi (2005) that demonstrates that as monetary policy shocks affect short-term rates more than long-term ones, they change the slope of the yield curve. Nevertheless, while there may be a differential in the extent of impact on the short-versus long-term rates, the sign of the policy rate is expected to be positive.

The liquidity aspect of monetary policy can be captured by money supply growth.[7] It is noteworthy, however, that besides the liquidity effect of money growth on interest rates whereby a rise in money growth is expected to cause a decline in interest rates, and money supply growth also has an inflation expectation effect wherein an increase in money supply growth impacts interest rates upwards through inflation expectations. The sign on money supply growth thus depends on the relative strength of the two effects. According to Cochrane (1989), the 'anticipated inflation effect dominates if money growth is a good predictor of future money growth if the lag from money growth to inflation is short, and if changes in money growth are largely anticipated'. He indicated that the liquidity effect should dominate if:

> Short-term changes in money growth are typically not interpreted as signals that long-term policy has changed, if the lag from money to inflation is long, and if changes in money growth are largely unanticipated. Furthermore, the existence of a liquidity effect implies that (expected) real returns vary over time. Cochrane (1989: 75)

The inflation rate is another important determinant of interest rates. This has been incorporated in various studies in different ways. For example, Rudebusch and Wu (2008) as well as Bekaert et al. (2005) show that the inflation rate targeted by the monetary authority, or the long-run equilibrium inflation rate is a crucial determinant of the term structure. Rudebusch and Wu (2008) show that the level of the interest rate is affected by market participants' views on the underlying or medium-term inflation target of the central bank.

The importance of the yield spread in predicting interest rates and serving as a proxy for economic activity and future inflation has been discussed in the literature. To elaborate, a rise in short-term rates induced by tight monetary policy is likely to result in a slowdown in real economic activity and thus the demand for credit. This reduction in demand is likely to reduce short-term rates and since long-term rates can be defined as the average of the expected short-term rates, this causes them to fall. Thus, the yield spread defined as the differential between the long-term and short-term rate also decreases resulting in a flatter yield curve. All other things remaining constant, changes in the slope of the yield curve are, therefore, predictors of economic activity with a flattening of the curve accompanied by reduced inflationary expectations. In the equation for the interest rate, the yield spread as defined earlier, therefore, enters with a positive sign.

---

[7] Dua et al. (2008) construct a measure of liquidity based on bank reserves. Money supply growth, however, gave a better fit in the current study and is, therefore, used here.

Table 1 Expected signs of independent variables

Variables	Expected sign
Policy rate	+
Liquidity (dm)	– /+
π	+
Yield spread	+
i^*	+
fp	+

The foreign interest rate and forward premium reflect the integration between domestic and global markets and the fact that the Indian money and foreign exchange markets have become intrinsically linked to each other, especially in view of commercial banks having a dominant presence in both these markets. The world interest rate (e.g. LIBOR) and the domestic rate are expected to be positively related since a rise in the foreign interest rate would lead to an outflow of capital implying a fall in the demand for domestic bonds and a rise in the domestic rate of interest. Finally, an increase in the forward premium is likely to result in an expectation of depreciation of the domestic currency raising the demand for foreign bonds relative to domestic bonds. This would result in lower domestic bond prices and a higher domestic rate of interest. Thus, the forward premium is expected to bear a positive coefficient.

The expected signs of the variables are, therefore, as given in Table 1.

It is expected that monetary policy variables would have a larger impact on shorter-term rates, while variables that denote economic activity, such as the yield spread, would have a bigger effect on longer-term rates.

4 Data and Empirical Model

The interest rates in this study are weekly observations of yields to maturity on riskless government securities. The interest rates examined are treasury bills 15–91 days, and government securities with residual maturity of 1, 5 and 10 years. The term spread or the variation in rates across these securities is due to their term to maturity only as these government securities do not differ in default risk, and tax effects.

The rates are based on secondary market outright transactions in government securities as reported in the Subsidiary Government Ledger (SGL) accounts at the RBI, Mumbai. The data are taken from the *Handbook of Statistics on the Indian Economy* and are described in Table A1. The period of analysis is from April 2001 to March 2012.

The variables included in the models used in the present study are based on the analysis in the previous section and are as follows: policy rate (repo rate[8]); inflation (π, calculated from the wholesale price index); yield spread (the 10-year government security rate minus the treasury bill rate of residual maturity 15–91 days); liquidity in the system (rate of growth of high-powered money); foreign interest rates (i_1^* and i_2^*, represent the LIBOR 3 and 6 months, respectively) and forward premium on the exchange rate of the US dollar for 3 and 6 months, respectively (fp_1 and fp_2).

The specific variables included in the various models are given below:

$$\textbf{Model A}: \textbf{Treasury Bill Rate}(\textbf{15}-\textbf{91 days}).$$
$$i_{(\text{TB}15-91)} = f(\text{repo rate liquidity inflation spread}, i_1^*, \text{fp}_1).$$
$$\textbf{Model B}: \textbf{government Security 1 Year}.$$
$$i_{(\text{GSec}1)} = f(\text{repo rate liquidity inflation spread}, i_2^*, \text{fp}_2).$$
$$\textbf{Model C}: \textbf{government Security 5 Years}.$$
$$i_{(\text{GSec}5)} = f(\text{repo rate liquidity inflation spread}, i_2^*, \text{fp}_2).$$
$$\textbf{Model D}: \textbf{government Security 10 Years}.$$
$$i_{(\text{GSec}10)} = f(\text{repo rate liquidity inflation spread}, i_2^*, \text{fp}_2).$$

The model specifications are essentially the same apart from the use of the 3-month LIBOR i_1^* and i_2^* and the forward premium fp_1 and fp_2 employed in the specification of the treasury bill rate compared to the 6-month rates in the other models.[9]

A preliminary analysis of the data employed in the study is presented in Tables 2 and 3. The summary statistics for the interest rates given in Table 2 show that the mean value increases with term to maturity. The correlation matrix reported in Table 3 gives that there is significant co-movement in the interest rates across the maturity spectrum. The data also show that the policy rate is highly correlated with the other interest rates. The strength of the correlation between the growth rate of high-powered money and the interest rates declines as we move towards higher maturity interest rates; the direction of correlation remains positive throughout. Furthermore, the inflation rate is correlated to a larger extent to the shorter-term interest rates than to those of longer maturity. The correlation matrix also shows that the foreign interest rate and forward premium are positively related to the interest rates. The interest rate spread is positively related to the longer-term interest rates with the magnitude being higher for the 10-year government security compared to the 5-year security.

The correlation matrix between the independent variables also displays interesting trends. The correlations between the 3- and 6-month LIBOR, the 3- and 6-month forward premium, respectively, are close to one. The repo rate is reasonably correlated with the foreign interest rate and forward premium (correlation coefficient around 0.5) and the rate of growth of high-powered money is also reasonably correlated with

[8] In the Indian context we use the repo rate that has emerged as a reference rate and a signalling mechanism for monetary policy actions.

[9] This specification was confirmed by the empirical estimations.

Table 2 Summary statistics: 6 April 2001–1 June 2012

Variables	Maximum	Minimum	Mean	Standard deviation
$i(\mathrm{TB}_{15\text{–}91})$	10.07	2.85	5.91	1.51
$i(\mathrm{GSEC}_1)$	9.85	2.67	6.53	1.45
$i(\mathrm{GSEC}_5)$	9.79	4.81	7.16	1.07
$i(\mathrm{GSEC}_{10})$	10.65	5.19	7.57	1.11
π	27.60	− 1.74	9.08	4.80
Spread	5.26	− 1.66	1.64	1.06
Repo rate	7.50	3.25	5.39	1.07
dm	67.91	− 20.24	11.58	9.81
i_1^*	5.73	0.25	2.30	1.78
fp_1	10.33	− 2.20	3.52	2.35

Table 3 Correlation matrix: 6 April 2001–1 June 2012

Variables	$i(\mathrm{TB}_{15\text{–}91})$	$i(\mathrm{GSEC}_1)$	$i(\mathrm{GSEC}_5)$	$i(\mathrm{GSEC}_{10})$
$i(\mathrm{TB}_{15\text{–}91})$	1.00	1.00	1.00	1.00
$i(\mathrm{GSEC}_1)$	0.91	0.85	0.91	0.12
$i(\mathrm{GSEC}_5)$	0.74	0.80	0.30	0.05
$i(\mathrm{GSEC}_{10})$	0.69	0.45	− 0.11	0.64
π	0.40	− 0.45	0.60	0.00
Spread	− 0.67	0.83	0.02	0.24
Repo rate	0.90	0.22	0.21	0.53
dm	0.15	0.29	0.53	
i_1^*	0.22	0.50		
fp_1	0.54			

Notes π is inflation (y-o-y); dm denotes growth rate of high-powered money (y-o-y); i_1^*—LIBOR (3-month); fp_1—forward premium (3-month)

Variables	π	Spread	Repo rate	dm	i_1^*	fp_1
π	1.00					
Spread	− 0.45	1.00				
Repo rate	0.22	− 0.58	1.00			
dm	0.46	− 0.19	0.19	1.00		
i_1^*	0.22	− 0.03	0.30	0.73	1.00	
fp_1	− 0.09	− 0.22	0.45	− 0.47	− 0.39	1.00

the inflation rate and the foreign interest rate. A caveat here is that the correlation analysis given earlier is merely indicative since the correlation coefficients are not tested for statistical significance, and the relationships between variables are best tested in a multivariate framework. A detailed econometric analysis is therefore necessary.

5 Econometric Methodology

This article analyses the relationship between the various interest rates examined in this study and their determinants in a cointegration framework. The interest rates are as follows: treasury bill 15–91 days rate and government securities with residual maturity of 1, 5 and 10 years rates. The determinants include the repo rate, rate of growth of high-powered money, inflation rate, interest rate spread, foreign interest rate and forward premium. A test for non-stationarity is first conducted followed by tests for cointegration and Granger causality. Generalised variance decompositions are then examined.

5.1 Tests for Non-stationarity

The classical regression model requires that the dependent and independent variables in a regression be stationary in order to avoid the problem of what Granger and Newbold (1974) called 'spurious regression' characterised by a high R2, significant t-statistics but results that are without economic meaning. A stationary series exhibits mean reversion, has a finite, time invariant variance and a finite covariance between two values that depends only on their distance apart in time, not on their absolute location in time. If the characteristics of the stochastic process that generated a time series change overtime, that is, if the series is non-stationary, it becomes difficult to represent it over past and future intervals of time by a simple algebraic model. Thus, the first econometric exercise is to test if all the series are non-stationary or have a unit root.

Several tests have been developed to test for the presence of a unit root. In this study, we focus on the Dickey–Fuller GLS or DF–GLS test (Elliott et al., 1996) since it has improved power compared to the standard ADF (Dickey and Fuller, 1979, 1981) test. We also report the results of the ADF test for comparison.

The DF–GLS procedure relies on demeaning and/or detrending a series prior to the implementation of the auxiliary ADF regression as follows:

$$y_t^d = y_y - \varphi' z_t$$

For detrending, $z_t = (1, t)'$ and φ_0 and φ_1 are estimated by regressing $[y_1, (1-\overline{\rho}L)y_2, \ldots, (1-\overline{\rho}L)y_T]$ on $[z_1, (1-\overline{\rho}L)z_2, \ldots, (1-\overline{\rho}L)z_T]$ where $\overline{\rho} = 1 + (\frac{\overline{c}}{T})$ with $\overline{c} = -13.5$, and L is the lag operator. For demeaning, $z_t = (1)'$ and the same regression is run with $\overline{c} = -7.0$ (see, Elliot et al., 1996 for details). The augmented Dickey–Fuller regression is then computed using the y_t^d series:

$$\Delta y_t^d = \alpha + \gamma y_{t-1}^d + \theta t + \sum_{i=2}^{p} \beta_i \Delta y_{t-i+1}^d + \varepsilon_t$$

Critical values for the GLS detrended test are taken from Elliott et al. (1996). Critical values for the GLS demeaned test are the same as those applicable to the no-constant, no-trend ADF test.

5.2 Cointegration

Cointegration refers to a long-run equilibrium relationship between nonstationary variables that together yield a stationary linear combination. Although the variables may drift away from the equilibrium for a while, economic forces act to restore equilibrium. The possibility of a cointegrating relationship between the variables is tested using the Johansen and Juselius (1990, 1992) methodology which is described below.

5.3 Granger Causality

The concept of Granger causality can be tested in the framework of the error correction model. The Granger causality approach analyses how much of the current variable y_t can be explained by its own past values and tests whether adding lagged values of other variables can improve its forecasting performance. If adding lagged values of another variable, x_t does not improve the predictive ability of y_t, we say that x_t does not Granger cause y_t. In the error correction framework, Granger causality can be tested by a joint test of the error correction term and the lags of x_t.

While cointegration gives the long-run relationship between variables, and Granger causality throws light on the predictive ability of other variables, innovation accounting methods that include impulse responses and variance decompositions capture the dynamic relationships between the variables. We next examine the variance decompositions.

5.4 Variance Decomposition Analysis

Variance decomposition breaks down the variance of the forecast error into components that can be attributed to each of the endogenous variables. Specifically, it provides a breakdown of the variance of the n-step ahead forecast errors of variable i which is accounted for by the innovations in variable j in the VAR. As in the case of the orthogonalised impulse response functions, the orthogonalised forecast error variance decompositions are also not invariant to the ordering of the variables in the VAR. Thus, we use the generalised variance decomposition which considers the proportion of the n-step ahead forecast errors of x_t which is explained by conditioning on the non-orthogonalised shocks but explicitly allows for the contemporaneous correlation between these shocks and the shocks to the other equations in the system.

As opposed to the orthogonalised decompositions, the generalised error variance decompositions can add up to more or less than 100% depending on the strength of the covariances between the different errors.

6 Empirical Results

6.1 Non-stationarity, Cointegration and Granger Causality

We first test for non-stationarity of all the variables. The results summarised in Table 4 gives that all the variables can be treated as non-stationary. Testing for differences of each variable confirms that all the variables are integrated of order one. Since the variables are integrated of order one, cointegration analysis is applied to examine the relationships between these non-mean reverting series. We use Johansen's FIML technique to test for cointegration between each of the interest rates, the repo rate, rate of growth of high-powered money, inflation, interest rate spread, foreign interest rate and forward premium. For all interest rates, the maximum eigenvalue test statistic strongly rejects the null hypothesis that there is no cointegration between the variables but does not reject the hypothesis that there is one cointegrating relationship between the variables for each interest rate. As reported in Table 5, the cointegrating vector for each interest rate suggests that each yield is positively related with the repo rate. The monetary policy rate gets transmitted across the term structure of interest rates represented here as the yields on government bonds of various maturity. We find the rate of growth of high-powered money, the inflation rate, interest rate spread, foreign interest rate and forward premium affect yields. The signs are, therefore, theoretically plausible and conform with the discussion in Sect. 3. The positive sign on the rate of growth of money supply suggests that the expected inflation effect outweighs the liquidity effect.

The most important aspect that we need to highlight here is that the yields on certain liquid securities like the 10-year benchmark are more responsive than others to expected changes in the policy rate. These yields respond to expected changes in the repo rate even before such changes materialise. So, the prevailing yield has in fact already aligned to the expected new level of the repo rate to such an extent that when the repo rate actually occurs there is very little transmission that remains to be done, if the expectations about the rate change are fulfilled. So, what the results of the model show here is the extent of transmission that remains and hence shows up as smaller than the actual. In fact, a good way to try and identify such movements in interest yields on a real-time basis is to look at the yield curve before and after the rate change. Interestingly, Fig. 2 depicts a situation of policy surprise, which is quite rare, when an expected repo rate change does not occur, so the market then has to quickly revert to the no-change level.

Table 4 Unit root test: 6 April 2001–1 June 2012

	DF–GLS (4)		ADF (4)		
Variable	At level	At first difference	At level	At first difference	Inference
$i(\mathrm{TB}_{15\text{–}91})$	− 1.36	− 2.87**	− 2.16	− 11.77	I(1)
$i(\mathrm{GSEC}_1)$	− 1.10	− 11.22	− 2.63	− 12.02	I(1)
$i(\mathrm{GSEC}_5)$	− 0.94	− 5.46	− 3.54	− 10.94	I(1)
$i(\mathrm{GSEC}_{10})$	− 0.83	− 11.49	− 3.44*	− 12.55	I(1)
π	− 2.82	− 3.67	− 2.89	− 6.69	I(1)
Spread	− 2.37	− 7.08	− 2.73	− 12.96	I(1)
Repo rate	− 0.26	− 8.99	− 0.51	− 9.16	I(1)
dm	− 1.80	− 6.10	− 1.89	− 16.80	I(1)
i_1^*	− 0.91	− 9.38	− 1.03	− 9.51	I(1)
fp_1	− 2.79	− 9.52	− 3.24	− 12.73	I(1)
Test critical values					
1% level		− 3.48		− 3.97	
5% level		− 2.89		− 3.42	
10% level		− 2.57		− 3.13	

Notes
1. π is inflation (y-o-y)
2. dm denotes growth rate of high-powered money (y-o-y)
3. i_1^*—LIBOR (3-month)
4. fp_1—forward premium (3-month)
5. *do not reject H0 at 1%
6. **reject H0 at 10%

Table 5 Cointegrating vectors (normalised values)

Interest rates/variables	π	Spread	Repo rate	dm	i_1^*	fp_1
$i(\mathrm{TB}_{15\text{–}91})$	0.085	0.198	1.145	0.015	0.009	0.172
$i(\mathrm{GSEC}_1)$	0.108	0.205	0.391	0.071	0.112	0.550
$i(\mathrm{GSEC}_5)$	0.052	0.500	0.326	0.037	0.127	0.328
$i(\mathrm{GSEC}_{10})$	0.088	0.760	0.637	− 0.012	0.200	0.294

The next step is to test whether the variables individually Granger cause each of the interest rates. The results reported in Table 6 indicate that the null hypothesis of no Granger causality is strongly rejected in Models A through D, thus justifying the inclusion of the right-hand side variables in the model.

To gauge the relative importance of the influences on interest rates, we analyse the impact of each of these variables further. We investigate the dynamic interaction of various shocks using the variance decomposition function. Instead of the orthogonalised impulse responses, we use generalised impulse responses and variance decompositions. The advantage of using the generalised impulse responses

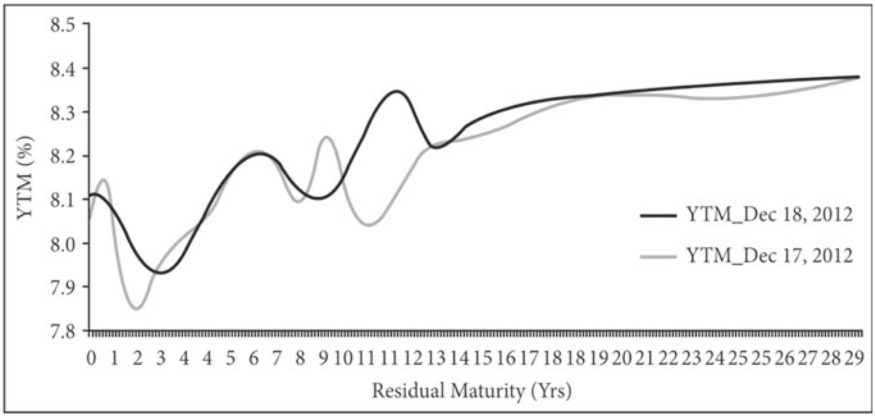


Fig. 2 YTM curves for 17 and 18 December 2012

is that the orthogonalised impulse response and variance decompositions depend on the ordering of the variables. If the shocks to the respective equations in VAR are contemporaneously correlated, then the orthogonalised and generalised impulse responses may be quite different. On the other hand, if shocks are not contemporaneously correlated, then the two types of impulse responses may not be that different and the orthogonalized impulse responses may not be sensitive to a re-ordering of the variables.

6.2 Generalised Variance Decompositions

Variance decompositions give the proportion of the *h*-periods ahead forecast error variance of a variable that can be attributed to another variable. These, therefore, measure the proportion of the forecast error variance in the interest rates that can be explained by shocks given to its determinants. The results reported in Table 7a–d provide variance decompositions for up to the 24-week forecast horizon for each interest rate.

Table 8 gives the prorated percentage decompositions for the 24-week forecast horizon.

This allows us to analyse the relative importance of the determinants of the interest rates for each interest rate as well as across interest rates. For instance, for the 15–91 days treasury bill rate, important determinants in descending order of importance include the forward premium, inflation rate and the rate of growth of high-powered money. In the case of 1-year government securities, the importance of the inflation rate and forward premium is switched and the remaining ordering for the three most important variables is the same as that of the 15–91 treasury bill rate. As we move towards longer maturity rates, the weight of the repo rate and the forward

Table 6 Granger causality tests

Null hypothesis	Number of lags	Calculated x^2 value[Prob.]	Conclusion
Model A: $i(TB_{15\text{–}91}) = f(\pi$, Spread, repo rate, dm, i_1^*, , $fp_1)$			
$i(\mathrm{TB}_{15\text{–}91})$ is not Granger caused by π	6	66.9137[0.000]	Reject null hypothesis
$i(\mathrm{TB}_{15\text{–}91})$ is not Granger caused by spread	6	62.4285[0.000]	Reject null hypothesis
$i(\mathrm{TB}_{15\text{–}91})$ is not Granger caused by repo rate	6	64.0934[0.000]	Reject null hypothesis
$i(\mathrm{TB}_{15\text{–}91})$ is not Granger caused by dm	6	58.0412[0.000]	Reject null hypothesis
$i(\mathrm{TB}_{15\text{–}91})$ is not Granger caused by i_1^*	6	66.8577[0.000]	Reject null hypothesis
$i(\mathrm{TB}_{15\text{–}91})$ is not Granger caused by fp_1	6	82.1795[0.000]	Reject null hypothesis
Model B: $i(GSEC_1) = f(\pi$, Spread, repo rate, dm, $i_1^*, fp_1)$			
$i(\mathrm{GSEC}_1)$ is not Granger caused by π	4	30.9829[0.000]	Reject null hypothesis
$i(\mathrm{GSEC}_1)$ is not Granger caused by spread	4	17.9262[0.003]	Reject null hypothesis
$i(\mathrm{GSEC}_1)$ is not Granger caused by repo rate	4	30.5908[0.000]	Reject null hypothesis
$i(\mathrm{GSEC}_1)$ is not Granger caused by dm	4	19.6072[0.001]	Reject null hypothesis
$i(\mathrm{GSEC}_1)$ is not Granger caused by i_1^*	4	26.6390[0.000]	Reject null hypothesis
$i(\mathrm{GSEC}_1)$ is not Granger caused by fp_1	4	49.2403[0.000]	Reject null hypothesis
Model C: $i(GSEC_5) = f(r$, Spread, repo rate, dm, $i_1^*, fp_1)$			
$i(\mathrm{GSEC}_5)$ is not Granger caused by π	3	45.0635[0.000]	Reject null hypothesis
$i(\mathrm{GSEC}_5)$ is not Granger caused by spread	3	34.2283[0.000]	Reject null hypothesis
$i(\mathrm{GSEC}_5)$ is not Granger caused by repo rate	3	33.4157[0.000]	Reject null hypothesis
$i(\mathrm{GSEC}_5)$ is not Granger caused by dm	3	33.2114[0.000]	Reject null hypothesis
$i(\mathrm{GSEC}_5)$ is not Granger caused by i_1^*	3	41.6421[0.000]	Reject null hypothesis
$i(\mathrm{GSEC}_5)$ is not Granger caused by fp_1	3	45.5947[0.000]	Reject null hypothesis
Model D: $i(GSEC_{10}) = f(\pi$, Spread, repo rate, dm, $i_1^*, fp_1)$			

(continued)

Table 6 (continued)

Null hypothesis	Number of lags	Calculated x^2 value[Prob.]	Conclusion
$i(GSEC_{10})$ is not Granger caused by π	3	14.2839[0.014]	Reject null hypothesis
$i(GSEC_{10})$ is not Granger caused by spread	3	18.5857[0.002]	Reject null hypothesis
$i(GSEC_{10})$ is not Granger caused by repo rate	3	14.6878[0.012]	Reject null hypothesis
$i(GSEC_{10})$ is not Granger caused by dm	3	22.6945[0.000]	Reject null hypothesis
$i(GSEC_{10})$ is not Granger caused by i_1^*	3	17.2947[0.004]	Reject null hypothesis
$i(GSEC_{10})$ is not Granger caused by fp_1	3	22.5461[0.000]	Reject null hypothesis

Notes
1. π is inflation (y-o-y)
2. dm denotes growth rate of high-powered money (y-o-y)
3. i_1^*—LIBOR (3-month)
4. fp_1—forward premium (3-month)

premium diminishes, while the weight of the interest rate spreads, and the own variable increases substantially. The inflation rate is also relatively less important in explaining variations in the 10-year rate. The results also show that a large proportion of the variation in the rates on the 5-year and 10-year government securities is attributed to the interest rate itself suggesting that the unexplained variation may be a result of cyclical factors that are important for longer-term rates and are not captured in the interest rate spread but are omitted from the estimations due to the lack of high frequency of the data available for these variables.

7 Conclusion

This article examines the determinants of the term structure of interest rates in India using weekly data from April 2001 through June 2012. The analysis covers treasury bills with residual maturity of 15–91 days and government securities of residual maturity 1, 5 and 10 years. The empirical estimates show that a long-run relationship exists between each of these interest rates and the repo rate (policy rate), rate of growth of high-powered money, inflation, interest rate spread, foreign interest rate and forward premium. These variables Granger-cause each of the interest rates. Furthermore, the normalised generalised variance decompositions suggest that the policy rate is more important in explaining the proportion of variation in short- to medium-term interest rates. The weight of the forward premium also diminishes as we move towards higher-maturity interest rates. The inflation rate and the rate

Table 7 Generalised variance decomposition

Horizon	i (TB_{15-91})	π	Spread	Repo rate	dm	i_1^*	fp_1
(a) *Model A*							
1	0.954	0.000	0.458	0.044	0.008	0.021	0.035
6	0.712	0.041	0.265	0.174	0.028	0.033	0.098
12	0.475	0.175	0.145	0.233	0.041	0.053	0.087
18	0.353	0.275	0.092	0.238	0.045	0.058	0.064
24	0.288	0.336	0.066	0.233	0.046	0.057	0.048
Horizon	$i(GSEC_1)$	π	Spread	Repo rate	dm	i_1^*	fp_1
(b) *Model B*							
1	0.965	0.010	0.028	0.058	0.003	0.008	0.027
6	0.746	0.106	0.033	0.110	0.014	0.037	0.130
12	0.632	0.187	0.029	0.120	0.021	0.051	0.155
18	0.577	0.230	0.027	0.119	0.024	0.054	0.165
24	0.549	0.255	0.026	0.118	0.026	0.055	0.169
Horizon	$i(GSEC_5)$	r	Spread	Repo rate	dm	i_1^*	fp_1
(c) *Model C*							
1	0.986	0.010	0.000	0.023	0.007	0.052	0.004
6	0.788	0.105	0.016	0.034	0.016	0.075	0.085
12	0.654	0.150	0.046	0.027	0.021	0.068	0.143
18	0.582	0.166	0.066	0.024	0.023	0.062	0.177
24	0.538	0.174	0.079	0.021	0.024	0.059	0.198
Horizon	$i(GSEC_{10})$	r	Spread	Repo rate	dm	i_1^*	fp_1
(d) *Model D*							
1	0.994	0.001	0.304	0.013	0.001	0.014	0.000
6	0.910	0.007	0.227	0.013	0.003	0.022	0.061
12	0.843	0.010	0.197	0.011	0.002	0.029	0.118
18	0.795	0.013	0.184	0.009	0.001	0.033	0.160
24	0.760	0.014	0.177	0.008	0.001	0.035	0.190

Table 8 Generalised variance decomposition (prorated in percentage terms)

Horizon	Interest rate	r	Spread	Repo rate	dm	i_1^*	fp_1
24 weeks $i(TB_{15-91})$	26.82	31.28	6.10	21.71	4.31	5.33	4.45
$i(GSEC_1)$	45.77	21.26	2.21	9.84	2.18	4.63	14.12
$i(GSEC_5)$	49.16	15.89	7.24	1.95	2.21	5.43	18.12
$i(GSEC_{10})$	64.13	1.19	14.92	0.69	0.11	2.94	16.01

of growth of high-powered money are also relatively less important in explaining variations in the 10-year rate. The results also show that a large proportion of the variation in the rates on the 5-year and 10-year government securities is attributed to the interest rate itself, suggesting that the unexplained variation may be a result of cyclical and fundamental factors that are important for longer-term rates but are omitted from the estimations here due to the lack of high frequency of data on these. These are cyclical factors that are not captured in the interest rate spread.

The article thus highlights the differential response of short- and longer-term rates to various determinants including monetary policy. Interest rates at the shorter end of the maturity spectrum are more responsive to changes in monetary policy measured by policy rates and the rate of growth of high-powered money. This impact peters out as maturity increases, showing that the longer-term rates are influenced by an additional set of factors like current and future economic activity, the output gap, fiscal policy and the global environment. The results provide great insight if expectations of the rates are factored in. In fact, the benchmark 10-year security which is most liquid in the term structure shows immense changes in yields related to policy rate expectations. Most of these changes occur in the benchmark yields well before the policy rate announcements, as the market factors in the rate change expectations well before the event, so when the rate changes occur, there is very little change that remains to happen in the yields if the anticipation of the market is fulfilled. It must be reiterated here, as stated at the onset, that government securities have limited liquidity across the maturities with the volumes concentrated in the benchmark securities with various measures aimed at improving liquidity in the G-Sec market we expect that the greater liquidity will further strengthen the transmission of monetary policy across the entire term structure of interest rates.

Going ahead, with the increase in depth of the secondary market for government securities, the transmission of monetary policy signals can be expected to rise, especially with a rise in liquidity across the term structure. The Gandhi Committee had recommended consolidation of the G-Sec outstanding, with the issuance of securities at various maturity points in conjunction with further steps like issuance of benchmark securities over a longer-term horizon, buybacks and switches. Such steps will indeed boost liquidity in the market. Further, when the upper-limit on the HTM classification comes down gradually as envisaged, the trading and liquidity in the secondary market for government securities will rise. The approach on this has been gradual in view of the possible impact of a reduction in the limit on HTM classification on the balance sheet of banks/PDs and other stakeholders (Table 9).

Questions to Think About

1. Can we predict future interest rates on the basis of the yield curve?
2. Describe the differential response of short- and longer-term rates to various determinants of interest rates.
3. If the empirical analysis in the chapter is conducted using monthly data, which other variables would you include in the estimations?

Table A1 Data definitions and sources

Variable	Definition	Source
Bank rate	Rate at which the Reserve Bank of India (RBI) lends to commercial banks	*Handbook of Statistics on the Indian Economy* and *RBI Bulletin*
CRR	Cash reserve ratio (CRR) is the amount of funds that the banks have to keep with RBI. If RBI decides to increase the per cent of this, the available amount with the banks comes down. RBI is using this method (increase of CRR rate), to drain out the excessive money from the banks	-do-
TB 15–91	Government of India Treasury Bills of residual maturity of 15–91 days based on the secondary market outright transactions in Government securities (face value) as reported in Subsidiary Government Ledger (SGL) accounts at RBI, Mumbai	-do-
GSEC1	Government of India dated securities of residual maturity of 1-year based on the secondary market outright transactions in Government securities (face value) as reported in SGL accounts at RBI, Mumbai	-do-
GSEC5	Government of India dated securities of residual maturity of 5-year based on the secondary market outright transactions in Government securities (face value) as reported in SGL accounts at RBI, Mumbai	-do-
GSEC10	Government of India dated securities of residual maturity of 10-year and above based on the secondary market outright transactions in Government securities (face value) as reported in SGL accounts at RBI, Mumbai	-do-
LIBOR 3-month	Three-month LIBOR on USD deposits	IFS
LIBOR 6-month	Six-month LIBOR on USD deposits	IFS
Repo	Repo rate is the rate at which the central bank lends to the commercial banks against their parking of government securities for meeting their day-to-day liquidity requirements	*Handbook of Statistics on the Indian Economy* and *RBI Bulletin*

(continued)

Table A1 (continued)

Variable	Definition	Source
Reverse Repo	Reverse repo rate is the rate which the central bank offers to the commercial banks when they park their excess funds with it by purchase of government securities	-do-
SLR	This is the amount a commercial bank needs to maintain in the form of liquid assets for prudential reasons and safety of depositors. It can be in cash, or gold or government approved securities (bonds) before providing credit to its customers. SLR rate is determined and maintained by the RBI in order to control the expansion of bank credit	-do-
fp 1-month	3-month forward premium	-do-
fp 2-month	6-month forward premium	-do-
Inflation	Both week-to-week and year-on-year inflation rate have been used	Weekly Statistical Supplement
dm	Growth in high-powered money year on year	-do-
Spread	The yield spread is defined as the difference between the Government of India dated securities on residual maturity of 10-year and above and the 15–91-day Treasury bills rate	-do-

Acknowledgements The authors gratefully acknowledge competent research assistance from Neeraj Kumar. They also acknowledge suggestions from participants at the Workshop on Macroeconomic Modelling and Policy Analysis, organised by the National Council for Applied Economic Research, Delhi on 26 July 2013. The views expressed in the article belong to the authors and not to the organisations they belong to. The errors, if any, are solely their responsibility.

References

Bekaert, G., Cho, S., & Moreno, A. (2005). New-Keynesian Macroeconomics and the Term Structure, WP W11340, NBER.

Bernanke, B., & Blinder, A. (1992). The federal funds rate and the channels of monetary transmission. *American Economic Review, 82*, 901–921.

Blinder, A. (2009). Talking about monetary policy: The virtues (and vices?) of Central Bank Communication, WP 274, Bank for International Settlements.

Campbell, J. Y., & Shiller, R. J. (1991). Yield spreads and interest rate movements: A bird's eye view. *Review of Economic Studies, 58*, 495–514.

Cochrane, J. H. (1989). The return of the liquidity effect: A study of the short-run relation between money growth and interest rates. *Journal of Business & Economic Statistics, 7*, 75–83.

Cook, T., & Hahn, T. (1989). The effect of changes in the federal funds rate target on market interest rates in the 1970s. *Journal of Monetary Economics, 24*, 331–351.
Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*, 427–431.
Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica, 49*, 1057–1072.
Dua, P., & Pandit, B. L. (2002). Interest rate determination in India: Domestic and external factors. *Journal of Policy Modeling, 24*, 853–875.
Dua, P., Raje, N., & Sahoo, S. (2008). Forecasting interest rates in India. *Margin: The Journal of Applied Economic Research, 2*, 1–41.
Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica, 64*, 813–836.
Froot, K. A. (1989). New hope for the expectations hypothesis of the term structure of interest rates. *Journal of Finance, 44*, 283–305.
Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics, 35*, 143–159.
Jalan, B. (2002). Research and policy developments in money, finance and external sector in India. *Macroeconomics and Monetary Policy—Issues for a Reforming Economy*, 162–182.
Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration with applications to the demand for money. *Oxford Bulletin of Economics and Statistics, 52*, 169–209.
Johansen, S., & Juselius, K. (1992). Testing structural hypothesis in a multivariate cointegration analysis of PPP and the UIP for UK. *Journal of Econometrics, 53*, 211–244.
Mishkin, F. S. (1988). The Information in the longer maturity term structure about future inflation, WP 3126, NBER.
Nachane, D. M., & Raje, N. (2007). Financial liberalisation and monetary policy. *Margin: The Journal of Applied Economic Research, 1*, 47–83.
Piazzesi, M. (2005). Bond yields and the federal reserve. *Journal of Political Economy, 113*, 311–344.
RBI. (2008). Report on currency and finance—2006–08. *The Banking Sector in India: Emerging Issues and Challenges.*
RBI. (2012). Report of the working group on enhancing liquidity in the government securities and interest rate derivatives markets.
Rudebusch, G., & Wu, T. (2008). A macro-finance model of the term structure, monetary policy and the economy. *Economic Journal, 118*, 906–926.
Sarantis, N., & Lin, S. X. (1999). The role of financial spreads in macroeconomic forecasting: Evidence for the UK. *Manchester School, 67*, 89–110.
Thornton, D. L. (2000). The relationship between the federal funds rate and the fed's federal funds rate target: Is it open market or open mouth operations? Discussion Paper 9, Economic Research Centre of the Deutsche Bundesbank.

Chapter 5
Monetary Transmission in the Indian Economy

Pami Dua and Anshumaan Tuteja

Abstract This paper examines monetary transmission channels of India during the period 1998 to 2015. In a structural VAR framework, we use a non-recursive strategy to identify monetary policy shocks using monthly data while controlling for international factors like global interest rates and oil prices affecting the Indian economy. Our results confirm that a contractionary shock lowers inflation as well as long-term expectations on inflation and output, while output response is low and insignificant. We also find the presence of the exchange rate channel and evidence of a weak asset price channel in the Indian economy.

Keywords Transmission of monetary policy · Structural VAR · India · Expectations channel · Monetary policy shocks

JEL Classification C32 · E52 · F41

1 Introduction

The channels of transmission mechanism of monetary policy link decisions of the central bank about the monetary system to adjustments in its final targets, typically stabilization of inflation and economic growth. These channels operate simultaneously in the economy and are well documented in the literature (see Boivin et al., 2010; Mishkin, 2012; Dua, 2020). A good understanding of their impact on the economy is vital for central banks to take appropriate policy decisions since the final targets are not under its direct control. In this paper, we examine the monetary transmission channels for the Indian economy from January, 1998 to December, 2015. This period coincides with the duration for which the Reserve Bank of India (RBI)

P. Dua
Department of Economics, Delhi School of Economics, University of Delhi, Delhi, India
e-mail: dua@econdse.org

A. Tuteja (✉)
Department of Economics, University of Warwick, Warwick, UK
e-mail: a.tuteja.1@warwick.ac.uk

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_5

set interest rates based on the multiple indicator approach. This era began with a shift from monetary targeting towards a broad-based framework that incorporated information about current as well as future economic fundamentals. This was followed by the adoption of the flexible inflation targeting (FIT) framework in 2016.

We estimate a structural vector autoregressive (SVAR) model using monthly data after controlling for the influence of external factors on the central bank's monetary policy actions. Restrictions on contemporaneous relations between endogenous variables help examine the significance of various channels of monetary policy in response to an exogenous interest rate shock. Our results highlight the presence of the interest rate channel, the exchange rate channel and expectations channel of transmission in a small open economy setting.

The present study contributes to the existing literature on the Indian economy in the following ways. First, we present evidence of the effectiveness of monetary policy on future economic activity and inflation expectations as proxied by the yield spread (Dua and Raje, 2014). A contractionary shock should reduce the yield spread because it is likely to result in a decline in future aggregate demand along with reduced likelihood of future rate hikes. Hence, the spread declines since long-term rates are an average of expected short rate for the maturity period of the long-term bond. This flattening of the yield curve thus signals lower growth and inflation expectations. Second, we utilize the shadow interest rate of the United States (U.S.) estimated by Wu and Xia (2016)[1] which allows the possibility of the policy rate to fall below the lower bound when monetary authorities follow expansionary policy, and the policy rate is stuck at the zero lower bound (ZLB). This measure captures the effects of quantitative easing as well as forward guidance adopted by the Board of Governors. The inclusion of such information is important since unconventional monetary policies (UMPs) played a significant role in movement of global capital flows, exchange rates and their management by central banks in Emerging Market Economies (Eichengreen and Gupta, 2015; Bowman et al., 2015; Tillmann, 2016; Patra et al., 2016). Other studies proxy for movements in the international interest rate using the Federal Funds Rate (FFR) (Paramanik and Kamaiah, 2014; Barnett et al., 2016). However, the FFR does not incorporate the impact of UMPs utilized by the U.S. Federal Reserve Board since the onset of the global financial crisis.

The rest of the paper is organized as follows. Section 2 gives a brief summary of the monetary policy framework adopted by India in the post-reform period. Section 3 presents an overview of potential channels through which monetary authorities can influence the rest of the economy. Section 4 summarizes the empirical studies focusing on the monetary policy transmission process in India. Section 5 describes the testable theories using our empirical approach. Section 6 discusses the econometric methodology. The description of data and empirical strategy is given in Sect. 7. The next section elucidates the results. Finally, Sect. 9 concludes with a summary of the study.

[1] This interest rate is an analytical approximation of the shadow rate in the Shadow Rate Term Structure Model (SRTSM) introduced by Black (1995).

2 Monetary Policy Framework of India

The monetary policy framework has undergone considerable change since inception of the Reserve Bank of India in 1934. The monetary policy objectives of the RBI are enshrined in the RBI Act, 1934 which was revised in 2016 to incorporate the FIT framework. The RBI's role is to maintain price stability while keeping in mind the objective of economic growth. Until the 1990s, the RBI was often forced to monetize budget deficits and control the resultant inflationary pressures. The cash reserve ratio (CRR) and statutory liquidity ratio (SLR) were deliberately kept high in order to force banks to buy a huge amount of government securities. Based on recommendations of the Chakravarty committee (1985), the RBI followed a monetary targeting approach with reserve money as the operating target and broad money as the intermediate target. The stability of the money demand function allowed RBI to follow this approach from 1985 to 1997.

In the 1990s, the framework evolved further while maintaining the core objectives of the central bank. The RBI's Working Group on Money Supply (1998) noted the impact of financial innovations and globalization on the predictive stability of the money demand function. It was also noted that deepening of financial markets would improve transmission of monetary policy by using price instruments. The central bank, therefore, switched to setting the interest rate based on MIA. The approach uses indicators that encompass the state of the economy across the goods market, financial markets conditions and labour market. This shift was supported by deregulation in the money markets and lowering of other quantity instruments such as CRR and SLR. Later, the RBI strengthened its policy framework by augmenting MIA with forward-looking variables that were sourced through surveys commissioned by the RBI to capture expectations of economic agents and the potential direction of the economy. A schematic representation of the approach by Dua (2020) is presented in Fig. 1. In May 2011, the RBI decided to use the repo rate as the sole indicator of monetary policy stance by explicitly linking all other rates to the repo rate. This improved implementation and transmission of monetary policy (Mohanty, 2012).

During the time period of MIA, several new mechanisms were created to steer market interest rates and provide adequate liquidity in the monetary system. The liquidity adjustment facility (LAF) was introduced to smoothen liquidity and curtail market volatility in the system in order to reduce the risk of liquidity shocks in the system.[2] The mechanism operates through repurchase (repo) auctions for injecting liquidity and reverse repurchase (reverse repo) auctions for absorbing liquidity in the system. The rates on repo[3] and reverse repo agreements act as a ceiling and floor,

[2] During the 2008 Global Financial Crisis, additional liquidity support was provided (up to 1% of Net Demand and Time Liabilities) under the LAF and the auctions were held at daily frequency instead of reporting Fridays for fine-tuning liquidity. Other measures included direct intervention in the foreign exchange market, raising interest rates on Foreign Currency Non-Resident (B) and Non-Resident (External) Rupee Account deposits. This proved vital in containing liquidity constraints emanating from risk aversion in lending and lack of availability of external borrowing were contained.

[3] After the introduction of the Marginal Standing Facility in 2011, it became the new upper bound for the corridor.

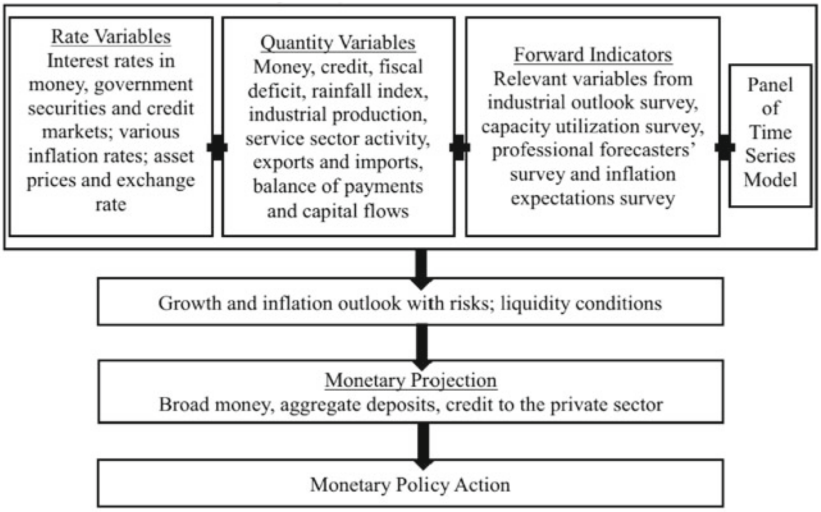


Fig. 1 Augmented multiple indicator approach operating framework. *Source* RBI Bulletin (December, 2011), Dua (2020)

respectively, to form a corridor for the the weighted average call money rate (WACR). This enhanced transparency in liquidity management in the Indian markets.

The next significant change in monetary policy was characterized by the shift to the inflation targeting approach based on the recommendations of the Urjit Patel Committee Report (2014). The objective of the FIT framework is to maintain the consumer price inflation (CPI) at a target 4% within a $\pm$ 2% band. This policy change has been taken with the view to stabilize and anchor inflation expectations in order to ensure price stability. A detailed exposition on the shift towards FIT and experience with it is provided in Dua (2020).

3 Channels of Monetary Policy Transmission

The transmission channels of monetary policy describe the linkages through which changes in monetary policy affect the final target of the central bank. During the period in which the RBI followed the multiple indicator approach, the policy was conducted by setting either the repo or the reverse repo rate and the final targets were economic growth and stable inflation. The traditional **interest rate channel** of monetary policy transmission postulates that a change in the policy rate of the central bank is transmitted to the operating target and the entire yield curve in money and bond markets. This ultimately stimulates consumption and investment and, thereby, aggregate demand. For a stylized representation of the channel in the case of India, see Dua (2020). The **credit channel** highlights the role of credit availability in the transmission process. It has been explored through two linkages: the bank lending channel and the balance sheet channel. The first channel is based on credit availability of commercial banks. For instance, an expansionary monetary policy leads to an increase in funds availability with banks which allows them to grant more loans and this spurs investment and economic growth. The second channel works through the impact of external finance premium associated with a firm's balance sheet. The external finance premium exists because lenders would like to hedge against the presence of informational asymmetries in the credit market. An expansionary policy leads to a strengthening of the balance sheet to the extent that it contains the floating rate debt. As a result, cost of capital declines due to lower external finance premium and this may subsequently lead to increase in investment activity of the firm. The **asset price channel** links changes in asset prices to changes in the aggregate demand. A monetary expansion increases attractiveness of non-interest bearing instruments such as equities and real estate. This raises asset prices and could lead to greater investment by firms and/or higher consumption by households due to the wealth effect. The transmission of monetary policy through **exchange rates** can play a critical role for globally integrated economies. This channel works through the interest parity condition wherein a change in the policy rate induces capital flows followed by a change in the exchange rate. This affects the trade balance as it impacts the relative demand of exports and imports, and therefore, aggregate demand. Finally, the **expectations channel** deals with expectations formation of agents about future economic fundamentals and responses of the central bank. A change in the expected path of interest rates may impact the medium-long-term maturities in the term structure of interest rates which could have a bearing on output and prices. Credibility of the central bank plays a key role here since economic agents shape their views about the future macroeconomic outcomes based on their beliefs about the central bank's ability and commitment towards anchoring monetary objectives.

It is worth mentioning here that the final effect of monetary policy on real variables occurs through a combination of complementary transmission channels. For example, a potent balance sheet channel presumes a strong interest rate channel that can affect the balance sheet of the firms. Also, a powerful balance sheet channel should reinforce the asset price channel through its impact on asset prices in the economy. This makes the exercise of identifying the various channels of transmission and evaluating their relative importance and efficacy a challenging task.

4 Literature Review

This section succinctly summarizes the empirical literature on transmission of monetary policy shocks for India. It is divided on the relative importance of the various channels of transmission of monetary policy shocks and their impact on the Indian economy. Some of the studies that have emphasized the interest rate channel include Al-Mashat (2003), Mohanty (2012), Khundrakpam and Jain (2012), Sengupta (2014) and Brandao-Marques et al. (2020). However, Banerjee et al. (2020) suggests that policy transmission via interest rate shocks is weak and in fact, shocks to the money supply have a relatively larger and persistent effect.

Al-Mashat (2003) employ vector error correction model (VECM) framework for quarterly data from 1980 to 2002 and find the exchange rate channel to be important in the transmission of monetary policy shocks to key macroeconomic variables. Bhattacharya et al. (2011) use the same method but find lack of financial development in India as a hindrance to effective transmission of monetary policy through the exchange rate.

For the asset price channel, Bhattacharyya and Sensarma (2008) do not find evidence of asset price channel while examining the monetary transmission of policy rates to domestic financial markets. Sengupta (2014) utilizes monthly data from April, 1993 and March, 2012 and employs VAR analysis. In contrast to the previous study, the author finds an increasing relevance of the asset price channel over the lending channel in the post-LAF era.

For examining presence of the lending channel, Pandit et al. (2006) use a bank level panel dataset. They find that banks reduce loans advanced to the economy in response to a rise in the monetary policy rate, as proxied by different indicators. Aleem (2010) employs a VAR model for the period 1996–2007 and concludes that the bank lending channel is significant in India. Khundrakpam and Jain (2012) utilize a SVAR model for quarterly data from 1996 to 2011 to examine the relative importance of various transmission channels in India and deduce that the bank lending channel is important.

Recent empirical studies on India have deviated from the standard analysis. Mishra et al. (2016) use composite indicators for capturing monetary policy stance of the RBI. These include a principal component analysis of several policy rates and a qualitative score variable that tracks changes in policy instruments. When the authors assume that the monetary authority receives information about real variables with a lag, which is closer to our identification strategy, they encounter the output and price puzzle. Other papers have emphasized the role of international factors for examining the impact of monetary policy shocks. Paramanik and Kamaiah (2014) include oil prices and Federal Funds Rate in their VAR model. They assume that output and prices are contemporaneously affected by other domestic variables such as money supply, interest rates and exchange rates. Their results encounter the price puzzle while output and exchange rate decline but are insignificant. Barnett et al. (2015) use a modified version of the identification scheme in Kim and Roubini (2000) to identify monetary policy shocks in a SVAR framework using data for the pre-financial crisis period. Their findings suggest that contractionary monetary shocks have no impact on output and a weak impact on prices in the short run. Mohanty and Rishabh (2016) use 10-year U.S. term premium for capturing external monetary policy influence. The authors find evidence of interest rate channel, asset price channel and the credit channel. However, they do not control for international prices, which has the potential to play a significant role in inflation dynamics of India. Moreover, the contemporaneous response of asset prices is positive.

Our work builds on these recent papers, especially those using a Kim and Roubini (2000) style VAR system with international variables but as outlined in the introduction, it has a few important differences. First, we provide new evidence on the impact of monetary shocks on expectations of the economy. Second, our sample covers the entire period of the multiple indicator approach. Third, our identification strategy differs with the above papers as we assume that output and inflation are slow-moving variables and do not respond contemporaneously to the monetary shock. Finally, we include the shadow Federal Funds Rate in our model since it allows us to control for conventional as well as unconventional monetary policy actions conducted by the US Federal Reserve Board over the sample period.

5 Empirical Model

The policy decisions of the central bank reflect their response to the prevailing and future economic conditions. This is often characterized as a systematic response of the central bank to the state of the economy (Christiano et al., 1999). For example, an increase in inflation is generally met by an increase in the policy rate. However, there may be instances during which the central bank's policy actions are unrelated to this systematic response. This could be related to a change in the monetary stance, change in the way the central bank responds to similar information, etc. Such responses are characterized as a monetary policy shock. Formally, we presume a monetary policy rule that characterizes monetary policy decisions of the central bank:

$$i_t = f(\boldsymbol{\Omega_t}) + \sigma_s \varepsilon_t^s$$

where i_t refers to the policy rate, $f(.)$ is a function that dictates the systematic response of the central bank to the information set $\boldsymbol{\Omega_t}$ at time t and $\sigma_s \varepsilon_t^s$ is the monetary policy shock, σ_s is the standard deviation of the shock and ε_t^s has unit-variance. The information set $\boldsymbol{\Omega_t}$ contains knowledge about the economy. In the case of the monetary indicator approach of the RBI, this includes knowledge of rate variables, quantity variables, forward indicators, liquidity conditions as well as outlook of growth, inflation and risks. We include relevant variables to empirically examine the working of various transmission channels. We further assume that $\boldsymbol{\Omega_t} = (\boldsymbol{\Omega_t^d} \bigcup \boldsymbol{\Omega_t^*})$ where $\boldsymbol{\Omega_t^d}$ refers to the domestic information set while $\boldsymbol{\Omega_t^*}$ is the international information set.

We begin with a model that includes five variables in the domestic information set, two variables in the international information set and some exogenous controls. We call this model A where:

$$\Omega_{t,A}^{\mathbf{d}} = \{\textbf{output}, \textbf{prices}, \textbf{exchange rate}, \textbf{policy rate}, \textbf{money supply}\},$$

$$\Omega_t^* = \{\textbf{foreign interest rate}, \textbf{oil price}, \textbf{foreign price}\}$$

$$\textbf{and } \Omega_{t,A} = (\Omega_{t,A}^{\mathbf{d}} \bigcup \Omega_t^*)$$

Since the aim is to examine the impact of monetary policy shock on the Indian macroeconomy, we include the final targets of the RBI—output and prices—the nominal exchange rate to gauge the exchange rate channel, the policy rate and the money supply. We expect an expansionary monetary policy to lead to an increase in output and prices. The inverse relationship between the interest rates and the exchange rate is characterized by the conclusions derived in accordance with the interest parity condition.

The international information set includes exogenous variables of which foreign interest rate represents the international interest rate. It is considered exogenous from the perspective of the RBI. Adjustment in the international rate may significantly impact exchange rates and portfolio investments. In the post-crisis world, several countries witnessed significant changes in their exchange rate due to the sudden movement in capital flows in response to announcements of tapering by the US Federal Reserve (Eichengreen and Gupta, 2015; Rajan, 2016). oil price and foreign price symbolize international supply side inflationary effects. We expect an increase in international supply side constraints to have an immediate impact on prices as per the mark-up rule. This may induce the central bank to increase interest rates on account of potential inflationary pressures.

In an extended version of the model, we also examine the strength of other transmission channels by adding one additional variable to $\boldsymbol{\Omega}_{t,A}$ of the base model. Model B is a six-variable system to test for the asset price channel, model C is a six-variable system tests for the expectations channel, and model D is a six-variable system tests for the credit channel:

$$\begin{aligned}\Omega_{t,B} &= \{\Omega_{t,A}, \textbf{asset prices}\}\\ \Omega_{t,C} &= \{\Omega_{t,A}, \textbf{yield spread}\}\\ \Omega_{t,D} &= \{\Omega_{t,A}, \textbf{credit}\}\end{aligned}$$

Finally, as a robustness exercise, we also estimate a model that includes all the three variables used in the extended version:

$$\boldsymbol{\Omega}_{t,E} = \{\boldsymbol{\Omega}_{t,A}, \textbf{asset prices}, \textbf{yield spread}, \textbf{credit}\}$$

6 Econometric Methodology

This section explains the econometric methodology adopted in the paper. We first test for the stationarity of the variables by employing the Dickey–Fuller generalized least squares (DF-GLS) test (Elliott et al., 1996), the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Kwiatkowski et al., 1992) and Lee and Strazicich (2001) test for unit root with structural breaks. We use majority rule to decide the order of integration. The lag length for these tests was decided by examining the Akaike information criterion (AIC), Schwarz information criterion (SIC) and the Hannan Quinn information criterion.

The monetary policy shocks in a system of equations can be estimated using a VAR framework. However, the standard VAR model has been criticized on the grounds that residuals are a combination of structural shocks of all the endogenous variables in the system. This hinders the use of VAR in studies whose objective is to understand the impact of exogenous structural shocks on the model.

To counter these methodological issues, Sims (1986) recommends identification of structural parameters of the VAR model in order to identify structural shocks. Since they are uncorrelated with each other, responses to a structural shock can be used to gauge the impact of monetary policy on the economy. The framework allows the possibility of placing zero restrictions on contemporaneous relationships between endogenous variables to identify the structural parameters. It is especially useful to model situations where variables do not respond immediately to each other. This fits well with the scenario of a central bank that takes monetary policy decisions based on the available information set, which may only include past observations of economic variables such as output and inflation. Therefore, we identify the exogenous monetary policy shocks using non-recursive restrictions on the contemporaneous matrix of the structural model. We then construct impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) using the structural decomposition.

The econometric methodology of the literature is divided on estimating a SVAR model with non-stationary variables. Studies that use variables in levels refer to Sims' argument against loss of vital information from differencing the data. In this study, our choice will be driven by the existence of a long-run relationship between our endogenous variables. In the presence of such a relationship, estimating a model with differenced data without the error correction term leads to misspecification.

Suppose we wish to estimate a structural model of the following form:-

$$\boldsymbol{A}\boldsymbol{x}_t = \boldsymbol{B}_0 + \sum_{i=1}^{k} \boldsymbol{B}_i \boldsymbol{x}_{t-i} + \sum_{j=0}^{m} \boldsymbol{C}_j \boldsymbol{z}_{t-j} + \boldsymbol{u}_t$$

where $\boldsymbol{x}_t$ represents a n-vector of endogenous variables, $\boldsymbol{z}_t$ represents a m-vector of exogenous variables, $\boldsymbol{A}$ is a $(n \times n)$ matrix of contemporaneous relationships between the endogenous variables, $\boldsymbol{B}_0$ is the intercept, $\boldsymbol{B}_i$ represents $(n \times n)$ matrix of parameters of lagged values of the endogenous variables, $\boldsymbol{C}_j$ represents $(n \times m)$ matrix of parameters of exogenous variables, and $\boldsymbol{u}_t$ represents a $(n \times 1)$ matrix of uncorrelated structural shocks with a diagonal variance–covariance matrix $\boldsymbol{\Sigma}_{\boldsymbol{u}}$. To obtain structural parameters of this model, we first estimate the reduced form VAR model:

$$\boldsymbol{x}_t = \boldsymbol{A}^{-1}\boldsymbol{B}_0 + \boldsymbol{A}^{-1} \sum_{i=1}^{k} \boldsymbol{B}_i \boldsymbol{x}_{t-i} + \boldsymbol{A}^{-1} \sum_{j=0}^{m} \boldsymbol{C}_j \boldsymbol{z}_{t-j} + \boldsymbol{A}^{-1}\boldsymbol{u}_t$$

$$\Rightarrow \boldsymbol{x}_t = \boldsymbol{D}_0 + \sum_{i=1}^{k} \boldsymbol{D}_i \boldsymbol{x}_{t-i} + \boldsymbol{e}_t$$

where $\boldsymbol{A}^{-1}\boldsymbol{B}_0 = \boldsymbol{D}_0$, $\boldsymbol{A}^{-1}\boldsymbol{B}_i = \boldsymbol{D}_i$ **and** $\boldsymbol{A}^{-1}\boldsymbol{u}_t = \boldsymbol{e}_t$.

This requires $\boldsymbol{A}$ to be invertible. Since every equation contains the same variables, the solution to the reduced form can be estimated using ordinary least squares (OLS) technique. The elements of $\boldsymbol{e}_t$ are a weighted average of the structural shocks. Since our primary interest lies in the structural shocks, we obtain u_t from reduced form estimates. Let the variance–covariance matrix of $\boldsymbol{e}_t$ be $\boldsymbol{\Sigma}$. Then, to estimate elements of $\boldsymbol{A}$, we use the following relationship between the covariance matrices of the structural shocks and the reduced form residuals,

$$\boldsymbol{\Sigma} = \boldsymbol{A}^{-1}\boldsymbol{\Sigma}_u \boldsymbol{A}^{-1'}$$

$$\Rightarrow \boldsymbol{\Sigma}_u = \boldsymbol{A}\boldsymbol{\Sigma}\boldsymbol{A}'$$

The above matrix provides a system of equations in structural parameters. However, they cannot be solved for a unique solution since the number of equations is lower than the number of parameters in the system. The number of unknowns include the $(n^2 - n)$ unknown elements of $\boldsymbol{A}$ (diagonal elements are unity) and are n unknown values on the diagonal of $\boldsymbol{\Sigma}_u$. Since $\boldsymbol{\Sigma}$ is a symmetric matrix, it contains $\frac{n(n+1)}{2}$ distinct elements. Hence, for exact identification of elements of $\boldsymbol{A}$ and $\boldsymbol{\Sigma}_u$, we require $n^2 - \frac{n(n+1)}{2} = \frac{n(n-1)}{2}$ restrictions on the structural model. If there are more than $\frac{n(n-1)}{2}$ restrictions, we have an over-identified system. In this situation, we estimate a restricted covariance matrix, $\boldsymbol{\Sigma}_R$, derived by maximizing the likelihood function *after* imposing restrictions on $\boldsymbol{\Sigma}_u$ and $\boldsymbol{A}$. The difference between $\boldsymbol{\Sigma}_R$ and $\boldsymbol{\Sigma}$ has a χ^2 distribution with $\frac{n(n-1)}{2}$ degrees of freedom. This forms a test for over-identifying restrictions. If the difference between $\boldsymbol{\Sigma}_R$ and $\boldsymbol{\Sigma}$ is significantly different from zero, then the restrictions are rejected.

Finally, we use the relation $\boldsymbol{A}^{-1}\boldsymbol{u}_t = \boldsymbol{e}_t \Rightarrow \boldsymbol{u}_t = \boldsymbol{A}\boldsymbol{e}_t$ in the vector moving average (VMA) representation to obtain the impulse response to structural shocks. We estimate one-standard deviation error bands around the impulse response functions (IRFs) using Monte Carlo integration. This nonlinear method is an improvement over the analytical method since the latter uses linearization to derive the error bands that become increasingly inaccurate with time.

7 Data and Identification Strategy

7.1 Data

In this study, we examine the monetary policy transmission channels in the Indian economy using monthly data for the period January, 1998–December, 2015. The domestic variables include output, prices, exchange rate, interest rates and money demand while the open economy is represented by the exchange rate, U.S. interest rates, crude price and prices of food in the international market.

We use index of industrial production (IIP) as a proxy for output. Although IIP reflects about one third of the economic activity in India, it is the only component of output that is available at monthly frequency. Prices are represented by wholesale price index (WPI). The exchange rate is the price of the Rupee against the dollar in home currency terms (USD). Narrow money (M1) is used as a proxy for money supply. During this period, several indicators were used by the RBI to operationalize its policy. For short-term management of liquidity, it used the repo rate and the reverse repo rate while it also relied on quantity instruments like the CRR and open market operations (OMO) for managing liquidity in the system. An implication of using several indicators is that none of these rates completely capture all the aspects of monetary policy stance. We, therefore, rely on the interbank CMR that responds swiftly to every movement of the RBI. It is known to capture changes in the monetary policy stance quickly and has been used extensively in studies on transmission channels. For examining the asset price channel, we use the Bombay Stock Exchange (BSE) stock market index, as an additional variable in the VAR model. We include bank credit to the economy to test the impact on lending. Finally, future economic activity and inflation expectations are measured by the yield spread between 10-year government securities and the 3-month treasury bill (Dua and Raje, 2014). The yield spread has been used extensively as a leading indicator of future economic growth and inflation (Estrella and Mishkin, 1998; Hamilton and Kim, 2000; Rudebusch and Williams, 2009; Bleaney et al., 2016). A contractionary shock should reduce the yield spread because it is likely to result in a decline in likelihood of future rate hikes. Since long-term rates are a weighted average of expected short rate, they also decline and, therefore, the yield spread is smaller and signals lower inflation expectations.

We also include several exogenous variables in our model to further account for external influences. The FFR has been extensively used in the literature as a proxy for the international prevailing interest rate. Central banks throughout the world respond to U.S. monetary policy decisions since monetary decisions of the US Federal Reserve impact the US dollar exchange rate and the US dollar commands the role of the vehicular currency. Hence, it is important to include FFR for controlling a systematic response of the RBI to foreign monetary shocks (Kim and Roubini, 2000). Since the FFR was stuck at the ZLB during the post-crisis period, we use the shadow interest rates provided by Wu and Xia (2016). Figure 2 plots the federal funds rate and the shadow rate for the period January, 2008–December, 2015. The

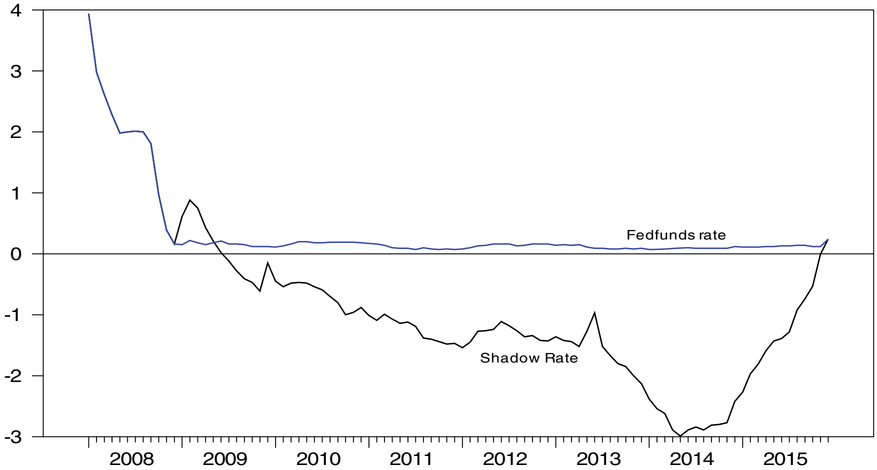


Fig. 2 Federal funds rate and Wu-Xia shadow rate

Wu-Xia shadow rate assumes a lower bound of 0.25%. The shadow rate mirrors FFR till December, 2008 and is negative from July, 2009 to November, 2015.

International oil price is used a proxy for international supply side inflationary effects. This controls for any endogenous response of the RBI to international inflationary pressures and isolates contractionary monetary shock from a negative supply shock in the international market. We use Brent oil prices prevailing in the global market as an indicator for crude prices. In India, an oil price shock also has drastic effects on the current account since crude has a share of 80% in total imports. Hence, it has the ability to play an important role in the dynamics of the economy. We also include a variable for international prices of food and commodities since they could also have a considerable impact on inflation in India.

International episodes of turmoil like the East Asian Financial crisis (1997–98), Dot-Com bubble (2000–01), the Global financial crisis (2007–09) and the Euro-Zone crisis (2010–12) are captured using a dummy variable. Uncertainty in global financial markets is captured by including the volatility index (VIX) based on S&P 500. Net financial investment flows is included to capture short-term disturbances to India that led the RBI to intervene in the foreign exchange market. The domestic endogenous variables, barring call money rate and exchange rate, have been de-seasonalized using the census X-12 method.

The data for the IIP, WPI, USD, M1, CMR and investment flows are sourced from the Reserve Bank of India website. The data for VIX, FFR and crude oil price have been obtained from the Federal Reserve of St. Louis' Website. The shadow interest rates are obtained from the Federal Reserve Bank of Atlanta. The indices for international food and commodity prices are sourced from the International Monetary Fund. The dummy variables for capturing crisis episodes was constructed using the business cycle data published by the Economic Cycle Research Institute (ECRI). The list of variables and their data sources is given in Table 3 in the appendix.

7.2 Identification of VAR Model

The identification of the model places restrictions on the contemporaneous relationships among the endogenous variables in the A matrix[4] motivated by two factors: first, on the basis of economic theory and second, on availability of data to the RBI at the time of making the decision. This follows from the idea that the monetary authority adjusts its stance according to the current period information available for the economy. This includes current period movements of prices, oil prices, FFR, money supply, and exchange rate. At the same time, monetary policy variables are assumed to have no current period impact on non-monetary policy variables. This is quite plausible given that we are using monthly data for our study.

The contemporaneous relationships in the model are identified using the following matrix:

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ a_{\text{ey}} & a_{\text{ep}} & 1 & a_{\text{ei}} & a_{\text{em}} \\ 0 & 0 & a_{\text{ie}} & 1 & a_{\text{im}} \\ a_{\text{my}} & a_{\text{mp}} & 0 & a_{\text{mi}} & 1 \end{bmatrix}$$

The 1st row represents the equation for output and its contemporaneous relationship with other endogenous variables in the system. In our model, we have assumed that real variables adjust sluggishly which forms the basis for our restrictions in this equation. Similarly, sticky prices in the short-run implies that there is no simultaneous effect of other variables. The exchange rate is a high-frequency series and responds swiftly to information about domestic as well as international information. We, therefore, do not place any restriction on its equation.

The next couple of equations depict the money market of the economy. The 4th row represents the reaction function of the monetary authority. The lack of information about current value of some variables implies that the monetary authority responds to these variables with a lag. Additionally, the authorities have real time information about the monetary aggregate and exchange rates. The 5th row pertains to the money demand equation. Theoretically, it has a contemporaneous relationship with real output and nominal interest rate. Hence, we leave relationships with output, prices and the interest rate unrestricted in this row.

In the extended versions of the model, we examine the strength of other transmission channels by adding a variable to the base model. The restrictions on the contemporaneous relationship of the additional variable in each of these models

[4] For a detailed discussion on alternate methods to identify the VAR, see Ramey (2016).

with other variables are given below:

$$\text{Model B: } \begin{bmatrix} 0 & 0 & a_{\text{ae}} & a_{\text{ai}} & a_{\text{am}} & 1 \end{bmatrix}$$
$$\text{Model C: } \begin{bmatrix} 0 & 0 & a_{\text{se}} & a_{\text{si}} & a_{\text{sm}} & 1 \end{bmatrix}$$
$$\text{Model D: } \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

We follow our identification strategy and keep the contemporaneous impact of asset prices and bank credit with exchange rate, interest rate and money on the stock market unrestricted while at the same time, restrict the impact of output and prices to be zero. For bank credit, we treat the movement of bank credit akin to the movement of a slow responding macroeconomic aggregate variable. Hence, we assume that it reacts to other variables in the system only with a lag. For model E, we combine the restrictions in the above models and further assume that asset prices and yield spreads react to each other contemporaneously while bank credit reacts to both the variables with a lag.

8 Results

We first discuss our results from tests of non-stationarity. The results of these tests are given in Table 1. The majority of the tests suggest that our variables are integrated of order one. In the next step, we test for the presence of a long-run relationship between the system of variables. We utilize the Johansen–Juselius cointegration test, and it confirms the presence of a long-run relationship between our endogenous variables as the null hypothesis of no cointegration is rejected at 1% level of significance. Thus, we utilize all variables in logarithm form except for the interest rate and exchange rate. We then conduct tests for lag order selection using various information criterion. The tests unanimously pick an optimal lag length of 2 for all our models. Finally, the Log-likelihood ratio for over-identification shows that our restrictions are not rejected at 10% level of significance.

The IRFs of a one-standard deviation monetary shock for model A are given in panel A of Fig. 3. We find that an unexpected policy rate hike leads to a significant

Table 1 Unit root tests

Panel A: Summary of unit root tests				
Variable	DF-GLS	KPSS	Lee and Strazicich	Overall inference
Call money rate	No	Yes	Yes	I (1)
IIP	Yes	Yes	No	I (1)
Exchange rate	Yes	Yes	No	I (1)
Money supply	Yes	Yes	No	I (1)
Wholesale price index	Yes	Yes	No	I (1)

persistent decline in output and prices over the 24-month horizon. However, the output response is insignificant. Other studies also observe a similar response of IIP to a monetary shock (Mishra et al., 2016; Sengupta, 2014, etc.) The price response suggests that inflation declines by about 0.13% within 1 quarter and the effect is persistent. The effect is larger than observed in Sengupta (2014). We also observe the phenomenon of exchange rate overshooting in India. The exchange rate appreciates strongly in the first month in response to a positive shock in CMR and then gradually depreciates starting the 2nd month. This corroborates the results found by Pandit et al. (2006), Aleem (2010) and suggests existence of the exchange rate channel. Finally, money supply falls in the expected direction in response to a contractionary shock.

Panel B of Fig. 3 shows the results for model B in which we evaluate the asset price channel by examining the impact on the stock market. The responses of variables included in the base model mirror those in panel A. The stock market response is negative on impact but insignificant. Looking at the persistence, there is no significant long-run impact of monetary policy on the stock market. Hence, we do not find evidence of the asset price channel. These results are in line with previous papers (e.g. Bhattacharyya and Sensarma, 2008; Sengupta, 2014; Mohanty and Rishabh, 2016) that find weak or insignificant negative impact. This might be due to the low stock market capitalization to GDP ratio of India (Mishra et al., 2016). Panel C shows results for model C where we add the yield spread to variables in the base model to examine the expectations channel. Our results suggest that a contractionary interest rate shock of 100 bps does, in fact, reduce the yield spread by about 20 bps on impact. This suggests that the RBI monetary policy transmitted to both the short and the long end of term structure of the yield curve and may influence future economic growth and inflation expectations. Panel D depicts results with bank credit to test existence of the credit channel. In response to a monetary shock, bank credit declines as per our expectations. The peak decline occurs around 10 months after the shock at about 0.15% and is persistent. As a robustness exercise, we also examine the response of monetary policy shocks on asset prices, yield spread and bank credit in a large eight variable system. The results presented in Panel E suggest that responses are qualitatively similar to the results obtained with the six-variable system.

The FEVDs are presented in Table 2. Every panel contains a table which states the *share* of monetary policy shocks in the forecast error variance decomposition of a variable at different horizons for a *specific* model. For example, for our base model (model A) shown in panel A, let a_{ij} be the elements of the FEVD table where i refers to variables of the system and j refers to the monetary policy shock. Then, a_{ij} describes the share of monetary policy shock in forecast error variance of variable i Further, every column describes a different horizon. For example, i states that the share of monetary shock in forecast error variance of IIP is 0.166% at the 12 months horizon.

Panel A: Base Model [$\Omega_{t,A}$]

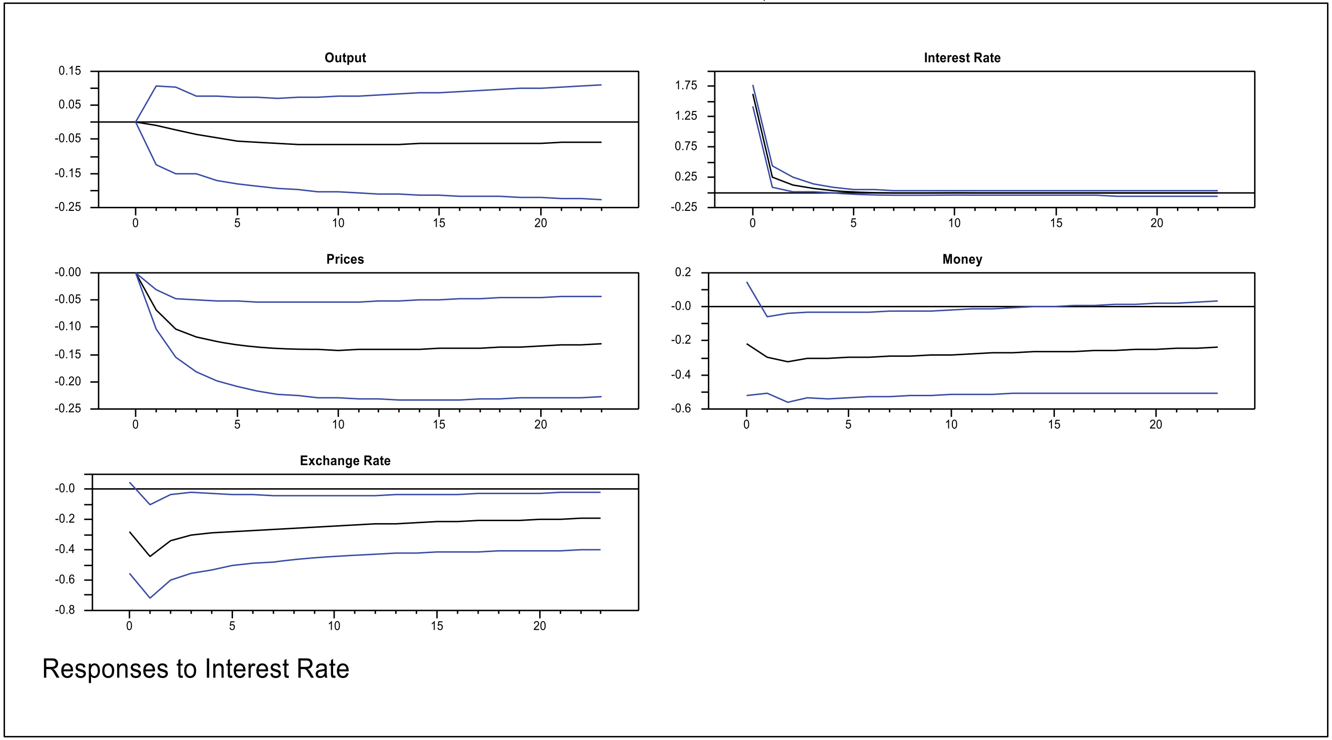


Fig. 3 Responses to one unit monetary policy contractionary shock. *Panel A* Base Model [$\Omega_{t,A}$]. *Panel B* Extended Model with Stock Market [$\Omega_{t,B} = \{\Omega_{t,A}, \text{asset prices}\}$]. *Panel C* Extended Model with Yield Spread [$\Omega_{t,C} = \{\Omega_{t,A}, \text{yield spread}\}$]. *Panel D* Extended Model with Bank Credit $\left[\Omega_{t,D} = \left\{\Omega_{t,A}, \text{credit}\right\}\right]$. *Panel E* Extended model with eight variables [$\Omega_{t,E} = \left\{\Omega_{t,A}, \text{asset prices, yield spread, credit}\right\}$]

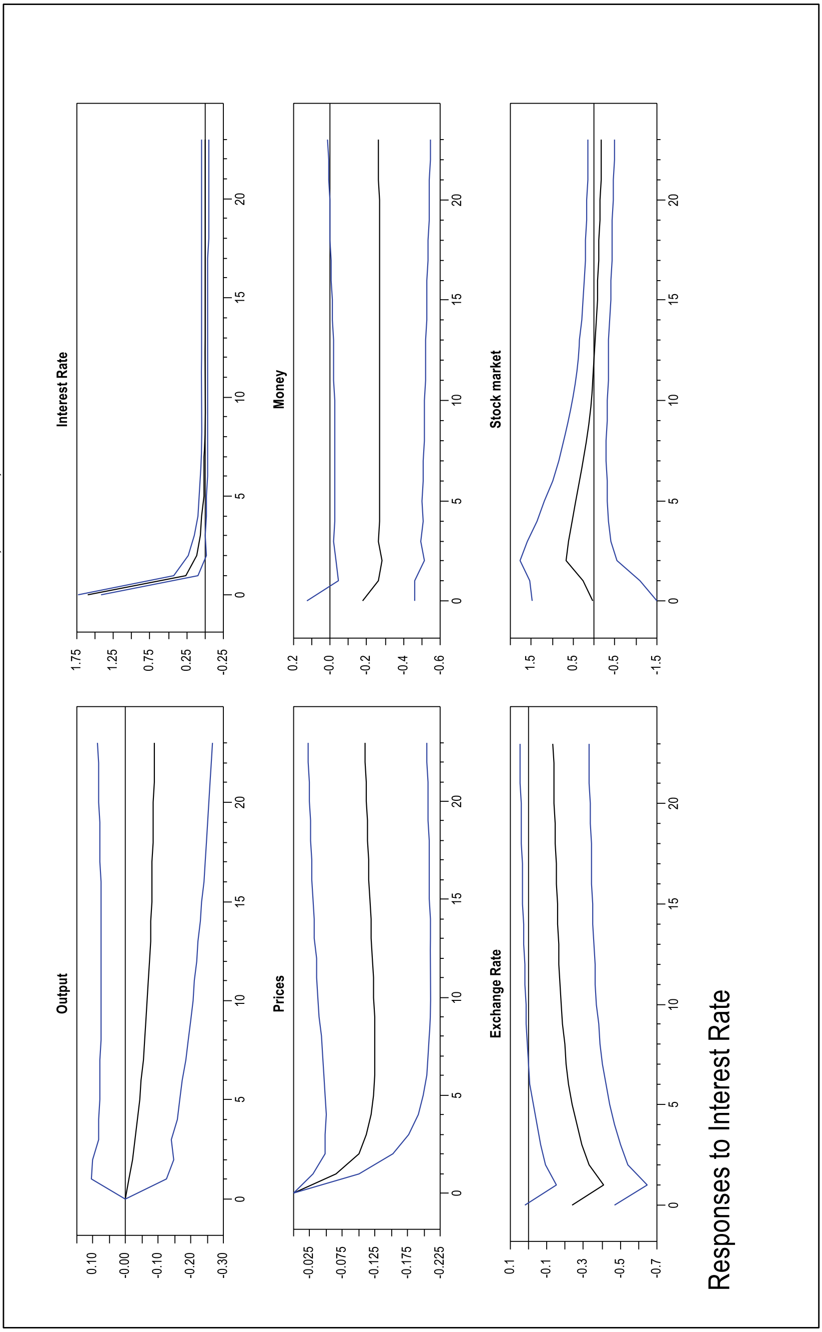


Fig. 3 (continued)

Panel C: Extended Model with Yield Spread [$\Omega_{t,C} = \{\Omega_{t,A}, \textit{yield spread}\}$]

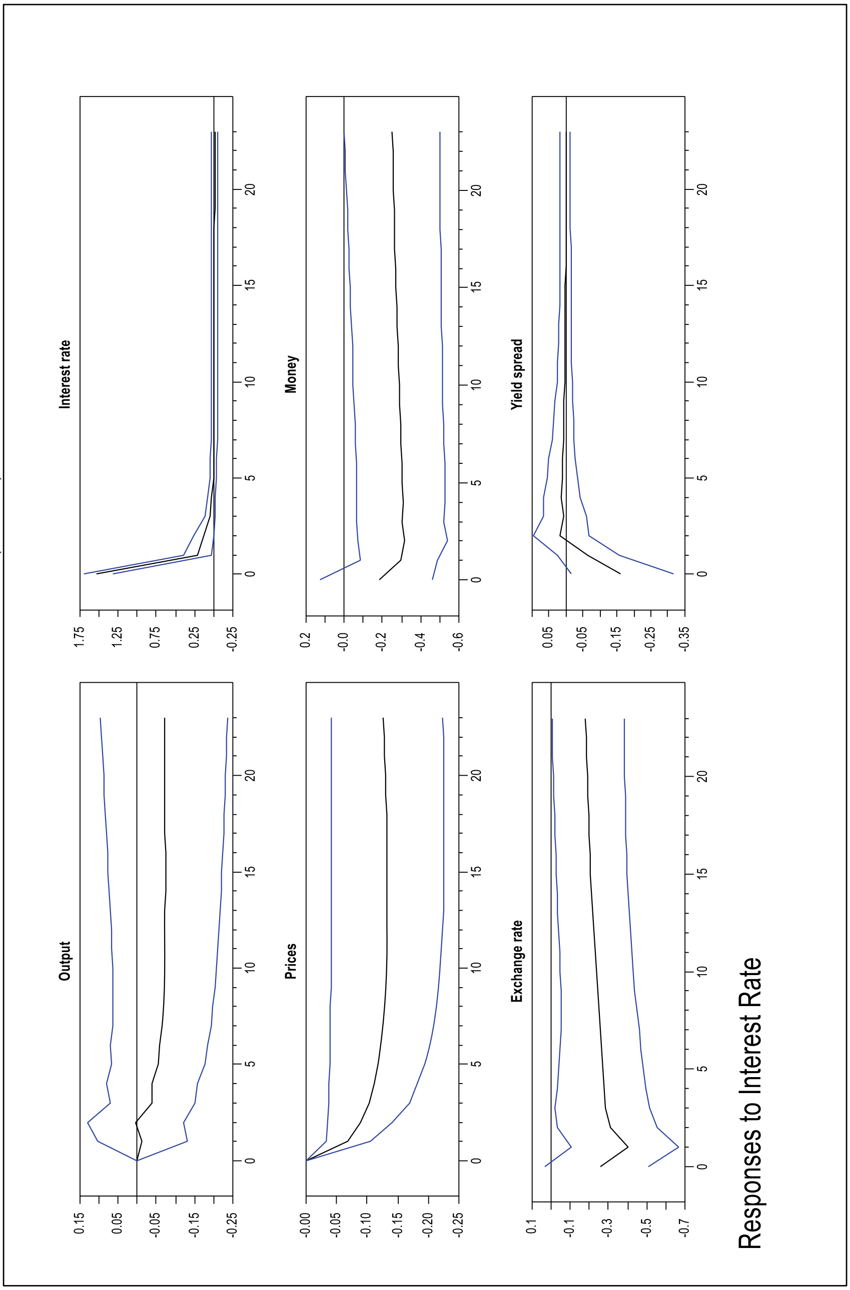


Fig. 3 (continued)

Panel D: Extended Model with Bank Credit [$\Omega_{t,D} = \{\Omega_{t,A}, credit\}$]

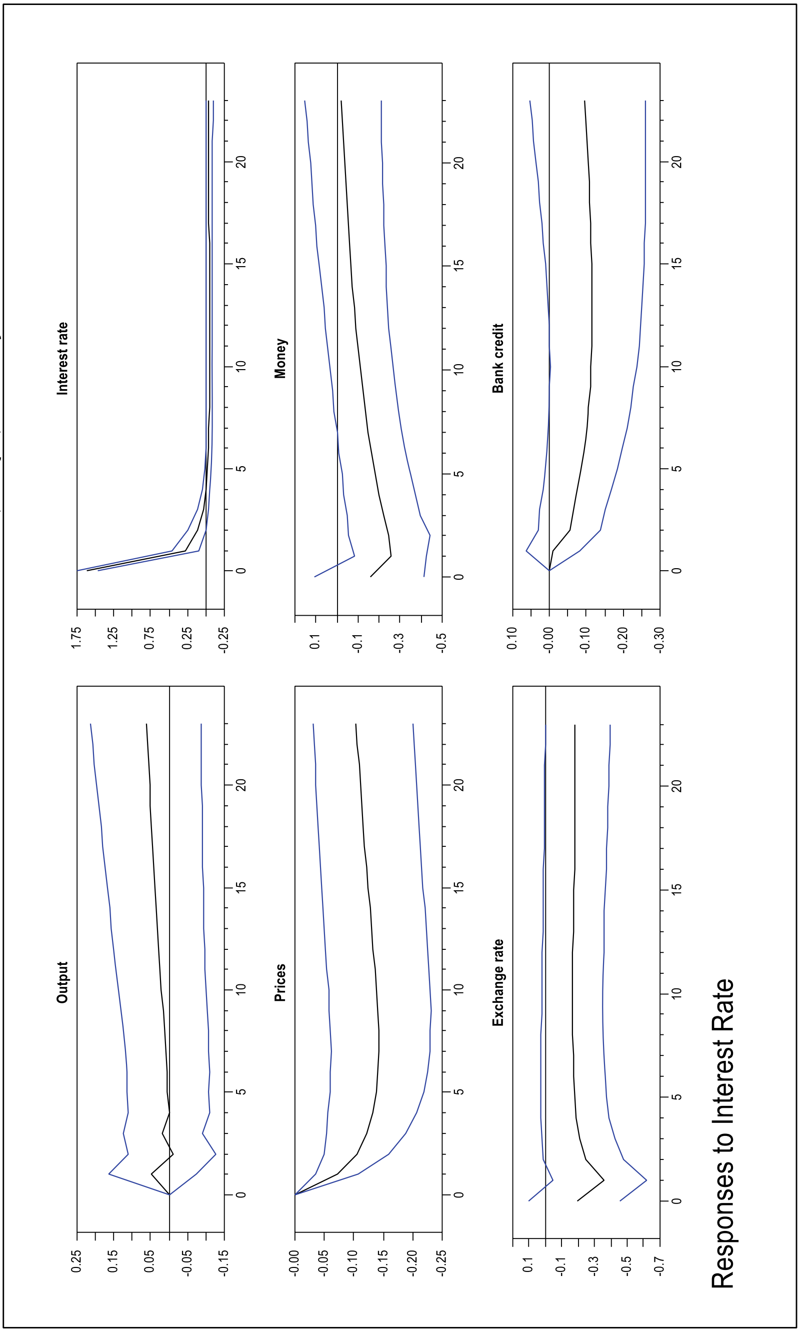


Fig. 3 (continued)

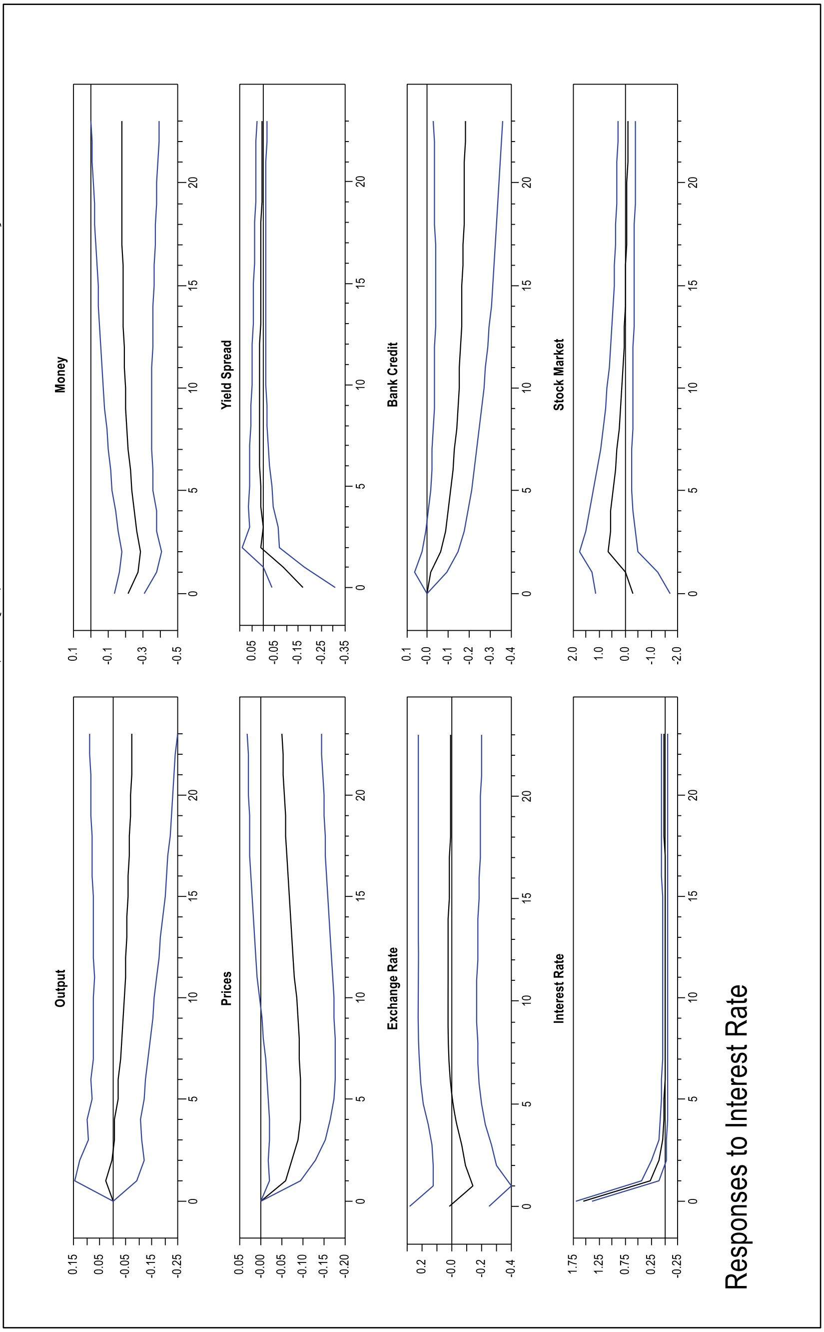


Fig. 3 (continued)

Table 2 Forecast error variance decomposition

Panel A—Base model [$\boldsymbol{\Omega}_{t,A}$]

Step	Output	Prices	Exchange rate	Policy rate	Money supply
1	0	0	4.266	92.895	1.022
12	0.166	5.36	5.4	74.904	6.604
24	0.218	6.695	4.855	66.086	5.724
36	0.184	7.26	4.511	58.449	4.541

Panel B—FEVD with stock market [$\boldsymbol{\Omega}_{t,B} = \{\boldsymbol{\Omega}_{t,A}, \text{asset prices}\}$]

Step	Output	Prices	Exchange rate	Policy rate	Money supply	Stock index
1	0	0	3.437	94.484	1.007	0.216
12	0.158	5.27	5.337	77.309	6.245	0.891
24	0.414	6.265	4.342	69.108	5.939	0.887
36	0.519	6.7	3.833	62.027	5.162	0.982

Panel C—FEVD with yield spread [$\boldsymbol{\Omega}_{t,C} = \{\boldsymbol{\Omega}_{t,A}, \text{yield spread}\}$]

Step	Output	Prices	Exchange rate	Policy rate	Money supply	Yield spread
1	0	0	3.207	94.085	1.043	28.437
12	0.302	5.228	4.608	75.628	6.764	19.327
24	0.333	6.596	4.105	66.521	5.841	18.094
36	0.27	7.095	3.83	58.921	4.748	16.92

Panel D—FEVD with bank credit [$\boldsymbol{\Omega}_{t,D} = \left\{\boldsymbol{\Omega}_{t,A}, \text{credit}\right\}$]

Step	Output	Prices	Exchange rate	Policy rate	Money supply	Bank credit
1	0	0	15.738	79.061	5.28	0
12	0.436	10.641	11.999	61.157	8.379	2.939
24	1.289	12.984	10.805	53.494	4.229	3.387
36	2.097	13.654	10.521	47.317	2.595	2.314

Let a_{ij} be the elements of the FEVD table where i refers to variables of the system and j refers to the monetary policy shock. Then, a_{ij} describes the share of monetary policy shock in forecast error variance of variable i. Further, every column describes a different horizon. For example, a_{12} states that the share of monetary shock in forecast error variance of IIP is 0.166% at the 12 months horizon.

Panel A shows that the monetary shock plays a minimal role in explaining variation in output across horizons. A similar picture emerges for prices as the interest rate shock explains about 5–6% of the variation over two years. Variance decomposition in exchange rate suggests that contribution of monetary shock is largely constant at about 4% at various horizons. The monetary shock is the major contributor in forecast error variance of the interest rate. It explains about 93% of the variation on impact and is pre-dominant even at the two-year horizon. The monetary aggregate is mainly affected by shocks in the interest rate. Over a period of two years, interest rate explains about 80% of the variation in money supply.

The FEVD for model B with stock prices is depicted in Panel B and is qualitatively similar to the base model. The monetary shock explains only 1% of the variation that too at a horizon of two years. This confirms the weak transmission of monetary policy to stock markets. The FEVD in panel C contains results for model C that examines the expectations channel. The shares are very similar to the base model despite the addition of the yield spread. The share of the monetary shock in forecast error variance of the yield spread is quite high relative to other variables in the system and is about 30% at one-month horizon. Moreover, it persists across time and declines slowly from about 20% at the one-year horizon to over 15% at the three-year horizon. Our last panel displays the share of monetary shocks in forecast error variance for the system with bank credit (model D). Monetary shocks are not the major determinant of variation in bank credit. There are a few other subtle differences. In particular, explanatory power of a policy rate shock across specifications is higher for output, prices and exchange rates. For WPI, the policy rate explains about 14% of the movement respectively at a horizon of 48 months. Similarly, variation in exchange rate is about 10% at the one-year horizon. Variation in money supply is explained by monetary shock for about 8% within the first year before tapering off.

9 Conclusion

The objective of the present study is to unearth possible monetary policy transmission channels that are at play in the Indian economy. We examine the impact of exogenous monetary policy shocks on the Indian economy during the multiple indicator approach using monthly data from January, 1998 to December, 2015. We rely on a Structural VAR-X model for a small open economy to identify the structural monetary policy shocks to conduct our analysis. The endogenous variables include domestic variables while exogenous variables include a mix of domestic and foreign variables. We capture the effects of the U.S. monetary policy stance at the Zero Lower Bound using the shadow interest rates as proposed by Wu and Xia (2016). We also include other exogenous variables in our exposition to control for international events such as international food and oil prices, crisis episodes of the Asian financial crisis, the Dotcom bubble, the U.S. financial crisis and the Eurozone crisis, domestic capital flows and the VIX as an indicator of financial uncertainty. Apart from studying the channels that are standard in the literature, our work provides new evidence on the impact of monetary shocks on expectations of the economy as measured by the yield spread.

We find evidence of active interest rate and exchange rate channels in the Indian economy. We do not observe any empirical puzzles and our results are broadly in line with economic theory. We find that contractionary monetary policy shock reins in price rise permanently while output response is weak. Further, the asset price channel is not an important channel in the transmission process. Contractionary monetary shock has a negative impact on bank lending that lasts almost the entire year after the shock. Finally, future outlook of growth and inflation expectations, as measured by the yield spread, show a decline following the contractionary shock. In addition, the economic significance of monetary shocks is highest for the yield spread and persists for well over a three-year horizon.

Questions to Think About

1. Suppose that the central bank decides to raise policy rates after anticipating a rise in expected inflation in the economy, but the econometrician does not include any information about expected inflation in the VAR. The findings from the VAR show a positive impulse response of prices to a contractionary monetary policy shock. Explain the potential role of the omission of expected inflation in the information set of the econometrician in observing this result.

   Hint: The estimated residual of the equation for monetary policy rule will contain the systematic positive policy response of the central bank to expected inflation. To resolve this, add an indicator for inflation expectations in the VAR. Refer: Sims (1992).
2. Suppose the central bank switches to Inflation Targeting during the sample period. Do we need to make any changes in the methodology to estimate the dynamic responses? Are there any additional data requirements?

   Hint: The model can be estimated for two sub-samples. A regime switching model can also be estimated. Refer: Sims and Zha (2006), Krolzig (2013).
3. Suppose that all variables in the system of equations are I(1) but the Johansen–Juselius test does not reject the null of no cointegration. How would you proceed to obtain dynamic responses to monetary policy shocks?

   Hint: Transform variables and estimate VAR. Refer: Enders (2015).

Appendix

Table 3 List of variables and data sources

Variable	Definition	Data source
Output (y_t)	Index of industrial production	www.rbi.gov.in
Prices (p_t)	Wholesale price index	www.rbi.gov.in
Exchange rate (e_t)	Indian rupee against U.S. Dollar	www.rbi.gov.in
Money supply (m_t)	M1 (narrow money)	www.rbi.gov.in
Interest rate (i_t)	Call money rate	www.rbi.gov.in
Stock index	BSE Sensex	www.rbi.gov.in
Credit	Bank Credit	www.rbi.gov.in
Interest rate of the U.S	Shadow Federal Funds Rate	www.stlouidfed.org
Long-term rate	GSEC 10-year rate	www.rbi.gov.in
Short-term rate	TBILL 3-month rate	www.rbi.gov.in
Yield spread	GSEC 10Y—TBILL 3M	www.rbi.gov.in
Oil prices	Crude oil price (Brent) ($)	www.stlouidfed.org
Crisis episodes dummy	$\begin{cases} 1 \text{ during periods of crisis} \\ 0 \text{ otherwise} \end{cases}$	www.businesscycle.com
Foreign inflow	Sum of net FII and net FDI	www.rbi.gov.in
Food prices	Food price index	http://data.imf.org
Commodity prices	Commodity price index	http://data.imf.org
Uncertainty index	CBOE VIX	www.stlouidfed.org
Rainfall	All India monthly rainfall	www.imdpune.gov.in

References

Al-Mashat, R. (2003),.Monetary policy transmission in India: Selected issues and statistical appendix, country report no. 03/261, IMF.

Aleem, A. (2010). Transmission mechanism of monetary policy in India. *Journal of Asian Economics, 21*, 186–197.

Banerjee, S., Basu, P., & Ghate, C. (2020). A monetary business cycle model for India. *Economic Inquiry, 58*(3), 1362–1386.

Barnett, W. A., Bhadury, S. S., & Ghosh, T. (2016). An SVAR approach to evaluation of monetary policy in India: Solution to the exchange rate puzzles in an open economy. *Open Economies Review, 27*, 871–893.

Bhattacharyya, I., & Sensarma, R. (2008). How effective are monetary policy signals in India? *Journal of Policy Modeling, 30*, 169–183.

Bhattacharya, R., Shah, A., & Patnaik, I. (2011). Monetary policy transmission in an emerging market setting, WP 11/5, IMF.

Black, F. (1995). Interest rates as options. *The Journal of Finance, 50*(5), 1371–1376.

Bleaney, M., Mizen, P., & Veleanu, V. (2016). Bond spreads and economic activity in eight European economies. *The Economic Journal, 126*, 2257–2291.

Boivin, J., Kiley, M. T., & Mishkin, F. S. (2010). How has the monetary transmission mechanism evolved over time? No. w15879, NBER.

Bowman, D., Londono, J. M., & Sapriza, H. (2015). US unconventional monetary policy and transmission to emerging market economies. *Journal of International Money and Finance, 55*, 27–59.

Brandao-Marques, M. L., Gelos, M. R., Harjes, M. T., Sahay, M. R., & Xue, Y. (2020). *Monetary policy transmission in emerging markets and developing economies*. International Monetary Fund.

Christiano, L, J., Martin, E., & Charles L. E. (1999) Monetary policy shocks: What have we learned and to what end?. *Handbook of Macroeconomics, 1*, 65–148.

Dua, P. (2020). Monetary policy framework in India. *Indian Economic Review, 55*, 117–154.

Dua, P., & Raje, N. (2014). Determinants of yields on government securities in India. *Margin: The Journal of Applied Economic Research, 8*, 375–400.

Elliot, B. E., Thomas, J. R., & James H. S. (1996). Efficient tests of the unit root hypothesis. *Econometrica, 64*(8), 13–36.

Eichengreen, B., & Gupta, P. (2015). Tapering talk: The impact of expectations of reduced federal reserve security purchases on emerging markets. *Emerging Markets Review, 25*, 1–15.

Enders, W. (2015). *Applied econometric time series fourth edition*. University of Alabama.

Estrella, A., & Mishkin, F. S. (1998). Predicting US recessions: Financial variables as leading indicators. *Review of Economics and Statistics, 80*, 45–61.

Hamilton, J. D., Kim, D. H. (2000). A re-examination of the predictability of economic activity using the yield spread.

Khundrakpam, J., & Jain, R. (2012). Monetary policy transmission in India: A peep inside the black box, WP 11, RBI.

Kim, S., & Roubini, N. (2000). Exchange rate anomalies in the industrial countries: A solution with a structural VAR approach. *Journal of Monetary Economics, 45*, 561–586.

Krolzig, H.-M. (2013). *Markov-switching vector autoregressions: Modelling, statistical inference, and application to business cycle analysis* (Vol. 454). Springer Science & Business Media.

Kwiatkowski, D. et al. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?. *Journal of econometrics, 54*,1–3, 159–178.

Lee, J., & Mark, C. S. (2001). Break point estimation and spurious rejections with endogenous unit root tests. *Oxford Bulletin of Economics and statistics, 63*(5), 535–558.

Mishkin, F. S. (2012). The Economics of Money, Banking and Financial Markets. *The Pearson Series in Economics.*

Mishra, P., Montiel, P., & Sengupta, R. (2016). Monetary transmission in developing countries: Evidence from India. *Monetary Policy in India*, 59–110.

Mohanty, D. (2012). Evidence of interest rate channel of monetary policy transmission in India, WP 6, RBI.

Mohanty, M. S., & Kumar, R. (2016). Financial intermediation and monetary policy transmission in EMEs: What has changed since the 2008 crisis? *Monetary Policy in India*, 111–150.

Pandit, B. L., Mittal, A., Roy, M., & Ghosh, S. (2006). Transmission of monetary policy and the bank lending channel: Analysis and evidence for India, Study Number 25, Department of Economic Analysis and Policy, RBI.

Paramanik, R. N., & Kamaiah, B. (2014). A structural vector autoregression model for monetary policy analysis in India. *Margin: The Journal of Applied Economic Research, 8*, 401–429.

Patra, M. D., Pattanaik, S., John, J., & Behera, H. K. (2016). Monetary policy transmission in India: Do global spillovers matter? WP 1 and 2, Vol. 37, RBI.

Rajan, R. (2016). Going Bust for Growth. *Progress and Confusion: The State of Macroeconomic Policy, 885,* 267–284.

Ramey, V. A. (2016). Macroeconomic shocks and their propagation. *Handbook of Macroeconomics, 2*, 71–162.

Reserve Bank of India. (2014). Report of the expert committee to revise and strengthen the monetary policy framework.

Reserve Bank of India. (1998). New monetary aggregates: An introduction.

Reserve Bank of India. (1985). Report on the working of the Indian monetary system.

Rudebusch, G. D., & Williams, J. C. (2009). Forecasting recessions: The puzzle of the enduring power of the yield curve. *Journal of Business & Economic Statistics, 27*, 492–503.

Sengupta, N. (2014). Changes in transmission channels of monetary policy in India. *Economic and Political Weekly, 49*, 62–71.

Sims, C. (1986). Are forecasting models usable for policy analysis? *Quarterly Review of the Federal Reserve Bank of Minneapolis, 10*, 2–16.

Sims, C. A. (1992). Interpreting the macroeconomic time series facts: The effects of monetary policy. *European Economic Review 36*(5), 975–1000.

Sims, C. A., & Zha, T. (2006). Were there regime switches in US monetary policy? *American Economic Review, 96*(1), 54–81.

Tillmann, P. (2016). Unconventional monetary policy and the spillovers to emerging markets. *Journal of International Money and Finance, 66*, 136–156.

Wu, J. C., & Xia, F. D. (2016). Measuring the macroeconomic impact of monetary policy at the zero lower bound. *Journal of Money, Credit and Banking, 48*, 253–291.

Chapter 6
India's Bilateral Export Growth and Exchange Rate Volatility: A Panel GMM Approach

Pami Dua and Ritu Suri

Abstract This paper empirically examines the effect of real exchange rate volatility on India's bilateral export growth. Additionally, we examine the impact of exchange rate volatility on growth in India's exports to developed and developing countries. For this purpose, we utilize panel data of India's twelve export trading partners, six developed (US, Hong Kong, Singapore, EZ, UK, Japan) and six developing countries (China, Indonesia, Brazil, South Africa, Malaysia and Thailand) from 2005 Q2 to 2019 Q2. We utilize panel GMM-IV technique to estimate a 'hybrid model' for India's export growth. Our findings suggest that while real exchange rate volatility significantly decreases growth in India's exports to developing countries, it has an insignificant impact on growth in India's exports to developed countries. However, the overall effect of exchange rate volatility upon India's export growth is found to be insignificant. Further, while we find that growth in India's exports to both developed and developing economies is positively affected by growth in real exchange rate, foreign income, domestic income and infrastructure, it is negatively influenced by domestic demand. Our findings indicate that both demand and supply-side factors are crucial for India's export growth.

Keywords Export growth in India · Exchange rate · Panel GMM-IV

JEL Classification F1 · F14 · F18 · F31

P. Dua
Department of Economics, Delhi School of Economics, University of Delhi, Delhi, India
e-mail: dua@econdse.org

R. Suri (✉)
Department of Economics, Lakshmibai College, University of Delhi, Delhi, India
e-mail: ritukumar@lb.du.ac.in

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_6

1 Introduction

International trade plays a significant role in an economy's growth.[1] Recognizing the importance of international trade, many developed and developing countries have drastically reduced their trade barriers in the last two decades. However, the liberalization process has been accompanied by higher exchange rate volatility. As a consequence, government intervention in the foreign exchange rate market has become recurrent in both developed and developing economies. Hence, a thorough analysis of the impact of exchange rate volatility on international trade will throw light on policy implications as well as impact on international markets.

As noted by Haile and Pugh (2013), several empirical studies based on developed and developing countries find that trade of developing economies is more sensitive to exchange rate volatility than trade of developed economies where forward, future and options markets are less developed. This raises an important policy issue for developing economies like India that seek to promote economic growth through liberalization and diversification of exports to developed as well as developing countries.

As per conventional economic theory (Akhtar and Hilton, 1984 and Demers, 1991), durable and persistent spells of volatility in the home currency against major invoicing currencies of the world generate destabilizing effects and thus adversely affect international trade. However, subsequent studies such as Franke (1991) demonstrate that exchange rate volatility can positively affect international trade. Thus, theoretically, the effect of exchange rate volatility on international trade is ambiguous. Furthermore, as observed by Marc and Ruta (2013) and Tsen (2014), the effect of exchange rate volatility on trade is empirically ambiguous. For India too, existing empirical studies such as Bahmani-Oskooee and Saha (2019) provide mixed results on the effect of exchange rate volatility on exports.

Most of the existing empirical studies that examine the impact of exchange rate volatility on exports are based on the export demand function. Theoretically, there are two sets of factors that affect exports, viz. internal and external factors. External factors are broadly represented by foreign demand, while internal factors are related to the supply-side conditions such as production capacity and domestic demand. The existing empirical literature consists of three kinds of studies, viz. studies that are based on the export demand function (such as Dua and Banerji, 2001 and Hooy et al., 2015), those that examine the export supply function (such as Edwards and Alves, 2006) and those that consider both demand and supply-side factors (such as Raissi and Tulin, 2015) in the export model. Furthermore, the last category consists of two kinds of studies, viz. studies based on structural approach (such as Jongwanich, 2007) in which export demand and export supply functions are modeled separately and the studies that adopt the non-structural approach; also called the eclectic or hybrid approach (such as Sahoo et al., 2015) in which demand and supply-side factors are examined in a single equation. However, as noted by Basarac Sertić et al., (2015,

[1] See Iyoha and Okim (2017).

p. 389), it has been broadly recognized in the literature that the determinants of export demand cannot entirely explain the export behavior.

Several early empirical studies on India's trade (such as Joshi and Little, 1994) are based on a structural model of export demand and supply. On the other hand, majority of the recent Indian studies (such as Bhanumurty and Sharma, 2013) use the eclectic approach in their analysis. Further, most of the studies based on the eclectic approach (such as Sahoo et al., 2015) have used time series analysis to examine the determinants of India's exports. Cheung and Sengupta (2013) and Nayak et al. (2013) are among the few panel data studies based on India. Furthermore, there is no consensus in the literature on the impact of demand and supply-side factors on India's exports. For instance, while Nayak et al. (2013) find the effect of India's GDP to be positive and significant, Sahoo et al. (2015) find it to be positive but insignificant.

With this backdrop, the purpose of this study is to analyze the effect of exchange rate volatility on India's bilateral export growth. We also analyze the impact of exchange rate volatility on growth in India's exports to developed and developing economies, respectively, using panel data from 2005 Q2 to 2019 Q2. For this purpose, we consider India's 12 major export destinations,[2] viz. US, China, Hong Kong, Singapore, Eurozone (EZ), UK, Japan, Indonesia, Brazil, South Africa, Malaysia and Thailand, that are further divided into two subgroups, viz. developed economies (US, EZ, UK, Japan, Hong Kong and Singapore) and developing economies (China, Indonesia, Brazil, South Africa, Malaysia and Thailand).[3] This study uses a hybrid export model, where potential determinants of demand for exports and supply for exports are considered as the explanatory variables. Thus, in addition to the traditional determinants of exports, viz. foreign income, relative price and exchange rate volatility, our model contains FDI and infrastructure as measures of export supply capacity and domestic demand pressure. Volatility of the real exchange rate is estimated using a univariate GARCH model. Panel generalized method of moments-instrumental variables (Panel GMM-IV) technique with fixed effects is used to estimate the model as it does not make any assumption about the variance–covariance matrix of residuals and also controls for endogenous variables and heterogeneity.

This paper contributes to the existing literature in three different aspects. First, this study uses a hybrid model to examine the impact of exchange rate volatility on India's export growth covering both demand-side and supply-side factors that affect export growth. Second, this study analyzes the effect of exchange rate volatility on growth in India's exports to developed as well as developing economies. Third, the econometric methodology used in this analysis explicitly considers the stationarity

[2] In the first step, the countries are ranked on the basis of their average share in India's exports of last five years (2011–2015), ten years (2006–2015) and fifteen years (2001–2015), where the average share has been calculated from the share of countries in total exports (obtained from the online database of India's Directorate General of Foreign Trade) in each respective year. Thereafter, a common set of India's 12 major export destinations is selected on the basis of three considerations (i) average export share of 1% or above, (ii) availability of quarterly data and (iii) robustness of fit of the model.

[3] It is noteworthy that unlike the existing literature (such as Vo and Zhang, 2019), this study uses panel dataset of India vis-à-vis developed and developing countries.

properties and cross-sectional dependence of variables usually ignored in existing panel studies.

The rest of this paper is organized as follows: Sect. 2 briefly discusses trends in India's exports. Section 3 discusses the export function utilized in this study and the expected signs. Data, empirical model and econometric methodology are presented in Sect. 4. Section 5 discusses the empirical results, and Sect. 6 outlines concluding remarks.

2 Trends in India's Exports

It can be seen from Fig. 1 that India's exports have shown an increasing trend during 2001 Q1–2019 Q2. In terms of the growth rates, Fig. 2 reveals that India's export growth depicts an increasing trend before a substantial drop during 2007 Q4–2008 Q1 that may be due to the outbreak of global financial crisis in 2007 Q4. After showing an increasing trend till 2011 Q1, India's export growth declined till 2015 Q4. The decrease in India's export growth in 2011 and 2012 may be attributed to the effect of the Eurozone crisis.[4] Thereafter, the slowdown in the world economy and India's declining competitiveness may have contributed to the decline in export growth. Figure 2 shows that after showing an increase till 2017 Q1, India's export growth depicts declining trend again in the following quarters. In addition to the slowdown in the world economy and trade, rising trade protectionism in the world may have contributed to India's muted export growth in recent quarters.

2.1 *India's Bilateral Exports: Developed Versus Developing Countries*

It can be seen in Fig. 3 that even before the liberalization of the Indian economy in 1991, the major destination countries for India's exports have been US, EU, UK and Japan. However, during 1990–2000, in addition to these economies, India exported to Hong Kong and Singapore. Further, Fig. 3 shows that since the year 2000, India's exports have diversified considerably with additional destinations such as South East Asian economies, (viz. Thailand, Malaysia and Indonesia), China, UAE, Brazil and South Africa. As a result, Indian exports to both developed and developing economies have increased tremendously since 2000, as seen in Fig. 4.

However, it can be observed from Fig. 5 that the share of US, UK, EU, Japan and Hong Kong in India's exports has decreased substantially since 2001. Furthermore, the share of Thailand, Malaysia, Singapore, Indonesia, China, Brazil and South Africa

[4] Dua and Tuteja (2015) find significant decrease in the rate of growth of exports from India and China to US and Eurozone, respectively, during global financial crisis 2007–09 and Eurozone crisis 2010–12.

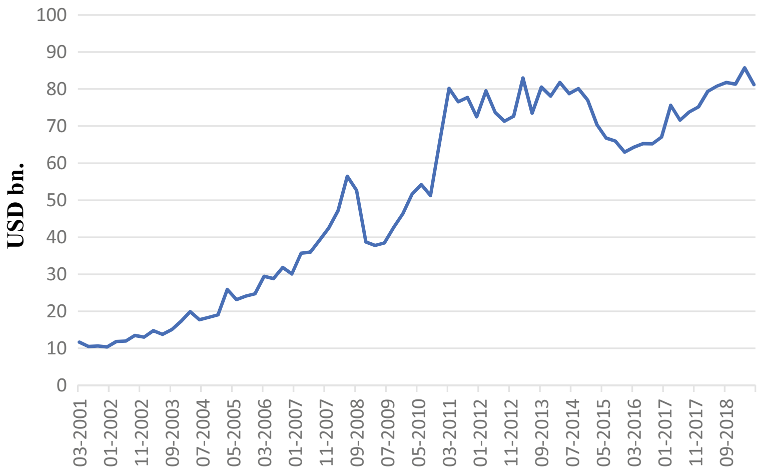


Fig. 1 India's exports in USD bn *Source* CEIC database

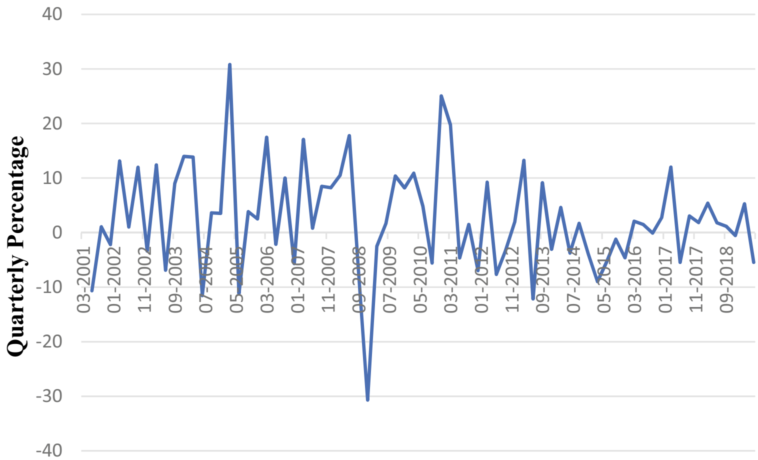


Fig. 2 Growth in India's exports (Quarter-on-Quarter) *Source* Authors' own calculations based on CEIC database

in India's exports has increased during the same period. Overall, Fig. 6 reveals that while the share of developed countries in India's exports has decreased, the share of developing countries in India's exports has increased during 2000–2019.

Further, Pant and Paul (2018) highlight that India's trade with developed economies is mixed including both inter-industry type (that mostly includes export of primary goods and import of manufacturing goods) and vertical intra-industry type (that involves exchange of differentiated goods produced under different technologies

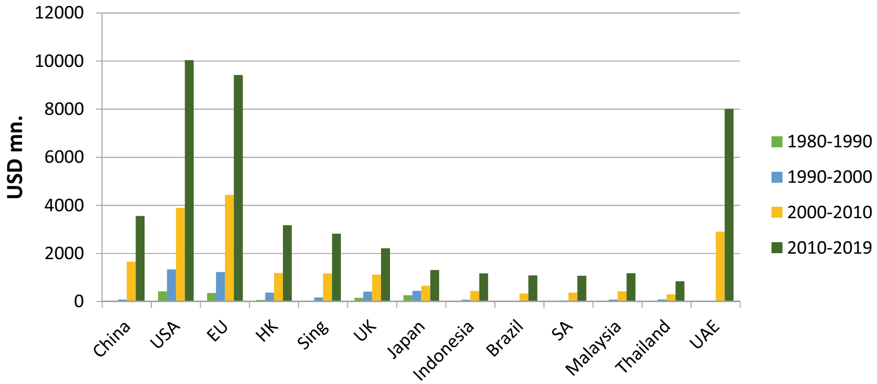


Fig. 3 Trends in India's bilateral exports (average) *Source* Authors' own calculations based on CEIC database

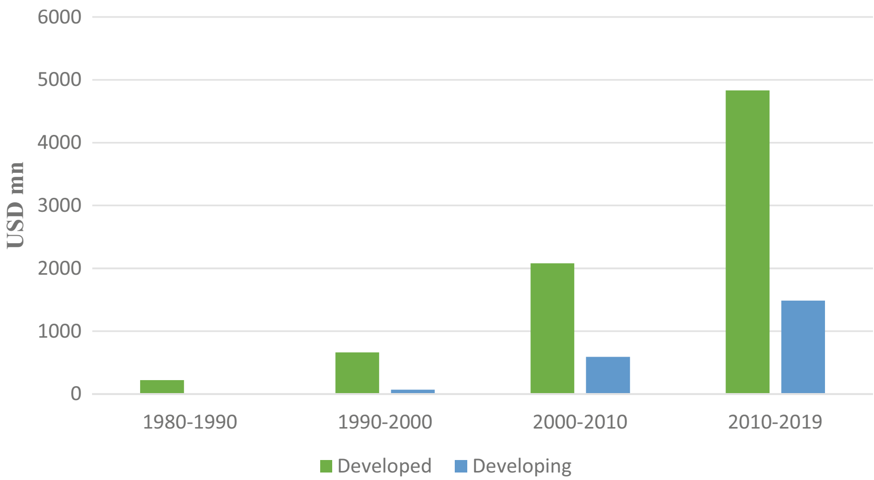


Fig. 4 Trends in India's bilateral exports (average) to developed and developing countries *Source* Authors' own calculations based on CEIC database

or are of different quality). Its trade with developing economies, however, is horizontal intra-industry type (that involves exchange of differentiated goods produced under a common increasing returns to scale technology).

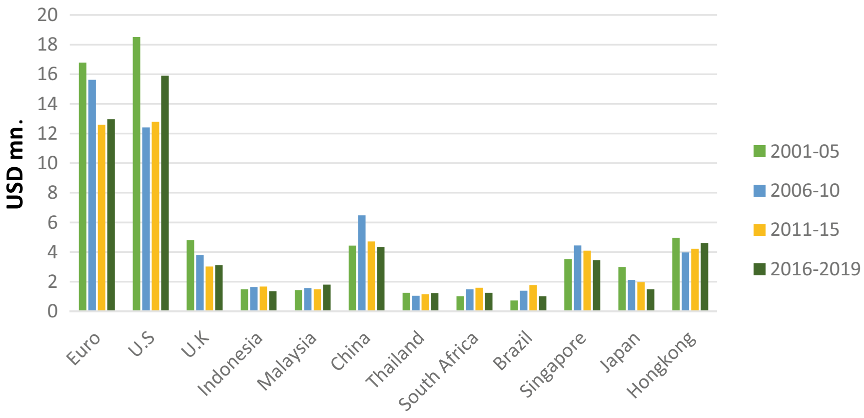


Fig. 5 Average share of India's twelve major export destinations in India's exports *Source* Authors' own calculations based on CEIC database

Fig. 6 Average share of developed and developing countries in India's exports *Source* Authors' own calculations based on CEIC database

3 Determinants of Exports

For analyzing the determinants of India's export growth, we develop an export function based on the recent theoretical and empirical literature. Thus, the ensuing discussion briefly describes the trade models employed in the literature. The two main theoretical models utilized in the existing literature are standard export demand model and 'gravity model'. According to the standard export demand model, a country's exports are determined by foreign demand and real exchange rate. Studies such as Armington (1969) provide theoretical foundations to the export demand model. In the 'gravity model', country's bilateral exports are a function of the GDP of the two countries and the distance between them. Studies like Eaton and Kortum (2002) provide theoretical validation to the gravity model.

A majority of the recent empirical studies (such as Wong, 2019) use a standard export demand model for analyzing the factors affecting country's total exports. On the other hand, 'gravity model' is primarily used in the empirical literature (see for instance, Yang and Gu, 2016) for examining determinants of a country's bilateral exports. Further, several extensions to the standard export demand model (such as Hall et al., 2010) and gravity model (such as Chit et al., 2010) have been utilized in the empirical literature in which variables such as exchange rate volatility, foreign trade agreements (FTA's), presence of common borders and colonial links have been added as additional explanatory variables in the model.

Some recent empirical studies such as Raissi and Tulin (2015) emphasize the role of supply constraints in explaining the exports behavior of developing economies like India. Empirical studies examine various variables that augment the country's export supply capacity such as domestic income (Shah, 2013), infrastructure (Ang et al., 2015), foreign direct investment (FDI) (Zhang, 2015) and domestic demand (Esteves and Rua, 2015).

Thus, on the basis of above discussion, the potential determinants of exports can be divided into two categories, viz. demand-side and supply-side factors. While we do not cover an exhaustive list of determinants,[5] we attempt to include factors that are potentially important in determining export growth of developing economies like India.

Demand-side Factors	*Supply-side Factors*
Real exchange rate	Real exchange rate
Volatility of exchange rate	Volatility of exchange rate
Foreign income	Domestic income
Free trade agreements	Infrastructure
	Foreign direct investment
	Domestic demand
	Free trade agreements

The export function can be expressed as a hybrid model as follows:

$$\begin{aligned} X_t = f\big(&REX_t(+), VEX_t(+/-), Y_t^*(+), Y_t(+), \\ &FTA(+), Infr_t(+), FDI_t(+/-), DD_t(+/-)) \end{aligned} \tag{1}$$

where

X_t bilateral exports of a country at time t
REX_t real exchange rate
Y_t^* foreign income at time t

[5] Some variables such as tariffs and expenditure on research and development are not included in the model due to the non-availability of quarterly data.

Y_t domestic income at time t
FTA foreign trade agreements
VEX_t volatility of exchange rate
$Infr_t$ infrastructure
FDI_t foreign direct investment
DD_t domestic demand

Equation (1) indicates the expected theoretical signs of variables in brackets. These variables are briefly discussed below.

3.1 Demand-side Factors

3.1.1 Real Exchange Rate

The standard demand function postulates that an increase in real exchange rate (where exchange rate is defined as the units of domestic currency per unit of foreign currency) makes exports more competitive, leading to an increase in exports. Majority of the empirical studies (such as Wong, 2017) find significant and positive effect of real exchange rate on exports.

3.1.2 Foreign Income

Foreign income proxies for the foreign demand for exports. The standard demand function and gravity model suggest that an increase in foreign income leads to an increase in exports. Furthermore, almost all empirical studies (such as Chit et al., 2010) find positive and significant impact of foreign demand on exports.

3.2 Supply-side Factors

3.2.1 Domestic Income

Gravity model advocates positive impact of domestic income on exports. However, as noted by Srinivasan (1998, pp. 235), there are two ways in which domestic income can affect exports. One, an increase in domestic income raises domestic demand, thereby decreases exports. On the other hand, an increase in domestic income is indicative of an increase in productive capacity which has a positive impact on exports. Nonetheless, majority of the existing empirical studies (such as Athukorala and Menon, 2010) find positive effect of domestic GDP on exports.

3.2.2 Exchange Rate Volatility

There is a huge theoretical and empirical literature that emphasizes the prominent role of exchange rate volatility in explaining export behavior. The earliest model was developed by Clark (1973), according to which, if an exporter is risk averse, an increase in exchange rate volatility decreases exports. However, as noted by Marc and Ruta (2013), his model was based on several strong assumptions such as perfect competition, the large role of the invoicing currency, the absence of imported inputs, the high aversion to risk and the absence of exchange rate hedging financial instruments. Dropping some or all of these assumptions makes the relationship between exchange rate volatility and exports ambiguous that can be observed in the five categories of models appraised by Marc and Ruta (2013). For instance, in the first category, De Grauwe (1988) and Dellas and Zilberfarb (1993) develop models in which the effect of increased volatility of exchange rates on trade depends heavily on the level of risk aversion of traders. According to their models, if the producers are sufficiently risk averse, an increase in exchange rate risk raises the expected marginal utility of revenue inducing them to increase their exports while if producers are not very risk averse, an increase in exchange rate risk reduces the expected marginal utility of revenue leading them to decrease their exports. Furthermore, a survey by Marc and Ruta (2013) and Tsen (2014) reveals that the empirical literature is inconclusive regarding the effect of exchange rate volatility on trade. Thus, in general, the impact of exchange rate volatility on international trade is theoretically and empirically ambiguous.

3.2.3 FDI

FDI flows are an essential part of the globalization process in which the developing countries majorly act as the main hosts for FDI from the developed world. The theoretical literature is inconclusive on the relationship between FDI and exports. Markusen (1984) develops a general equilibrium model of a multinational firm that produces the same good in multiple countries (also known as horizontal FDI). According to this model, FDI has a negative effect on exports when the foreign affiliates set up by the multinationals cater to the export markets of the host country. However, studies such as Fosfuri et al. (2001) conclude that FDI contributes to export growth through various sources such as augmenting domestic capital for exports, helping transfer of technology and new products for exports, facilitating access to new and large foreign markets, and providing training for the local workforce. Further, the empirical evidence on the effect of FDI on exports is mixed. For instance, while Zhang (2015) finds positive impact of FDI on exports, Gupta et al. (2015) estimate a negative effect.

3.2.4 Infrastructure

Infrastructure plays an important role in determining country's productive capacity. Several studies such as Raissi and Tulin (2015) illustrate positive effect of good infrastructure on the level of exports.

3.2.5 Domestic Demand

In a developing and emerging economy like India, domestic demand is expected to play a crucial role in its export performance. In its naïve form, domestic demand is expected to decrease exports as it diverts resources available for the export sector toward domestic consumption and also it decreases export competitiveness by fueling inflation. However, the theoretical literature (Ball, 1961) is inconclusive regarding the relationship between domestic demand and exports. Further, almost all empirical studies (such as Esteves and Rua, 2015) find negative impact of domestic demand on exports.

4 Empirical Model, Data and Econometric Methodology

4.1 Empirical Model

The model estimated is of the following form[6]:

$$\begin{aligned}\dot{X}_{it} = \omega + \sum_{k=1}^{n} \alpha_k \dot{X}_{it-k} + \sum_{l=0}^{n} \beta_l \, R\dot{E}X_{it-l} + \sum_{p=0}^{n} \gamma_p V_{it-p} + \sum_{q=0}^{n} \delta_q \, \dot{Y}_{t-q} \\ + \sum_{r=0}^{n} \theta_r \, F\dot{D}I_{t-r} + \sum_{r=0}^{n} \varphi_r \dot{Y}_{it-s} + \sum_{s=0}^{n} \vartheta_s GAP_{it-u} + \sum_{v=0}^{n} \partial_v \, IN\dot{F}R_{t-v} + \varepsilon_{it}\end{aligned} \tag{2}$$

where

$\dot{X}_{it}$ growth in value of total exports from India to country i,

$R\dot{E}X_{it}$ growth in real exchange rate of rupee vis-à-vis currency of country i,

V_{it} volatility in real exchange rate of rupee vis-à-vis currency of country i,

$\dot{Y}_{it}$ growth in weighted real income of country i, where weights are the share of country i in total exports of India at time period t,

$\dot{Y}_t$ growth in India's real income,

[6] FTA is not included in the final model as the sign of this variable in different specifications estimated was not robust.

GAP_t $Y_t - Y_t^*$ Y_t^* represents natural output level measured by trend level of India's real GDP,

$\dot{INFR}_t$ growth in India's infrastructure index and

$\dot{FDI}_t$ growth in India's foreign direct investment.

4.2 Data

This study is based on secondary data at quarterly frequency sourced from CEIC database and Federal Reserve Bank of St. Louis database. Data definitions and sources are given in Table 6 in the Appendix. The sample under study is from 2005 Q2 to 2019 Q2. The dependent variable (Y_t) is the value of India's exports (in US dollar million).[7] The bilateral real exchange rate between India and trading partner i is measured as $(P_i^*.e_i)/P$, where P_i^* and P are the foreign and domestic consumer price indices, respectively (2010 = 100), and e_i (INR per unit of trading partner's currency) is the bilateral nominal exchange rate. Foreign income (Y_t^*) is measured as GDP of the trading partner weighted by their respective share in India's exports. Domestic income (Y_t) is India's GDP in US dollar million. FDI_t is India's net FDI in US dollar million. $Infr_t$ is India's infrastructure index which is a combined index of eight core industries, viz. coal, crude oil, natural gas, refinery products, fertilizers, steel, cement and electricity. Domestic demand pressure (DD_t) is measured as the output gap. Output gap is defined as the deviation of India's real GDP (Y_t) from natural output.[8] Trend level of real GDP is taken as a proxy for natural output, measured using Hodrick–Prescott filter (Hodrick and Prescott, 1997).

Volatility of real exchange rate is measured as conditional volatility estimated using the appropriate GARCH model for each country. We find while component GARCH (1, 1) model is the best model for US, China, South Africa and Brazil, PARCH (1, 1) model for UK and EGARCH (1, 1) is the best model for Indonesia, Japan, Thailand, Malaysia, Singapore, Eurozone and Hong Kong.

4.3 Econometric Methodology

Unit root testing is becoming increasingly important in panel data studies. We utilize Fisher ADF (Choi, 2001), Hadri (2000), Breitung and Das (2005), and Pesaran (2007) panel unit root tests to analyze the stationarity properties of our panel variables (Exports, Real Exchange Rate, Volatility of real exchange rate and foreign income). Out of these, Hadri (2000), Breitung and Das (2005), and Pesaran (2007) unit root tests are robust in the presence of cross sectional correlation. Furthermore,

[7] Due to problems in obtaining an appropriate price deflator for bilateral exports, several studies such as Nazlioglu (2013) use nominal value of exports rather than real exports in the analysis.

[8] As utilized by several studies such as Shah (2013).

for checking the stationarity property of our time series variables (domestic GDP, FDI, infrastructure and domestic demand), we utilize Dickey–Fuller generalized least squares (DF-GLS) test suggested by Elliott et al. (1996), Ng-Perron (2001) and Lee and Strazicich (2003) test.

As explained in Hsiao (2014, p. 12 and p. 340), ignoring cross-sectional dependence in panel data can cause substantial bias in the estimates. Thus, in the second step, we employ Pesaran (2004) CD test for testing cross-sectional dependence in our panel data. In the final step, we employ panel GMM-IV estimator (with fixed effects) developed by Driscoll and Kraay (1998) that is robust to the presence of heteroscedasticity, serial correlation and cross-sectional dependence in panel data. Finally, for diagnostic testing, we utilize Durbin–Wu–Hausman endogeneity test, Hansen J test of over-identifying restrictions and Sanderson–Windmeijer under identification test.

5 Results

The descriptive statistics for exchange rate volatility are given in Table 1. It can be seen from Table 1 that mean and standard deviation of real exchange rate volatility for developing countries are higher as compared to mean and standard deviation of real exchange rate volatility for developed countries.

Further, real exchange rate volatility is maximum for Japan among developed countries and for Brazil among developing countries. It can be observed from Figs. 7

Table 1 Descriptive statistics for real exchange rate volatility (2005 Q2–2019 Q2)

	Mean V_{it}	Standard deviation V_{it}
Developed countries (Overall)	16.593	10.188
Euro	22.169	7.274
US	15.081	9.178
UK	13.915	4.396
Singapore	7.964	1.844
Japan	23.165	13.203
Hong Kong	17.266	11.678
Developing countries (Overall)	20.83	22.382
Indonesia	38.833	37.6
Malaysia	8.26	3.541
China	18.116	17.398
Thailand	8.651	1.789
South Africa	23.666	16.338
Brazil	27.454	18.691

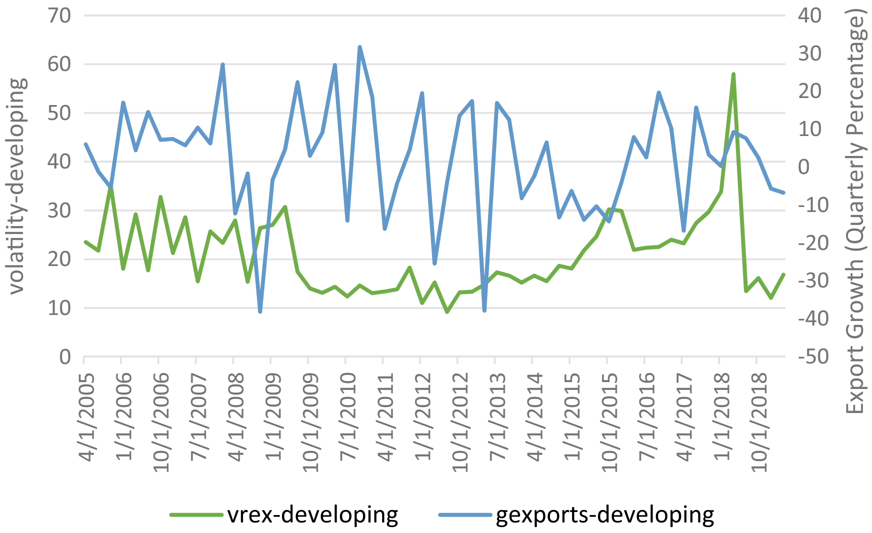


Fig. 7 Export growth and real exchange rate volatility: developing countries *Source* Authors' own calculations

and 8 that quarterly export growth and real exchange volatility of India with developing and developed countries have shown different trend over the sample period. We therefore attempt to examine the impact of real exchange rate volatility on growth in India's exports to developed and developing countries.

5.1 Unit Root Tests and Cross-Sectional Dependence Test

The results of unit root tests by majority rule indicate that export growth, real exchange rate growth, real exchange rate volatility, domestic income growth, foreign income growth, FDI growth, infrastructure growth and output gap are stationary in all the three panels.[9] Pesaran's CD test on panel variables for India vis-à-vis developed countries, developing countries and the total panel of twelve countries (Table 2) shows presence of considerable cross-sectional dependence in export growth, real exchange rate and volatility of real exchange rate for all the three panels.

[9] The unit root tests on the level variables in (1) show that while exports, real exchange rate, domestic GDP, foreign GDP, FDI and infrastructure are non-stationary of order one, exchange rate volatility and output gap are stationary. Thus, we utilize export growth, real exchange rate growth, domestic income growth, foreign income growth, infrastructure growth, exchange rate volatility and output gap in our analysis. The results of unit root tests are available from authors upon request.

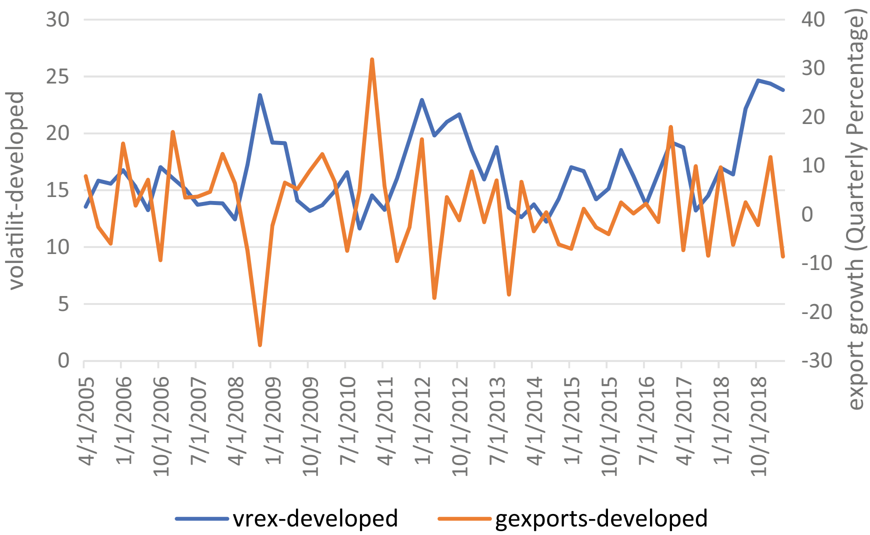


Fig. 8 Export growth and real exchange rate volatility: developed countries *Source* Authors' own calculations

Table 2 Pesaran CD test (2005 Q2–2019 Q2)

Variable	CD statistic (P-Value)		
	Developed countries	Developing countries	Total Panel
$\dot{X}_{it}$	5.86 (0.00)	4.26 (0.00)	11.04 (0.00)
$\dot{Y}_{it}$	0.19 (0.84)	1.09 (0.27)	1.05 (0.29)
$R\dot{E}X_{it}$	12.66 (0.00)	7.51 (0.00)	19.52 (0.00)
V_{it}	−1.07 (0.28)	−0.18 (0.86)	−1.69 (0.09)

5.2 *Panel Estimation Results*

In view of the above findings, we apply GMM-IV technique to three panels, India vis-à-vis its twelve major export destinations,[10] viz. US, China, Hong Kong, Singapore, Eurozone (EZ), UK, Japan, Indonesia, Brazil, South Africa, Malaysia and Thailand, that are further divided into two panels, India vis-a-vis six developed economies

[10] India vis-à-vis six developed countries panel implies panel of India's exports to six major developed export destinations. Similarly, India vis-à-vis developing countries panel implies panel of India's exports to six major developing export destinations, and India vis-à-vis twelve major export destinations implies panel of India's exports to twelve major developing and developed export destinations.

(US, EZ, UK, Japan, Hong Kong and Singapore) and India vis-à-vis six developing economies (China, Indonesia, Brazil, South Africa, Malaysia and Thailand).[11] The results of each of these panels are discussed below.

5.2.1 India vis-à-vis Six Developed Countries

The results of panel GMM-IV (with fixed effects) estimation of (2) for the panel of India vis-à-vis developed countries are presented in Table 3. We find that in case of developed countries, the coefficient of exchange rate volatility is positive and statistically insignificant. Turning to other parameters in (2), we find that all the estimated coefficients have expected signs. Further, all the estimated coefficients except θ_0 (coefficient of FDI growth)[12] are significant at 1% or 10% level of significance. It can be seen from the diagnostic tests[13] reported in Table 3 that the Hansen's J statistic is insignificant which shows that all instruments utilized are valid.

For analyzing the relative importance of demand-side and supply-side determinants of India's export growth vis-à-vis developed countries, we also conduct Wald exclusion test. The null hypothesis is that the demand-side factors taken together or the supply-side factors taken together do not jointly significantly affect export growth. Our results indicate that both demand-side and supply-side factors jointly significantly affect India's export growth vis-à-vis developed countries.[14]

5.2.2 India vis-à-vis Developing Countries

The results of panel GMM-IV (with fixed effects) estimation of (2) for the panel of India vis-à-vis developing countries are reported in Table 3. We find that in the case of developing countries, the coefficient of exchange rate volatility is negative and statistically significant at 5%. Further, we find that other estimated coefficients of (2) for this panel are similar to the corresponding coefficients in the panel of developed countries, viz. the signs of all coefficients are consistent with our expectations and all estimated coefficients except θ_0 (coefficient of FDI growth) are significant at 1%, 5% or 10% level of significance. Further, as before, we find that all instruments used are valid (Table 3). Finally, as found in the panel of developed countries, both demand and supply-side factors are important for India's export growth vis-à-vis developing countries.

[11] It is noteworthy that unlike the existing literature (such as Vo and Zhang, 2019), this study uses panel dataset of India vis-à-vis developed and developing countries.

[12] Though θ_0 is insignificant, its t-statistic is greater than one.

[13] The underidentification test on each endogenous variable for all the three panels reveals that each endogenous variable is identified, i.e., all instruments utilized are relevant. The results of the underidentification test are available from the authors upon request.

[14] The results of the Wald test are available from authors upon request.

Table 3 Panel GMM-IV (with fixed effects) results (2005 Q2–2019 Q2) Dependent Variable : $\dot{X}_{it}$

Variable	Coefficient	India vis-à-vis its twelve major export destinations	India vis-a-vis six developed economies	India vis-a-vis six developing economies
$\dot{X}_{it-1}$	α_1	−0.078*** (0.000)	−0.208*** (0.000)	−0.305*** (0.000)
$\dot{X}_{it-2}$	α_2		−0.152*** (0.000)	
$\dot{X}_{it-3}$	α_3	−0.052*** (0.000)	−0.168* (0.000)	
$\dot{X}_{it-4}$	α_4		0.041*** (0.004)	
$R\dot{E}X_{it}$	β_0	2.565*** (0.000)	2.432*** (0.000)	1.392*** (0.000)
V_{it}	γ_0	−0.036 (0.457)	0.083 (0.241)	−0.037** (0.038)
$\dot{Y}_t$	δ_0	0.254 (0.508)	0.462* (0.11)	0.324* (0.349)
$F\dot{D}I_t$	θ_0	0.036 (0.202)	0.035 (0.15)	0.012 (0.626)
$\dot{Y}_{it}$	φ_0	0.845*** (0.000)	0.743*** (0.000)	0.904*** (0.000)
$Y_{i\dot{t}-1}$	φ_1			0.314*** (0.001)
GAP_{t-2}	ϑ_2	−1.7E-04*** (0.002)		
GAP_{t-3}	ϑ_3		−1.8E-04*** (0.000)	−7.1E-05*** (0.001)
$IN\dot{F}R_t$	∂_0	1.008*** (0.012)	1.093*** (0.003)	
$IN\dot{F}R_{t-3}$	∂_3	1.851*** (0.000)	1.698*** (0.000)	1.389*** (0.000)
D_{it}	τ	−1.165 (0.545)	1.051 (0.739)	−1.619 (0.339)
R^2		0.598	0.594	0.837
Hansen's J test*		1.107 ($p = 0.893$)	0.714 ($p = 0.982$)	6.133 ($p = 0.408$)
Hausman endogeneity test		1.438 ($p = 0.837$)	5.154 ($p = 0.271$)	1.215 ($p = 0.875$)

(continued)

Table 3 (continued)

Variable	Coefficient	India vis-à-vis its twelve major export destinations	India vis-a-vis six developed economies	India vis-a-vis six developing economies
Rank/underidentification test		$R\dot{E}X_{it}$: 12.63 ($p = 0.027$) V_{it}: 142.84 ($p = 0.00$) $\dot{Y}_t$: 24.41 ($p = 0.00$) $F\dot{D}I_t$: 74.92 ($p = 0.00$)	$R\dot{E}X_{it}$: 26.11 ($p = 0.00$) V_{it}: 66.42 ($p = 0.00$) $\dot{Y}_t$: 62.43 ($p = 0.00$) $F\dot{D}I_t$: 122.38 ($p = 0.00$)	$R\dot{E}X_{it}$: 95.88 ($p = 0.00$) V_{it}: 165.71 ($p = 0.00$) $\dot{Y}_t$: 115.44 ($p = 0.00$) $F\dot{D}I_t$: 86.3 ($p = 0.00$)
Wald test Null hypothesis: Foreign demand does not significantly affect India's export growth		1604.94 ($p = 0.00$)	338.22 ($p = 0.00$)	3709.56 ($p = 0.00$)
Wald test Null hypothesis: Export supply capacity and domestic demand do not significantly affect India's export growth		66.66 ($p = 0.00$)	94.64 ($p = 0.00$)	51.43 ($p = 0.00$)

*** indicate significance at 1% ** indicate significance at 5% * indicate significance at 10%

5.2.3 India vis-à-vis Twelve Major Export Destination Countries

From the reported results of panel GMM-IV (with fixed effects) estimation in Table 3, it is seen that for the whole panel of India vis-à-vis twelve countries, the coefficient of exchange rate volatility is negative but insignificant. Turning to other parameters in (2), we find that all the estimated coefficients have expected signs. Further, all the estimated coefficients except θ_0 (coefficient of FDI growth) and δ_0 (coefficient of domestic GDP growth) are significant at 1% level of significance.[15]

As shown in Table 3, in this panel also, we find that all instruments utilized are valid. Further, our results on the significant impact of both demand and supply-side variables on India's export growth hold in this panel.

[15] Though θ_0 is insignificant, its t-statistic is greater than one.

5.3 *Inferences and Discussion*

5.3.1 Exchange Rate Volatility and India's Export Growth in Developed and Developing Economies

Our findings indicate that while exchange rate volatility adversely affects growth in India's exports to developing countries, growth in India's exports to developed countries is not affected by exchange rate risk. This may be due to higher vulnerability of developing countries vis-à-vis developed countries to shocks in exchange rate markets (Grier and Sallwood, 2013; and Broda and Romalis, 2011). Though there has been a huge surge in capital flows in developed as well as developing countries since 1990s, developed countries have less capital account restrictions as compared to developing countries. For instance, as shown in Table 4, according to Chinn and Ito index of financial openness described in Chinn and Ito (2006), developing countries rank very low in financial openness as compared to developed countries. Thus, traders in developed countries tend to have lower portfolio risk vis-à-vis traders in developing countries (Hall et al., 2010, pp. 1517).

Further, as shown in Table 5, developed countries have deeper, broader and stable financial institutions and markets. Thus, the presence of capital account restrictions and the absence of developed financial forward markets in India and its developing trading partners strengthen the impact of exchange rate risk on exports. Further, Pant and Paul (2018) observe that while India's trade with developed economies is both intra-industry and inter-industry type, its trade with developing countries is

Table 4 Financial openness measure: Chinn and Ito index

	2005	2014	2017
Developed countries			
EU (average)	1.7935	1.776	2.047
US	2.389	2.389	2.346
UK	2.389	2.389	2.346
Japan	2.389	2.389	2.346
Singapore	2.389	2.389	2.346
Hong Kong	2.389	2.389	2.346
Developing countries			
Indonesia	1.091	−0.126	−0.1411
Malaysia	−0.126	−0.126	−0.1411
Thailand	−0.126	−0.126	−1.21
China	−1.188	−1.188	−1.21
South Africa	−1.188	−1.188	−1.21
Brazil	0.133	−0.126	−1.21

Source Graduate Institute of International and Development Studies

Table 5 Financial development measures

Panel A: financial institutions

	Financial depth		Access		Efficiency		Stability	
	2008–10	2013–15	2008–10	2014	2008–10	2013–15	2008–10	2013–15
Developed countries	113.3	89.6	204.3	87.1	3.8	4.1	21.6	14.4
Developing countries	34.5	34.9	580.2	33.4	8.8	7.5	18.1	12.1

Note
1. Financial depth—private credit by deposit money banks to GDP (%), access—account at a formal financial institution (%, age 15+), efficiency—bank lending-deposit spread (%), stability—bank Z-score
2. Source Global Financial Development Report 2013, 2017–18

Panel B: financial markets

	Financial depth		Access		Efficiency		Stability	
	2008–10	2013–15	2008–10	2013–15	2008–10	2013–15	2008–10	2013–15
Developed countries	111.1	110.8	42.4	43.8	84.4	42.2	34.1	15.6
Developing countries	42.5	44.8	47.6	48.2	37.2	21.3	33.2	15.4

Note
1. Financial depth—stock market capitalization + outstanding domestic private debt securities to GDP (%), access—market capitalization excluding top ten companies to total market capitalization (%), efficiency—stock market turnover ratio (%), stability—stock price volatility
2. Source Global Financial Development Report 2013, 2017–18

intra-industry type that involves exchange of same differentiated goods. As per the theoretical and empirical literature,[16] higher exchange rate volatility that increases transaction costs has greater effect on trade in differentiated goods than trade in homogenous goods. Thus, the stronger response of India's export growth with developing economies to changes in exchange rate volatility found in this study may be due to the difference in the type of India's trade with developed and developing economies.

Lastly, as exchange rate volatility is higher in developing economies vis-à-vis developed economies, exchange rate risk in the former is also greater that possibly makes India's export growth with developing economies more sensitive to exchange rate volatility than India's export growth with developed economies.

It is noteworthy that the results of panel for India vis-a-vis twelve major export destinations conceal important differences between the developed and developing economies in their response to volatility of real exchange rate. The results of India vis-a-vis twelve major export destinations panel indicate negative and insignificant impact of exchange rate volatility on India's export growth. However, our findings

[16] See Rauch (1999); Broda and Romalis (2011) and Clark et al. (2004) for details.

indicate that this may be due to the insensitivity of developed countries vis-à-vis developing countries to shocks in exchange rate market.

5.3.2 Importance of Demand-side and Supply-side Factors in India's Export Growth

We find that domestic income growth, foreign income growth, real exchange rate growth, infrastructure growth and FDI growth have positive impact on growth in India's exports to developed and developing countries. Furthermore, we find that growth in India's exports to developed as well as developing countries is adversely affected by domestic demand. Our results also bring to the fore evidence regarding the importance of demand-side and supply-side factors in India's export growth. We find that for India, growth in foreign demand and export supply capacity are pivotal for growth in India's exports to both developed and developing countries.

Further, our findings on adverse impact of exchange rate volatility on India's export growth and positive and significant impact of growth in real exchange rate, domestic GDP and foreign GDP on India's export growth are similar to the findings of Srinivasan and Kalaivani (2012). However, we differ from their study in two main aspects. First, we consider the role of domestic demand, FDI and infrastructure in India's export behavior. Second, our analysis reveals the differences in the response of India's export growth with developed and developing countries to changes in exchange rate volatility.

6 Conclusion

The present study attempts to examine the impact of exchange rate volatility on India's export growth using a hybrid model consisting of both demand-side and supply-side determinants, viz. real exchange rate volatility, output gap, growth in foreign real GDP (weighted by export partner's share in India's exports), growth in FDI, growth in bilateral real exchange rate, India's GDP growth and infrastructure growth. Further, given the diversification of India's exports in terms of destination during the last decade, we investigate the effect of exchange rate volatility on growth in India's exports to developed and developing countries.

Overall, the effect of exchange rate volatility on India's export growth is found to be negative and insignificant. The results of our study reveal that in terms of India's export destinations, while growth in its exports to developing countries is significantly and adversely affected by exchange rate volatility, growth in its exports to developed countries is not sensitive to exchange rate risk. We find that growth in bilateral real exchange rate, FDI, domestic income and infrastructure positively affects India's export growth with developed as well as developing economies. Furthermore, domestic demand is found to adversely affect India's export growth. We also find that both demand-side and supply-side factors are vital for India's export growth. Thus, the findings of this study can have significant implications for India's trade policy.

Appendix

See Table 6.

Table 6 Definition of variables and data sources

Variable	Definition	Data Source
X_t	Value of India's exports in US dollar million	CEIC
Y_t^*	GDP of the trading partner weighted by their respective share in India's total exports	CEIC and Federal Reserve Bank of St. Louis database
Y_t	India's GDP in US dollar million	CEIC
REX_t	Real exchange rate = $(P_i^*.e_i)/P$ where P_i^* and P are the foreign and domestic consumer price indices, respectively (2010 = 100), and e_i (INR per unit of trading partner's currency) is the bilateral nominal exchange rate	CEIC
$VREX_t$	Conditional volatility of real exchange rate measured using appropriate GARCH model for each country Component GARCH (1, 1) model is used for US, China, South Africa and Brazil, PARCH (1, 1) model is used for UK, and EGARCH (1, 1) is used for Indonesia, Japan, Thailand, Malaysia, Singapore, Eurozone and Hong Kong	Constructed
$Infr_t$	India's infrastructure index which is a combined index of eight core industries, viz. coal, crude oil, natural gas, refinery products, fertilizers, steel, cement and electricity	CEIC
FDI_t	India's FDI in US dollar million	CEIC
DD_t	DD_t is measured as the output gap. Output gap is defined as the difference between India's real GDP and trend level of real GDP. Trend level of real GDP is measured using Hodrick–Prescott filter	Constructed

Questions to Think About

1. This chapter uses panel GMM-IV technique to estimate the empirical model used in this chapter. What is the difference between panel FMOLS and panel GMM-IV technique?

   Hint: Panel FMOLS technique (Pedroni, 2000) is used to estimate co-integrating relationship between the variables assuming cross-sectional independence. Panel GMM-IV technique does not make any assumption about the variance–covariance matrix of residuals.
2. What is the advantage of using non-structural or hybrid approach over structural approach, where export demand or export supply is modeled separately?

   Hint: Specification error/omitted variable bias
3. Examine various methods to measure exchange rate volatility.

   Hint: Standard deviation of exchange rate, moving sample standard deviation of exchange rate levels, realized volatility, GARCH measure of volatility

   Refer: Chit et al. (2010); Bauwens et al. (2012).

References

Akhtar, M. A., & Hilton, R. S. (1984). *Exchange rate uncertainty and international trade: Some conceptual issues and new estimates from Germany and the US, Research Paper 8403*. Federal Reserve Bank of New York.

Ang, J. B., Madsen, J. B., & Robertson, P. E. (2015). Export performance of the Asian miracle economies: The role of innovation and product variety. *Canadian Journal of Economics, 48*, 273–309.

Armington, P. S. (1969). A theory of demand for products distinguished by place of production. *IMF Staff Papers, 16*, 159–178.

Athukorala, P. C., & Menon, J. (2010). Global production sharing, trade patterns, and determinants of trade flows in East Asia, WP 41, Asian development bank working paper series on regional integration.

Bahmani-Oskooee, M., & Nouira, R. (2019). On the impact of exchange rate volatility on Tunisia's trade with 16 partners: An asymmetry analysis. *Economic Change and Restructuring*, 1–22.

Bahmani-Oskooee, M., & Saha, S. (2019). Exchange rate risk and commodity trade between US and India: An asymmetry analysis. *Journal of the Asia Pacific Economy*, 1–21.

Ball, R. J. (1961). Credit restriction and the supply of exports. *Manchester School Economics Social Studies, 29*, 161–172.

Basarac Sertić, M., Vučković, V., & Škrabić Perić, B. (2015). Determinants of manufacturing industry exports in European Union member states: A panel data analysis, *Ekonomska Istraživanja*, *28*, 384–397.

Bauwens, L., Hafner, C., & Laurent, S. (2012). Volatility models. *Handbook of volatility models and their applications*, (pp. 1–45).

Bhanumurty, N. R., & Sharma, C. (2013). *Does weak rupee matter for India's manufacturing exports, WP 115*, National Institute of Public Finance and Policy.

Breitung, J., & Das, S. (2005). Panel unit root tests under cross-sectional dependence. *Statistica Neerlandica, 59*, 414–433.

Broda, C., & Romalis, J. (2011). Identifying the relationship between trade and exchange rate volatility. In *Commodity prices and markets*. University of Chicago Press.

Cheung, Y. W., & Sengupta, R. (2013). Impact of exchange rate movements on exports: An analysis of Indian non-financial sector firms. *Journal of International Money and Finance, 39*, 231–324.

Chinn, M. D., & Ito, H. (2006). What matters for financial development? Capital controls, institutions, and interactions. *Journal of Development Economics, 81*, 163–192.

Chit, M. M., Rizov, M., & Willenbockel, D. (2010). Exchange rate volatility and exports: New empirical evidence from the emerging East Asian economies. *The World Economy*, 239–263.

Choi, I. (2001). Unit root tests for panel data. *Journal of International Money and Finance, 20*, 249–272.

Clark, M. P. B., Wei, S. J., Tamirisa, M. N. T., Sadikov, M. A. M., & Zeng, L. (2004). *A new look at exchange rate volatility and trade flows, occasional paper 235*. International Monetary Fund.

Clark, P. B. (1973). Uncertainty, exchange risk, and the level of international trade. *Western Economic Journal, 11*, 302–313.

De Grauwe, P. (1988). Exchange rate variability and the slowdown in growth of international trade. *IMF Staff Papers, 35*, 63–84.

Dellas, H., & Zilberfarb, B. Z. (1993). Real exchange rate volatility and international trade: A reexamination of the theory. *Southern Economic Journal*, 641–647.

Demers, M. (1991). Investment under uncertainty, irreversibility and the arrival of information over time. *Review of Economic Studies, 58*, 333–350.

Driscoll, J. C., & Kraay, A. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics, 80*, 549–560.

Dua, P., & Banerji, A. (2001). *A leading index for India's exports, study 23*. Development Research Group, Reserve Bank of India.

Dua, P., & Tuteja, D. (2015). Global recession and Eurozone debt crisis: Impact on exports of China and India, WP 242, CDE-DSE.

Eaton, J., & Kortum, S. (2002). Technology, geography and trade. *Econometrica, 70*, 1741–1779.

Edwards, L., & Alves, P. (2006). South Africa's export performance: Determinants of export supply. *South African Journal of Economics, 74*, 473–500.

Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica, 64*, 813–836.

Esteves, P., & Rua, A. (2015). Is there a role for domestic demand pressure on export performance. *Empirical Economics, 49*, 1173–1189.

Fosfuri, A., Motta, M., & Ronde, T. (2001). Foreign direct investment and spillovers through workers' mobility. *Journal of International Economics, 53*, 205–222.

Franke, G. (1991). Exchange rate volatility and international trading strategy. *Journal of International Money and Finance, 10*, 292–307.

Grier, K. B., & Smallwood, A. D. (2013). Exchange rate shocks and trade: A multivariate GARCH-M approach. *Journal of International Money and Finance, 37*, 282–305.

Gupta, S. D., Raychaudhuri, A., & Haldar, S. K. (2015). Determinants of exports of information technology in India: An empirical analysis. *South Asia Economic Journal, 16*, 64–81.

Hadri, K. (2000). Testing for stationarity in heterogeneous panel data. *Econometrics Journal, 3*, 148–161.

Haile, M. G., & Pugh, G. (2013). Does exchange rate volatility discourage international trade? A meta-regression analysis. *The Journal of International Trade and Economic Development, 22*, 321–350.

Hall, S., Hondroyiannis, G., Swamy, P. A. V. B., Tavlas, G., & Ulan, M. (2010). Exchange rate volatility and export performance: Do emerging market economies resemble industrial countries or other developing countries. *Economic Modelling, 27*, 1514–1521.

Hodrick, R. J., & Prescott, E. C. (1997). Postwar US business cycles: An empirical investigation. *Journal of Money, Credit and Banking, 29*, 1–16.

Hooy, C. W., Law, S. H., & Chan, T. H. (2015). The impact of renminbi real exchange rate on ASEAN disaggregated exports to China. *Economic Modelling, 47*, 253–259.

Hsiao, C. (2014). *Analysis of panel data*, No. 54, Cambridge University Press.

Iyoha, M., & Okim, A. (2017). The impact of trade on economic growth in ECOWAS countries: Evidence from panel data. *CBN Journal of Applied Statistics, 8*, 23–49.

Jongwanich, J. (2007). Determinants of export performance in East and Southeast Asia, WP 106, Asian Development Bank.

Joshi, V., & Little, I. M. D. (1994). *India: Macroeconomics and political economy 1964–1991*. Washington and Oxford University Press.

Lee, J., & Strazicich, M. C. (2003). Minimum lagrange multiplier unit root test with two structural breaks. *Review of Economics and Statistics, 85*, 1082–1089.

Marc, A., & Ruta, M. (2013). The relationship between exchange rates and international trade: A literature review. *World Trade Review, 12*, 577–605.

Markusen, J. R. (1984). Multinational, multi-plant economies and the gains from trade. *Journal of International Economics, 16*, 205–266.

Nayak, S., Aggarwal, V., & Mann, P. (2013). India's manufacturing export dynamics: An analysis of technology intensity transition, WP 6, Centre for WTO Studies.

Nazlioglu, S. (2013). Exchange rate volatility and Turkish industry-level export: Panel cointegration analysis. *The Journal of International Trade and Economic Development: an International and Comparative Review, 22*, 1088–1107.

Newey, W. K., & West, K. D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, 777–787.

Ng, S., & Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica, 69*, 1519–1554.

Nicita, A. (2013). Exchange rates, international trade and trade policies. *Policy issues in international trade and commodities*, No. 56, UNCTAD Study Series.

Panda, S., & Mohanty, R. (2015). Effects of exchange rate volatility on exports: Evidence from India. *Economics Bulletin, 35*, 305–312.

Pant, M., & Paul, A. (2018). The role of regional trade agreements: In the case of India. *Journal of Economic Integration, 33*, 538–571.

Pedroni, P. (2000). Fully modified OLS for heterogeneous cointegrated panels. In *Advances in econometrics: Nonstationary panels, panel cointegration and dynamic panels* (Vol. 15, pp. 93–130).

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels, discussion paper 1240, *IZA Discussion Papers.*

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross section dependence. *Journal of Applied Econometrics, 22*, 265–312.

Raissi, M., & Tulin, V. (2015). Price and income elasticity of Indian exports—The role of supply-side bottlenecks, WP 161, IMF.

Rauch, J. E. (1999). Networks versus markets in international trade. *Journal of International Economics, 48*, 7–35.

Sahoo, B. K., Nauriyal, D. K., & Mohapatar, S. (2015). Software exports from India: An econometric exploration. *Journal of Asia-Pacific Business, 16*, 274–301.

Shah, A. (2013). *Deficit conundrums: The determinants of India's export behavior, doctoral dissertation.* Haverford College, Pennsylvania.

Srinivasan, T. N. (1998). India's export performance: A comparative analysis. In I. J. Ahluwalia, & I. M. D. Little (Eds.), *India's economic reforms and development essay for Manmohan Singh.* Oxford University Press.

Srinivasan, P., & Kalaivani, M. (2012). *Exchange rate volatility and export growth in India: An empirical investigation*, MPRA Paper 43828. University Library of Munich.

Tenreyro, S. (2007). On the trade impact of nominal exchange rate volatility. *Journal of Development Economics, 82*, 485–508.

Truong, H. Q., Dong, C. V., & Nguyen, H. H. (2019). Determinants of trade flows and trade structure between Korea and ASEAN. *East Asian Economic Review, 23*, 55–88.

Tsen, W. H. (2014). Exchange rate volatility and international trade. *Journal of Stock and Forex Trading, 3*, 14–21.

Vo, D. H., & Zhang, Z. (2019). Exchange rate volatility and disaggregated manufacturing exports: Evidence from an emerging country. *Journal of Risk and Financial Management*, 12.

Wong, H. T. (2017). Exchange rate volatility and bilateral exports of Malaysia to Singapore China, Japan, the USA and Korea. *Empirical Economics, 53*, 459–492.

Wong, H. T. (2019). Volatility and bilateral exports in Malaysia. *International Journal of Business and Society, 20*, 605–626.

Yang, G., & Gu, Q. (2016). Effects of exchange rate variations on bilateral trade with a vehicle currency: Evidence from China and Singapore. *Journal of International Money and Finance, 68*, 50–73.

Zhang, K. H. (2015). What drives export competitiveness? The role of FDI in Chinese manufacturing. *Contemporary Economic Policy, 33*, 499–512.

Chapter 7
Aggregate and Sectoral Productivity Growth in the Indian Economy: Analysis and Determinants

Pami Dua and Niti Khandelwal Garg

Abstract This study analyses and compares estimates of labour productivity growth and total factor productivity growth for the Indian economy as provided by four databases, viz., India KLEMS (IKLEMS), Asian Productivity Organization (APO), Penn World Tables (PWT9.1) and The Conference Board's Total Economy Database (TED) over the period 1981–2015. It investigates determinants of productivity growth of the Indian economy based on measures of productivity growth from the four datasets using GMM method. It also examines the trends and determinants of productivity growth of the major components of industry and services sectors, viz., manufacturing and market services, respectively. The study finds that while there are differences in the estimates of productivity growth across various datasets that may be attributed to differences in the definitions, methods of measurement and revisions of databases, the trends are broadly similar. Further, the econometric results of the study are robust across all databases and indicate that capital deepening, technological progress, government size, institutional quality, share of agriculture in GDP and openness are significant determinants of productivity growth of the Indian economy over the period 1981–2015. Further, results on the disaggregate analysis indicate that capital deepening, technology, government size, productivity growth of the other sector and openness are significant determinants of labour productivity growth of both manufacturing and market services of India over the period 1981–2015. A comparison of results across the two sectors further suggests that while there exist significant spillover effects between sectors, the impact is stronger from services to manufacturing than the other way around.

Keywords Measurement of productivity · Labour productivity · TFP · Aggregate and sectoral · GMM

JEL Classification C2 · O47

P. Dua
Department of Economics, Delhi School of Economics, University of Delhi, Delhi, India
e-mail: dua@econdse.org

N. K. Garg (✉)
Department of Economics, Kirori Mal College, University of Delhi, Delhi, India
e-mail: nkgarg@kmc.du.ac.in

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_7

1 Introduction

The Indian economy has emerged as one of the largest economies of the world in the last few years with a considerable rise in its share in world GDP (7.9% in 2019) and a consistently high rate of growth of GDP over a long period of time, as seen in the World Economic Outlook, IMF (2020). The correlation between growth in the economy and increase in productivity is well established. In fact, studies based on India KLEMS[1] database have shown that both labour productivity as well as total factor productivity witnessed remarkable growth in the Indian economy in the post liberalization period, as seen in Goldar (2018) and Erumban and Ark (2018). At the same time, there have been developments in constructing productivity measures for the Indian economy both at the national as well as international level. Thus, it may be insightful to examine if there are differences in the estimates of productivity growth for the Indian economy across various datasets.

Since growth in productivity leads to economic growth and can sustain it in the long run, it becomes imperative to examine the factors that lead to growth in productivity and hence that in output of the Indian economy. Moreover, the Indian economy has undergone significant structural changes over the past three and a half decades with decline in the share of agriculture and increase in that of services.[2] In particular, services sector has emerged as the largest sector of the economy accounting for more than half of the economy's GDP. Furthermore, within services, the market services of trade, transport and communication, financial and business services, etc. have shown maximum growth as compared to other constituents of services contributing to the growth of overall services sector, as seen in Goldar (2018).

Against this backdrop, the current study examines trends in various measures of productivity growth for the Indian economy based on different databases, viz., India KLEMS, Penn World Tables version 9.1, The Conference Board's Total Economy Database and Asian Productivity Organization data (IKLEMS, PWT9.1, TED and APO from now on) and makes a comparison thereof over the period 1981 to 2015. The study further investigates the determinants of productivity growth on the basis of a comprehensive model using GMM estimation. Since market services have shown most growth in GDP and productivity, the paper also investigates the trends and determinants of labour productivity growth and total factor productivity growth of the major components of industry and service sectors, viz., manufacturing and market services, respectively.

[1] KLEMS stands for K-capital, L-labour, E-energy, M-materials and S-services.

[2] The share of agriculture declined from 34.5% (approx.) in 1981 to 16.5% (approx.) in 2015 while that of services rose from 38% (approx.) in 1981 to 58% (approx.) in 2015 (APO, 2018).

The paper is structured as follows. Section 2 discusses trends in productivity growth in India since 1981 and a comparison of measures of productivity growth. The theoretical and empirical literature on determinants of productivity growth is elaborated upon in Sect. 3, while Sect. 4 discusses the econometric methodology used to estimate the model. The data used in the study is discussed in Sect. 5 which is then followed by econometric results in Sect. 6. Section 7 gives the conclusions.

2 Productivity Growth in the Indian Economy: Measures, Definitions and Trends

2.1 Concepts of Productivity Growth

Productivity refers to output per unit of input. The growth in productivity indicates growth in output that is net of growth in inputs. We may define productivity either partially (a single factor productivity like labour productivity or capital productivity) or totally (total factor productivity). Labour productivity and total factor productivity are the two most widely used measures of productivity. While total factor productivity is a more comprehensive measure of productivity as it controls for growth in both labour and capital inputs, labour productivity is a useful indicator of the overall welfare[3] of an economy.

2.1.1 Labour Productivity Growth

Labour productivity growth is defined as the rate of growth of output net of the rate of growth of labour input. Labour input can be further classified into total employment (persons engaged) or hours worked by the persons engaged. Hours worked are considered as a better measure of labour input as compared to actual persons engaged as they reflect the actual input of labour in the production process and can easily account for full-time employment or part-time employment or absenteeism, OECD Manual (2001). However, obtaining data on hours worked is much more difficult, especially at a disaggregate level as compared to data on persons engaged.

2.1.2 Total Factor Productivity Growth

Total factor productivity (TFP) may be defined as output per unit of combined inputs. There are two approaches to calculate TFP: gross output approach and gross value-added approach. Under the gross output approach, TFP is calculated as the ratio of gross output to a combined input which is a weighted sum of inputs, viz., energy,

[3] Labour productivity is close to GDP per capita though not the same.

materials, services, labour and capital. On the other hand, under the gross value-added approach, TFP is defined as the ratio of gross value added to a combined input which is a weighted sum of labour and capital. Thus, the TFP based on gross output approach is a broader concept than that based on gross value-added approach as it takes into consideration the contribution of primary inputs apart from labour and capital. Considering gross value-added approach, rate of growth of TFP can be written as:

$$\dot{\text{TFP}} = \dot{y} - s_L\left(\dot{Emp} + \dot{labqual}\right) - s_K \dot{Kserv} \tag{1}$$

where dot above each variable denotes its rate of growth; y is gross value added or GDP, s_L and s_K are the shares of labour and capital in GDP and add up to one under the assumption of constant returns to scale; Emp is the total employment, $labqual$ is the measure of quality of labour; $kserv$ is the measure of capital services. Thus, under the gross value-added approach, TFP growth is calculated as the residual left after deducting weighted sum of rates of growth of inputs from the rate of growth of output where the weights are taken to be shares of the respective inputs in total income.

While labour quantity is measured either by persons engaged or average hours worked by persons employed and indicates the quantity of labour input, it does not incorporate composition and hence quality of labour input. Since there are different types of labour employed in the production process based on the skill and education levels, they may contribute differently to production. Thus, calculating TFP using only labour quantity may hide these differential contributions of labour input and may lead to overestimation of TFP.

Further, different types of capital inputs are used in the production process, for instance, residential buildings, machinery, structures, information technology, communication technology, etc. These inputs differ in terms of their rates of depreciation and hence in terms of their rates of return. Thus, data on capital services[4] instead of capital stock is constructed which gives a true measure of the actual contribution of each capital input into the production process.

2.2 *Different Concepts of Productivity Growth for the Indian Economy*

The data on labour productivity and total factor productivity for the Indian economy is available with many databases. These databases differ both in terms of the coverage

[4] It may be noted here that while capital services is a weighted sum of capital stock of each asset, capital stock is a simple sum.

as well as definitions and measurement of variables used to estimate various productivity measures.[5] We discuss each of these databases separately in the following sub-sections.

2.2.1 India KLEMS Database

The IKLEMS 2018 dataset is a comprehensive database released by RBI that provides annual data on many variables, viz., gross output, gross value added (GVA), capital stock, capital services,[6] employment, labour quality, energy input, materials input, services input, factor income shares, labour productivity and total factor productivity (TFP) growth for 27 industries from all the sectors of the Indian economy over the period 1980–81 to 2015–16.

2.2.2 Penn World Tables [9.1 Database]

Penn World Tables version 9.1 (PWT 9.1)[7] is a recently released database by Feenstra et al. (2015) that provides comprehensive data on many variables including GDP, employment, hours worked, capital stock, capital services, human capital index, labour productivity and total factor productivity for 184 countries (including India) around the world over the period 1950–2017. The data on all the aforementioned variables is provided at the aggregate level only. Furthermore, all the variables are available in levels that may be converted to rates of growth.

2.2.3 The Conference Board's Total Economy Database (TED)

The Conference Board's Total Economy Database (TED) provides annual data on Gross Domestic Product (GDP), population, employment, hours worked, growth of capital services, labour productivity and its growth and total factor productivity (TFP) growth for 124 countries (including India) of the world from 1950 to 2017. Since this database provides data on rates of growth of total factor productivity and that of capital input unlike PWT database, therefore it is useful to analyse rates of growth. The data is available at the aggregate economy level on aforementioned variables.

---

[5] Please refer to Table 1 for details.

[6] While capital stock is a simple sum of capital stocks of all assets for an industry, capital services is a weighted average of capital stocks of each asset (calculated separately) with share of each asset in total capital income as the weight. Thus, capital services as opposed to capital stock controls for the heterogeneity across assets and thus quality of each capital asset and provides a better contribution of each asset into the production process. The 2018 version of the IKLEMS database was downloaded from RBI's website: https://rbi.org.in/Scripts/KLEMS.aspx.

[7] This version of the database was released in April 2019 and is available from download at https://www.rug.nl/ggdc/productivity/pwt/.

2.2.4 Asian Productivity Organization (APO) Database

Asian Productivity Organization (APO) database provides data on Gross Domestic Product (GDP), employment, hours worked, capital stock, capital services, labour productivity, total factor productivity (TFP) at an aggregate level for 34 Asian economies (including India) over the period 1970–2016. The database also provides data on Gross Domestic Product (GDP) and total employment of the broad sectors and their sub-sectors, viz., agriculture, forestry and fishing, mining and quarrying, manufacturing,[8] construction, utilities,[9] wholesale and retail trade, transport, storage and communications, financial intermediation, real estate, renting[10] and business and community, personal and social services of these economies. Further, the data on TFP is available only at aggregate economy level.

2.2.5 Comparison of Variants of Labour and Total Factor Productivity Growth Across the Four Databases

A comparison of definitions of productivity and its growth across the four databases reveals the following differences across them as given in Tables 1 and 2.

First of all, while the three international data sources provide data on various measures of productivity at an aggregate economy level or at a broad sectoral level, India KLEMS provides data at the level of industry for 27 industries of the Indian economy across all sectors.

Furthermore, IKLEMS[11] database has only one measure of quantity of labour input available that is total employment, while other three databases have data on hours worked as well.

Moreover, while IKLEMS defines labour productivity in terms of gross value added at market price, the international sources define it in terms of Gross Domestic Product. This could clearly lead to differences in the estimates of productivity depending upon the magnitude of differences between GVA and GDP.

While IKLEMS, PWT9.1 and TED account for labour quantity, labour quality and capital services for constructing total factor productivity, APO database only controls for labour quantity and capital services, and hence, it may be an overestimate of TFP as compared to the other three databases, see Eq. (1) above.

[8] For certain countries, further disaggregated data on manufacturing industries is also provided.

[9] Utilities are also referred to as electricity, gas and water supply.

[10] The APO database additionally provides data on GDP and total employment of two components of the financial intermediation, real estate, renting and business services sector, viz., financial intermediation and real estate for all 34 Asian economies.

[11] Refer to Das et al. (2017) for further details on methodology.

Table 1 Availability of databases for India

Data source	Number of countries covered	Availability for India	Level of aggregation	Time period	Measure of productivity
The conference board's total economy database (TED)	124 countries	✓	Aggregate economy	1950–2017	Labour productivity and TFP (1950–2016)
Penn world tables (PWT) 9.1	184 countries	✓	Aggregate economy	1950–2017	Labour productivity and TFP
Asian productivity organization (APO) database	34 Asian economies	✓	Aggregate and 25 industries across the three broad sectors	1970–2016	Labour productivity and TFP at the aggregate level while labour productivity at the sectoral level
India KLEMS (IKLEMS)	Indian Economy	✓	Aggregate and 27 industries of India across all the three broad sectors	1980–81 to 2015–16	Both labour and total factor productivity[13]

Notes
1. *Source* Authors' own elaboration from TED, PWT9.1, APO and IKLEMS databases

Furthermore, while IKLEMS approach controls for labour quality as well as capital services, their approach is industry based in which the variables are first constructed at industry level and then added up to get the aggregate economy variables.

Thus, the industry approach may give different estimates as compared to the aggregate one. On the other hand, both TED[12] and PWT9.1 control for capital services and labour quality while constructing TFP and also follow the aggregate approach. However, the two databases construct their own measures of capital services and labour quality that may lead to differences in the overall measure of TFP across them. We discuss trends in various measures of productivity growth across various definitions at both aggregate and disaggregate level subsequently.

[12] Refer to Vries and Erumban (2017) for further details.

Table 2 Reasons for definitional differences in TFP growth rate across databases

Database	Definition of output	Definition of capital input	Definition of labour input		Definition of LP	Definition of TFP
TED	GDP at basic price	Capital stock[14] and capital services (Kserv)	Labour quantity is measured both by total employment (E) as well as average number of hours worked (H)	Labour quality index is constructed and provided separately	GDP/E GDP/H	Capital services, labour quantity and labour quality incorporated in the measurement of TFP $\text{TFP}gr = \text{GDP}gr - s_L(labqtgr + LabQlgr) - s_K(Kservgr)$
APO	GDP at basic price	Capital stock and capital services (Kserv)	Labour quantity is measured both by total employment (E) and average number of hours worked[15] (H)	No data on labour quality provided	GDP/E GDP/H for aggregate economy. GDP/E for sectors	Only capital services and labour quantity incorporated in the measurement of TFP $\text{TFP}gr = \text{GDP}gr - s_L(Labqtgr) - s_K(Kservgr)$

(continued)

[13] IKLEMS provides TFP growth data for 25 2-digit level industries. In order to find TFP growth rate of aggregate economy and that of major economic sectors, we have used Production Possibilities Frontier approach following Goldar (2018).

[14] While capital services incorporate heterogeneity of capital assets and thus capital quality, capital stock assumes homogeneity of assets.

[15] The APO's estimates of TFP do not incorporate labour quality changes, and hence, they tend to overestimate the TFP growth.

Table 2 (continued)

Database	Definition of output	Definition of capital input	Definition of labour input		Definition of LP	Definition of TFP
PWT9.1	GDP at basic price	Capital stock and capital services (Kserv)	Labour quantity measured both by total employment (E) and average number of hours worked (H)	Data on labour quality is provided separately	GDP/E GDP/H	Capital services, labour quantity and labour quality incorporated in TFP measurement $\mathrm{TFP}gr = \mathrm{GDP}gr - s_L(Labqtgr + LabQlgr) - s_K(Kservgr)$
IKLEMS	Gross value added (GVA) at market price	Capital stock and capital services (Kserv)	Labour quantity is measured only by total employment (E)	Data on labour quality index provided separately	GVA/E at both aggregate and industry levels	Capital services, labour quantity and labour quality incorporated in TFP measurement $\mathrm{TFP}gr_j = \sum_{j=1}^{n} v_j GVAgr_j - s_L\left(\sum_{j=1}^{n} m_j(Empgr_j + LabQlgr_j)\right) - s_K\left(\sum_{j=1}^{n} n_j Kservgr\right)$

Notes
1. *Source* Authors' elaboration from IKMS 2018, PWT9.1, TED 2018 and APO 2018
2. s_L and s_K are the shares of labour and capital in the total income. j refers to jth industry as defined in IKLEMS database; gr refers to growth rate; $Labqt$ denotes labour quantity; and $LabQl$ denotes labour quality

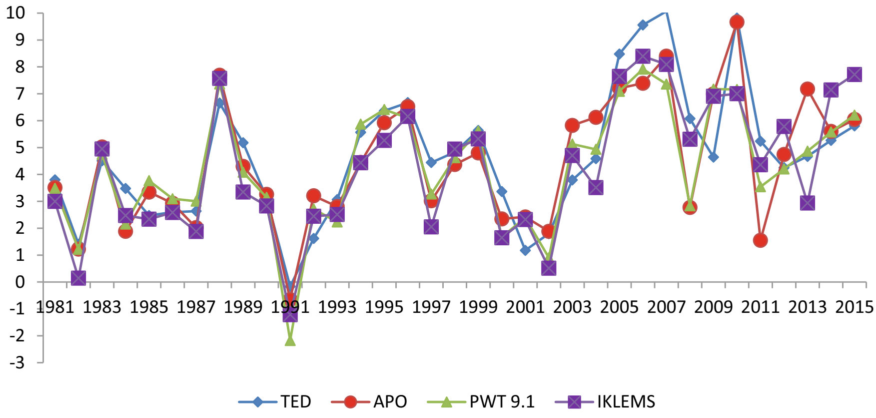


Fig. 1 Aggregate labour productivity growth rates (persons engaged based): 1981–2015. *Notes* 1. *Source* Authors' computations from TED, APO, PWT9.1 and IKLEMS databases

2.3 Trends in Labour and Total Factor Productivity Growth

2.3.1 Aggregate Economy

1.1 *Trends in Labour Productivity Growth*

We now discuss the trends in labour productivity growth[16] of the aggregate economy over the period 1981–2015. The trends as shown in Fig. 1 reveal that labour productivity growth rate increases over the period 1981–2015. While the sub-period of 1981 to 1992 was one of moderate growth, the growth rate rose sharply in 1990s and further in 2000s. The growth rate declined considerably during the macroeconomic crisis of 1991 and recovered soon after. While the trends in growth rate of labour productivity show some differences in absolute numbers across various estimates, the broad trends are the same. In fact, simple correlations between trends in labour productivity growth from various databases, as shown in Table 3, and decadal averages (as shown in Fig. 2) show similar trends across various databases. Goldar (2018) also finds similar results while comparing estimates of labour productivity growth from IKLEMS database and TED over the period 1981–2011.

1.2 *Trends in Total Factor Productivity Growth*

We now discuss trends in TFP growth rate for the Indian economy. As depicted in Fig. 3, TFP growth has shown cyclical growth over the period 1981–2015. Further, the broad trends in TFP growth are same across all the four variants of TFP. In fact, the TFP growth is in tandem with the GDP growth rate of the Indian economy over

[16] Labour productivity growth is employment based as this is the only measure consistently available across all four databases. Moreover, while IKLEMS uses GVA to compute labour productivity growth, other databases use GDP.

Table 3 Ordinary correlations between trends in aggregate labour productivity growth (persons engaged based) from four alternative databases over 1981–2015

Database	IKLEMS	PWT9.1	APO	TED
IKLEMS	1			
PWT9.1	0.92	1.00		
APO	0.85	0.93	1.00	
TED	0.87	0.87	0.85	1.00

Notes
1. *Source* Author's Computation from IKLEMS, PWT9.1, APO and TED

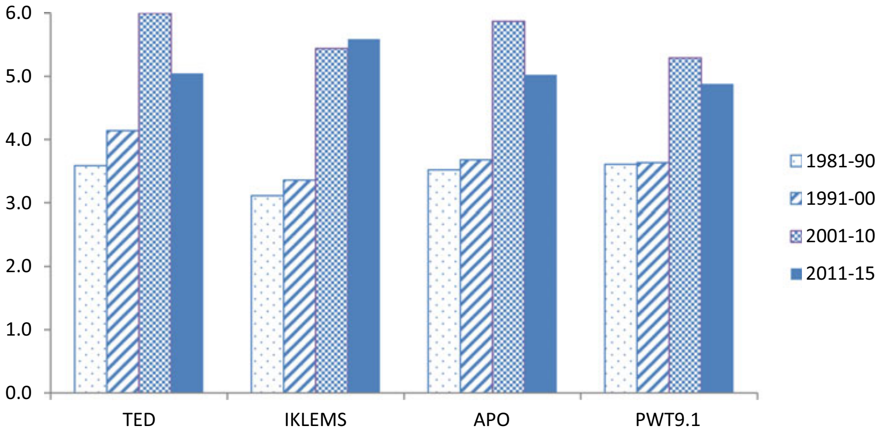


Fig. 2 Decadal averages of aggregate labour productivity growth (persons engaged based) over 1981–2015. *Notes* 1. *Source* Authors' own computations taking data from TED, PWT9.1, IKLEMS and APO

the period 1981–2015, see Fig. 3. Further, simple correlations between trends in TFP growth of various databases are strong, see Table 4.

The decadal averages of annual growth rates of TFP as shown in Fig. 4 further indicate that the magnitudes differ substantially across the four datasets. These differences can be attributed to differences in methods of estimations of TFP growth, especially to estimates of labour quality and capital services by the different databases. For instance, the estimates of TFP growth in APO's database are much higher in magnitude than those of other databases as labour quality is not accounted for while calculating TFP growth in APO estimates. These differences in the trends are in tandem with the explanations for differences in definitions of productivity growth as discussed above.

1.3 *Trends in Sectoral Labour and Total Factor Productivity Growth*

The Indian economy has undergone significant structural transformation over the last three and a half decades with services sector emerging as the largest sector of

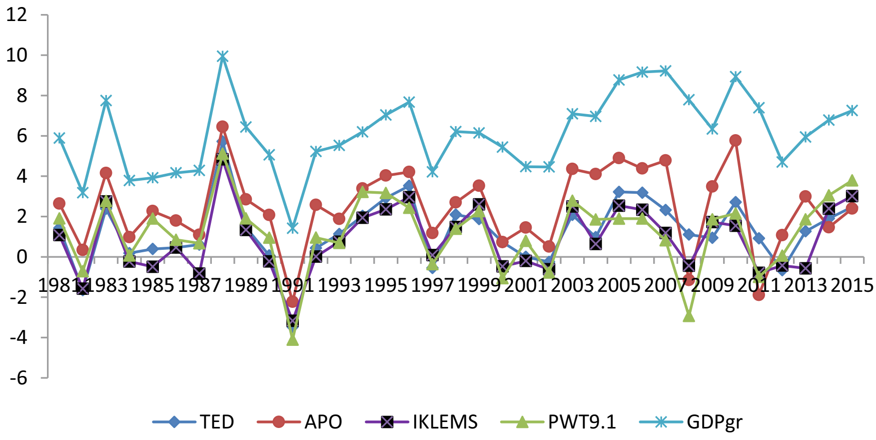


Fig. 3 Aggregate TFP growth and GDP growth: 1981–2015. *Notes* 1. *Source* Authors' computations from TED, APO, IKLEMS and PWT9.1. 2. TED, APO, IKLEMS and PWT9.1 refer to the TFP growth rates according to the four databases respectively

Table 4 Ordinary correlations between trends in aggregate TFP growth from four alternative databases over 1981–2015

Database	IKLEMS	PWT 9.1	APO	TED
IKLEMS	1			
PWT9.1	0.86	1.00		
APO	0.80	0.83	1.00	
TED	0.91	0.79	0.79	1.00

Notes
1. *Source* Author's computation from IKLEMS, PWT9.1, APO and TED

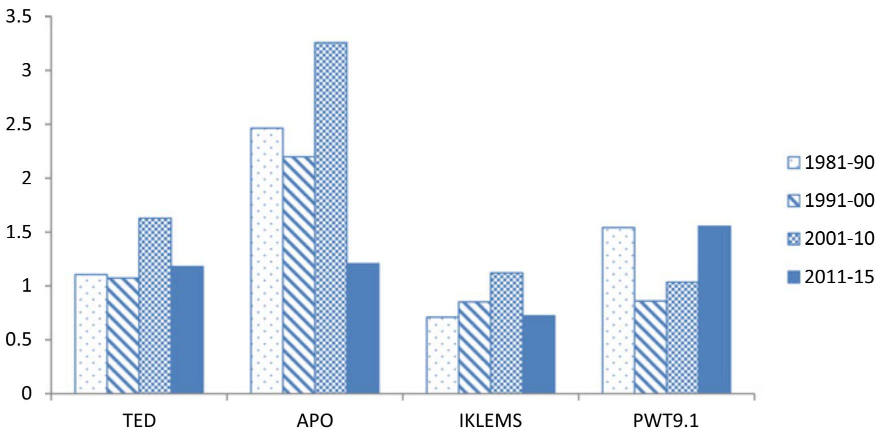


Fig. 4 Decadal averages of aggregate TFP growth over four sub-periods using alternative databases over 1981–2015. *Notes* 1. *Source* Authors' own computations taking data from TED, PWT and APO

Table 5 Growth rate of labour productivity (based on persons engaged) in manufacturing and market services in quinquennial sub-periods from two alternative databases over 1981–2015

Time period	Manufacturing sector		Market services sector	
	IKLEMS	APO	IKLEMS	APO
1981–85	3.23	3.56	1.24	5.07
1986–90	5.08	5.16	2.69	6.27
1991–95	5.06	1.74	3.79	3.50
1996–00	2.46	0.38	4.12	2.85
2001–05	3.47	6.40	5.72	3.98
2006–10	8.34	11.29	8.42	8.74
2011–15	4.94	4.05	7.54	4.27

Notes
1. *Source* Authors' own computations taking data from IKLEMS and APO

the economy accounting for more than 50% of GDP currently. Furthermore, while agriculture sector has shown considerable decline in its share, the share of industry has remained stable. Thus, industry and services account for more than 75% of the GDP of the Indian economy as of 2018, WDI (2019).

Further, the data shows that manufacturing[17] accounts for the maximum share of industry, while market services constitute the largest sub-sector of services (with manufacturing and market services accounting for more than 60% of industry and services GDP, respectively). In fact, market services have contributed more than the non-market services to the growth of overall services sector over the period 1981–2015, Goldar (2018). Thus, we deal with the manufacturing and market services sectors in this study.

We now discuss the trends in labour and total factor productivity growth of these sectors subsequently over the period 1981–2015. It may be noteworthy that only two variants of labour productivity growth are available at disaggregate level, viz., IKLEMS and APO databases. The trends in labour productivity growth of manufacturing sector as shown in Table 5 suggest that there has been a rise in the growth rate over the period 1981–2015 according to both variants. However, there are differences in the actual estimates of productivity growth across the two variants. One plausible reason for differences is that output measure in IKLEMS is GVA while that in APO is GDP.

As far as market services are concerned, while the rate of growth of productivity was moderate in the period 1981–85, the rate increased considerably during 1986–90 on an average. Thus, the labour productivity of market services shows remarkable

[17] It may be useful to note here that industry comprises four sectors, viz., mining, manufacturing, construction and electricity, gas and water supply, while services sector comprises **market services**, viz., trade, hotels and restaurants, transport and storage, financial services and business services, and **non-market services** that consist of public administration and defense, compulsory social services, education, health and social work and other services.

Table 6 Growth rate of TFP in manufacturing and market services in quinquennial sub-periods over 1981–2015

Year	Manufacturing	Market services
1981–85	−0.59	1.23
1986–90	1.40	0.69
1991–95	0.33	1.60
1996–00	−1.89	2.65
2001–05	1.39	3.28
2006–10	1.57	2.64
2011–15	1.90	1.35

Notes
1. *Source* Authors' own computations taking data from IKLEMS

growth over the period 1981–2015 according to both variants, and the differences in rate of growth of labour productivity across the two variants are only marginal.

As far as TFP growth is concerned, we notice that only one estimate of TFP growth (in IKLEMS) is available at the disaggregate level. The trends in TFP growth as shown in Table 6 indicate that there was a considerable improvement in the productivity growth of manufacturing sector over the period 1981–2015 and some improvement in the case of market services sector.

3 Determinants of Labour Productivity Growth

3.1 Aggregate Economy Model

Labour productivity may be determined by a number of variables including capital deepening, workforce skills, technology, inflation, and financial development, quality of institutions and macroeconomic variables, Dua and Garg (2019a). We briefly discuss each of these determinants subsequently.

3.1.1 Capital Deepening, Human Capital and Technological Progress

Dua and Garg (2019a) and references cited therein[18] suggest that aggregate labour productivity ($\boldsymbol{Prod}$) may be positively influenced by physical inputs of capital deepening ($\boldsymbol{k}$) and human capital ($\boldsymbol{HK}$) and also technological progress ($\boldsymbol{Tech}$). While increase in capital deepening and human capital add to productivity of labour by adding physical capital and skills for every unit of labour, more technological progress in terms of innovative activities undertaken by firms create and add to the knowledge base and thus raise the productivity of labour.

[18] See Dua and Garg (2019a) for details.

3.1.2 Macroeconomic Factors

2.1 ***Domestic Factors***

Certain macroeconomic factors may also influence productivity of an economy. These have been classified into domestic and external factors by Dua and Garg (2019a). We follow their model and incorporate these variables in our model of productivity. Among domestic factors are the policy variables of monetary $(\boldsymbol{M})$ and fiscal policy. Two indicators of monetary policy are generally used, money supply and interest rate. An increase in money supply reduces interest rate that in turn induces more investment and hence capital accumulation and therefore leads to increase in labour productivity.

Government size ($\boldsymbol{G}$) used as a fiscal indicator may influence productivity either positively or negatively. An increase in the role of government may reduce productivity if government and private sectors compete for resources and government's expenditure is not efficient, while if government's expenditure is more of complementary in nature and is done efficiently, it may boost investment by the private sector and may in turn increase productivity. Thus, an increasing role of government could either be more beneficial or harmful for the overall productivity of an economy and the net impact may depend upon relative magnitudes of the two impacts.

2.2 ***External factors***

Trade openness ($\boldsymbol{Tradeopen}$) and financial openness ($\boldsymbol{Finopen}$) are the external factors that are expected to boost productivity in an economy.[19] In particular, it is argued that trade openness, i.e. imports of new machinery and other capital goods from developed economies may increase the knowledge base in an economy which in turn leads to technological progress in the host economy, thus increasing labour productivity. Moreover, by exporting products to other countries, the exporting firms become more competitive which in turn affects their productivity positively.

Furthermore, financially more open economies tend to have higher productivity both because more financial openness brings in more FDI as well as more financially open economies tend to have better domestic financial markets, improvements in institutions, etc. Kose et al. (2009). Thus, it can be concluded that increased openness (either in terms of exchange of goods and services or exchange of capital) of an economy to the rest of world leads to higher overall labour productivity of that economy.

Apart from the above factors of basic inputs, technological progress and macroeconomic factors, Dua and Garg (2019a) suggest additional factors that may influence productivity of an economy. These are discussed below.

2.3 ***Additional Factors: Inflation ($\boldsymbol{\pi}$)***

Inflation is expected to affect productivity negatively as an increase in inflation increases uncertainty that either delays the decisions by entrepreneurs to do investments or makes them choose inputs in sub-optimal combinations. Increased inflation

[19] See Dua and Garg (2019a) for details and more references.

also diverts resources away from productive activities towards the non-productive activities (costs of fighting inflation) and hence affects the productivity of labour adversely, as seen in Jarrett and Selody (1982).

2.4 *Additional Factors: Financial Development* ($FinDev$)

Financial development is considered to be another determinant of labour productivity. It is argued that the more financially developed an economy, the better will be the channelization of savings and hence more capital accumulation and technological progress in the economy (Levine, 1997). Thus, more financial development of an economy is productivity enhancing.

2.5 *Additional Factors: Quality of Institutions* ($Inst$)

Economic institutions such as the structure of property rights and the presence of markets may be important for economic growth because they influence the structure of economic incentives in a society (Acemoglu et al., 2004). In other words, stronger system of property rights incentivizes individuals to undertake more investment in both physical as well as human capital which in turn increases productivity. Hence, quality of institutions is expected to affect productivity positively.

2.6 *Additional Factors: Share of agriculture in GDP* (S^{GDP})

Recently, Loko and Diouf (2009) show that a fall in the share of agriculture sector in GDP of a developing economy leads to rise in total factor productivity of that economy. The argument comes from a dual-economy model developed by Poirson (2000) in which as factors of production move away from traditional sector, which is assumed to be less productive to the modern sector, a relatively high-productivity sector, the overall productivity in the economy goes up.

Thus, on the basis of the above discussion, we may write the model for aggregate labour productivity as follows:

$$\begin{aligned} LP_t = \mathrm{f}\big(&k_t, HK_t, Tech_t, S_t^{GDP}, FinDev_t, \\ &G_t, \pi_t, M_t, Inst, Tradeopen_t, Finopen_t\big) \end{aligned} \tag{2}$$

The expected signs of the coefficients of all the variables as discussed above are summarized in Table 7 below.

While the above model is for the levels of labour productivity, we apply it to rates of growth of labour productivity and transform the other variables accordingly.

3.2 *Sectoral Model*

The above sub-section dwells on various potential factors that may influence labour productivity of an economy along with their explanations on the basis of the stylized model developed by Dua and Garg (2019a). In the current sub-section, we discuss factors that may affect productivity of various sectors of an economy. Dua and Garg

Table 7 Expected signs of independent variables

Variable	Expected sign
Aggregate-level variables (dependent variables: LP_t)	
k	+
$Tech$	+
HK	+
S_{it}^{GDP}	−
$FinDev$	+
G	±
π	−
$Inst$	+
M	±
$Tradeopen$	+
$Finopen$	+
Sector-specific variables (dependent variable: $Prod^m$) $m, n = Manufacturing\ sector\ or\ Market\ services\ sector$	
Variable	*Expected sign*
k^m	+
HK^m	+
π^m	−/+
$Tradeopen^m$	+
Cross-sectoral variables (dependent variable: $Prod^m$)	
Variable	*Expected sign*
$Prod^n$	+

(2019b) develop a stylized model of productivity of a sector and apply it to various sectors and sub-sectors of the panels of developing and developed economies of Asia–Pacific. We adopt the model from that study and apply it to the manufacturing and market services sectors of India in the current study.

The basic model for sectoral productivity remains same as that for the aggregate economy except that variables are defined at sectoral level. Thus, labour productivity of sector m ($\boldsymbol{Prod^m}$) may be influenced positively by capital deepening ($\boldsymbol{k^m}$)**,** human capital ($\boldsymbol{HK^m}$) and technological progress ($\boldsymbol{Tech^m}$) of that sector. However, the effect of these variables may vary across sectors. For instance, since manufacturing sector is more capital and R&D intensive, the impact of capital deepening and R&D is expected to be higher on it as compared to services sector, Efthyvoulu (2012).

Further, sectoral inflation ($\boldsymbol{\pi^m}$) has been identified as important determinant of productivity of a sector. While aggregate inflation is expected to affect productivity negatively, the empirics[20] suggest that the sign and significance of the impact may

[20] See for instance Bulman and Simon (2003).

depend upon the structure of an industry when examining the impact of sector-specific inflation.

While a plethora of studies[21] have examined the impact of trade openness on productivity and have found mixed results, studies[22] examining impact of sectoral trade openness ($\boldsymbol{Tradeopen^m}$) on productivity across sectors find that the impact of trade openness may vary across sectors. For instance, it is argued that goods sectors are more trade intensive than services that in turn may cause a stronger impact of trade openness on goods sectors than on services, therefore considering sectoral trade openness may bring out the differential impact of trade openness on each sector's productivity better than aggregate trade openness.[23]

Apart from above variables, productivity of a sector may be affected by productivity of another sector because of presence of inter linkages across sectors. For instance, manufacturing sector may use output of services sector as an input into its production process and may in turn supply some of its output to the services sector as its input. Given such interdependence, an exogenous positive shock to the productivity of manufacturing sector leads to more production in manufacturing, in turn affecting the productivity and hence growth of services sector and vice-versa, as seen in Balakrishnan et al. (2017). Thus, we consider another variable, namely productivity of sector n ($\boldsymbol{Prod^n}$) into our model of labour productivity of sector.

Finally, productivity of a sector may also be affected by certain aggregate level variables like **policy variables, institutional quality and financial openness**. They have already been explained in Sect. 3.1 above under aggregate economy model. Thus, on the basis of above discussion, we can write the model for labour productivity of sector m as follows:

$$\begin{aligned} Prod_t^m = f\big((k)_t^m, HK_t^m, Tech_t^m, Prod_t^n, \pi_t^m, \\ G_t, M_t, Inst., Tradeopen_t^m, Finopen_t\big) \end{aligned} \quad (3)$$

where

m, n = Manufacturing or Market services.

The expected signs of the coefficients of all the variables as discussed above are summarized in Table 7 above. A comparison of the aggregate and sectoral models as given in Eqs. (2) and (3) respectively suggests that the variables: capital deepening, human capital, technological progress and openness affect not only the productivity of aggregate economy but also that of various sectors. However, considering these variables at the sectoral level may lead to differential impacts across sectors depending upon the nature of these sectors.

---

[21] Refer to Dua and Garg (2019b).

[22] Efthyvoulu (2012), Park and Shin (2012).

[23] See Dua and Garg (2019b) and the references cited therein for details.

Further, policy variables and institutional quality are common to sectors and the aggregate economy because they are determined from external forces and may be taken as exogenous variables. Finally, share of agriculture is considered as an indicator of structural shifts that may have an impact on aggregate productivity instead of sectoral productivity. Due to inter-sectoral linkages between the sectors, an additional factor, viz., productivity of other sector is considered in sectoral model.

While the model set out in Eq. (3) is for the levels of labour productivity of a sector, we use it for rates of growth of labour productivity and transform rest of the variables also in rates of growth terms. We discuss the econometric methodology used to estimate the models set out in Eqs. (2) and (3) in the subsequent sections.

4 Econometric Methodology

We first check the stationarity properties of our series using Dickey Fuller-Generalized Least Squares (DF-GLS) test proposed by Elliot et al. (1996) and another test that assumes null of stationarity developed by Kwiatkowski et al. (1992). If both the tests suggest that the series is stationary, then we conclude that the series is stationary.

Having checked the stationarity properties of all our variables, we estimate the model of productivity growth as set out in Eq. (2) for the aggregate economy and Eq. (3) for the sectors above. We use Generalized Method of Moments (GMM) estimation technique for the purpose as it allows for endogeneity of variables and does not require any assumptions about the data generating process. The GMM estimator requires only the specification of a set of moment conditions that are deduced from the assumptions underlying the econometric model to be estimated. Moreover, the method may be useful to researchers who deal with a variety of moment or orthogonality conditions derived from the theoretical properties of their economic models.

We discuss the GMM estimation technique subsequently. Suppose that a sample of T observations $(z_1, z_2, \ldots\ldots\ldots\ldots z_T)$ is drawn from the joint probability distribution function

$$f(z_1, z_2, \ldots\ldots\ldots\ldots z_T; \theta_0)$$

where θ_0 is a $q \times 1$ vector of true parameters, belonging to the parameter space, Θ. Here, z_t would typically contain one or more endogenous variables and a number of predetermined and/ or exogenous variables. Let $m(.)$ be an r-dimensional vector of functions, then a population moment condition takes the form

$$E[m(z_t; \theta_0)] = 0, \text{ for all t.} \tag{4}$$

In particular, the GMM estimator[24] of θ, $\widehat{\theta_T}$, based on Eq. (4), is

$$\widehat{\theta_T} = argmin\{M_T^{'}(\theta)A_T M_T(\theta)\} \tag{5}$$

where A_T is a $r \times r$ positive semi-definite, possibly random, weighting matrix.

We assume that A_T converges to a unique, positive definite, non-random matrix and $M_T(\theta) = \frac{1}{T}\sum_{t=1}^{T} m(z_t, \theta)$.

Since we expect our variables such as capital deepening, productivity growth, share of agriculture, openness to be endogenous, estimating the model using OLS may lead to inconsistent estimates. Hence, we conduct the Hausman (1978)'s test for the consistency of OLS. Under the null hypothesis of no misspecification, the OLS estimator is consistent, asymptotically normal and asymptotically efficient. If the null hypothesis is rejected, using OLS may give biased and inconsistent estimates, and hence, use of GMM may be justified.

The estimation of a model using GMM technique also requires specification of instruments due to the presence of endogenous variables. Thus, we use the first and second lags of variables such as productivity growth, capital deepening, government size and certain exogenous variables like money growth, etc. as instruments in our analysis.

We conduct Hansen (1982)'s test to check validity of the overidentifying restrictions. Finally, in order to ensure that the estimated model does not suffer from serial correlation, we conduct the Cumby and Huizinga (1992) test. The test has an advantage over the standard LM, Breusch and Pagan (1980) test for serial correlation as it allows for the presence of endogenous regressors.

5 Data

We use growth of labour productivity and growth of total factor productivity as our dependent variables where labour productivity is defined on the basis of total persons engaged for the Indian economy on an aggregate basis as well as for the manufacturing and market services sectors over the period 1981–2015. We use aggregate-level data for human capital and technological progress for manufacturing and market services sectors due to paucity of data on sectoral basis.

The definitions of variables used for potential determinants of productivity growth at both aggregate and sectoral levels are provided in Table 8 below along with the sources of data.

[24] See Pesaran (2015), Chap. 10 for details.

Table 8 Variable definitions and sources of data

Variable	Definition	Source of data
Prod	Labour productivity of the aggregate economy (GDP divided by total employment)	IKLEMS, APO, PWT9.1 and TED
$Prod_j$	Labour productivity in sector j (GVA in sector j divided by total employment in sector j)	IKLEMS and APO
k (capital services per worker in sector or aggregate)	Capital services of each sector/aggregate divided by total employment in that sector/aggregate	IKLEMS, APO, PWT9.1 and TED
HK (human capital)	Gross enrolment in tertiary/secondary education; labour quality data from corresponding productivity databases	WDI (2019); IKLEMS, APO, PWT9.1 and TED
Tech (technological progress)	Stock of total patent applications/stock of R&D expenditure	Calculated using PIM taking data on patent applications from WDI (2018) and R&D expenditure from ministry of science and technology report on research and development statistics (2017–18)
G (government size)	Rate of growth of general government final consumption expenditure	WDI (2019)
Inst. (institutional quality)	Economic freedom index	Fraser institute
Tradeopen (trade openness)	Sum of exports and imports as a ratio of GDP	WDI (2019)
Finopen (financial openness)	Various measures of de facto financial openness as given in Lane and Milessi-Ferretti database (2017)	Lane and Milessi-Ferretti database (2017) and KOF Swiss Economic Institute
π (inflation)	Rate of growth of GDP deflator	WDI (2019) for aggregate and IKLEMS and APO (2019) for sectoral

Notes
1. *Source* Authors' own elaboration

6 Econometric Results

The current section reports the econometric results of the estimation of model of productivity growth for the Indian economy. We first estimate the model of labour productivity growth (see Sect. 6.1.1 for details) at the aggregate level for each of the four variants by IKLEMS, APO, PWT9.1 and TED. These databases provide different estimates of labour productivity growth and capital deepening.[25] Therefore, these two variables differ across the four models, while measures of other determinants[26] of productivity growth as set out in Sect. 3.1 remain same.

The study then estimates the model of TFP growth using four variants[27] of TFP growth as provided by four datasets, viz., IKLEMS, APO, PWT9.1 and TED. This is discussed in Sect. 6.1.2.

We also estimate the model of labour productivity growth of two sub-sectors, viz., manufacturing and market services of the Indian economy using definition of productivity growth and capital deepening of each sector from each of the two databases, viz., IKLEMS and APO. The results for the manufacturing and market services sectors are reported and discussed in Sects. 6.2.1 and 6.2.2, respectively.

In each case, the estimation involves three steps, viz., checking the stationarity properties of the variables, estimating the model using GMM and conducting diagnostic tests to check the robustness of estimated models.

6.1 Aggregate Economy

6.1.1 Labour Productivity Growth

The results on unit root[28] tests suggest that labour productivity growth, total factor productivity growth, capital deepening, labour quality, money growth and government size are all stationary in levels. On the other hand, inflation, share of agriculture, institutional quality, trade openness, financial openness are all non-stationary in levels and stationary in first differences, that is $I(1)$.

To maintain consistency in the order of integration across variables, we consider first difference of variables that are $I(1)$ and levels of variables that are $I(0)$ and estimate the model set out in Sect. 3.1. The additional instruments considered in our analysis are first and second lags of endogenous variables (productivity growth, capital deepening and share of agriculture), exogenous variables, viz., government size and institutional quality and predetermined variables of technological progress and openness and their lags.

We estimate four models of productivity growth using different variants of productivity growth (as mentioned above), and the results suggest that capital deepening, technological progress, institutional quality, government size, openness and share of

[25] While the databases provide data on capital services and employment, we calculate capital deepening as the ratio of capital services and employment for each database.

[26] While IKLEMS, PWT and TED provide their own estimates of human capital, APO does not have any estimates for human capital. Thus, we kept a single measure of human capital, viz., secondary school enrolment across all the four models.

[27] See Sect. 2.2.5 for definitions of TFP growth across four databases.

[28] Results on unit root tests are not reported here due to brevity of space, but they are available from authors upon request.

Table 9 Aggregate economy GMM estimation results: Labour Productivity growth

Dependent variable: aggregate labour productivity growth ($Prodgr$)				
	Coefficients (p-values)			
Variable\database	IKLEMS	PWT9.1	APO	TED
kgr	0.48(0.00)***	0.48(0.00)***	0.41(0.00)***	0.55(0.00)***
Tech	5.94(0.24)	10.58(0.04)**	6.53(0.35)	3.86(0.47)
G	0.08(0.26)	0.017(0.76)	0.018(0.81)	0.012(0.88)
Inst.	3.21(0.00)***	2.79(0.01)**	2.49(0.06)*	4.16(0.00)***
Share_Agri	−0.09(0.78)	−0.13(0.59)	−0.13(0.73)	−0.082(0.83)
Tradeopen			0.21(0.04)**	
Finopen	0.30(0.27)	0.018(0.71)	0.12(0.05)*	0.009(0.98)
J (Hansen's J-statistic)	2.99(0.88)	7.11(0.62, 9)	3.84(0.57, 5)	3.92(0.56, 5)
Hausman	5.12(0.07)	0.006(0.99, 2)	2.55(0.27, 2)	0.56(0.75, 2)
CH (Cumby-Huizinga)	0.23(0.62, 1)	1.53(0.21, 1)	1.16(0.28, 1)	0.39(0.52, 1)

Notes
1. Endogenous regressors are kgr and $share_{agri}$. kgr and G refer to growth rate of capital to labour ratio and growth rate of general government final consumption expenditure, respectively
2. $Tech$, $Inst.$, $Share\_agri$, $Tradeopen$ and $Finopen$ are the relative changes in R&D to GDP ratio, Economic Freedom Index, share of agriculture in GDP, trade openness and financial openness

agriculture in GDP influence productivity growth in all the four models. The signs of all the coefficients conform to economic theory.

The diagnostic tests[29] conducted to check the validity of the models suggest that Hansen's J-statistic for overidentifying restrictions and the CH test for serial correlation are not rejected at 1% level of significance, see Table 9 above. This indicates that the overidentifying restrictions are valid, as shown in Table 9, in the case of all four models and the models do not suffer from any serial correlation. Thus, all the four models estimated are robust to the diagnostic tests conducted.

Thus, the determinants of labour productivity growth are robust to the variant of productivity used. Further, while the estimated coefficients differ in their absolute magnitudes across the four models, the results are qualitatively same, see Table 9. These differences in the magnitudes of coefficients could be attributed to differences in the definitions and measurement of productivity growth and capital deepening (as explained in Sect. 3 above) and of revisions in their estimates across the four databases.

The empirical results (as shown in Table 9) suggest that an increase in growth of capital deepening is associated with an increase in productivity growth of the Indian economy. The result corroborates with the findings of Goldar et al. (2017) who show that capital services was a major contributor to economic growth of India over the

[29] We also conduct the Hausman (1978) test for the consistency of OLS, and the null hypothesis of consistency of OLS is not rejected in all the cases, but we still proceed with GMM estimation technique.

period 1980–81 to 2014–15 using IKLEMS database. Further, Nomura (2018) also shows that capital stock contributes the most to economic growth of Asian economies over the period 1970–2014 using APO database. The results suggest further that while capital deepening is an important factor in influencing labour productivity growth of Indian economy, technological progress as measured by R&D expenditure may also affect productivity growth positively and may thus be encouraged.

A shift of resources away from agriculture to industry and services as measured by a decline in the share of agriculture in GDP may enhance labour productivity growth of the Indian economy. This may be indicative of structural changes and their impact on the Indian economy. Krishna et al. (2017) also find that structural change in the Indian economy has contributed positively to the growth of labour productivity over 1980–81 to 2010–11 using IKLEMS database. The result further finds support from studies by Mcmillan and Rodrik (2011) and Vu (2017) who find a positive and significant impact of structural change on labour productivity growth of Asian economies.

The results further suggest that expansionary fiscal policy as indicated by higher government expenditure may be productivity enhancing. This indicates that in the case of Indian economy, more government expenditure has a crowding-in effect on private business investment and thus leads to more capital accumulation and hence higher productivity growth. Better institutions as measured by increase in Economic Freedom Index further increase productivity growth of the Indian economy.

Finally, more openness of the economy to the rest of the world not only brings in more capital for the firms but also better technology and a more competitive environment to work with and thus adds to the labour productivity growth of the economy.

6.1.2 Total Factor Productivity (TFP) Growth

We now discuss the results of model of productivity growth as set out in Eq. (2) using TFP growth as the dependent variable and how these results compare with those in previous sub-section. It may be noted that capital deepening will no longer be a determinant here because capital input is already incorporated while constructing the estimates of TFP growth. Further, while TFP growth (the dependent variable in the model) varies across the four models, the measures of determinants of productivity growth are kept same across them. Thus, we proceed with the same model as in Eq. (2) above but without capital deepening on the right-hand side.

The unit root test[30] results suggest that the TFP growth based on all four databases is stationary in levels. Thus, we proceed to estimate the model set out in Eq. (2) using GMM using each of the four variants of TFP growth. The results (see Table 10) indicate that technological progress, share of agriculture, government size, institutional quality and openness are significant determinants of TFP growth over the period

[30] The unit root test results are not reported here due to brevity of space but are available from authors upon request.

Table 10 Aggregate economy GMM estimation results: TFP growth

Dependent variable: aggregate total factor productivity growth ($TFPgr$)				
	Coefficients (p-values)			
Variables\database	IKLEMS	PWT9.1	APO	TED
Tech	1.668(0.78)	9.04(0.09)*	14.10(0.00)***	6.649(0.27)
G	0.067(0.14)*	0.001(0.97)	−0.072(0.05)**	0.067(0.25)
Inst.	2.57(0.03)**	3.201(0.02)**	3.498(0.00)***	2.491(0.02)**
Share_Agri	−0.063(0.85)	−0.262(0.39)	−0.465(0.09)*	−0.122(0.81)
Tradeopen				
Finopen	0.133(0.63)	0.015(0.82)	1.088(0.00)***	0.0710(,12)*
J (Hansen's J)	4.148(0.84,8)	3.383(0.84,7)	2.097(0.83,5)	1.95(0.58,3)
Hausman	2.41(0.12,1)	1.044(0.30,1)	0.23(0.63,1)	1.66(0.19,1)
CH (Cumby-Huizinga)	0.106(0.74,1)	0.416(0.51,1)	0.055(0.81,1)	0.724(0.39,1)

Notes
1. Endogenous regressor is $Share\_Agri$. kgr and G refer to growth rate of capital to labour ratio and growth rate of general government final consumption expenditure, respectively
2. $Tech$, $Inst.$, $Share\_agri$, $Tradeopen$ and $Finopen$ are the relative changes in R&D to GDP ratio, Economic Freedom Index, share of agriculture in GDP, trade openness and financial openness

1981–2015. While technological progress, government size, institutional quality and openness affect productivity growth positively, the impact of share of agriculture is negative. The results are robust to the different variants of TFP growth, see Table 10. All the models estimated are robust to diagnostic tests.

Thus, the results indicate that capital deepening; technological progress, government size, institutional quality, openness and share of agriculture are significant determinants of productivity growth of the Indian economy over the period 1981–2015 using all the four variants of TFP growth. However, the magnitudes of coefficients of variables on the RHS vary across the four models which is as expected given the differences in the estimates of TFP growth across four models.

6.2 Disaggregate Economy

Two databases, viz., IKLEMS and APO provide data on labour productivity growth[31] for the Indian economy at disaggregate level as well. We therefore examine the determinants of productivity growth at disaggregate level using estimates of productivity

[31] While IKLEMS database provides data on TFP growth at disaggregate level, it is not available with any other data source. We investigate the determinants of productivity growth using TFP for manufacturing and market services sectors and find that the results are robust to the use of TFP instead of labour productivity for the two sectors. The results are available upon request from authors.

growth from the two databases. We investigate two broad sub-sectors, viz., manufacturing and market services for the purpose and discuss the results for each sub-sector separately in the subsequent sections.[32]

6.2.1 Manufacturing Sector

We discuss the econometric estimation of the model set out in Eq. (3) in Sect. 3.2 above for labour productivity growth of manufacturing sector using both variants (IKLEMS and APO) in the current section and that for market services in the next subsection. The unit root test[33] results suggest that labour productivity growth, growth rate of capital deepening, human capital are stationary in levels, while trade openness is non-stationary in levels but stationary in first differences. Thus, we consider productivity growth of both manufacturing and market services sectors, capital deepening and labour quality in levels while trade openness in first differences. While these are all sector-specific variables, we also consider certain aggregate variables as discussed and considered in Sect. 3.2 above.

We estimate various models according to Eq. (3) set out in Sect. 3.2 above using GMM estimation technique and select the final model on the basis of the robustness of the overall fit. The results as reported in Table 11 suggest that labour productivity growth of manufacturing sector is influenced by capital deepening, technological progress, government size, institutional quality, productivity growth of services sector and openness. *The results are consistent across the two variants of labour productivity growth for the manufacturing sector.* Further, both models meet all the diagnostic tests conducted to check the robustness of the models, see Table 11.

Thus, the model of productivity growth of manufacturing sector as estimated above is robust to alternative variants of labour productivity growth used although there are differences in the magnitudes of coefficients across the two models.

One plausible explanation for these differences could be that the construction of productivity growth and capital deepening are based on different assumptions across the two databases which in turn lead to differences in their estimates.

Moreover, the signs of all the coefficients are as expected using both variants of labour productivity growth. Thus, the results suggest that more capital per unit of labour leads to increase in the growth of labour productivity of the manufacturing sector of India. Technological progress as measured by R&D expenditure as a ratio of GDP is another significant determinant of productivity growth in the manufacturing sector.

Furthermore, a rise in government size and better institutional quality are productivity enhancing for the manufacturing sector of the Indian economy. Thus, increase in government expenditure turns out to be complementary to the private investment leading to a rise in capital accumulation and hence more productivity growth in the sector. The results further indicate that opening up the manufacturing sector to

[32] Refer to Sect. 2.3.2. for details on why we choose these two sub-sectors for the analysis.

[33] Unit root test results are not reported here but available from authors upon request.

Table 11 Sectoral GMM estimation results

Dependent variable: labour productivity growth of sector j ($LPgr_j$)
(j = Manufacturing, Market Services)

Coefficients (p-values)

Sector →	Manufacturing		Market services	
Variable\database	IKLEMS	APO	IKLEMS	APO
kgr_j	0.03(0.89)	0.60(0.00)***	0.50(0.00)***	0.63(0.00)***
Tech	17(0.17)	12(0.01)**	3.48(0.44)	9.93(0.04)**
G	0.003(0.98)	0.15(0.06)*	0.09(0.11)	0.23(0.00)***
Inst.	5.38(0.17)	1.56(0.17)		
$LPgr_k$	0.49(0.01)**	0.32(0.00)***	0.049(0.54)	0.13(0.11)*
$Tradeopen_j$	0.006(0.87)		0.57(0.01)	0.16(0.23)
Finopen	0.30(0.71)	1.06(0.00)***	0.68(0.01)	0.03(0.30)
J (Hansen's J)	4.86(0.43, 5)	4.29(0.74, 7)	2.55(0.63, 4)	3.13(0.37, 3)
Hausman	2.50(0.28, 2)	0.65(0.72, 2)	0.16(0.92, 2)	0.15(0.92, 2)
CH (Cumby-Huizinga)	0.16(0.68, 1)	0.22(0.63, 1)	4.24(0.04, 1)	0.57(0.45, 1)

Notes
1. $j, k = MarketServicesorManufacturing$
2. Endogenous regressors: kgr_j, $LPgr_k$.kgr and G refer to growth rate of capital to labour ratio and growth rate of general government final consumption expenditure, respectively
3. $Tech$, $Inst.$, $Share\_agri$, $Tradeopen$ and $Finopen$ are the relative changes in R&D to GDP ratio, Economic Freedom Index, share of agriculture in GDP, trade openness and financial openness

the rest of the world may lead to higher productivity growth of the sector. Thus, allowing freer international flow of goods and capital in the manufacturing sector of the economy may be beneficial.

Another key finding of the study is that productivity growth of services sector has a positive and significant impact on productivity growth of manufacturing sector. It is well known that manufacturing sector requires a number of services to distribute its output like transportation, finance, real estate and communications. An improvement in productivity growth of these services sectors reduces the prices of their product which in turn benefits the manufacturing sector that could produce more output with fewer inputs. Thus, there exist significant spillover effects from services sector to manufacturing sector of the economy.

To conclude, productivity growth of manufacturing sector is not only influenced by factors specific to this sector namely capital deepening and trade openness but also cross-sectoral variables and aggregate-level variables.

6.2.2 Market Services Sector

We now discuss the results for market services sector using both variants of labour productivity growth, viz., IKLEMS and APO. The unit root test results suggest that productivity growth (both IKLEMS and APO definitions), capital deepening (both IKLEMS and APO definitions) and human capital growth are stationary in levels, while trade openness is non-stationary in levels and stationary in first differences. So, we consider trade openness in first differences so as to have consistency in order of integration across all variables.

We then estimate our model set out in Sect. 3.2 above using GMM estimation technique. The results as reported in Table 11 suggest that capital deepening, technological progress, government size, institutional quality, productivity growth of manufacturing sector and openness are significant determinants of productivity growth of services sector.

The model is robust to alternative variants of labour productivity growth for the market services sector. The results on diagnostic tests suggest that both the models meet the diagnostic tests.

Thus, the results indicate that capital deepening is a positive and significant determinant of productivity growth of market services sector of the Indian economy. Thus, further growth in physical inputs, viz., capital per worker is productivity enhancing for the services sector. The result is in line with the study by Goldar et al. (2017) which shows that capital stock has been the largest contributor of growth of Indian economy over the period 1980–81 to 2010–11 using IKLEMS database.

While technological progress also affects productivity growth of services sector positively, the impact is not significant. A plausible explanation for this could be that most of the R&D expenditure takes place in manufacturing sector and the aggregate level of R&D expenditure may not pick up the impact on productivity growth of market services sector. The results further indicate that better institutional quality and more government expenditure both influence productivity growth of market services sector positively and significantly.[34] Thus, a better economic institutional environment in terms of a more conducive business climate and labour laws is favourable for the services sector. Further, more government expenditure is not only beneficial to the manufacturing sector but also to the market services sector of the Indian economy.

Furthermore, the productivity growth of manufacturing sector has a positive impact on the productivity growth of market services sector though the impact is not significant. Balakrishnan et al. (2017) find similar result in the context of manufacturing and market services of the Indian economy over the period 1965–66 to 2009–10.

The results further suggest that both trade openness and financial openness have a positive and significant influence on the productivity growth of services sector. Thus, deregulation and more integration of the services sector of the Indian economy with the rest of the world may be fruitful.

The results for the two sub-sectors indicate that capital deepening, technological progress, expansionary fiscal policy, institutional quality, productivity of the other sector and openness are determinants of productivity growth of both manufacturing as well as market services sectors. However, the impact of these variables differs across the two sectors. First of all, while productivity growth of one sector affects

[34] Both are significant up to 21% level of significance.

that of other, the impact is stronger from services to manufacturing sector. Thus, the results suggest evidence of significant asymmetric spillover effects across the two sectors. The result finds support from a study by Balakrishnan et al. (2017) who show an asymmetry in the positive feedback mechanism across manufacturing and services sectors of the Indian economy over the period 1965–66 to 2009–10. This result also corroborates with the findings of Dua and Garg (2019b) in the context of manufacturing and market services of developing and developed Asia–Pacific economies over the period 1980–2014.

Secondly, while trade openness affects productivity growth of both manufacturing and services sectors positively, the impact is significant only in the case of services sector.[35] Given that services sector has emerged as the largest economic sector in the Indian economy post liberalization, the result may be expected. The result also corroborates with the findings of Abizadeh and Pandey (2009) who find that the impact of trade openness has been stronger for productivity growth of services sector as compared to agriculture and industry in the post-90 s period in the context of OECD economies over the period 1980–2000.

To conclude, above results suggest that while both manufacturing and services sectors are important for the Indian economy and both have contributed to the overall labour productivity growth, services sector has both a direct as well as indirect impact on productivity growth through other sectors. Moreover, the impact of greater openness of the services sector of the Indian economy to the rest of the world may indicate greater potential in this sector as compared to other sectors to exploit the openness policies.

7 Conclusion

The current study examines trends and determinants of various measures of productivity growth for the Indian economy at both aggregate as well as disaggregate levels using different variants of productivity growth. At the aggregate level, the study considers both labour and total factor productivity growth estimated by four databases, viz., India KLEMS, Asian Productivity Organization (APO), Penn World Table (PWT9.1) and The Conference Board's Total Economy Database (TED).

The analysis of the trends in labour productivity growth over the period 1981–2015 indicates that while there are differences in the absolute magnitudes of productivity growth rates estimated by the four databases, the trends are broadly similar. Further, the analysis of the trends in TFP growth using all the four databases indicates substantial differences in the estimates of productivity growth that may be explained by the differences in the definitions and estimation methods used for constructing the database on TFP growth.

[35] The coefficient is significant at 21% level of significance in the case of services, while the p-value is 0.78 in the case of manufacturing sector.

Further, the study considers labour productivity growth at disaggregate level for the broad sub-sectors, viz., manufacturing and market services sectors of the Indian economy as provided by two databases, viz., IKLEMS and APO over the period 1981–2015. The investigation of trends of labour productivity growth of manufacturing and market services sectors reveals that the broad trends in productivity growth of the two sectors are similar across the two variants though they differ in magnitudes.

We use stylized model of labour productivity developed by Dua and Garg (2019a) at the aggregate level and the model of labour productivity developed by Dua and Garg (2019b) at the sectoral level to examine determinants of productivity growth using all the four databases.

Using GMM estimation technique, the study finds that capital deepening, technological progress, government size, institutional quality, share of agriculture and openness are significant determinants of aggregate labour productivity growth of Indian economy over the period 1981 to 2015. The results further indicate that while there are differences in the magnitudes of coefficients across the four databases of labour productivity growth estimates, the results are qualitatively similar. Thus, the determinants of productivity growth are robust to alternative variants of labour productivity growth used. Further, the results are also found to be robust to alternative measures of productivity growth, i.e. TFP growth and its estimates across various databases. The results are found to be broadly similar to those found in Dua and Garg (2019a) for the emerging and developing Asia–Pacific economies over the period 1980–2014.

The results on sectoral analysis indicate that capital deepening, technological progress, government size, institutional quality, productivity growth of other sector and openness are significant determinants of labour productivity growth of both sub-sectors. However, the impact of productivity growth of other sectors is stronger from services to manufacturing than other way around indicating greater response of manufacturing sector to productivity growth of services sector. Further, trade openness is found to have a stronger impact on the productivity growth of services than that of manufacturing sector. The results are further found to be robust to alternative databases of labour productivity growth used for the two sub-sectors. Similar results are also found by Dua and Garg (2019b) in the context of manufacturing and services sectors of emerging and developing Asia–Pacific economies over the period 1980–2014.

A comparison of results across aggregate and sectoral analysis indicates that while certain factors like capital deepening, technology, government size, openness, etc. are positive and significant determinants of both aggregate as well as disaggregate productivity growth, other factors like productivity growth of the other sector are relevant only for sectoral analysis. Moreover, there are differences in the influence of these factors across sectors. Thus, the study finds robust determinants of productivity growth both at aggregate and disaggregate levels for the Indian economy.

Questions to Think About

1. The current study analyses the productivity growth of the Indian economy and its major sectors, viz., manufacturing and market services for the period 1981 to 2015. Do you expect any changes in the results if the analysis is extended up to 2019 (pre-Covid-19 period) and later?

   Hint: Use updated data from the databases described in the chapter to re-estimate the models in the light of current data.
2. How do the estimates of productivity growth of India compare with those of other major emerging Asian economies for which data is available?

   Hint: APO database provides data for emerging Asian economies that can be used to study the productivity growth performance of these countries.
3. Apply the model described in the chapter to other countries using panel framework.

   Hint: One may use panel data techniques like Group-Mean Fully Modified OLS for the analysis. Refer: Dua and Garg (2019a)

References

Abizadeh, S., & Pandey, M. (2009). Trade openness, structural change and total factor productivity. *International Economic Journal, 23*, 545–559.

Acemoglu, D., Johnson, S., & Robinson, S. (2004). *Institutions as the fundamental cause of growth, WP 10481*. National Bureau of Economic Research.

Asian Productivity Organization (APO) Database (2019). Available for download at https://www.apo-tokyo.org/

Balakrishnan, P., Das, M., & Parameswaran, M. (2017). The internal dynamic of indian economic growth. *Journal of Asian Economics, 50*, 46–61.

Breusch, T. S., & Pagan, A. R. (1980). The lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies, 47*, 239–253.

Bulman, T., & Simon, J. (2003). Productivity and inflation, paper no. 10, Reserve Bank of Australia Discussion Paper.

Cumby, R. E., & Huizinga, J. (1992). Testing the autocorrelation structure of disturbances in ordinary least squares and instrumental variables regressions. *Econometrica, 60*, 185–195.

Das, D. K., Erumban, A. A., Aggarwal, S., & Das, P. C. (2017). Measuring productivity at the industry level: The India KLEMS database. *Data Manual*.

Dua, P., & Garg, N. K. (2019a). Determinants of labour productivity: Comparison between developing and developed countries of Asia–Pacific. *Pacific Economic Review, 24*, 686–704.

Dua, P., & Garg, N. K. (2019b). Sectoral analysis of productivity in the developing and developed economies of Asia–Pacific. *Indian Growth and Development Review, 13*, 37–71.

Efthyvoulu, G. (2012). The impact of financial stress on sectoral productivity. *Economic Letters, 116*, 240–243.

Elliot, B. E., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests of the unit root hypothesis. *Econometrica, 64*, 13–36.

Erumban, A. A., & Van Ark, B. (2018). Productivity in the global economy. In D. K. Das (Ed.), *Productivity dynamics in emerging and industrialized countries.* Routledge.

Feenstra, R. C., Robert, I., & Timmer, M. P. (2015). The next generation of the penn world table. *American Economic Review, 105*, 3150–3182.

Goldar, B.N. (2018), Sources of Growth and Structural Changes in the Indian Economy since 1980, in *Productivity Dynamics in Emerging and Industrialized Countries*, ed. D.K. Das, Routledge, India.

Goldar, B., Krishna, K. L., Aggarwal, S. C., Das, D. K., Erumban, A. A., & Das, P. C. (2017). Productivity growth in India since the 1980s: The KLEMS approach. *Indian Economic Review, 52*, 37–71.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica, 50*, 1029–1054.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica, 46*, 1251–1271.

IMF Database. (2020). World economic outlook—October. Available for download on https://www.imf.org/en/Publications/WEO/weo-database/2020/October

Jarrett, J. P., & Selody, J. G. (1982). The productivity-inflation nexus in Canada. *The Review of Economics and Statistics, 64*, 361–367.

Kose, M. A., Prasad, E. S., & Terrones, M. E. (2009). Does openness to international financial flows raise productivity growth. *Journal of International Money and Finance, 28*, 554–580.

Krishna, K. L., Erumban, A. A., Das, D. K., Aggarwal, S., & Das, P. C. (2017). Industry *origins of economic growth and structural change in India*, WP 273. Centre for Development Economics, DSE.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics, 54*, 159–178.

Lane, P., & Milesi-Feretti, G. M. (2017). *International financial integration in the aftermath of the global financial crisis, WP 115*, IMF.

Levine, R. (1997). Financial development and economic growth: Views and agenda. *Journal of Economic Literature, 35*, 688–726.

Loko, B., & Diouf, M. A. (2009). *Revisiting the determinants of productivity growth: What's New, WP 225*. IMF.

McMillan, M. S., & Rodrik, D. (2011). *Globalization, structural change and productivity growth, WP 17143*. National Bureau of Economic Research.

Nomura, K. (2018). Productivity growth in Asia and its country origins. In D. K. Das (Ed.), *Productivity dynamics in emerging and industrialized countries*. Routledge.

OECD. (2001). *Measuring productivity—OECD manual: Measurement of aggregate and industry-level productivity growth*. OECD Publishing. https://doi.org/10.1787/9789264194519-en

Park, D., & Shin, K. (2012). *The service sector in Asia: Is it an engine of growth, WP 322*. Asian Development Bank.

Pesaran, M. H. (2015). *Time series and panel data econometrics*. Oxford University Press.

Poirson, H. (2000). *Factor reallocation and growth in developing countries, WP 94*. IMF.

RBI (2018) *Measuring productivity at the industry level—The India KLEMS database*. https://rbi.org.in/Scripts/KLEMS.aspx

Vries, K. D., & Erumban, A. A. (2017). *Total economic database: A detailed guide to its sources and methods*. The Conference Board. https://www.conference-board.org/data/economydatabase/total-economy-database-methodology

Vu, K. M. (2017). Structural change and economic growth: Empirical evidence and policy insights from Asian economies. *Structural Change and Economic Dynamics, 41*, 64–77.

World Development Indicators Database. (2019). October, Available for download on https://www.imf.org/en/Publications/WEO/weo-database/2020/October

Part II
Forecasting the Indian Economy

Chapter 8
Forecasting the INR/USD Exchange Rate: A BVAR Framework

Pami Dua, Rajiv Ranjan, and Deepika Goel

Abstract This paper uses vector autoregression and Bayesian vector autoregression techniques to forecast the Indian Re/US dollar exchange rate. It extends the Dua and Ranjan (2010, 2012) model by including the domestic–foreign differential of the rate of return in stock prices as well as global oil prices as determinants of the exchange rate in addition to monetary model fundamentals (i.e. differential in money supply, interest rate and inflation), forward premium, volatility of capital flows, order flows and central bank intervention. The estimation period is July 1996–January 2017, while an analysis of the out-of-sample forecasting performance is undertaken from February 2017 to January 2019. The main findings are as follows: (i) Granger causality tests reveal that the exchange rate is granger caused by all the determinants considered, including differential of the rate of return of stock prices and global oil prices. (ii) Forecast accuracy of the extended model that includes stock market information and global oil prices is somewhat better than Dua and Ranjan (2010, 2012) model, especially at the longer end. (iii) Bayesian vector autoregressive models generally outperform their corresponding VAR variants. (iv) Turning points are difficult to predict.

Keywords Exchange rate · VAR and BVAR models · Forecasting · Stock price differential · Oil prices

JEL Classification C11 · C32 · C53 · F31 · F47

P. Dua (✉)
Department of Economics, Delhi School of Economics, University of Delhi, Delhi 110007, India
e-mail: dua@econdse.org

R. Ranjan
Monetary Policy Department, Reserve Bank of India, Mumbai, India
e-mail: rajivranjan@rbi.org.in

D. Goel
Department of Economics, Aryabhatta College, University of Delhi, New Delhi, India
e-mail: deepika@aryabhattacollege.ac.in

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_8

1 Introduction

Movements in exchange rates have important implications for the economy's business cycle, trade and capital flows and are therefore crucial to understanding financial developments and changes in economic policy. Thus, timely forecasts of exchange rates can provide valuable input to policymakers and stakeholders in the sphere of international finance and trade. Nevertheless, the empirical literature is sceptical about the possibility of accurately predicting exchange rates. The seminal paper by Meese and Rogoff (1983) has shown that models based on economic fundamentals are unable to outperform a naïve random walk. Empirical research undertaken since then have provided mixed evidence on the success of economic models to predict exchange rates. No particular model seemed to have worked best uniformly at all times/horizons. Further, the volatility of exchange rates also at times have weakened the link between macroeconomic fundamentals and the exchange rate. The weak link between the fundamentals and the exchange rate has been termed "an exchange rate disconnection puzzle" (Engel, 2000).

Dua and Ranjan (2010, 2012), however, have found that macroeconomic fundamentals contribute significantly towards forecasting the INR/USD exchange rate. The underlying model includes the differential between the domestic and foreign counterparts of the following: money supply; output; interest rate; inflation; trade balance. In addition, it includes capital inflows, volatility of capital flows, order flows, forward premium and central bank intervention. The best fitting empirical model includes, besides the monetary model fundamentals (i.e. differential in money supply, output and interest rate), volatility of capital flows, order flows, forward premium and central bank intervention. The study finds that the inclusion of these additional variables, besides the monetary model fundamentals, improves the forecasts of the exchange rate.

This paper extends Dua and Ranjan (2010, 2012) study in two ways. First, based on Hau and Rey (2006); Aggarwal (1981); Branson (1986) and Sahoo et al. (2018), this paper extends the model estimated by Dua and Ranjan (2010, 2012) to include the differential of rate of return in stock prices and global oil prices as additional variables that can influence the exchange rate. With increasing integration with the global economy, changes in the stock market conditions may have an influence on the exchange rate. Global oil prices have a significant impact on exchange rates and also improve the forecasts of the exchange rates (Salisu et al., 2021). Second, Dua and Ranjan (2010, 2012) estimate the model using monthly data from July 1996 to December 2006 while out-of-sample forecasting performance is evaluated from January 2007 to June 2008. This paper extends the time period of estimation from July 1996[1] to January 2017, with the out-of-sample forecasting performance evaluated from February 2017 to January 2019.

Estimation is conducted in a VAR framework as well as in a Bayesian VAR (BVAR) model. The study also compares the forecast performance of the VAR model with the BVAR model. The rest of the paper is organised as follows. Section 2 reviews

[1] The starting period is based on availability of data for all the series.

the exchange rate models. Section 3 explains the empirical model used in the study. Section 4 enumerates the econometric methodology, while Sect. 5 gives the empirical results. Section 6 concludes the paper.

2 Exchange Rate Models

2.1 Purchasing Power Parity, Monetary and Portfolio Balance Models

The literature on the modelling of the exchange rate ranges from the traditional PPP theory, monetary models and portfolio balance models to models incorporating capital flows and intervention by the central bank to the more recent models based on the microstructure of the foreign exchange markets. Dua and Ranjan (2010, 2012) document a comprehensive review of the evolution of models explaining exchange rate determination. The description below is based on the review in Dua and Ranjan (2010, 2012).

The earliest and simplest model of exchange rate determination, known as the ***purchasing power parity (PPP) theory*****,** represented the application of the "law of one price". This states that arbitrage forces will lead to the equalisation of goods prices internationally once the prices are measured in the same currency. It was observed initially that there were deviations from PPP in the short-run, but in the long-run PPP holds in equilibrium. Reasons for the failure of PPP, however, have been attributed to heterogeneity in the baskets of goods considered for construction of price indices in various countries, presence of transportation cost, imperfect competition in the goods market and increase in the volume of global capital flow particularly during the last few decades.

The failure of PPP models gave way to ***monetary models****,* which took into account the possibility of capital/bond market arbitrage apart from the goods market arbitrage assumed in the PPP theory. In the monetary models, it is the money supply in relation to money demand in both home and foreign countries, which determines the exchange rate. The prominent monetary models include the flexible and sticky-price monetary models of exchange rates as well as the real interest differential model and Hooper–Morton's extension of the sticky-price model. In this class of asset market models, domestic and foreign bonds are assumed to be perfect substitutes.

The ***flexible-price monetary model*** (Frenkel, 1976) assumes that prices are perfectly flexible. Consequently, changes in the nominal interest rate reflect changes in the expected inflation rate. A relative increase in the domestic interest rate compared to the foreign interest rate implies that the domestic currency is expected to depreciate through the effect of inflation, which causes the demand for the domestic currency to fall relative to the foreign currency. In addition to flexible prices, the model also assumes uncovered interest parity, continuous purchasing power parity and the existence of stable money demand functions for the domestic and foreign economies.

In the ***sticky-price monetary model*** (originally due to Dornbusch, 1976), changes in the nominal interest rate reflect changes in the tightness of monetary policy. When the domestic interest rate rises relative to the foreign rate of interest, it is because there has been a contraction in the domestic money supply relative to the domestic money demand without a matching fall in prices. The higher interest rate at home attracts a capital inflow, which causes the domestic currency to appreciate. Since PPP holds only in the long-run,[2] an increase in the money supply does not depreciate the exchange rate proportionately in the short-run. This model retains the assumption of stability of the money demand function and uncovered interest parity, but replaces instantaneous purchasing power parity with a long-run version.

Frankel (1979) argued that a drawback of the Dornbusch (1976) formulation of the sticky-price monetary model was that it did not allow a role for differences in secular rates of inflation. He develops a model that emphasises the importance of expectation and rapid adjustment in capital markets. The innovation is that it combines the assumption of sticky prices with that of flexible prices with the assumption that there are secular rates of inflation. This yields the ***real interest differential model***.

Hooper and Morton (1982) extend the sticky-price formulation by incorporating changes in the long-run real exchange rate. The change in the long-run exchange rate is assumed to be correlated with unanticipated shocks to the trade balance. Accordingly, they introduced the trade balance in the exchange rate determination equation. A domestic (foreign) trade balance surplus (deficit) indicates an appreciation (depreciation) of the exchange rate.

The four models discussed above can be derived from the following equation specified in logs with starred variables denoting foreign counterparts:

$$e_t = \gamma + \delta\left(m_t - m_t^*\right) + \phi\left(y_t - y_t^*\right) + \alpha\left(i_t - i_t^*\right) + \beta\left(\pi_t - \pi_t^*\right) + \eta\left(\mathrm{tb}_t - \mathrm{tb}_t^*\right) + \mu_\mathrm{t}$$

where e = price of foreign currency in domestic currency

m = money supply.

y = real output.

i = nominal interest rate.

π = inflation.

tb = trade balance.

The alternative testable hypotheses are as follows:

Flexible price model: $\delta > 0$, $\alpha > 0$, $\phi < 0$, $\beta = \eta = 0$.

Sticky-price model: $\delta > 0$, $\alpha < 0$, $\phi < 0$, $\beta = \eta = 0$.

Real interest differential model: $\delta > 0$, $\alpha < 0$, $\phi < 0$, $\beta > 0$, $\eta = 0$.

Hooper–Morton model: $\delta > 0$, $\alpha < 0$, $\phi < 0$, $\beta > 0$, $\eta < 0$.

[2] See Dua and Ranjan (2010, 2012) for review of studies on PPP.

These models can be further extended to incorporate portfolio choice between domestic and foreign assets.[3] The ***portfolio balance model*** assumes imperfect substitutability between domestic and foreign assets and introduces current account in the exchange rate equation. It is a dynamic model of exchange rate determination that allows for the interaction between the exchange rate, current account and the level of wealth. For instance, an increase in the money supply is expected to lead to a rise in domestic prices. The change in prices would affect net exports, implying changes in the current account of the balance of payments. This, in turn, affects the level of wealth (via changes in the capital account) and consequently, the asset market and exchange rate behaviour. Under freely floating exchange rates, a current account deficit (surplus) is compensated by accommodating transactions in the capital account, i.e. capital account surplus (deficit). This has implications for the demand and supply of currency in the foreign exchange market, which can lead to appreciation (depreciation) of the exchange rate. Thus, the coefficient of the current account differential in the exchange rate model is hypothesised to have a positive sign. The theoretical model can be expressed (as a hybrid model) as follows:

$$\begin{aligned} e_t \; = \; & \gamma + \delta\left(m_t - m_t^*\right) + \phi\left(y_t - y_t^*\right) + \alpha\left(i_t - i_t^*\right) \\ & + \beta(\pi_t - \pi_t^*) + \eta\left(\mathrm{tb}_t - \mathrm{tb}_t^*\right) + \theta\left(\mathrm{ca}_t - \mathrm{ca}_t^*\right) + \mu_t \end{aligned}$$

where ca denotes current account balance and $\theta > 0$

2.2 Capital Flows, Volatility of Capital Flows, Forward Premium

With an increase in liberalisation and opening up of the capital accounts world over, capital flows have become increasingly important in determining exchange rate behaviour.[4] The relation between capital flows and exchange rates is hypothesised to be negative (with the exchange rate defined as the price of foreign currency in domestic currency) with inflow implying purchase of domestic assets by foreigners leading to appreciation of the domestic currency when there is no government intervention in the foreign exchange market or if there is persistent sterilised intervention and vice versa for outflows.

Dua and Sen (2009) developed a model which examines the relationship between the real exchange rate, level of capital flows, volatility of the flows, fiscal and monetary policy indicators and the current account surplus and find that an increase in capital inflows and their volatility lead to an appreciation of the exchange rate. The theoretical sign on volatility can, however, be positive or negative.

[3] The monetary models were criticised by the proponents of the portfolio models namely Branson (1983, 1984), Isard (1980), Dooley and Isard (1982) as the monetary models assumed perfect substitutability of domestic assets and foreign assets.

[4] Dua and Sen (2009), Kohli (2001).

The forward premium measured by the difference between the forward and spot exchange rate can provide useful information about future exchange rates.[5] According to covered interest parity, the interest differential between two countries equals the premium on the forward contracts. Thus, if domestic interest rates rise, the forward premium on the foreign currency will rise and the foreign currency is expected to appreciate. The exchange rate defined as the price of foreign currency in domestic currency and the forward premium are therefore expected to be positively related.

2.3 Microstructure Framework

The microstructure theory provides an alternative view to the determination of exchange rates. Unlike macroeconomic models that are based on public information, micro-based models suggest that some agents may have access to private information about fundamentals or liquidity that can be exploited in the short-run. A distinctive feature of the microstructure models is the central role played by transactions volume or order flows in determining nominal exchange rate changes (Medeiros, 2005; Bjonnes and Rime, 2003).

Order flow is the cumulative flow of transactions, with a positive or negative sign depending on whether the initiator of the transaction is buying or selling. An increase in order flow (i.e. an increase in the volume of positively signed transactions) will generate forces in the foreign exchange market such that there is pressure on the domestic currency to depreciate. Hence, the order flow and the exchange rate are positively related. The explanatory power or information content of order flow depends on the factors that cause it. Order flow is most informative when it is caused due to dispersion of private information amongst agents with respect to macroeconomic fundamentals (Evans and Lyons, 2005), whereas it is less informative when it is caused due to management of inventories by the foreign exchange dealers in response to liquidity shocks.

If the dealers of foreign exchange are heterogeneous and there exists information asymmetry in the market, then order flow will capture the reaction of the market (obtained from aggregating the different reactions of the dealers having different information sets) to changes in macroeconomic fundamentals and news related to changes in economic conditions. Another aspect of microstructure theory that has drawn attention is the liquidity effect of order flow. Studies in the literature have empirically tested whether the relationship between order flow and exchange rates is due to liquidity effects that are temporary in nature, such as the herding behaviour of foreign exchange dealers (Breedon and Vitale, 2004).

[5] Clarida and Taylor (1997), Della Corte et al. (2007).

2.4 Intervention

With the growing importance of capital flows in determining exchange rate movements in most emerging market economies, intervention in foreign exchange markets by central banks has become necessary from time to time to contain volatility in foreign exchange markets and as a result plays an important role in influencing exchange rates in countries that have managed floating regime.

The motive of central bank intervention may be to align the current movement of exchange rates with the long-run equilibrium value of exchange rates; to maintain export competitiveness; to reduce volatility and to protect the currency from speculative attacks.[6]

Intervention can be sterilised or non-sterilised. In case of non-sterilised intervention, purchase of foreign exchange (to prevent appreciation) increases money supply which reduces the rate of interest and increases demand. This leads to capital outflow on one hand and an increase in import demand on the other. All these lead to an increase in the demand for foreign currency, and hence, the exchange rate depreciates. Thus, non-sterilised intervention and exchange rates are positively related.

While non-sterilised intervention directly influences the exchange rate through the monetary channel, sterilised intervention also influences exchange rate through different channels—by changing the portfolio balance, through the signalling channel where sterilised purchase of foreign currency will lead to a depreciation of the exchange rate if the foreign currency purchase is assumed to signal a more expansionary domestic monetary policy and more recently, the noise-trading channel, according to which, a central bank can use sterilised interventions to induce noise traders to buy or sell currency. Hence, the overall effect of sterilised intervention on exchange rates is ambiguous.

Based on the above frameworks, Dua and Ranjan (2010, 2012) derive the following theoretical model:

$$\begin{aligned} e_t = {} & \gamma + \delta(m_t - m_t^*) + \phi(y_t - y_t^*) + \alpha(i_t - i_t^*) + \beta(\pi_t - \pi_t^*) \\ & + \eta(\mathrm{tb}_t - \mathrm{tb}_t^*) + \theta(\mathrm{ca}_t - \mathrm{ca}_t^*) + \nu\mathrm{cap}_t + \rho\mathrm{vol}_t + \omega\mathrm{fdpm}_t \\ & + \psi\mathrm{of}_t + \xi\mathrm{int}_t + \mu_t \end{aligned}$$

where

cap_t = capital inflow.
vol_t = volatility of capital flows.
fdpm_t = 3-month forward premia.
of_t = order flow.
int_t = central bank intervention.

The additional signs are as follows: $\theta > 0$; $\nu < 0$; $\rho >$ or < 0; $\omega > 0$; $\psi >$ or < 0; and $\xi >$ or < 0.

[6] See Dua and Ranjan (2010, 2012) for a review of studies that survey the literature on modelling the reaction function of the central bank and assessing the effectiveness of intervention.

Table 1 Signs of variables: dependent variable e_t

Variables	Expected sign	Estimated sign
$i_t - i_t{}^*$	$+ / -$	$-$
$y_t - y_t{}^*$	$-$	$-$
$m_t - m_t{}^*$	$+$	$+$
fdpm_t	$+$	$+$
vol_t	$+ / -$	$-$
Δof_t	$+ / -$	$+$
Δint_t	$+$	$+$

Notes
(1) e_t: Log of exchange rate of India (Rs. /$)
(2) i_t-$i_t{}^*$: Difference between Indian (domestic) and US (foreign) Treasury bill rate
(3) y_t-$y_t{}^*$: Difference between log of Indian and US index of industrial production
(4) m_t-$m_t{}^*$: Difference between log of Indian and US money supply
(5) fdpm_t: 3-month forward premia
(6) vol_t: Volatility of capital inflows
(7) of_t: Order flow
(8) int_t: Government intervention in open market

3 Empirical Models—Dua and Ranjan (2010, 2012) Model and Its Extension

Based on the above considerations, Dua and Ranjan (2010, 2012) estimate the following best-fit empirical model:

$$e_t = \text{f}\left(\left(i_t - i_t^*\right),\ \left(y_t - y_t^*\right),\ \left(m_t - m_t^*\right),\ \text{fdpm}_t,\ \text{vol}_t,\ \Delta\text{of}_t,\ \Delta\text{int}_t\right)$$

For variables that are nonstationary and endogenous, the signs correspond to those obtained in the cointegrating equation. In the case of exogenous variables (e.g. order flow and intervention, which are also stationary) signs and significance are determined in a vector error correction framework. The empirical signs of all the variables conform to economic theory.

The objective of the current study is to forecast INR/USD exchange rate by using the model developed by Dua and Ranjan (2010, 2012) and its extension that includes differential of rate of return on stock prices and global oil prices to examine whether the additional information on stock prices and global oil prices improve the forecast performance. Both the models are estimated from July 1996 through January 2017, and the out-of-sample forecast performance of the models is evaluated from February 2017 to December 2019.

The advantage of using the stock return differential as a predictor of exchange rates is that the stock price data is readily available. Unlike macroeconomic data,[7]

[7] Chen and Hsu (2019), Salisu et al., 2020.

there is no time lag in the publication and they are not subjected to revisions. Inclusion of oil prices is likely to improve the predictability of exchange rates as it may contain useful information for forecasting the movements in the exchange rate (Qiang et al., 2019; Salisu et al., 2021).

3.1 Exchange Rate and Stock Prices

According to the available literature, there are two main types of theoretical models that analyse the linkages between exchange rates and stock prices. The traditional approach based on "flow-oriented" models (Dornbusch and Fischer, 1980)[8] suggests that causality runs from the exchange rate to the stock prices, whereas the portfolio approach based on "stock-oriented" models (Branson, 1983; Frankel, 1983) suggests the opposite. In the first case, assuming that the Marshall–Lerner condition holds, a more competitive exchange rate will improve the trade position of an economy and stimulate the real economy through firm profitability and stock market prices (Caporale et al., 2014; Granger et al., 2000). However, there will be an increase in production costs by domestic firms that import inputs, leading to a reduction in the firms' sales and their earnings, which in turn will lead to a decline in their stock prices. Hence, the impact of exchange rates on stock prices can be either positive or negative.

The portfolio approach (Branson, 1986, Frankel, 1983) is also called the "stock" approach. The portfolio balance theory (PBT) states that a relative increase in the stock prices of the home economy will increase the wealth of the domestic investors. This will increase the demand for money in the home economy, leading to an increase in the rate of interest. This will then lead to an inflow of foreign funds and the domestic currency will appreciate. In this case, causality flows from stock prices to the exchange rate, wherein a strong equity market is associated with currency appreciation. (Granger et al., 2000; Kollias et al., 2012; Salisu and Ndako (2018); Chen and Hsu, 2019).

The empirical literature in this regard includes Ulku and Demirci (2012) that examines PBT for eight European emerging markets and finds validity for the same. The results are based on daily and monthly data for the period January 2003 to October 2010. Salisu and Ndako (2018) lend support to the portfolio balance theory for the full OECD, the Euro area and the non-Euro area for the period May 2004–June 2017.[9]

The theoretical link between stock return differential and exchange rate can also be explained by the uncovered equity parity (UEP). According to the UEP, when foreign equity holdings outperform their domestic counterparts, domestic investors are exposed to the higher exchange rate and hence repatriate some of the foreign

[8] See Aggarwal (1981), Phylaktis and Ravazzolo (2005); Dellas and Tavlas (2013); Sui and Sun, 2016; Raza et al., 2016; Zivkov et al., 2018.

[9] See Salisu and Ndako (2018) for a review of literature on portfolio balance approach.

equity to mitigate their exchange rate risk (Curcuru et al., 2014). This rebalancing usually results in the selling of foreign currency, thus, leading to foreign currency depreciation. UEP theory suggests that a strong equity market is associated with currency depreciation because of portfolio rebalancing (Chen and Hsu, 2019).

Some empirical studies provide evidence in support of the UEP.[10] The paper by Hau and Rey (2006) develops an empirical model that integrates analysis of exchange rates, equity prices, and equity portfolio flows. This study uses daily data on 17 OECD countries relative to the USA for the period 1980–2001. The study provides empirical evidence that suggests that a strong equity market is associated with currency depreciation in line with UEP theory contradicting the conventional wisdom of currency appreciation under exuberant equity market.

Curcuru et al. (2014) also find support for the UEP hypothesis when they analyse the data on U.S. investors' monthly equity positions across 42 markets for the period January 1990 to December 2010. They show that U.S. investors rebalance away from equity markets that recently performed well and move into equity markets just prior to relatively strong performance, suggesting tactical reallocations to increase returns rather than reduce risk.

Chen and Hsu (2019) examine daily exchange rate predictability with stock return differentials using the seven most-traded currencies, the USD, EUR, JPY, GBP, AUD, CHF and CAD. USD is used as the numeraire. The results of the study are also consistent with UEP theory. They provide evidence that exchange rate changes are predictable with stock return differentials.

Empirical literature examines the causality link between stock prices and the exchange rate. Studies report either unidirectional or bidirectional causal relationship between exchange rate and stock prices.[11] Xie et al. (2020) examine the exchange rate-stock price nexus for a group of advanced and emerging countries. They employ bootstrapped panel Granger non-causality tests and find that the stock prices are helpful for predicting the exchange rates, but not vice versa.

The empirical literature supports strong correlation between stock prices and exchange rate in advanced and developed economies as suggested by Curcuru et al. (2014); Hau and Rey (2006); Melvin and Prins (2015); Chen and Hsu (2019). However, the evidence for the emerging markets is weak.[12] Bahmani–Oskooee and Sujata Saha (2015), Lin (2012) shows that where capital mobility is low, economic integration acts as the cause of the linkage, and thus, it supports the flow-orientated

[10] Bohn and Tesar, (1996); Griffin et al., (2004); Cenedese et al., (2016) finds evidence against UEP in that strong equity market is associated with exchange rate appreciation.

[11] Some studies have found unidirectional causality from exchange rates to stock prices (Bhutto and Chang, 2019 and the references cited therein), or from stock prices to exchange rates (Liang et al., 2013, Wong 2017 and references cited therein). There are few studies that have also found bidirectional causality between exchange rate and stock prices (See Bahmani-Oskooee and Saha (2015) and the references cited therein for a review of different studies).

[12] Kim (2011), Ulku and Demirci (2012), Baur and Miyakawa (2013), Aftab et al. (2018) provide evidence for failure of the UEP hypothesis in emerging markets. Also see, Bahmani-Oskooee and Sujata Saha (2015), Lin (2012) for reasons for weak correlation between stock prices and exchange rate in emerging markets.

model. But where capital mobility is more, financial integration acts as the cause of the linkage which in turn favours the stock-oriented model. They also suggest that the relationship between exchange rate and stock prices is sensitive to the frequency of data used, study period chosen, the country considered, and other macro variables included in the model. Lin (2012) also finds that the co-movement between exchange rates and stock prices becomes stronger during crisis periods when compared with relatively normal periods.

Thus, empirical evidence suggests that relationship between the exchange rate markets and the stock markets are not homogeneous across all the economies examined. The sign of the correlation between stock return differentials and exchange rate movements is ambiguous in theory. The portfolio balance approach suggests that strong equity markets are associated with exchange rate appreciation, while UEP suggests that strong equity markets are associated with exchange rate depreciation. Nevertheless, empirical literature provides an indication about exchange rate predictability using information from stock markets.

3.2 Exchange Rate and Oil Prices

The exchange rate is one of the important channels through which the effect of international crude oil price shock is passed to the financial markets and the economy. According to the theoretical literature, the link between oil price and the exchange rate is analysed from different channels.[13] First, according to the terms of trade channel an oil price increase will be followed by a depreciation of currencies in those countries with large oil dependence in the tradable sector since the price level in those countries will increase.[14] Second, through the wealth and portfolio channels an increase in oil prices, leads to transfer of wealth to oil exporting countries, and this is reflected in an improvement in the current account balance, so that currencies of oil exporting countries are expected to appreciate while currencies of oil importers are expected to depreciate after an oil price increase.

However, as explained by Turhan et al. (2014) and Qiang et al. (2019), the link between the oil exchange rates may be positive or negative, and it may also change from one period to another. Turhan et al. (2014) examines the dynamic relationship between oil prices and exchange rates in G20 countries and find a negative correlation between oil prices and exchange rates. Ju et al. (2014) study the macroeconomic effects of China's international crude oil price shocks and empirically find that oil price shocks have a negative impact on China's GDP and exchange rate.

Qiang et al. (2019) discuss different channels through which an oil shock can affect an oil-importing country. An increase in international oil price leads to a commodity price rise and hence inflation in the economy. This increases the cost of exporting

[13] See Fratzscher et al., 2013; Sharma, 2017; Wen et al., 2020, Orzeszko (2021) for review on causality between oil prices and exchange rates.

[14] See Qiang et al., 2019; Salisu et al., 2021.

Table 2 Variables in augmented model

Variable	Explanation	Expected signs
$\mathrm{ror}_t - \mathrm{ror}_t^*$	Difference of rate of return on Indian and US stock prices	$+/-$
Oil_t	Log difference of monthly global oil prices	$+/-$

goods in the economy; lower the cost of importing goods and will eventually cause a decline in export foreign exchange earnings and an increase in the foreign exchange expenditure, thus leading to rise in exchange rate of foreign currency and fall in the exchange rate of the local currency. Inflation will also reduce the country's real interest rates, causing capital outflows and ultimately leading to the depreciation of the national currency.

Qiang et al. (2019) concluded that international crude oil price fluctuations can also affect the exchange rate of oil-importing countries through the balance of payments, speculative trading, and expectations. However, the influence level depends on the relative degree of dependence of the country on oil imports, which cannot be generalised.

In the light of the above discussion, the empirical model estimated by Dua and Ranjan (2010, 2012)—Model 1 below—is augmented as follows:

Model 1

$$e_t = \mathrm{f}\left(\left(i_t - i_t^*\right),\ \left(y_t - y_t^*\right),\left(m_t - m_t^*\right),\mathrm{fdpm}_t,\mathrm{vol}_t,\Delta\mathrm{of}_t,\Delta\mathrm{int}_t\right)$$

Model 2

$$e_t = \mathrm{f}\left(\left(i_t - i_t^*\right),\ \left(y_t - y_t^*\right),\ \left(m_t - m_t^*\right),\ \mathrm{fdpm}_t,\ \mathrm{vol}_t,\Delta\mathrm{of}_t,\Delta\mathrm{int}_t,\ \mathrm{ror}_t - \mathrm{ror}_t^*,\ \mathrm{oil}_t\right)$$

The expected signs of the additional variables in the augmented model are given in Table 2.

The present study evaluates whether Model 2 can improve the forecast accuracy of Model 1 in predicting the Re/$ exchange rate.

Rates of return are computed from stock prices of India and U.S. The Indian stock prices are measured by CNX Nifty 50 index computed as average values of every month with base Nov. 1995 = 1000, and the U.S. stock prices are taken on the basis of S&P 500 index which is computed as average values of every month with base Nov. 1995 = 1000. The rate of return of Indian and US stock prices is calculated as log of average value of stock prices in the current period minus log of average value of stock prices in the previous time period. Oil prices are calculated as log difference of monthly global oil prices.

Data definitions and the sources of the variables are given in Table 14 in the appendix.

4 Econometric Methodology

This study employs vector autoregressive (VAR), VECM and Bayesian vector autoregressive (BVAR) models to estimate the Dua and Ranjan (2010, 2012) model and its augmented variant as described previously. Tests for nonstationarity are first conducted followed by tests for cointegration and Granger causality. Finally, VAR and Bayesian vector autoregressive (BVAR) models are estimated and tested for out-of-sample forecast accuracy. This section briefly describes the tests for nonstationarity, VAR and BVAR modelling, cointegration and Granger causality and tests for out-of-sample forecast accuracy.

4.1 Testing for Nonstationarity

The first econometric step in the exercise is to test whether the series is nonstationary or whether they contain a unit root. We focus on Dickey–Fuller generalised least squares (DF-GLS) test proposed by Elliot et al. (1996) and the KPSS test proposed by Kwiatkowski et al. (1992). The presence of unit roots in time series has implications for statistical inference in the classical framework, since the OLS estimators and the corresponding statistics do not have the standard asymptotic distributions. Bayesian methods are generally preferred when the testable hypothesis is the presence of a unit root. This is because traditional tests have extremely low power, especially against trend stationary alternatives (Nankervis et al., 1988). Sims (1988) therefore argues that Bayesian theory provides a more reasonable procedure for inference than classical hypothesis testing. Hence, the study also conducts the Bayesian unit root test.

According to Dua and Mishra (1999), Bayesian methods take the data as given but assume that the true parameter is random. Classical methods, on the other hand, regard the true parameter of interest as unknown and fixed and examine the behaviour of the estimator in repeated samples. Bayesian inference depends on the given sample and the posterior distribution which varies with the product of the likelihood function and the prior distribution.

According to Dua and Mishra (1999), if the model is given as $y_t = \rho y_{t-1} + \varepsilon_t$, the test statistic is the square of the conventional t-statistic for $\rho = 1$ and is compared with the Schwarz criterion, which has an asymptotic Bayesian justification and is considered as the asymptotic Bayesian critical value. This is approximately given as

$$\tau = \left(2\log(1-\alpha)/\alpha\right) - \log\left(\sigma_\rho^2\right) + 2\log\left(1 - 2^{-\frac{1}{s}}\right) \tag{4}$$

where $\sigma_\rho^2 = \sigma^2 / \sum y_{t-1}^2$, σ^2 is the variance of e_t and for monthly data $s = 12$.

'Alpha' gives the prior probability on the stationary part of the prior; the remaining probability is concentrated on $\rho = 1$. The choice of the prior weight can have a significant effect on the statistic given above. "Marginal Alpha" is the value for alpha at which the posterior odds for and against the unit root are even. A higher value of "marginal alpha" favours the presence of unit root. Since the first and last terms in the expression for the critical value are constant for a given prior and data, a small τ favours no unit root. Therefore, if t^2 is greater than τ, we reject the null hypothesis of a unit root.

Sims (1988) considers a non-informative prior in the unit root test proposed under Sims (1988).[15]

If two of these three tests indicate nonstationarity for any series, we conclude that the series has a unit root.

4.2 VAR, BVAR and VECM Modelling

A vector autoregressive (VAR) model offers an approach, particularly useful for forecasting purposes. This method is multivariate and does not require specification of the projected values of the exogenous variables. Economic theory is used only to determine the variables to include in the model.

Although the approach is "atheoretical", a VAR model approximates the reduced form of a structural system of simultaneous equations. VAR model does not totally differ from a large-scale structural model. Rather, given the correct restrictions on the parameters of the VAR model, they reflect mirror images of each other.

The VAR technique uses regularities in the historical data on the forecasted variables. Economic theory only selects the economic variables to include in the model. An unrestricted VAR model (Sims, 1980) is written as follows:

$$y_t = C + A(L)y_t + e_t \tag{5}$$

where $y =$ an $(n \times 1)$ vector of variables being forecast;

$A(L) =$ an $(n \times n)$ polynomial matrix in the back-shift operator L with lag length p, i.e. $AL = A_1L + A_2L^2 + \dots\dots\dots + A_pL^p$.

$C =$ an $(n \times 1)$ vector of constant terms; and

$e =$ an $(n \times 1)$ vector of white noise error terms

The model uses the same lag length for all variables. There is one serious drawback of the VAR model that over parameterisation produces multicollinearity and loss of degrees of freedom that can lead to inefficient estimates and large out-of-sample forecasting errors. One solution excludes insignificant variables/lags based on statistical tests.

An alternative approach to overcome over-parameterisation uses a Bayesian VAR model is used as described in Litterman (1981), Doan et al. (1984), Todd (1984), Litterman (1986), and Spencer (1993). Instead of eliminating longer lags and/or less

[15] Subsequently the use of flat priors has been questioned widely in the literature (Phillips, 1991) and Bayesian unit root tests with informative priors have been designed (Koop, 1992). However these other tests are computationally burdensome.

important variables, the Bayesian technique imposes restrictions on these coefficients on the assumption that these are more likely to be near zero than the coefficients on shorter lags and/or more important variables. If, however, strong effects do occur from longer lags and/or less important variables, the data can override this assumption. Thus, the Bayesian model imposes prior beliefs on the relationships between different variables as well as own lags of a particular variable. If these beliefs (restrictions) are appropriate, the forecasting ability of the model should improve. The Bayesian approach to forecasting, therefore, provides a scientific way of imposing prior or judgmental beliefs on a statistical model. Several prior beliefs can be imposed so that the set of beliefs that produces the best forecasts is selected for making forecasts. The selection of the Bayesian prior, of course, depends on the expertise of the forecaster.

The restrictions on the coefficients specify normal prior distributions with means zero and small standard deviations for all coefficients with decreasing standard deviations on increasing lags, except for the coefficient on the first own lag of a variable that is given a mean of unity. This so-called Minnesota prior was developed at the Federal Reserve Bank of Minneapolis and the University of Minnesota.

The standard deviation of the prior distribution for lag *m* of variable *j* in equation *i* for all *i*, *j*, and *m*–*S*(*i*, *j*, *m*) can be expressed as function of a small number of hyper parameters: *w*, *d*, and *a* weighting matrix f(*i*,*j*). This allows the forecaster to specify individual prior variances for a large number of coefficients based on only a few hyperparameters. The standard deviation is specified as follows:

$$\begin{aligned}
\mathrm{S}(i,\ j, m) &= \{w * \mathrm{g}(m) * \mathrm{f}(i,\ \ j)\}\mathrm{si/sj};\\
\mathrm{f}(i,\ j) \quad &= 1,\ \text{if}\ i = j;\\
&= k\ \text{otherwise}(0 < k < 1);\ \text{and}\\
\mathrm{g}(m) \quad &= m^{-d},\ \ d > 0.
\end{aligned} \tag{6}$$

The term s_i equals the standard error of a univariate autoregression for variable *i*. The ratio s_i/s_j scales the variables to account for differences in units of measurement and allows the specification of the prior without consideration of the magnitudes of the variables. The parameter w measures the standard deviation on the first own lag and describes the overall tightness of the prior. The tightness on lag *m* relative to lag 1 equals the function g(*m*), assumed to have a harmonic shape with decay factor *d*. The tightness of variable *j* relative to variable *i* in equation i equals the function f(*i*, *j*).

To illustrate, assume the following hyperparameters: $w = 0.2$; $d = 2.0$; and $\mathrm{f}(i, j) = 0.5$. When $w = 0.2$, the standard deviation of the first own lag in each equation is 0.2, since $\mathrm{g}(1) = \mathrm{f}(i, j) = s_i/s_j = 1.0$. The standard deviation of all other lags equals $0.2[s_i/s_j\{\mathrm{g}(m)\mathrm{f}(i, j)\}]$. For $m = 1, 2, 3, 4$, and $d = 2.0$, $\mathrm{g}(m) = 1.0, 0.25, 0.11, 0.06$, respectively, showing the decreasing influence of longer lags. The value of f(*i*, *j*) determines the importance of variable *j* relative to variable *i* in the equation for variable *i*, higher values implying greater interaction. For instance, $\mathrm{f}(i, j) = 0.5$ implies that relative to variable *i*, variable *j* has a weight of 50%. A tighter prior occurs by decreasing *w*, increasing *d*, and/or decreasing *k*. Examples of selection of hyperparameters are given in Dua and Ray (1995), Dua and Smyth (1995), Dua and Miller (1996) and Dua and Mishra (1999), Dua and Ranjan (2010, 2012).

The BVAR method uses Theil's (1971) mixed estimation technique that supplements data with prior information on the distributions of the coefficients. With each restriction, the number of observations and degrees of freedom artificially increase by one. Thus, the loss of degrees of freedom due to overparameterisation does not affect the BVAR model as severely.

The above description of the VAR and BVAR models assumes that the variables are stationary. If the variables are nonstationary, they can continue to be specified in levels in a BVAR model because as pointed out by Sims et al. (1990, p.136) "……the Bayesian approach is entirely based on the likelihood function, which has the same Gaussian shape regardless of the presence of nonstationarity, [hence] Bayesian inference need take no special account of nonstationarity". Furthermore, Dua and Ray (1995) show that the Minnesota prior is appropriate even when the variables are cointegrated.

In the case of a VAR, Sims (1980) and others, e.g. Doan (2018), recommend estimating the VAR in levels even if the variables contain a unit root. The argument against differencing is that it discards information relating to comovements between the variables such as cointegrating relationships. The standard practice in the presence of a cointegrating relationship between the variables in a VAR is to estimate the VAR in levels or to estimate its error correction representation, the vector error correction model, VECM. If the variables are nonstationary but not cointegrated, the VAR can be estimated in first differences.

The possibility of a cointegrating relationship between the variables is tested using the Johansen and Juselius (1990) methodology. The concept of Granger causality can also be tested in the VECM framework. For example, if two variables are cointegrated, i.e. they have a common stochastic trend, causality in the Granger (temporal) sense must exist in at least one direction (Granger, 1986; 1988). Since Granger causality is also a test of whether one variable can improve the forecasting performance of another, it is important to test for it to evaluate the predictive ability of a model.

4.3 Evaluation of Forecasting Models

Evaluation of the forecasting models is based on RMSE, Theil's U (Theil, 1966), and the Diebold–Mariano (1995) test. The models are initially estimated using monthly data over the period July 1996 to January 2017 and tested for out-of-sample forecast accuracy from February 2017 to January 2019. Recursive forecasts are generated from one-through twelve-months-ahead and out-of-sample forecast accuracy of estimated models is assessed. The forecast accuracy of the VAR technique versus the BVAR method is also evaluated.

4.3.1 Thiel's Inequality Coefficient: Quadratic Loss Criteria

To test for accuracy, the Theil coefficient that implicitly incorporates the naïve forecasts as the benchmark is used. If A_{t+n} denotes the actual value of a variable in period $(t + n)$, and ${}_tF_{t+n}$ the forecast made in period t for $(t + n)$, then for T observations, the Theil U-statistic is defined as follows:

$$U = \left[\sum (A_{t+n} -_t F_{t+n})^2 \Big/ \sum (A_{t+n} - A_t)^2\right]^{0.5} \tag{7}$$

The U-statistic measures the ratio of the root mean square error (RMSE) of the model forecasts to the RMSE of naive, no-change forecasts (forecasts such that ${}_tF_{t+n} = A_t$). The RMSE is given by the following formula:

$$\mathrm{RMSE} = \left[\sum (\mathrm{A_{t+n}} -_\mathrm{t} \mathrm{F_{t+n}})^2 \Big/ T\right]^{0.5} \tag{8}$$

A comparison with the naïve model is, therefore, implicit in the U-statistic. A U-statistic of 1 indicates that the model forecasts match the performance of naïve, no-change forecasts. A U-statistic > 1 shows that the naïve forecasts outperform the model forecasts. If U is < 1, the forecasts from the model outperform the naïve forecasts. The U-statistic is, therefore, a relative measure of accuracy and is unit-free.

Since the U-statistic is a relative measure, it is affected by the accuracy of the naïve forecasts. Extremely inaccurate naïve forecasts can yield $U < 1$, falsely implying that the model forecasts are accurate. This problem is especially applicable to series with trend. The RMSE, therefore, provides a check on the U-statistic and is also reported.

4.3.2 Modified Diebold Mariano (DM) Test

The Diebold–Mariano test compares the forecast performance of alternative models; i.e., it tests the null hypothesis of no difference in the accuracy of two competing forecasts. Let $\underset{1t}{\hat{Y}}$ and $\underset{2t}{\hat{Y}}$, where $t = 1{,}2\ldots n$, be a pair of h-step ahead forecasts of Y_t and e_{1t} and e_{2t} be the associated forecast errors. If g(e) be a function (e.g. mean square error) of the forecasts errors, then the null hypothesis of equality of expected forecast performance is: $\mathrm{E}[\mathrm{g}(e_{1t}) - \mathrm{g}(e_{2t})] = 0$. Define $\mathrm{d_t} = \mathrm{g}(e_{1t}) - \mathrm{g}(e_{2t})$; $t = 1{,}2{,}\ldots n$. For optimal h-step ahead forecasts, the sequence of forecasts errors follows a moving average process of order h–1. Therefore, it is assumed that for h-step ahead forecasts, all autocorrelations of order h or higher of the sequence d_t are zero. Then, the variance of $\overline{d}$ $(= n^{-1} \sum\limits_{t=1}^{n} d_t)$ is asymptotically,

$$V(\overline{d}) \overset{a}{\approx} n^{-1}\left[\gamma_o + 2\sum_{k=1}^{h-1}\gamma_k\right], \tag{9}$$

where γ_k is the kth autocovariance of d_t. This autocovariance can be estimated by

$$\underset{k}{\hat{y}} = n^{-1}\sum_{t=k+1}^{n}(d_t - \overline{d})(d_{t-k} - \overline{d}). \tag{10}$$

The Diebold–Mariano test statistic is given by

$$S_1 = \left[\hat{V}(\overline{d})\right]^{-1/2}\overline{d} \tag{11}$$

where $\hat{V}(\overline{d})$ is the estimated variance of $\overline{d}$. Under the null hypothesis, Diebold–Mariano test statistic has an asymptotic standard normal distribution.

Harvey et al. (1997) note that the Diebold–Mariano test could be seriously oversized as the prediction horizon, h, increases. They therefore provide a modified Diebold–Mariano test statistic

$$S_1^* = \left[\frac{n + 1 - 2h + n^{-1}h(h-1)}{n}\right]^{-1/2} S_1 \tag{12}$$

Harvey et al. also recommend a further modification of comparing the statistics with critical values from the student's t distribution with (n–1) degrees of freedom, rather than from the standard normal distribution.

5 Empirical Results

The empirical estimation is initiated by testing the variables for stationarity. Tests for the existence of cointegrating relationship(s) and granger causality are conducted. To estimate VAR models, if all variables are nonstationary and integrated of the same order, the Johansen test is conducted for the presence of cointegration. If a cointegrating relationship exists, the VAR model can be estimated in levels. The concept of Granger causality can also be tested in the VECM framework. BVAR models are also estimated, and the out-of-sample forecast accuracy is tested.

A statistical analysis of the exchange rate over the period under consideration shows the volatility of the exchange rate. Table 3 reports the summary statistics of the exchange rate over the full period and sub-periods**.** The summary statistics reveal that while standard deviation in the estimation period (July 1996–Jan. 2017) is 8.33 and in the out-of-sample forecasting period (Feb. 2017–Jan. 2019) is 3.06, the standard deviation for the entire period is as high as 9.57 indicating volatility

Table 3 Summary statistics for exchange rate

Time period	Number of observations	Mean	Maximum	Minimum	Standard deviation
July 1996–Jan. 2019	271	50.03	73.63 (Oct. 2018)	35.51 (July 1996)	9.57
July 1996–Jan. 2017	247	48.4	68.24 (Feb 2016)	35.51 (July 1996)	8.33
Feb. 2017–Jan. 2019	24	68.87	73.63 (Oct. 2018)	63.64 (Jan. 2018)	3.06
Feb. 2017–Jan. 2018	12	64.75	67.06 (Feb. 2017)	63.64 (Jan. 2018)	0.92
Feb. 2018–Jan. 2019	12	68.98	73.63 (Oct. 2018)	64.37 (Feb. 2018)	2.99

of the exchange rate. The forecasting period is further divided into two sub-periods (refer Fig. 1), which is February 2017–January 2018 (sub-period 1) and February 2018–January 2019 (sub-period 2). Table 3 also shows that volatility in the first sub-period is 0.92 as compared to the second sub-period, showing volatility of 2.99. This volatility is reflected in the full out-of-sample forecasting period–Feb 2017 to January 2019.

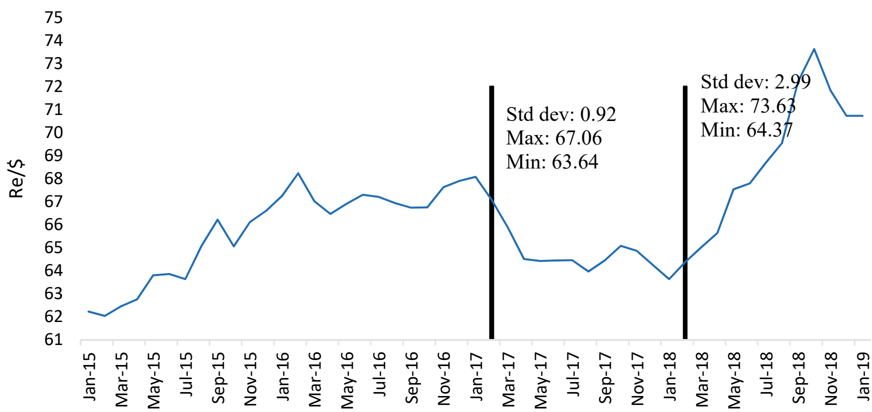


Fig. 1 Exchange rate-Re/$

Table 4 Bayesian Unit Root Test: July 1996–January 2017

Variable	Test statistic	Schwarz limit	Marginal alpha
e_t	0.076	10.101	0.9677
$i_t - i_t^*$	2.921	8.534	0.7675
$y_t - y_t^*$	0.146	10.882	0.9772
$m_t - m_t^*$	2.096	11.913	0.9643
for_t	10.767	7.346	0.0348
vol_t	16.174	6.928	0.002
of_t	46.430	6.090	0.00
int_t	70.588	5.853	0.00
$\text{ror}_t - \text{ror}_t^*$	155.38	5.537	0.00
Δoil_t	181.707	5.678	0.00

Table 5 Unit root test summary: July 1996–January 2017

Variable	DF-GLS	KPSS	Bayesian unit root	Inference
e_t	I(1)	I(1)	I(1)	I(1)
$i_t - i_t^*$	I(1)	I(1)	I(1)	I(1)
$y_t - y_t^*$	I(1)	I(1)	I(1)	I(1)
$m_t - m_t^*$	I(1)	I(1)	I(1)	I(1)
for_t	I(1) [(a)]	I(1)[(b)]	I(0)	I(1)
vol_t	I(1) [(a)]	I(1)	I(0)	I(1)
of_t	I(0)	I(0)	I(0)	I(0)
int_t	I(0)	I(0)	I(0)	I(0)
$\text{ror}_t - \text{ror}_t^*$	I(0)	I(1)	I(0)	I(0)
Δoil_t	I(0)	I(0)	I(0)	I(0)

Notes
(1) Null of unit root is not rejected at 5% sig. level and rejected at 10% sig. level
(2) Null of stationarity is rejected at 5% sig. level but is not rejected at 1% sig. level
(3) Null of unit root is not rejected at 1% sig. level

5.1 *Testing for Nonstationarity*

The first step in the estimation of the models is to test for nonstationarity. Three alternative tests are used, i.e. the Dickey–Fuller generalised least squares test, the KPSS test and a Bayesian unit root test based on Sims (1988).[16]

If at least two of the three tests show the existence of a unit root, the series is considered as nonstationary. Tables 4 and 5 report the results for the Bayesian unit root test and the inference drawn from the classical and Bayesian unit root tests, respectively. The results suggest that apart from order flow, intervention, difference

[16] DF-GLS AND KPSS tests are reported in the appendix in Table 15.

of rate of return on Indian and US stock prices and global oil prices, all other variables are nonstationary.

The Bayesian unit root test presents the following picture. The test statistic for the exchange rate, interest rate differential, differential between Indian and foreign output; differential between Indian and foreign money supply, when compared with the asymptotic Schwarz limit fails to reject the null of a unit root process. The marginal alpha's for these variables is also high indicative of a unit root process. On the other hand, the test statistic for the order flows, central bank intervention and difference of rate of return on Indian and US stock prices and global oil prices does not reject the null of stationarity with high values of the test statistic when compared with the Schwarz limit and low values of marginal alphas.

5.2 *Testing for Cointegration*

We use Johansen's FIML technique to test for cointegration between the exchange rate, interest rate differential, money supply differential, output differential, volatility of capital inflows, the forward premium and first difference of order flows and central bank intervention based on our empirical specification (Model 1). Since order flows and the official intervention are stationary, they are treated as exogenous variables in the first specification when testing for the presence of a cointegrating relationship. We then extend the model and include the difference in the rates of return on Indian and US stock prices and global oil prices as additional exogenous variables (Model 2). The appropriate order of VAR in case of Model 1 is 2 as suggested by the lag specification test. The cointegrating vector is given below. The long-run relationship captured by the cointegrating vector shows that empirical signs of all the variables conform to economic theory[17,18]

$$e_t = -0.161\left(i_t - i_t^*\right) - 1.17\left(y_t - y_t^*\right) + 0.748\left(m_t - m_t^*\right) + 0.028\text{for}_t + 0.188\text{vol}_t$$

For Model 2, the cointegrating relationship is as follows and the empirical signs of the variables conform to the economic theory.[19]

$$\begin{aligned} e_t &= -0.139\left(i_t - i_t^*\right) - 0.931\left(y_t - y_t^*\right) + 0.602\left(m_t - m_t^*\right) \\ &\quad + 0.039(\text{for}_t) + 0.160(\text{vol}_t) \end{aligned}$$

---

[17] The expected signs of each variable as per the economic theory are also given in Table 1 and 2.

[18] The coefficient of the error correction term (−0.004) is negative and less than one in absolute value in the equation for the exchange rate. The t-statistic (−3.74) with a p-value of 0.00. This implies that the exchange rate adjusts to the discrepancy from the long-run relationship to ensure that the system moves towards the long-run relationship.

[19] The coefficient of the error correction term (−0.005) is negative and less than one in absolute value with a p-value of 0.001. This implies that the exchange rate adjusts to the discrepancy from the long-run relationship to ensure that the system moves towards the long-run relationship.

Following the estimation of the error correction equations, we test for Granger causality using the vector error correction model (VECM).

The Granger causality tests, undertaken for both Models 1 and 2 using the VECM, show that all variables, namely interest rate differential, money supply differential, output differential forward premium, volatility of capital flows, order flows, central bank intervention significantly Granger cause INR/USD exchange rate. The difference between rates of return in stock prices and global oil prices also significantly Granger cause the exchange rate. Results on Granger Causality are reported in Table 6. These results thus justify the inclusion of all the variables that Granger causes the exchange rate, since these variables can potentially improve the predictive performance of the model.

Models 1 and 2 are estimated both in VAR and in BVAR frameworks, and their predictive ability is evaluated over three out-of-sample periods, viz. February 2017 through January 2018, February 2017 through January 2019 and the whole period, February 2017–January 2019. As noted earlier, the sub-period February 2017–January 2018 is relatively more stable than the other periods. Results for this period are therefore examined in detail.

5.3 *Empirical Results: Out-Of-Sample Forecasts-February 2017–January 2018*

5.3.1 VAR Models: February 2017–January 2018

The forecast accuracy statistics for the VAR models are reported in Table 7. The results suggest that:

- Both models exhibit a rise in RMSE as forecast horizon increases till 6 months ahead and fluctuate after that, suggesting a decrease in forecast accuracy at least for the initial horizons.
- 3-month average Theil U-statistic consistently falls for both models. Theil U-statistic is generally lower for Model 2 as compared to Model 1, indicating that inclusion of stock market information and oil prices may produce better forecasts.
- Modified DM test (Table 8) suggest that Model 2 performs better than Model 1 for all short-term forecast horizons and at the long-end, thus, providing some evidence in support of the fact that information on stock markets and global oil prices produces more accurate forecasts.

Table 6 Granger causality tests

Null	Lags	CHSQ(2)	Inference
Model 1: $e_t = \mathrm{f}\big((\mathrm{i_t} - \mathrm{i_t^*}), (y_t - y_t^*), (m_t - m_t^*), \mathrm{fdpm}_t, \mathrm{vol}_t, \Delta\mathrm{of}_t, \Delta\mathrm{int}_t\big)$			
e_t is not granger caused by $i_t - i_t^*$	1	15.14[0.001]	Reject null hypothesis
e_t is not granger caused by $y_t - y_t^*$	1	18.51[0.000]	Reject null hypothesis
e_t is not granger caused by $m_t - m_t^*$	1	16.59[0.002]	Reject null hypothesis
e_t is not granger caused by for_t	1	16.31[0.004]	Reject null hypothesis
e_t is not granger caused by vol_t	1	15.43[0.009]	Reject null hypothesis
e_t is not granger caused by of_t	1	4.81[0.000]*	Reject null hypothesis
e_t is not granger caused by int_t	1	− 2.11[0.035]*	Reject null hypothesis
Model 2: $e_t = \mathrm{f}\big((i_t - i_t^*), (y_t - y_t^*), (m_t - m_t^*), \mathrm{fdpm}_t, \mathrm{vol}_t, \Delta\mathrm{of}_t, \Delta\mathrm{int}_t, \ \mathrm{ror}_t - \mathrm{ror}_t^*, \Delta\mathrm{oil}_t\big)$			
e_t is not granger caused by $i_t - i_t^*$	1	14.44[0.001]	Reject null hypothesis
e_t is not granger caused by $y_t - y_t^*$	1	17.78[0.00]	Reject null hypothesis
e_t is not granger caused by $m_t - m_t^*$	1	14.81[0.001]	Reject null hypothesis
e_t is not granger caused by for_t	1	16.35[0.002]	Reject null hypothesis
e_t is not granger caused by vol_t	1	14.89[0.001]	Reject null hypothesis
e_t is not granger caused by of_t	1	4.67[0.000]*	Reject null hypothesis
e_t is not granger caused by int_t	1	− 1.94[0.054]*	Reject null hypothesis
e_t is not granger caused by $\mathrm{ror}_t - \mathrm{ror}_t^*$	1	− 2.33[0.012]*	Reject null hypothesis
e_t is not granger caused by $\Delta\mathrm{oil}_t$	1	− 3.21[0.001]*	Reject null hypothesis

Note *t-statistics from the error correction model

Table 7 Forecasting performance of VAR models (February 2017–January 2018)

VAR models									
Out-of-sample forecast accuracy: February 2017–January 2018									
Month Ahead	No. Obs	RMSE				THEIL'S U			
		Model 1		Model 2		Model 1		Model 2	
			3-mth avg		3-mth avg		3-mth avg		3-mth avg
1	12	0.8742	**1.1761**	0.8234	**1.1001**	1.2368	**1.0327**	1.1650	**0.9686**
2	11	1.1623		1.1080		0.9243		0.8811	
3	10	1.4917		1.3688		0.9369		0.8597	
4	9	1.7098	**1.7118**	1.5238	**1.5258**	1.0497	**0.9704**	0.9355	**0.8648**
5	8	1.6231		1.4337		0.9278		0.8195	
6	7	1.8024		1.6199		0.9338		0.8393	
7	6	2.0010	**2.0413**	1.7982	**1.6860**	0.9743	**1.0080**	0.8756	**0.8327**
8	5	2.0892		1.7069		1.0725		0.8763	
9	4	2.0336		1.5530		0.9772		0.7463	
10	3	1.5514	**1.2887**	1.0091	**0.8869**	0.5558	**0.3828**	0.3615	**0.2580**
11	2	1.4495		0.8242		0.3980		0.2263	
12	1	0.8652		0.8273		0.1947		0.1862	
Monthly Average		**1.5545**		**1.2997**		**0.8485**		**0.7310**	

Notes
(1) Accuracy measures are calculated using antilog of forecast and actual values although the models are estimated using logs
(2) Optimal lags for all VAR models is 2
Bold in the column are 3-month averages and bold in row are monthly averages

5.3.2 BVAR Models: February 2017–January 2018

The hyperparameter in the prior has been set as $w = 0.2$, $d = 1$, $k = 0.7$ for all except volatility of capital flows and differential in rate of return in stock prices, which have a tighter interaction parameter of 0.3 and 0.2, respectively.[20]

Forecast accuracy statistics for the BVAR models are reported in Table 9. The modified DM test results are in Table 10.

The main findings that emerge from the BVAR framework are as follows:

- RMSE declines towards the longer end for Model 1 and Model 2. This suggests generally forecast accuracy increases in BVAR framework with an increase in the forecast horizon.

[20] To estimate the BVAR model, a grid search is undertaken over the period February 2017–January 2018 to select the optimal prior, i.e. the combination of hyper parameters that yields the most accurate forecasts. The comparison of results from the optimal prior, i.e. $w = 0.2$, $d = 1$, $k = 0.7$ for all except $k = 0.3$ for volatility of capital flows and $k = 0.2$ for differential in rate of return in stock prices are reported in Table 16 in the appendix along with results from alternative priors.

Table 8 Modified DM test for VAR models (February 2017–January 2018)

Month ahead	Model 1 versus Model 2
1	2 is better than 1 [b]
2	2 is better than 1 [d]
3	2 is better than 1 [c]
4	2 is better than 1 [b]
5	2 is better than 1 [b]
6	2 is better than 1 [b]
7	2 is better than 1 [b]
8	2 is better than 1 [a]
9	2 is better than 1 [a]
10	2 is better than 1 [b]
11	2 is better than 1 [c]
12	2 is better than 1 [a]

Notes
(1) "Better" implies "yields more accurate forecasts"
(2) **a**: significant at 1%; **b**: significant at 5%; **c**: significant at 10%; **d**: significant at 15%; **e**: significant at 20%; **f**: significant at 25%

- 3-month average Theil U-statistic generally falls with an increase in the forecast horizon.
- Modified DM test suggests that Model 2 generally performs better than Model 1 for shorter and longer forecast horizon, implying that information on stock markets and global oil prices produces more accurate forecasts at the shorter and longer end.

5.3.3 VAR Versus BVAR Models: February 2017–January 2018

The modified Diebold Mariano test results for the comparison of VAR and BVAR for Models 1 and 2 are reported in Table 11.

- BVAR Models 1 and 2 generally perform better than the corresponding VAR model, especially at longer and shorter horizons.
- Figs. 4a through 4c in the appendix illustrate the 3, 6 and 9-month ahead out-of-sample forecasts made using both VAR and BVAR versions of Model 1. Likewise, Fig. 5a through 5c in the appendix report the same on the basis of Model 2. The differences between the direction of forecasts made using Model 1 and Model 2 are not obvious from the graphs. However, Fig. 5b and 5c show that in case of Model 2, both 3-month and 9-month ahead forecasts produced by BVAR framework are closer to the actual exchange rate values. The benefits of including stock market information and oil prices emerges more clearly in the Diebold–Mariano test.
- We also examine the direction of forecasts made around a turning point. This is illustrated by using Model 2 to forecast made in November 2017. The forecasts

Table 9 Forecasting performance of BVAR models (February 2017–January 2018)

BVAR models									
Out-of-sample forecast accuracy: February 2017–January 2018									
Month ahead	No. Obs.	RMSE				THEIL'S U			
			Model 1		Model 2		Model 1		Model 2
			3-mth avg.		3-mth avg.		3-mth avg.		3-mth avg.
1	12	0.5576	**0.9639**	0.5497	**0.9461**	0.7888	**0.8087**	0.7777	**0.7945**
2	11	1.0248		1.0061		0.8149		0.8001	
3	10	1.3093		1.2826		0.8223		0.8056	
4	9	1.3050	**1.3927**	1.3016	**1.4194**	0.8012	**0.7882**	0.7991	**0.8023**
5	8	1.3975		1.4213		0.7988		0.8124	
6	7	1.4756		1.5352		0.7645		0.7954	
7	6	1.5496	**1.3258**	1.5631	**1.2947**	0.7545	**0.6553**	0.7611	**0.6400**
8	5	1.3659		1.3270		0.7012		0.6812	
9	4	1.0618		0.9940		0.5102		0.4776	
10	3	0.4213	**0.7411**	0.3192	**0.5188**	0.1509	**0.1950**	0.1143	**0.1386**
11	2	0.5779		0.4643		0.1587		0.1275	
12	1	1.2242		0.7728		0.2755		0.1739	
Monthly Average		**1.1059**		**1.0447**		**0.6118**		**0.5938**	

Notes
(1) Accuracy measures are calculated using antilog of forecast and actual values although the models are estimated using logs
(2) Hyperparameters for all BVAR models are: $w = 0.2$, $d = 1$, $k = 0.7$ for all variables excluding volatility of capital flows and differential of rate of return on stock prices, $k = 0.3$ for volatility of capital flows and $k = 0.2$ for differential of rate of return on stock prices
(3) Optimal number of lags is 2 for Model 1 and Model 2
Bold in the column are 3-month averages and bold in row are monthly averages

Table 10 Modified DM test for BVAR models (February 2017–January 2018)

Month ahead	Model 1 versus Model 2
1	2 is better than 1 [d]
2	2 is better than 1 [e]
3	Indifferent
4	Indifferent
5	Indifferent
6	2 is better than 2 [f]
7	Indifferent
8	2 is better than 1 [f]
9	2 is better than 1 [b]
10	2 is better than 1 [a]
11	2 is better than 1 [f]
12	2 is better than 1 [b]

Notes
(1) "Better" implies "yields more accurate forecasts"
(2) **a**: significant at 1%; **b**: significant at 5%; **c**: significant at 10%; **d**: significant at 15%; **e**: significant at 20%; **f**: significant at 25%

are shown in Fig. 2 and highlight that forecaster tend to miss the turning point in October 2017.

5.3.4 Summary: February 2017–January 2018

- Inclusion of stock market information and oil prices improves the accuracy of forecasts.
- BVAR models yield more accurate forecasts than VAR models.

5.4 Empirical Results: Out-Of-Sample Forecasts-February 2018–January 2019

The forecasting performance of VAR and BVAR empirical models for Model 1 and Model 2 is compared using RMSE and Theil's U for the second sub-period February 2018–January 2019. Forecast accuracy statistics for both VAR and BVAR are provided in Tables 12 and 13, respectively.

Results suggest the following:

- For VAR, RMSE for both models rise with an increase in the forecast horizon implying a deterioration in forecast accuracy. Theil's U values are greater than one indicating that VAR forecasts are worse than naïve.

Table 11 Modified DM test for VAR and BVAR models (February 2017–January 2018)

	Model 1	Model 2
Month ahead	VAR versus BVAR	VAR versus BVAR
1	BVAR better than VAR[c]	BVAR better than VAR[d]
2	Indifferent	Indifferent
3	BVAR better than VAR[f]	Indifferent
4	BVAR better than VAR[d]	BVAR better than VAR[e]
5	BVAR better than VAR[e]	Indifferent
6	BVAR better than VAR[d]	Indifferent
7	BVAR better than VAR[c]	BVAR better than VAR[e]
8	BVAR better than VAR[a]	BVAR better than VAR[b]
9	BVAR better than VAR[b]	BVAR better than VAR[b]
10	BVAR better than VAR[b]	BVAR better than VAR[d]
11	BVAR better than VAR[c]	BVAR better than VAR[d]
12	BVAR better than VAR[b]	BVAR better than VAR[c]

Notes
(1) "Better" implies "yields more accurate forecasts"
(2) **a**: significant at 1%; **b**: significant at 5%; **c**: significant at 10%; **d**: significant at 15%; **e**: significant at 20%; **f**: significant at 25%

- For BVAR, RMSE increases for both the models up to 12-months ahead implying a decrease in forecast accuracy. Theil's U values are greater than 1 implying that BVAR forecasts are worse than naïve forecasts.
- For both VAR and BVAR models, RMSEs and Theil Us are higher than those for the sub-period February 2017–January 2018.
- Since VAR and BVAR models yield Theil's U greater than 1, the DM test is not reported for Model 1 versus Model 2.
- Since in general, this sub-period exhibits inaccurate forecasts, the comparison between VAR and BVAR framework is not considered.
- Inaccuracy of the forecast may be attributed to the high volatility in exchange rate in this period as denoted by high standard deviation. It may be noted that in 2018, a combination of rising US interest rates, a stronger dollar and the intensification of trade tensions between USA and China led to market pressures and

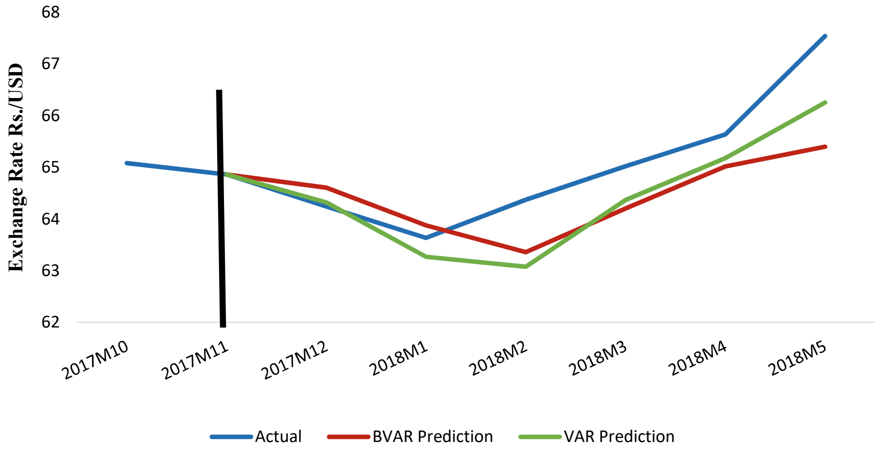


Fig. 2 Multi-period forecasts made in November 2017

Table 12 Forecasting performance of VAR models (February 2018–January 2019)

VAR models									
Out-of-sample Forecast Accuracy: February 2018 to January 2019									
Month ahead	No. obs	RMSE				THEIL'S U			
		Model 1		Model 2		Model 1		Model 2	
			3-mth avg		3-mth avg		3-mth avg		3-mth avg
1	12	1.3352	**2.3866**	1.3707	**2.4363**	1.0312	**1.0621**	1.0587	**1.0862**
2	11	2.3720		2.4440		1.0347		1.0661	
3	10	3.4526		3.4942		1.1204		1.1339	
4	9	4.4624	**5.5232**	4.3984	**5.3648**	1.1962	**1.2230**	1.1790	**1.1890**
5	8	5.5160		5.3094		1.2378		1.1914	
6	7	6.5912		6.3866		1.2349		1.1966	
7	6	7.6245	**8.3657**	7.3841	**8.0992**	1.2367	**1.2279**	1.1977	**1.1889**
8	5	8.5376		8.2847		1.2268		1.1905	
9	4	8.9349		8.6289		1.2203		1.1785	
10	3	8.7067	**8.9650**	8.3074	**8.4551**	1.2720	**1.3005**	1.2136	**1.2266**
11	2	8.8161		8.2759		1.3087		1.2285	
12	1	9.3723		8.7820		1.3208		1.2376	
Monthly average		**6.3101**		**6.0888**		**1.2034**		**1.1727**	

Notes
(1) Accuracy measures are calculated using antilog of forecast and actual values although the models are estimated using logs
(2) Optimal lags for all VAR models is 2
Bold in the column are 3-month averages and bold in row are monthly averages

Table 13 Forecasting performance of BVAR models (February 2018–January 2019)

BVAR Models									
Out-of-sample forecast accuracy: February 2018–January 2019									
Month ahead	No. Obs	RMSE				Theil's U			
		Model 1		Model 2		Model 1		Model 2	
			3-mth avg		3-mth avg		3-mth avg		3-mth avg
1	12	1.3405	**2.5165**	1.3259	**2.4801**	1.0353	**1.1120**	1.0240	**1.0965**
2	11	2.5577		2.5191		1.1157		1.0988	
3	10	3.6515		3.5952		1.1849		1.1667	
4	9	4.6113	**5.6191**	4.5668	**5.5879**	1.2361	**1.2457**	1.2242	**1.2382**
5	8	5.5754		5.5428		1.2511		1.2438	
6	7	6.6706		6.6540		1.2498		1.2467	
7	6	7.6797	**8.4709**	7.6832	**8.5143**	1.2457	**1.2429**	1.2462	**1.2490**
8	5	8.5950		8.6368		1.2351		1.2411	
9	4	9.1380		9.2229		1.2480		1.2596	
10	3	8.7469	**8.9710**	8.8421	**9.0743**	1.2779	**1.3013**	1.2918	**1.3162**
11	2	8.7597		8.8484		1.3003		1.3135	
12	1	9.4065		9.5325		1.3256		1.3434	
Monthly average		**6.3944**		**6.4141**		**1.2255**		**1.2250**	

Notes

(1) Accuracy measures are calculated using antilog of forecast and actual values although the models are estimated using logs

(2) Hyperparameters for all BVAR models are: $w = 0.2$, $d = 1$, $k = 0.7$ for all variables excluding volatility of capital flows and differential of rate of return on stock prices, $k = 0.3$ for volatility of capital flows and $k = 0.2$ for differential of rate of return on stock prices

(3) Optimal number of lags is 2 for Model 1 and Model 2

Bold in the column are 3-month averages and bold in row are monthly averages

portfolio outflows in some emerging market economies including India causing depreciation and high volatility in currency markets.

- This period includes a turning point in July 2018. We examine the direction of forecasts made around a turning point. This is illustrated by using Model 2 to forecast from August 2018 up to January 2019. Forecasts are shown in Fig. 3 and highlight that forecaster tend to miss the turning point. Forecasts exhibit a downward trend, while the series has moved upwards.

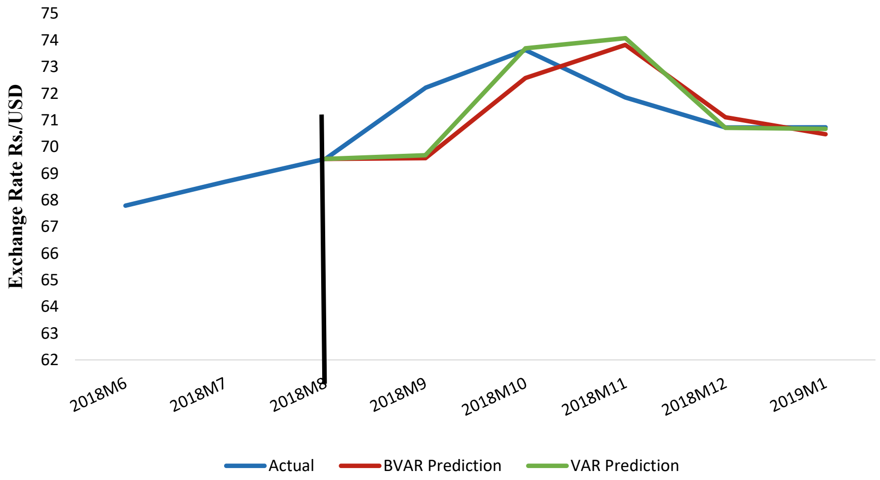


Fig. 3 Multi-period forecasts made in August 2018

5.5 Empirical Results: Out-Of-Sample Forecasts-February 2017–January 2019

The out-of-sample forecast period is finally considered for the full period from February 2017–January 2019.[21]

- In VAR model, RMSE increases consistently with the forecast horizon, resulting in Theil's U greater than 1. This implies that forecast accuracy decreases with an increase in forecast horizons.
- For BVAR models, RMSE increases consistently with forecast horizon, resulting in Theil's U greater than 1. This further implies a decrease in forecast accuracy as the forecast horizon increases.
- For both VAR and BVAR models, RMSEs and Theil Us are higher than those for the sub-period February 2017–January 2018.

6 Conclusion

This study forecasts INR/USD exchange rate based on two models, viz. the model estimated in Dua and Ranjan (2010, 2012) and an augmented version of the model that incorporates the differential of the rate of return in stock prices and global oil prices applying VAR and Bayesian VAR framework. The study also evaluates the forecast performance of these two frameworks. Dua and Ranjan (2010, 2012)

[21] The results are not given here for brevity and can be obtained from the author upon request.

employed a hybrid model that includes the fundamentals of the monetary and portfolio balance models as well as capital inflow volatility, forward rate, order flows, official intervention. In addition, keeping in mind the increasing linkages between stock markets across the globe, the difference between the rates of return in stock prices is included in the model. Moreover, given the dependency of the economy on oil imports and the linkages of oil with dollars and hence the exchange rate, the model also includes global oil prices. The results of the exercise suggest a cointegrating relationship between the exchange rate, money supply differential, interest rate differential, output differential, forward rate, volatility of the capital inflows. The coefficients in the cointegrating relationship are supported by theory. The error correction equation for the exchange rate also indicates that the exchange rate adjusts to move the system to the long-run relationship. Tests of Granger causality also indicate that all the variable Granger cause the exchange rate. In a similar manner, the inclusion of the difference between the rates of return in the stock prices and oil prices also yields a cointegrating relationship between the variables under study. The coefficients in the cointegrating relationship are supported by theory.

The study firstly examines whether the model augmented by difference between the rates of return on the stock prices and oil prices improves the forecast accuracy of the model given by Dua and Ranjan (2010, 2012). Secondly, the study evaluates the forecasting performance of a VAR model versus a BVAR model. The main findings of the study are as follows:

1. Forecast accuracy of the model can be improved by including stock market information and global oil prices in the model.
2. Information on stock prices and oil prices helps to improve forecasts, especially on the longer end.
3. BVAR models outperform their corresponding VAR variants.
4. Inaccuracy of forecasts in 2018 can be attributed to the high volatility in the exchange rate in this period. In 2018, a combination of factors such as rising US interest rates, a stronger dollar and the intensification of trade tensions between the US and China led to market pressures and portfolio outflows in some emerging market economies including India causing depreciation and high volatility in currency markets.
5. Turning points are difficult to predict as shown using Model 2 with predictions made in November 2017 and August 2018

Appendix

See Tables 14, 15 and 16, Figs. 4 and 5

Table 14 Data definitions and data sources

Variable	Definition	Source
e	Indian rupee/US dollar spot exchange rate	RBI Database of Indian Economy www.dbie.rbi.org.in
i	Auctions of 91 day Government of India Treasury bills	RBI Database of Indian Economy www.dbie.rbi.org.in
i^*	3-month treasury bill of the US, secondary market	Federal Reserve Bank of St. Louis Economic Data www.fred.stlouisfed.org
Y	Index of industrial production of India seasonally adjusted using Census X12	RBI Database of Indian Economy www.dbie.rbi.org.in
Y^*	Industrial production index for US	Federal Reserve Bank of St. Louis Economic Data www.fred.stlouisfed.org
M	M3 for India	RBI Database of Indian Economy www.dbie.rbi.org.in
M^*	M2 for the US	Federal Reserve Bank of St. Louis Economic Data www.fred.stlouisfed.org
For	Three-month forward premium (% per annum)	RBI Database of Indian Economy www.dbie.rbi.org.in
cap	Capital flows measured by Foreign Direct Investment plus Foreign Private Investment Inflows in India in US $ Billion	RBI Database of Indian Economy www.dbie.rbi.org.in
vol	We consider three different approaches as discussed by Pagliari and Ahmed Hannan (2017). These three different measures are: (a) Standard deviations over a rolling window (RW): Volatility of capital inflows measured by three period moving average standard deviation of sum of FDI and FII: $\mathrm{vol}_t = \left[\left(\frac{1}{m}\right)\sum_{i=1}^{m}\{Z_{t+i-1} - Z_{t+i-2}\}^2\right]^{1/2}$ where m = 3 and Z is cap (b) Estimated standard deviations produced by a GARCH(1,1) model (c) Estimated standard deviations produced by an ARIMA (1,1,0) model	Calculated Results reported use option (a). All three measures yield similar results but results are not reported for options (b) and (c) for the sake of brevity
of	Order flow-Turnover in foreign exchange market in US $ billion	RBI Database of Indian Economy www.dbie.rbi.org.in
int	(Purchase minus Sale) of US Dollars by RBI	RBI Database of Indian Economy www.dbie.rbi.org.in

(continued)

Table 14 (continued)

Variable	Definition	Source
spi_t	CNX Nifty 50 index (average values of every month, Nov. 1995 = 1000)	RBI Database of Indian Economy www.dbie.rbi.org.in
spi_t^*	S&P 500 index(USA) (average values of every month, Nov. 1995 = 1000)	Federal Reserve Bank of St. Louis Economic Data www.fred.stlouisfed.org
ror_t	Rate of return of Indian stock prices calculated as log spi_t − log $spi_{t\text{-}1}$	Calculated
ror_t *	Rate of return of US stock prices calculated as log spi_t^* − log $spi_{t\text{-}1}^*$	Calculated
Oil_t	Crude oil (petroleum), simple average of three spot prices; Dated Brent, West Texas Intermediate, and the Dubai Fateh	IMF Primary Commodity Database https://data.imf.org

Table 15 DF-GLS and KPSS (with constant and trend) unit root tests: July 1996–January 2017

Variable	DF-GLS	KPSS (lag = 8)
e_t	− 1.51	0.451
$i_t - i_t^*$	− 1.88	0.281
$y_t - y_t^*$	− 1.13	0.323
$m_t - m_t^*$	− 0.83	0.400
for_t	− 2.38	0.524
vol_t	− 2.11	2.12
of_t	− 4.54	0.106
int_t	− 8.41	0.107
$spi_t - spi_t^*$	− 1.20	0.355
$ror_t - ror_t^*$	− 12.37	0.227
Δoil_t	− 12.63	0.047
Critical values		
10%	− 2.62	0.119
5%	− 2.92	0.146
1%	− 3.46	0.216

Questions to Think About

1. This chapter shows that addition of stock prices in the exchange rate model helps in improving its predictability. What is the expected relationship between exchange rate and stock prices in (i) developed and (ii) developing economies?

   Hint: Estimate the direction of relationship between stock prices and exchange rate in different economies and compare their results. Refer: Salisu et al. (2020).

Table 16 Forecasting performance of optimal BVAR models compared with forecasting performance of other possible hyperparameters

BVAR models									
Theil U2									
Month ahead	No. obs	Model 1				Model 2			
		Optimal BVAR	Alternative BVAR model			Optimal BVAR	Alternative BVAR model		
		$w = 0.2$ $k = 0.7, 0.3, 0.2$ $d = 1$	$w = 0.2$ $k = 0.7, 0.3, 0.2$ $d = 2$	$w = 0.2$ $k = 0.7, 0.5, 0.5$ $d = 1$	$w = 0.2$ $k = 0.5, 0.5, 0.5$ $d = 1$	$w = 0.2$ $k = 0.7, 0.3, 0.2$ $d = 1$	$w = 0.2$ $k = 0.7, 0.3, 0.2$ $d = 2$	$w = 0.2$ $k = 0.7, 0.5, 0.5$ $d = 1$	$w = 0.2$ $k = 0.5, 0.5, 0.5$ $d = 1$
1	12	0.740	0.776	0.749	0.766	0.778	0.807	0.785	0.795
2	11	0.792	0.837	0.804	0.822	0.800	0.836	0.809	0.821
3	10	0.810	0.866	0.824	0.839	0.806	0.843	0.816	0.827
4	9	0.805	0.857	0.815	0.820	0.799	0.822	0.811	0.811
5	8	0.801	0.808	0.802	0.797	0.812	0.806	0.819	0.807
6	7	0.766	0.766	0.755	0.748	0.795	0.775	0.793	0.777
7	6	0.755	0.742	0.740	0.730	0.761	0.724	0.748	0.724
8	5	0.699	0.632	0.678	0.646	0.681	0.584	0.651	0.600
9	4	0.507	0.416	0.483	0.435	0.478	0.360	0.439	0.371
10	3	0.149	0.333	0.250	0.182	0.114	0.307	0.102	0.143
11	2	0.159	0.432	0.284	0.264	0.127	0.417	0.152	0.248
12	1	0.275	0.544	0.304	0.388	0.174	0.440	0.178	0.264

(continued)

Table 16 (continued)

BVAR models								
Average	0.605	0.667	0.624	0.620	0.594	0.643	0.592	0.599

Notes
(1) Accuracy measures are calculated using antilog of forecast and actual values although the models are estimated using logs
(2) Hyperparameters are: (a) Optimal BVAR model 1a and 2a: $w = 0.2$, $d = 1$, $k = 0.7$ for all variables excluding volatility of capital flows and differential of rate of return on stock prices, $k = 0.3$ for volatility of capital flows and $k = 0.2$ for differential of rate of return on stock prices, (b) Models 1b and 2b: $w = 0.2$, $d = 2$, $k = 0.7$ for all variables excluding volatility of capital flows and differential of rate of return on stock prices, $k = 0.3$ for volatility of capital flows and $k = 0.2$ for differential of rate of return on stock prices. (Lag decay is 2 as compared to 1 in model 1a and 2a), (c) Model 1c and 2c: $w = 0.2$, $d = 1$, $k = 0.7$ for all variables excluding volatility of capital flows and differential of rate of return on stock prices, $k = 0.5$ for volatility of capital flows and $k = 0.5$ for differential of rate of return on stock prices. (interaction parameters for volatility of capital flows for differential of rate of return on stock prices is same at $k = 0.5$ as compared to these being different in 1b and 2b), (d) Model 1d and 2d: $w = 0.2$, $d = 2$, $k = 0.5$ for all variables (it is an example of a symmetric matrix of interaction parameters)
(3) Optimal number of lags is 2 for Model 1 and Model 2

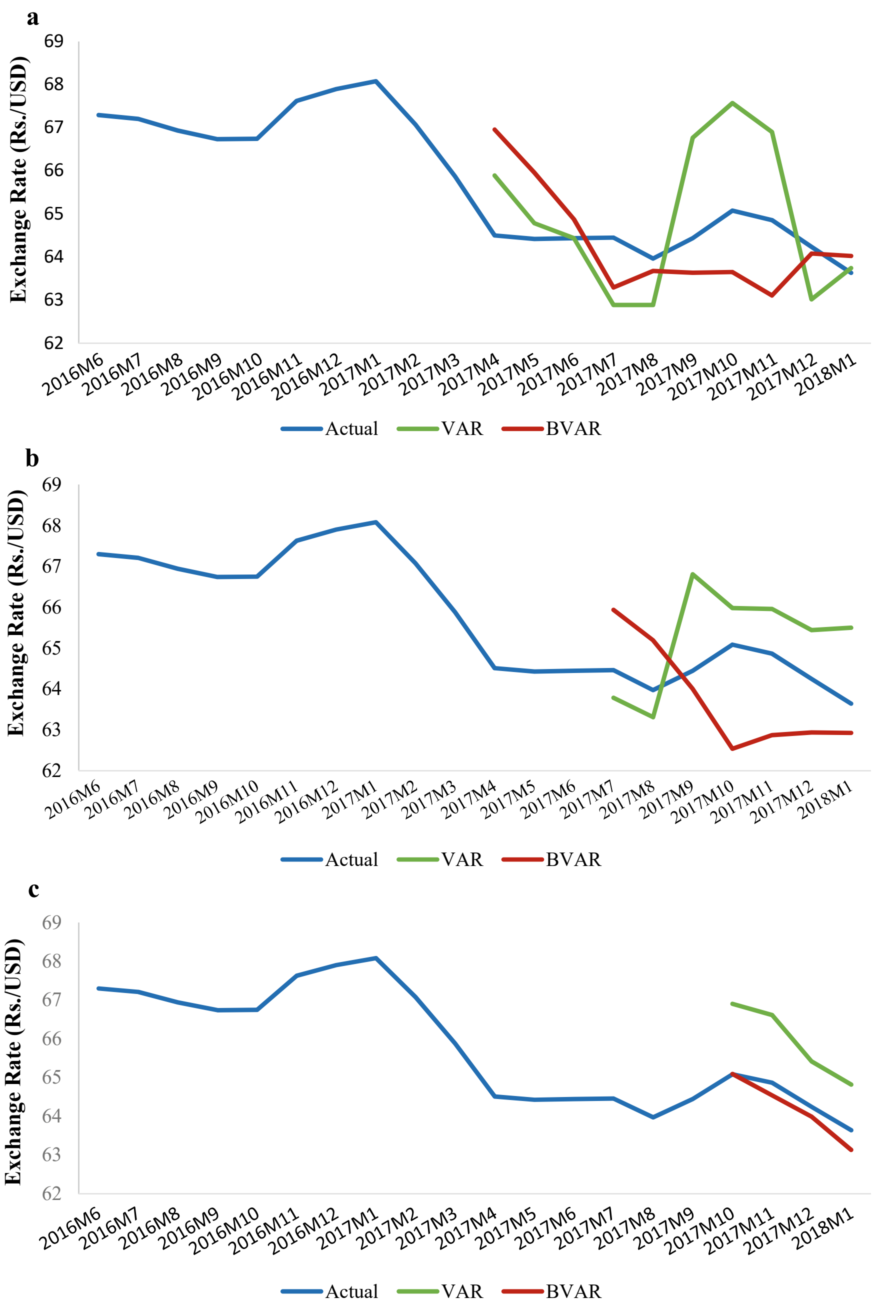


Fig. 4 **a** Model 1: 3-Month ahead forecast: Feb 2017–Jan 2018, **b** 6-Month ahead forecast: Feb 2017–Jan 2018, **c** Model 1: 9-Month ahead forecast: Feb 2017–Jan 2018

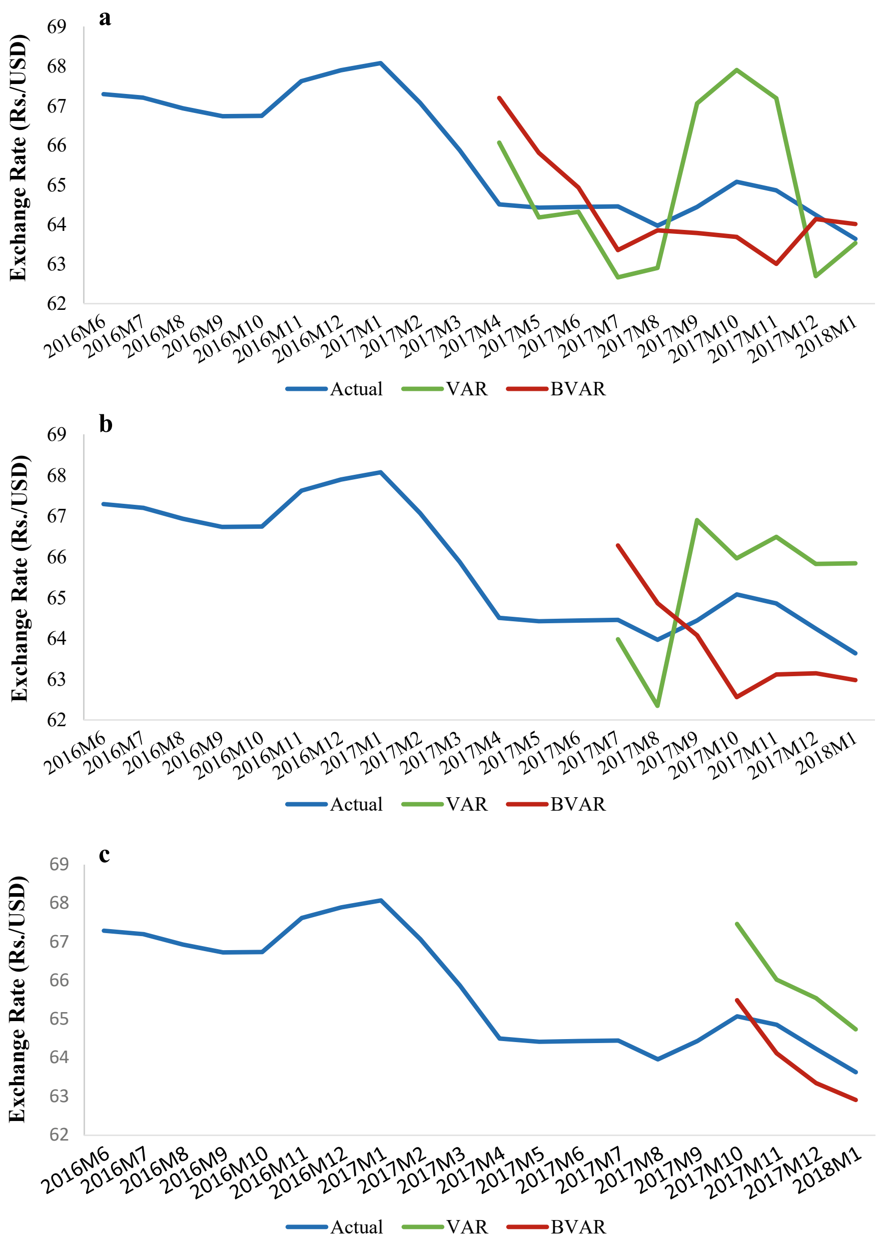


Fig. 5 **a** Model 2: 3-Month ahead forecast: Feb 2017–Jan. 2018, **b** Model 2: 6-Month ahead forecast: Feb. 2017–Jan. 2018, **c** Model 2: 9-Month ahead forecast: Feb. 2017–Jan. 2018

2. What are the various types of hyperparameters used for the Minnesota Prior? What are the implications of changing the hyperparameters for "overall tightness" and "Lag decay"?

   Hint: Construct different combination of hyperparameters and analyse the result. Refer: Dua, Raje and Sahoo (2003).

3. This chapter includes the domestic–foreign differential of the rate of return of stock prices as well of global oil prices as determinants of the exchange rate in addition to monetary model fundamentals (i.e. differential in money supply, interest rate and inflation), forward premium, volatility of capital flows, order flows and central bank intervention. Test the significance of these determinants of exchange rate in a cointegrating framework.

   Hint: Refer: Dua and Ranjan (2010, 2012).

References

Aftab, M., Ahmad, R., & Ismail, I. (2018). Examining the uncovered equity parity in the emerging financial markets. *Research in International Business and Finance, 45*, 233–242.

Aggarwal, R. (1981). Exchange rates and stock prices: A study of us capital markets under floating exchange rates. *Akron Business and Economics Review, 22*(2), 7–12.

Bahmani-Oskooee, M., & Saha, S. (2015). On the relation between stock prices and exchange rates: A review article. *Journal of Economic Studies*.

Baur, D. G., & Miyakawa, I. (2013). International investors, exchange rates and equity prices. *FIRN Research Paper*.

Bhutto, N. A., & Chang, B. H. (2019). The effect of the global financial crisis on the asymmetric relationship between exchange rate and stock prices. *High Frequency, 2*(3–4), 175–183.

Bjønnes, G. H., & Rime, D. (2003). *Dealer behavior and trading systems in foreign exchange markets*, *WP*. Norges Bank.

Bohn, H., & Tesar, L. L. (1996). US equity investment in foreign markets: Portfolio rebalancing or return chasing? *The American Economic Review, 86*(2), 77–81.

Branson, W. H. (1983). Macroeconomic determinants of real exchange risk. In R. J. Herring (Ed.), *Managing foreign exchange risk*. Cambridge: Cambridge University Press.

Branson, W. H. (1984). A model of exchange rate determination with policy reaction: Evidence from monthly data. In P. Malgrange, & P. A. Muet (Eds.), *Contemporary macroeconomic modelling*. Oxford.

Branson, W. H. (1986). The limits of monetary coordination as exchange rate policy. *Brookings Papers on Economic Activity, 1986*(1), 175–194.

Breedon, F., & Vitale, P. (2004). *An empirical study of liquidity and information effects of order flow on exchange rates*, *paper no. 4586*. Centre for Economic Policy Research.

Caporale, G. M., Hunter, J., & Ali, F. M. (2014). On the linkages between stock prices and exchange rates: Evidence from the banking crisis Of 2007–2010. *International Review of Financial Analysis, 33*, 87–103.

Cenedese, G., Payne, R., Sarno, L., & Valente, G. (2016). What do stock markets tell us about exchange rates? *Review of Finance, 20*(3), 1045–1080.

Chen, S. S., & Hsu, C. C. (2019). Do stock markets have predictive content for exchange rate movements? *Journal of Forecasting, 38*(7), 699–713.

Clarida, R. H., & Taylor, M. P. (1997). The term structure of forward exchange premiums and forecastability of spot exchange rates: Correcting the errors. *Review of Economics and Statistics, 70*, 508–511.

Curcuru, S. E., Thomas, C. P., Warnock, F. E., & Wongswan, J. (2014). Uncovered equity parity and rebalancing in international portfolios. *Journal of International Money and Finance, 47*, 86–99.
de Medeiros, O. R. (2005). *Order flow and exchange rate dynamics in Brazil*. Brazil: Universidad de Brasília.
Della Corte, P., Sarno, L., & Tsiakas, I. (2007). An *economic evaluation of empirical exchange rate models, paper 6598.* CEPR.
Dellas, H., & Tavlas, G. (2013). Exchange rate regimes and asset prices. *Journal of International Money and Finance, 38*, 85–94.
Diebold, F. X., & Mariano, R. S. (2002). Comparing predictive accuracy. *Journal of Business & economic statistics, 20*(1), 134–144.
Doan, T. A. (2018). *RATS user's manual, version 10.* Estima.
Doan, T. A., Litterman, R. B., & Sims. (1984). Forecasting and conditional projection using realistic prior distributions. *Econometric Reviews, 3*, 1–100.
Dooley, M., & Isard, P. (1982). A portfolio balance rational expectations model of the dollar mark exchange rate. *Journal of International Economics, 12*, 257–276.
Dornbusch, R. (1976). Expectations and exchange rate dynamics. *Journal of Political Economy, 84*, 1161–1176.
Dornbusch, R., & Fischer, S. (1980). Exchange rates and the current account. *The American economic review, 70*(5), 960–971.
Dua, P., & Ray, S. C. (1995). A BVAR model for the Connecticut economy. *Journal of Forecasting, 14*, 217–227.
Dua, P., & Miller, S. M. (1996). Forecasting Connecticut home sales in a BVAR framework using coincident and leading indexes. *The Journal of Real Estate Finance and Economics, 13*(3), 219–235
Dua, P., & Mishra, T. (1999). Presence of persistence in industrial production: The case of India. *Indian Economic Review*, 23–38.
Dua, P., Raje, N., & Sahoo, S. (2003). Interest rate modelling and forecasting in india. *Department of Economic Analysis and Policy, Reserve Bank of India.*
Dua, P., & Sen, P. (2009). Capital flow volatility and exchange rates: The case of India. In *Macroeconomic Management and Government Finances*, *Asian Development Bank.* Oxford University Press.
Dua, P., & Ranjan, R. (2010). *Exchange rate policy and modelling in India, DRG Study No. 33.* Reserve Bank of India.
Dua, P., & Ranjan, R. (2012). *Exchange rate policy and modelling in India.* Oxford University Press.
Elliott, G., Rothenberg, T. J., & James, H. (1996). Stock. Efficient tests for an autoregressive unit root. *Econometrica, 64*(4), 813–836.
Engel, C. (2000). *Comments on Obstfeld and Rogoff's "The six major puzzles in international macroeconomics: Is there a common cause?"*
Evans,M. D. D., & Lyons, R. K. (2007). How is macro news transmitted to exchange rates? NBER.
Evans, M. D., & Lyons, R. K. (2005). Meese-Rogoff redux: Micro-based exchange-rate forecasting. *American Economic Review, 95*(2), 405–414.
Frankel, J. A. (1979). On the mark: A theory of floating exchange rates based on real interest differentials. *American Economic Review, 69*, 610–622.
Frankel, J. A. (1983). Monetary and portfolio-balance models of exchange rate determination, In J.S. Bhandari and B. H. Putnam (eds.), Economic Interdependence and Flexible Exchange Rates, MIT Press: Cambridge, 84–115.
Fratzscher, M., Schneider, D., & Van Robays, I. (2013). *Oil prices, exchange rates and asset prices.* CESifo Area Conference on Macro.
Frenkel, J. A. (1976). A monetary approach to the exchange rate: doctrinal aspects and empirical evidence. *Scandinavian Journal of Economics, 78*, 200–224.
Granger, C.W.J. (1986). Developments in the study of cointegrated economic variables. *Oxford Bulletin of Economics and Statistics 48*, 213–228.

Granger, C.W.J. (1988) Some Recent Developments in a Concept of Causality, Journal of Econometrics 39:199-211.

Granger, C. W., Huang, B. N., & Yang, C. W. (2000). A bivariate causality between stock prices and exchange rates: Evidence from recent asianflu. *The Quarterly Review of Economics and Finance, 40*(3), 337–354.

Griffin, J. M., Nardari, F., & Stulz, R. M. (2004). Are daily cross-border equity flows pushed or pulled? *Review of Economics and Statistics, 86*(3), 641–657.

Harvey, D., Laybourne, S., & Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting, 13*, 281–291.

Hau, H., & Rey, H. (2006). Exchange rates, equity prices, and capital flows. *The Review of Financial Studies, 19*(1), 273–317.

Hooper, P., & Morton, J. (1982). Fluctuations in the dollar: A model of nominal and real exchange rate determination. *Journal of International Money and Finance, 1*, 39–56.

Isard, P. (1980). Lessons from an empirical model of exchange rates. *IMF Staff Papers, 34*, 1–28.

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration with applications to money demand. *Oxford Bulletin of Economics and Statistics 52*, 169–210.

Ju, K., Zhou, D., Zhou, P., & Wu, J. (2014). Macroeconomic effects of oil price shocks in China: An empirical study based on Hilbert-Huang transform and event study. *Applied Energy, 136*, 1053–1066.

Kim, H. (2011). The risk adjusted uncovered equity parity. *Journal of International Money and Finance, 30*(7), 1491–1505.

Kohli, R. (2001). *Real exchange rate stabilisation and managed floating: Exchange rate policy in India*, *WP 59*. ICRIER.

Kollias, C., Mylonidis, N., & Paleologou, S. M. (2012). The nexus between exchange rates and stock markets: Evidence from the euro-dollar rate and composite European stock indices using rolling analysis. *Journal of Economics and Finance, 36*(1), 136–147.

Koop, G. (1992). Objective Bayesian unit root tests. *Journal of Applied Econometrics, 7*(1), 65–82.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?. *Journal of econometrics, 54*(1–3), 159–178.

Liang, C. C., Lin, J. B., & Hsu, H. C. (2013). Re-examining the relationships between stock prices and exchange rates in ASEAN-5 using panel granger causality approach. *Economic Modelling, 32*, 560–563.

Lin, C. H. (2012). The co-movement between exchange rates and stock prices in the Asian emerging markets. *International Review of Economics & Finance, 22*(1), 161–172.

Litterman, R. B. (1981). *A Bayesian procedure for forecasting with vector auto regressions*, *WP*. Federal Reserve Bank of Minneapolis.

Litterman, R. B. (1986). Forecasting with Bayesian vector auto regressions–five years of experience. *Journal of Business & Economic Statistics, 4*, 25–38.

Meese, R. A., & Rogoff, K. (1983). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of International Economics, 14*(1–2), 3–24.

Melvin, M., & Prins, J. (2015). Equity hedging and exchange rates at the London 4 pm fix. *Journal of Financial Markets, 22*, 50–72.

Nankervis, J. C., & Savin, N. E. (1996). The level and power of the bootstrap t test in the AR (1) model with trend. *Journal of Business & Economic Statistics, 14*(2), 161–168.

Orzeszko, W. (2021). Nonlinear causality between crude oil prices and exchange rates: Evidence and forecasting. *Energies, 14*(19), 6043.

Pagliari, M. S., & Hannan, S. A. (2017). The volatility of capital flows in emerging markets: Measures and determinants. *International Monetary Fund*.

Phillips, P. C. (1991). To criticize the critics: An objective Bayesian analysis of stochastic trends. *Journal of Applied Econometrics, 6*(4), 333–364.

Phylaktis, K., & Ravazzolo, F. (2005). Stock prices and exchange rate dynamics. *Journal of International Money and Finance, 24*(7), 1031–1053.

Qiang, W., Lin, A., Zhao, C., Liu, Z., Liu, M., & Wang, X. (2019). The impact of international crude oil price fluctuation on the exchange rate of petroleum-importing countries: A summary of recent studies. *Natural Hazards, 95*(1), 227–239.

Raza, N., Shahzad, S. J. H., Tiwari, A. K., & Shahbaz, M. (2016). Asymmetric impact of gold oil prices and their volatilities on stock prices of emerging markets. *Resources Policy, 49*, 290–301.

Salisu, A. A., & Ndako, U. B. (2018). Modelling stock price-exchange rate nexus in OECD countries: A new perspective. *Economic Modelling, 74*, 105–123.

Sahoo, A., Moharana, S., & Dash, M. (2018). Relationship between macroeconomic variables and stock market trend. *Journal of Management* (*JOM*), *5*(3).

Salisu, A. A., Cuñado, J., Isah, K., & Gupta, R. (2021). Oil price and exchange rate behaviour of the BRICS. *Emerging Markets Finance and Trade, 57*(7), 2042–2051.

Salisu, A. A., Cuñado, J., Isah, K., & Gupta, R. (2020). Stock markets and exchange rate behaviour of the BRICS. *Journal of Forecasting*.

Sharma, N. (2017). Cointegration and causality among stock prices, oil prices and exchange rate: Evidence from India. *International Journal of Statistics and Systems, 12*(1), 167–174.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica, 48*, 1–48.

Sims, C. A. (1988). Bayesian skepticism on unit root econometrics. *Journal of Economic dynamics and Control, 12*(2–3), 463–474.

Sims, C. A., Stock, J. H., & Watson, M. W. (1990). Inference in linear time series models with some unit roots. Econometrica: *Journal of the Econometric Society,* 113–144.

Spencer, D. E. (1993). Developing a Bayesian vector autoregression forecasting model. *International Journal of Forecasting, 9*, 407–421.

Sui, L., & Sun, L. (2016). Spillover effects between exchange rates and stock prices: Evidence from BRICS around the recent global financial crisis. *Research in International Business and Finance, 36*, 459–471.

Theil, H. (1966). *Applied Economic Forecasting*, Amsterdam: North-Holland.

Todd, R. M. (1984). Improving economic forecasting with Bayesian vector autoregression. *Quarterly Review* (fall, pp. 18–29). Federal Reserve Bank of Minneapolis.

Turhan, M. I., Sensoy, A., & Hacihasanoglu, E. (2014). A comparative analysis of the dynamic relationship between oil prices and exchange rates. *Journal of International Financial Markets Institutions and Money, 32*, 397–414.

Ülkü, N., & Demirci, E. (2012). Joint dynamics of foreign exchange and stock markets in emerging Europe. *Journal of International Financial Markets Institutions and Money, 22*(1), 55–86.

Wen, D., Liu, L., Ma, C., & Wang, Y. (2020). Extreme risk spillovers between crude oil prices and the US exchange rate: Evidence from oil-exporting and oil-importing countries. *Energy*, *212*.

Wong, H. T. (2017). Real exchange rate returns and real stock price returns. *International Review of Economics & Finance, 49,* 340–352.

Xie, Z., Chen, S. W., & Wu, A. C. (2020). The foreign exchange and stock market nexus: new international evidence. *International Review of Economics & Finance, 67*, 240–266.

Živkov, D., Balaban, S., & Djurašković, J. (2018). What multiscale approach can tell about the nexus between exchange rate and stocks in the major emerging markets? *Czech Journal of Economics and Finance, 68*(5), 491–512.

Chapter 9
Forecasting India's Inflation in a Data-Rich Environment: A FAVAR Study

Pami Dua and Deepika Goel

Abstract The study develops a multivariate Factor-Augmented VAR (FAVAR) model of inflation for India to forecast India's inflation. The analysis covers both WPI and CPI measures of inflation. Factors are extracted for determinants of inflation such as output, monetary and credit indicators, interest rate, fiscal indicators, exchange rate, minimum support prices, food inflation, rainfall and foreign inflation using 117 economic time series. The study further evaluates the forecasting performance of the FAVAR model vis-à-vis the VECM model and univariate ARIMA/ARIMA-GARCH models. The models are estimated using monthly data covering the period 2001:05 to 2016:06, and out-of-sample forecasts are generated for the period 2016:07 to 2018:01. The FAVAR model for both measures of inflation suggests that in terms of normalized generalized variance decompositions, maximum variation in WPI inflation in India is explained by exchange rate factor, followed by Minimum Support Price inflation and then by inflation expectations, whereas maximum variation in CPI inflation is explained by expected inflation followed by monetary and credit factor, fiscal factor and finally by output factor. The forecasting exercise suggests that FAVAR emerges as the best model in terms of various forecast accuracy measures. The Modified Diebold Mariano test also suggests that the forecasts from the multivariate FAVAR model are significantly more accurate than the univariate ARIMA-GARCH model and the multivariate VECM model for almost all horizons.

Keywords Forecasting inflation · Factor models · FAVAR · Principal components · VECM

JEL Classification C32 · C51 · E31 · E37

P. Dua
Department of Economics, Delhi School of Economics, University of Delhi, Delhi, India
e-mail: dua@econdse.org

D. Goel (✉)
Department of Economics, Aryabhatta College, University of Delhi, New Delhi, India
e-mail: deepika@aryabhattacollege.ac.in

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_9

1 Introduction

Price stability is one of the main objectives of monetary policy formulation by the central bank. Any instability in prices affects the decision of economic agents in the economy to consume, save or invest. The role of prices gets further accentuated in providing signals to ensure efficient allocation of resources and achieve goals of maximum and sustainable level of output and employment. Thus, the economy is highly influenced by factors which affect the rate of change of prices, that is, inflation in the economy. Inflation also impacts the external competitiveness of an economy in terms of its export prices and can also affect foreign investment. Expectations of inflation also play a major role in negotiating and setting wage contracts. Forecasts of inflation are especially important in an inflation targeting framework, where the monetary authority has an explicit target level of inflation which is also announced to the public. It is assumed that by maintaining price stability, monetary policy can contribute to long term growth of the economy.

Various time series methods have been used for forecasting inflation ranging from simple univariate techniques including exponential smoothing, ARIMA and ARIMA-GARCH to multivariate techniques such as simultaneous equation models,[1] vector autoregressive (VAR) models,[2] vector error correction models (VECM),[3] structural VAR models,[4] time varying VAR,[5] Bayesian VAR models[6] and Factor-Augmented VAR models.[7]

Classification of a specific study on the basis of univariate or multivariate approach to forecasting is not justifiable as the recent developments largely focus on the comparison of forecasting techniques. Faust and Wright (2013) compare the forecasting performance of VAR, BVAR, FAVAR, TVP-FAVAR, DSGE and survey-based models for the US economy. Zeyyad Mandalinci (2017) compare the forecasting performance of ARMA, BVAR, FAVAR, UCSV, TVP-VAR, TVP-FAVAR models for 29 different emerging market economies. Dieter Gerdesmeir et al. (2017) compare the forecasting performance of VAR, VECM, BVAR and FAVAR models for the Euro area inflation.

---

[1] See, e.g. Mariano et al. (2010), Basturk et al. (2014), Petrovska et al. (2017).

[2] See, e.g. Callen and Dongkoo (1999), Ramakrishnan and Vamvakidis (2002), Thomakos and Bhattacharya (2005), Clark and McCracken (2010), Banbura and Mirza (2013), Younus and Roy (2016), Hoa (2017).

[3] See, e.g. Mensah and Bouwmia (2003), Onder (2004), Moser et al. (2007), Tao Sun (2004), Hubrich (2005), Ciccarelli and Mojon (2010), Faust and Wright (2013), Zeyyad Mandalinci (2017).

[4] See, e.g. Bihan and Sedillot (2000), Ramirez et al. (2010).

[5] See, e.g. Nadal-De Simone (2000), Faust and Wright (2013), Salman Huseynov et al. (2014), Kavtaradze and Mokhtari (2018).

[6] See, e.g. Rumler and Valderrama (2010), Hulagu and Sahinoz (2012), Biswas et al. (2010), Faust and Wright (2013).

[7] See, e.g. Stock and Watson (1999, 2002, 2006), Gosselin and Tkacz (2001), Forni et al. (2003), Eickmeier and Zieglar (2006), Gavin and Kliesen (2008), Ramirez (2010), Bordoloi et al. (2010), Figueiredo (2010).

Some of the more recent studies that forecast inflation in India are Paul et al. (2015), Dholakia and Kadiyala (2018). Aye et al. (2015) use VAR, BVAR and BFAVAR models to forecast key macroeconomic variables in the economy including WPI inflation. They estimate the models from April 1997 to December 2006 and analyse out-of-sample forecast performance from January 2007 to October 2011. The authors find that the performance of each model varies across different horizons. Dholakia and Kadiyala (2018) use a combination of different time series-based techniques to forecast CPI-Combined (CPI-C) inflation. The time period considered by them is January 2011 to October 2016, and forecasts are obtained for the next 12-month period. They consider univariate ARIMA model, hybrid ARIMAX, three variable VAR including inflation, output gap and policy rate, VARX with oil prices and exchange rates as exogenous variables and VECM for forecasting inflations at various relevant horizons. They find that multivariate models based on Philips curve specifications fail to outperform univariate ARIMA-based models. Their study also finds that combining alternative models based on MSE of the models improves forecast accuracy over any individual model.

It merits mention here that Dua and Goel (2021) model WPI and CPI inflation in the Indian economy in a Phillips curve framework based on the specification of Dua and Gaur (2010). This framework encompasses a far more extensive list of variables compared to the study by Dholakia and Kadiyala (2018). The current study is based on this comprehensive framework in a FAVAR model. Various studies show that the larger information set captured by factor models helps in producing more accurate forecasts. According to Stock and Watson (1999, 2005), factor models outperform other benchmark models for the US economy. Eickmeier and Ziegler (2006) note that factor models tend to outperform small-scale models for predicting inflation for US and Euro area. In their survey of models for forecasting exchange rates and inflation, Kavtaradze and Mokhtari (2018) find that factor-based models generate superior forecasts relative to all other models.

In this study, we forecast inflation using a FAVAR model where factors are extracted for determinants of inflation such as output, monetary and credit indicators, interest rate, fiscal indicators, exchange rate, minimum support prices, food inflation, rainfall and foreign inflation using 117 economic time series. The study further evaluates the forecasting performance of the FAVAR model vis-à-vis the VECM model and univariate ARIMA/ARIMA-GARCH model. All these models are estimated using monthly data covering the period 2001:05 to 2016:06, and out-of-sample forecasts are generated for the period 2016:07 to 2018:01. Forecasts are generated for the period July 2016 to January 2018 using recursive estimation for a horizon of 1 to 12 months. Forecasts are evaluated for accuracy, and the Diebold Mariano test is also conducted to evaluate whether the difference in accuracy of forecasts from alternative models is significant or not.

We forecast inflation based on both WPI and CPI-IW[8] series using monthly data for the Indian economy. Until 2013, RBI provided inflation projections in terms

[8] We use CPI-Industrial Worker since the historical data for the CPI-Combined series is available only after January 2011.

of WPI alone, because it was the only measure of prices at a national level and CPIs traditionally addressed prices facing specific sections of society (CPI-Industrial Worker, CPI-Agricultural Labour, CPI-Rural Labour). Based on RBI's Report of the Expert Committee to Revise and Strengthen the Monetary Policy Framework (RBI, 2014; Chairman: Dr Urjit R Patel), WPI does not capture price movements in non-commodity producing sectors like services, which constitute close to two-thirds of economic activity in India. It also does not generally reflect price movements in all wholesale markets as the price quotes of some of the important commodities like milk, LPG and the like are basically taken from retail markets. Movements in WPI often reflect large external shocks and also subject to large revisions. The report also states that the true inflation that consumers face is in the retail market which is close to indicators of the cost of living. CPI is familiar to large segments of the population and often used in both public and private sectors as a reference in the provision of government benefits or in wage contracts and negotiations. Almost all central banks in advanced economies and emerging market economies use CPI as their primary price indicator. Against this backdrop, we forecast both WPI and CPI inflation and compare the forecasts generated from the two measures of inflation.

The study is organized as follows. Section 2 provides a theoretical background to model inflation. Empirical framework for the paper is explained in Sect. 3. Estimation methodology encompassing FAVAR models for WPI and CPI inflation is presented in Sect. 4. Various aspects of forecast performance are also explained in this section. Estimation results are given in Sect. 5, and Sect. 6 concludes.

2 New Keynesian Phillips Curve

The New Keynesian Phillips Curve (NKPC) follows the staggered contract model of Taylor (1980) and Calvo (1983) with sticky nominal wages and prices in a setup with forward-looking agents. It combines the traditional Phillips Curve with optimizing behaviour by price setters and rational expectations. In its augmented form; it also allows for some inflation inertia, either in the form of indexation to past inflation or backward-looking inflation expectations.

Dua and Gaur (2010) show that following the NKPC model, the framework for examining inflation in the context of a general forward-looking Phillips Curve is as follows

$$\Pi_t = \alpha + \beta E_t(\Pi_{t+1}) + \sum_{i=1}^{n} \gamma_i D_t + \sum_{i=1}^{n} \lambda_i X_t + \sum_{i=1}^{n} \psi_i Z_t + \sum_{i=1}^{n} \Phi_i T_t + \varepsilon_t \quad (1)$$

where π denotes inflation rate, E is the expectations operator, D denotes domestic demand side factors, X represents external demand side factors, Z represents domestic supply side factors, and T represents external supply side factors.

Table 1 Potential determinants of inflation

Determinants	Expected sign
Expected inflation	+
Domestic demand factors:	
• Real economic activity	+
• Output gap	
• Monetary policy	
• Rate of growth of money supply	+
• Interest rate	−
• Fiscal policy	+
• Fiscal deficit	
External demand factors	
• Nominal exchange rate	+
• Import inflation	+
Domestic supply factors	
• Food inflation	+
• Food production	+
• Rainfall (deviation from normal)	+
• MSP	+
• Differential between wage inflation and productivity growth per worker	+
• Fertilizer inflation	+
• Domestic fuel inflation	+
External supply factors	
• International oil prices	+
• International food prices	+

The potential determinants of inflation can be primarily classified into demand side factors and supply side factors. Dua and Gaur (2010) and Dua and Goel (2021) provide an extensive list of variables that affect inflation. The list of potential determinants is presented below. Along with each variable, their expected signs are also given according to economic theory (Table 1).

3 Empirical Model

In this paper firstly, we model WPI and CPI inflation in the Indian economy in a Phillips Curve framework using a FAVAR framework. The study further evaluates the forecasting performance of the FAVAR model vis-à-vis the VECM model and univariate ARIMA/ARIMA-GARCH model.

Based on Dua and Goel (2021), which follows Dua and Gaur (2010) determinants of inflation were firstly identified in a cointegrating VAR framework.[9] It was found that there is a long-run relationship between inflation and its determinants, namely inflation expectations, output gap, rate of growth of money supply, interest rate, exchange rate, global oil inflation, minimum support price inflation, fiscal deficit and deviation of actual rainfall from normal. The following equation describes our estimated model in a cointegrating framework.

$$\pi^{\text{WPI/CPI}} = f\left(\underset{+\,+\,+\,+\,+\,+\,+\,-\,+\,+}{\pi^{e}, y - y^{*}, e, oil_{\text{inf}}, \text{raindev}, \pi^{\text{food}}, \Delta M, i, fd, \pi^{\text{msp}}}\right) \quad (2)$$

where
π = inflation (WPI or CPI)
π^{e} = expected inflation
y-y^{*} = output gap
e = exchange rate
Oil = international oil prices
ifp = international food prices
π^{msp} = minimum support prices
ΔM = rate of growth of money supply
raindev = deviation of actual rainfall from normal
i = interest rate.

For the time period 2001M5–2016M6, the estimated cointegrating equation is found to have correct signs which are in accordance with economic theory and also aligned with Dua and Goel (2021). The estimated cointegrating equation for WPI inflation is given below:

$$\begin{aligned}\Pi^{\text{WPI}} &= 0.75\Pi^{e} + 1.78y - y^{*} + 0.18\Delta M \\ &\quad + 0.09e - 0.01i + 0.002\ \text{oil}_{\text{inf}} + 0.03\Pi^{\text{msp}}\end{aligned}$$

The signs of the explanatory variables are in line with economic theory which suggests that any rise in expected inflation in the economy has a positive impact on the wholesale price inflation. Any positive rise in the output gap would imply that the actual output is greater than the potential output, which implies that the demand for goods in the economy is more than the supply thus leading to inflationary pressures in the economy. An increase in the rate of growth of money supply leads to higher inflation due to increase in economic activity which stimulates spending. Similarly, an increase in exchange rate (depreciation) leads to higher inflation due to rising import prices and rising demand for exports. An increase in interest rate will lead to a rise in saving and fall in spending. Aggregate demand shrinks as a result thus lowering inflation. An increase in global oil prices will have a pass-through effect on domestic fuel prices thus leading to inflationary pressures in the economy. Given the

[9] See Dua and Goel (2021).

fact that India has adopted fuel prices to be more market determined, this can result in an inflationary spiral in the economy. Finally, the minimum support prices lead to inflationary pressures through their impact on prices of agricultural goods.

Similarly, the estimated cointegrating equation for CPI-IW inflation is given below:
$\Pi^{\mathrm{CPI}} = 1.02\Pi^{e} + 0.11y - y^{*} + 0.12\Delta\mathrm{M} + 0.06e - 0.11i + 0.007\ \mathrm{ifp}_{\mathrm{inf}} + 0.02\Pi^{\mathrm{msp}}$
The signs of the explanatory variables are in line with economic theory.

Based on the cointegrating framework provided in Dua and Goel (2021), we categorize variables into broad categories, construct factors and then estimate Factor-Augmented VAR (FAVAR). The estimated model for FAVAR is specified as follows:

$$\pi^{\mathrm{WPI/CPI}} = \mathrm{f}\left(\pi^{e}, \left(y - y^{*}\right)^{f}, M^{f}, e^{f}, i^{f}, f^{f}, (\pi^{\mathrm{msp}})^{f}, \mathrm{oil}^{f},\ \mathrm{rain}^{f}\right) \tag{3}$$

Equation 3 represents inflation determination in the FAVAR framework where the symbols have their usual meaning and superscript f denotes the corresponding factor.

In a FAVAR framework, we categorize all these variables into broad categories as real economic activity, monetary factor, interest rate factor, exchange rate factor, fiscal factor, external factor, minimum support prices inflation factor, food inflation factor rainfall and inflation expectations. The factors constructed in the FAVAR framework are explained below.

Real economic activity factor can be used to explain the macroeconomic concept of "output gap", providing a summary of the real activity situation in the economy. It can include all measures which describe output produced in the economy such as industrial production, capacity utilisation, unemployment, real GDP. Since we are using monthly data, we consider industrial production in different economic sectors such as mining, manufacturing and electricity, use-based sectors and core infrastructure sectors of the economy. Any positive shock to real economic activity measure should affect inflation positively.

Monetary factor comprises a number of money stock variables. It also includes credit factors, which explains private credit and bank loans variable. With this factor, we are able to understand the credit channel effects on inflation, which is expected to have a positive impact on inflation.

Exchange rate factor includes both trade-based and export-based nominal effective exchange rate for 36 and 6 countries. It also considers exchange rates of India with respect to some important currencies like USD, Euro, SDR, GBP and Japanese Yen. The bilateral exchange rates used also indicate the important trading partners of India such as USA, UK and Japan (Dua and Suri, 2019)). A depreciation in the home currency would increase inflation through increase in the prices of imports. Hence, a positive shock in exchange rate factor is expected to have a positive effect on inflation.

Interest rate factor combines a number of short-run and long-run interest rates like call money rate, repo rate, 15–91-day Treasury bill rate and 1-year, 5-year and 10-year government security rate. It also includes data on deposits, bank reserves that explains a number of public and private bonds interest rates, at different maturities. A positive shock to interest rates in the economy is likely to lower inflation.

Fiscal factor includes the total government receipts and expenditure and different measures of deficit in the government accounts. This factor throws light on the fact as to how various government policies would affect headline inflation in the long run. Any positive fiscal activity in the economy is likely to have a positive impact on inflation.

Oil factor captures the influence of a number of foreign variables on domestic inflation like foreign commodity price inflation, energy inflation, oil inflation and non-energy inflation. Any spike in international commodity prices such as fuel and food is likely to increase domestic inflation.

Inflation expectations give us an insight into future inflation if they are measured as forward looking. A higher expectation of future inflation will tend to raise inflation today as demand for goods would increase in the current period. Expectations are assumed to be observables in the model since they are derived from actual inflation rates as 3-month ahead forecasts.

Rainfall has been an important factor explaining inflation dynamics in the Indian economy through its impact on agricultural production. This consists of actual rainfall in the economy during different months and their deviations from the normal. Since India is primarily an agrarian economy, any adverse impact on the production of this sector would have spillover effects on the secondary and tertiary sectors of the economy.

Food Inflation Factor consists of constituents of food articles like cereals, pulses, fruits, vegetables, edible oil, milk, manufacturing food items, etc., which are likely to have a positive impact on overall inflation. Food is considered one of the important drivers of inflation especially in the developing economies (Walsh, 2011).

MSP Inflation Factor includes minimum support prices of all food grains and non-food grains in the economy. It is assumed that any increase in agricultural prices affects the overall inflation positively but with a time lag.

Input Inflation Factor incorporates all those variables which capture the use of inputs in agricultural production in the economy. Any increase in the prices of agricultural inputs like diesel, fertilizers, electricity would lead to an increase in the prices of agricultural products and hence overall inflation in the economy.

Based on this explanation, we can summarize the expected signs of these factors that are presented in the table as follows (Table 2):

The factors thus constructed for different categories are considered as unobservable contained in the information set. All the series have been transformed to stationary series and seasonally adjusted, if necessary. Moreover, the series are

Table 2 Expected signs of factors

Factors	Expected signs
Real economic activity	+
Monetary	+
Interest rate	−
Exchange rate	+
Fiscal	+
Oil	+
Rainfall	+
MSP inflation	+
Input inflation	+
Food inflation	+

demeaned and standardized. This is done to eliminate the scale effects which could have an adverse impact on the factors that are calculated. The structural factors are constructed using principal component approach by Stock and Watson (2002).

In Eq. (3), we treat oil^f, $rain^f$ and the model specific dummies as exogenous variables. The rest of the variables are treated as endogenous variables.

4 Econometric Methodology

4.1 Unit Root Testing

All the variables are firstly tested for unit roots. In order to use them in a FAVAR framework, they are converted into stationary series. The classical tests used to check for the presence of unit roots are Dickey Fuller Generalized Least Squares (DF-GLS), Phillips Perron (PP) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS). The presence of unit roots in time series has implications for statistical inference in the classical framework since the OLS estimators, and the corresponding statistics do not have the standard asymptotic distributions. Sims (1988) therefore argues that Bayesian theory provides a more reasonable procedure for inference than classical hypothesis testing. Dua and Mishra (1999) argue that when the testable hypothesis is the presence of a unit root, the Bayesian methods are generally preferred to the traditional tests, as these tests have extremely low power, especially against trend stationary alternatives (DeJong et al., 1988). This paper, therefore, also uses the Bayesian framework in addition to other classical tests for testing unit roots.

4.2 FAVAR Model

In the FAVAR framework, a large number of economic variables are contained in a smaller VAR including both latent and observed variables. It can be viewed as a specific Dynamic Factor Model (DFM) where some factors are observed variables. Factor-Augmented VAR was first proposed by Bernanke, Bovin and Eliasz (2005, QJE). Both observable and unobservable variables jointly follow a vector autoregressive process which would further determine the co-movements of a large number of observable variables. The inclusion of unobservable variables is an important aspect of FAVAR model as these unobservable factors capture some important structural shocks to the economy but cannot be represented by specific macroeconomic aggregates. They consider a more general, unrestricted version of a FAVAR model. According to Lutkepohl (2014), Factor-Augmented VAR models summarize the information contained in a large panel of variables in a small number of factors and include those factors in the VAR analysis. By summarizing a large set of variables in factors, these models impose additional structure on the data that reduces the dimensionality of the estimation problem, and hence, standard estimation procedures can be applied. The factors can be static or dynamic.

Using Stock and Watson (2016) and Lutkepohl (2014), the model may be represented as:

$$\mathrm{A(L)}\begin{bmatrix} F_t \\ y_t \end{bmatrix} = W_t \tag{4}$$

where W_t is $(R+K)$-dimensional white noise, $\mathrm{A(L)} = \mathrm{A_0} + \mathrm{A_1 L} + \cdots + \mathrm{ApL^P}$ is a $((R+K)\times(R+K))$ matrix operator, F_t is a vector of R unobserved common factors that are related to a large number of N informational variables x_t by the observation equation:

$$x_t = \Lambda^F F_t + \Lambda^y y_t + e_t \tag{5}$$

Following Stock and Watson (2005), DFM in static form can be written as:

$$Y_t = \Lambda F_t + A(L)Y_{t-1} + v_t \tag{6}$$

$$F_t = \Gamma(L)F_{t-1} + G\eta_t \tag{7}$$

where Λ is nxf matrix, f is the number of static factors, and G is fxq. These equations are called static for DFM since F_t appears in measurement equation without any lags.

VAR form of DFM can be written as:

$$\begin{bmatrix} F_t \\ y_t \end{bmatrix} = \begin{bmatrix} \Gamma(L) & 0 \\ \Lambda\Gamma(L) & A(L) \end{bmatrix}\begin{bmatrix} F_{t-1} \\ y_{t-1} \end{bmatrix} + \begin{bmatrix} \in_{F_t} \\ \in_{X_t} \end{bmatrix} \tag{8}$$

where

$$\begin{bmatrix} \in_{F_t} \\ \in_{X_t} \end{bmatrix} = \begin{bmatrix} I \\ \Lambda \end{bmatrix} G\eta_t + \begin{bmatrix} 0 \\ V_t \end{bmatrix} \tag{9}$$

In order to estimate factors, we need to write relation between "informational" time series X_t, observed variables Y_t, and factors F_t as follows:

$$x_t = \Lambda^F F_t + \Lambda^y y_t + e_t \tag{10}$$

where X_t denotes an $N \times 1$ vector of correlation time series and Y_t a vector of $M \times 1$ observations of macroeconomic variables which are a subset of X_t.

Λ^F is a $N \times k$ matrix of factor loadings, Λ^y is a $N \times M$ matrix of coefficient that bridges the observable Y_t and macroeconomic dataset, and et is the vector of $N \times 1$ error terms.

These terms are mean zero, normally distributed and uncorrelated with a small cross-correlation.

Bernanke et al. (2005) propose two methods to estimate FAVAR. The first estimation procedure of FAVAR consists of a two-step PC approach proposed by Bernanke et al. (2005). The second estimation method involves a one-step likelihood approach, implemented by Gibbs sampling, which leads to joint estimation of both the latent factors and the impulse responses. The two methods can be complement of each other, with the first one being computationally simple, and the second providing possibly better inference in finite sample at the cost of increased computational cost.

4.2.1 Estimation of Factors

In FAVAR, one of the important exercises is the estimation of factors. The problem of estimating factor structure is quite complicated and non-standard. The factors can be extracted using three approaches:

1. The static principal components as in Stock and Watson (2002)
2. The dynamic principal component approach (frequency domain) as in Forni et al. (2005)
3. The dynamic principal component approach (time domain) as in Doz et al. (2011, 2012).

This paper uses the first approach where factors are constructed based on the structural approach as described by Stock and Watson (2002), Belviso and Milani (2005), Bernanke and Boivin (2003) using principal components method. The advantage of using factors in a structural form is that they have an economic meaning which makes it easier to interpret responses that emerge from the shocks to these factors.

Factors are obtained from observation Eq. (5) by imposing the orthogonality restriction F'F/T = I. This implies that $\hat{F} = \sqrt{T}\hat{G}$ where $\hat{G}$ is eigenvectors corresponding to the K largest eigenvalues of XX' sorted in descending order. Stock and Watson (2002) showed that factors can be consistently estimated by first r principal components of X, even in presence of moderate changes in the loading matrix Λ.

Bai and Ng (2002) proposed a set of selection criteria to choose k that are generalizations of BIC and AIC criteria. In the second step, we estimate FAVAR equation replacing F_t by $\widehat{F_t}$. Following Bernanke et al. (2005), Y_t is removed from the space covered by principal components. Bai and Wang (2015) show that under suitable identification conditions, inferential theory can be developed for such a two-step estimator, which differs from a standard large-factor model. Confidence bands for the impulse responses can be readily constructed using the theory.

Belviso and Milani (2005), Bernanke and Boivin (2003) and Bagliano and Morana (2009) propose an alternative approach that makes it easier to give economic meaning to the common factors. They divided the dataset into different categories of variables and estimated each common factor separately as the principal component having the largest eigenvalue in each category. This method of extracting common factors from each group can also avoid contamination from series potentially unrelated to the phenomenon of interest. Each factor is identified as a basic force that governs the economy as "real activity", "foreign sector", "credit sector" and so on.

The factors obtained in the above-mentioned manner are included in a VAR model. This is similar to augmenting vector autoregression with "structural" factors. Belviso and Milani (2005) also name this approach as Structural Factor-Augmented VAR (SFAVAR). The VAR estimated using these identified factors describes the dynamics of the economy. This description is found to be more accurate in the literature than a standard VAR because a data-rich environment is considered.

A useful feature of the FAVAR is that the impulse response function of all variables to the fundamental shocks can be readily calculated.

4.2.2 Forecast Error Variance Decompositions

Forecast error variance decompositions (FEVD) measure the contribution of each type of shock to the forecast error variance. It decomposes the variation in a variable into the component shocks to other variables in the VAR. Both computations are useful in assessing how shocks to economic variables reverberate through a system.

There are two types of FEVD analysis, generalized and orthogonalized. The study uses generalized variance decompositions suggested by Koop et al. (1996) and developed by Pesaran and Shin (1998) which are independent of the ordering of the variables. The generalized variance decomposition considers the forecast error variance of the N-step ahead forecasts, explained by conditioning on the non-orthogonalized shocks, but explicitly allowing for contemporaneous correlation between these shocks and shocks to other equations in the system.

One of the basic differences in using FEVD for FAVAR as compared to the traditional VAR setup is that the analysis is carried out for a set of factors which in turn are computed using the principal component method explained in the previous subsection. For a FAVAR, forecast error variance decompositions would decompose the variation in the dependent variable into the component shocks to other factors in the FAVAR. These factors contain a lot of information about the economy as they incorporate multiple macroeconomic variables as compared to VAR.

4.2.3 Steps in FAVAR Estimation

- Define an information set which contains all macroeconomic variables that are related to the observed variable.
- All variables are converted into stationary series to combine them into factors.
- Variables in the information set are classified into different categories on the basis of economic theory.
- Using static principal component approach variables in each category is combined to construct factors.
- Factors are derived as the principal component having the largest eigenvalue in each category.
- These factors are then plugged into a VAR along with the observed variable to carry out further analysis.[10]
- FAVAR is estimated using a two-step principal component approach.
- Shocks are given to the factors in VAR equation to study the impact on the observed variable through impulse responses and forecast error variance decompositions.

4.2.4 Algorithm for Generating Forecasts

The paper models WPI and CPI inflation in India in a FAVAR framework. Next, we generate forecasts from these models, and forecasting performance of the model is compared with VECM and univariate model. We evaluate the forecasting performance of these models at different horizons.

Recursive method is used to generate forecasts from a model. If there exist T time periods 1, 2, …, t, t + 1, t + 2, …, T, then a model is first estimated for time period 1 to t and forecasts are produced for t + 1 …. T. In the next step, the model is estimated for time periods 1 to t + 1 and forecasts are made for t + 2 …. T and so on. In this way, one can obtain n-period ahead forecasts, "*n*" ranging from 1 to T-t.

If A_{t+n} = Actual observation at time $t + n$.

${}_tF_{t+n}$ = Forecast for time $t + n$ based on information at time t.

then $e_{t+n} = A_{t+n} - {}_tF_{t+n}$ = Forecast error

and

[10] See, e.g. Liu and Jansen (2007, 2011), Lombardi et al. (2012) and Fernald et al. (2014).

$$PE_{t+n} = \text{the percentage error} = \frac{(\mathrm{A}_{t+n} -_t \mathrm{F}_{t+n})}{(\mathrm{A}_{t+n})} \times 100 \tag{11}$$

The evaluation of forecasts is done using different forecast accuracy measures for each of the forecast horizon. These are described in the sections that follows.

4.3 *Evaluation of Forecasting Models*

The best forecasting model is one that produces the most accurate forecasts (Dua et al, 2003). This implies that the forecasted values must be close to the actual values and should move in the direction of the actual series. Evaluation of the forecasting models is based on RMSE, Theil's U (Theil, 1966) and the Diebold and Mariano (1995) test. The forecast evaluation measures used in the paper are described as follows:

4.3.1 Root Mean Square Error (RMSE)

This is an absolute measure of accuracy, and higher the value, the worse the forecast.

$$\text{RMSPE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(e_{t+n}^2\right)} \tag{12}$$

where $e_{\mathrm{t+n}} = \mathrm{A}_{\mathrm{t+n}} - {}_{\mathrm{t}}\mathrm{F}_{\mathrm{t+n}}$

Although RMSE is better than calculating mean error (ME) or mean absolute error (MAE)[11] measures, it should not be relied on solely as this measure involves averaging the square of the errors over observations that have different degree of variability. Hence, we calculate percentage errors to overcome this problem.

4.3.2 Root Mean Square Percentage Error (RMSPE)

This is a relative measure of accuracy, and higher the value, the worse the forecast.

$$\text{RMSPE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(PE_{t+n}^2\right)} \tag{13}$$

where PE_{t+n} = the percentage error.

[11] $\text{ME} = \frac{1}{T}\sum_{t=1}^{T} e_{t+n}, \ \text{MAE} = \frac{1}{T}\sum_{t=1}^{T} |e_{t+n}|$

4.3.3 Thiel's Inequality Coefficient: Quadratic Loss Criteria

While the others are standard measures in the literature, Theil's inequality coefficient is more popularly used. This method answers the question of whether by using a particular technique, are we doing better than a no change forecast, i.e. a naïve forecast. For this, we calculate the following index, U2:

$$\text{Theil's U2} = \sqrt{\frac{\sum_{t=1}^{T}(A_{t+n} -_t F_{t+n})^2}{\sum_{t=1}^{T}(A_{t+n} - A_t)^2}} \tag{14}$$

If U2 > 1, then forecasts are worse than the naïve forecasts, whereas if U2 < 1, forecasts are more accurate than the naïve forecasts.

4.3.4 Diebold Mariano Test

While accuracy of forecasts from two different models may be different, we test whether this difference is statistically significant or not using the Modified Diebold Mariano test, which is a variant of the DM test given in Diebold and Mariano (1995). Harvey et al. (1997) note that as the forecast horizon increases, the Diebold Mariano test statistic becomes oversized leading to false rejection of the null hypothesis.

The Modified Diebold Mariano test compares the forecast performance of alternative models based on the null hypothesis of no difference of the accuracy of two competing forecasts.

The modified statistic is given by

$$S_1^* = \left[\frac{T + 1 - 2n + T^{-1}n(n-1)}{T}\right]^{-1/2} S_1 \tag{15}$$

Harvey et al. (1997) also recommended that the modified statistic should be compared with the critical values from the student's t-distribution with T-1 degrees of freedom, instead of the standard normal distribution.

4.3.5 Data and Sources

The present study uses monthly data for the Indian economy for the period 2001:5 up to 2016:06. Inflation (π_t) is measured as the year-on-year growth rate of the Wholesale Price Index (WPI). An alternative measure of inflation, viz., CPI-IW inflation is also considered in the paper. Since 2011, government has started using CPI (Rural + Urban) index as a measure of inflation. However, in the absence of historical series of this measure, the study uses CPI-IW indices. The FAVAR model used in the paper to forecast inflation incorporates 117 different economic variables, which are classified into different categories depending on the indicator they relate to. Apart from these, the model also includes expected inflation[12] series in the FAVAR model described in the previous section.

Index of Industrial Production for different sectors that is mining, electricity and manufacturing as well as the use-based indices are used in order to construct an index for real economic activity. This index also includes core infrastructure sectors in the economy. Output gap for each of these indices is then constructed using the Christiano-Fitzgerald asymmetric band-pass filter.[13] This filter relies on the theory of spectral analysis of time series data. This methodology is used to transpose time series fluctuations represented in the time domain, to fluctuations in the frequency domain. Assuming that business cycle fluctuations correspond to a well-defined band of frequencies, it is then possible to apply the filter to the observed output series and isolate the observations corresponding to the pre-defined band, obtaining the output's cyclical component.[14]

All the series are transformed to stationary series and seasonally adjusted, if necessary. Moreover, the series are demeaned and standardized. This is done to eliminate the scale effects which could have an adverse impact on the factors that are calculated.

Table 10 in the appendix summarizes the data, their sources and the transformations made for each of the variables as used in the model.

5 Empirical Results

5.1 Unit Root Testing

All variables are first tested for unit roots using the classical tests such as Dickey Fuller Generalized Least Squares (DF-GLS), Phillips Perron (PP) and Kwiatkowski, Phillips, Schmidt and Shin (KPSS). In addition, the Bayesian unit root tests are also conducted. The results for each variable are reported in Table 10 in the appendix. After checking for the unit roots, they are then converted into stationary series.

[12] Expected inflation is calculated by univariate method using past data of inflation.

[13] According to Almeida and Felix (2006), there are some problems associated with the HP filter. The first one comes from the choice of the appropriate smoothing parameter λ, which is largely discretionary. A second shortcoming is commonly known as the end-of-sample problem, which results from the fact that towards the edges of the sample, as leads and lags become unavailable, the HP filter gradually turns into an asymmetric filter, overemphasizing the importance of the last observations. This way, estimates of trend output for recent history suffer from bias. Finally, many studies refer that when used with data that is integrated or nearly integrated, the HP filter can induce spurious cycles, i.e. it can generate cycles even if they are not present in the original data.

[14] See Christiano and Fitzgerald (2003).

Table 3 Forecast error variance decompositions (FEVD): WPI inflation

	Factors							
Horizon	$\pi^{WPI(own)}$	π^{e}	Y-Y*	ΔM	i	e	fd	π^{msp}
0	89.23	1.04	1.79	1.6	0.02	5.14	0.98	0.2
4	63.83	7.04	2.79	4.93	0.34	12.04	2.16	6.88
8	56.58	8.08	3.15	5.58	2.81	10.78	3.8	9.23
12	55.84	8.22	3.11	5.66	3.26	11.04	3.76	9.11
16	55.39	8.28	3.21	5.64	3.38	11.01	3.77	9.32
20	55.11	8.3	3.22	5.68	3.47	10.95	3.83	9.43
24	55.07	8.31	3.22	5.68	3.5	10.95	3.83	9.43

5.2 Forecast Error Variance Decompositions (FEVD)

Variance decompositions give the proportion of the h-periods ahead forecast error variance of a variable that can be attributed to another variable. These, therefore, measure the proportion of the forecast error variance of inflation that can be explained by shocks given to its determinants at different horizons. For our analysis, the generalized decomposition technique is used. Results in Table 3 suggest that at the end of 24-month horizon, around 11% of forecast error variance of WPI inflation is explained by the exchange rate factor, followed by MSP inflation (9%) and then expected inflation (8%). About 6% of forecast error variance in WPI inflation is explained by monetary factors at the end of 24-month horizon. Forecast error variance in inflation explained least by real economic activity, interest rate and fiscal factors which is about 3% each. This implies that overall variation in WPI inflation can be managed by controlling for exchange rate fluctuations and keeping agricultural prices under control.

In contrast, forecast error variance in CPI-IW inflation is explained the most by inflation expectations by about 17% variation and monetary factors which explains 7% of forecast error variance in CPI-IW inflation at the end of 24-month horizon. Exchange rate, fiscal factors and output gap factors each explain only 4% of total variation in CPI inflation. Least forecast error variance is explained by interest rate factor (3%) at the end of 24-month horizon. (Refer Table 4).

5.3 Evaluation of Forecasts

The section discusses the forecast results of FAVAR model of WPI and CPI inflation in India. To check for the accuracy of forecasts, out-of-sample forecasts for FAVAR model are compared with univariate ARIMA-GARCH models and then with multivariate VECM model. This exercise is carried out for both WPI and CPI measures of inflation. The models are estimated from May 2001 to June 2016. Out-of-sample

Table 4 Forecast error variance decompositions (FEVD): CPI inflation

	Factors							
Horizon	$\pi^{CPI(own)}$	π^{e}	Y-Y*	ΔM	i	e	fd	π^{msp}
0	75.35	19.4	1.38	0.17	0.05	3.31	0.24	0.1
4	64.37	18.15	2.5	6.28	1.8	3.21	2.26	1.43
8	59.05	17.01	3.57	7.19	2.36	3.33	3.71	3.77
12	58.78	16.68	3.81	7.14	2.4	3.47	3.8	3.91
16	58.53	16.58	3.89	7.11	2.49	3.55	3.91	3.94
20	58.38	16.54	3.92	7.14	2.49	3.6	3.92	4.01
24	58.33	16.53	3.95	7.13	2.49	3.6	3.94	4.03

forecasts are generated from July 2016 to January 2018. The models are further tested using the Modified Diebold Mariano test to see whether the differences in forecasts between them are statistically significant or not.

5.3.1 Out-Of-Sample Forecasts—July 2016 to January 2018: WPI Inflation

The forecast accuracy results for different models in case of WPI inflation are reported in Table 5. Tables 7, 8 and 9 give the Diebold Mariano test across various models. The main results are summarized below:

1. Examination of RMSE suggests that forecasts generated from ARIMA-GARCH are more inaccurate than FAVAR and VECM models. Among the two multivariate models, FAVAR has lower RMSE as compared to the VECM model.
2. The "U" statistic is close to one for ARIMA-GARCH and VECM model but is lower for FAVAR.
3. For ARIMA-GARCH and VECM model, although RMSE is increasing with the increase in forecast horizon, this pattern is not corroborated by Theil's "U" possibly because the accuracy of the naïve forecasts is worsening more than those generated from the univariate model or VECM. FAVAR, however, shows a consistent decline in "U" with an increase in forecast horizon.
4. Modified Diebold Mariano test suggests that forecasts from the ARIMA-GARCH model are statistically more accurate than the VECM model at shorter horizons, whereas at longer horizons, VECM model outperforms the results from ARIMA-GARCH. FAVAR model is statistically more accurate than the univariate and the VECM model at all horizons.
5. Figure 1a to 1d in the appendix give the 3, 6, 9 and 12-month ahead forecasts made using ARIMA-GARCH, VECM and the FAVAR models. The plots show that forecasts from the FAVAR model are more accurate in predicting the actual WPI inflation. The predicted values are closer to the actual values, and the forecasts

Table 5 Out-of-sample forecast accuracy (July 2016 to January 2018): WPI inflation

		ARIMA-GARCH				VECM				FAVAR			
Summary	N	RMSPE	RMSE	Theil's U	**3-month average U**	RMSPE	RMSE	Theil's U	**3-month average U**	RMSPE	RMSE	Theil's U	**3-month average U**
1 M ahead	19	2.05	1.42	0.84		1.76	1.67	0.99		1.97	1.79	1.06	
2 M ahead	18	2.62	2.35	0.83		2.67	2.30	0.81		1.99	1.73	0.61	
3 M ahead	17	2.81	3.27	0.88	**0.85**	2.93	3.38	0.91	**0.90**	1.75	1.60	0.43	**0.70**
4 M ahead	16	2.52	3.95	0.92		2.86	4.46	1.04		1.58	1.09	0.25	
5 M ahead	15	2.48	4.38	0.94		3.23	4.68	1.01		2.40	1.60	0.35	
6 M ahead	14	2.83	4.81	0.97	**0.94**	3.22	4.45	0.90	**0.98**	2.87	1.95	0.39	**0.33**
7 M ahead	13	3.55	5.15	0.97		3.52	4.94	0.93		2.93	1.99	0.38	
8 M ahead	12	3.04	4.85	0.86		3.23	4.67	0.83		3.01	2.08	0.37	
9 M ahead	11	4.07	5.68	0.94	**0.93**	3.15	5.06	0.84	0.87	3.00	2.07	0.35	**0.37**
10 M ahead	10	4.30	5.55	0.86		3.47	5.17	0.81		3.10	2.11	0.33	
11 M ahead	9	2.92	5.64	0.88		2.37	5.31	0.83		0.52	0.96	0.15	
12 M ahead	8	4.50	5.46	0.90	**0.88**	4.50	4.41	0.73	0.79	4.50	0.95	0.16	**0.21**
Average		**3.14**	**4.38**	**0.90**		**3.08**	**4.21**	**0.89**		**2.47**	**1.66**	**0.40**	

Bold in the column are 3-month averages and bold in the row are annual average generated are able to capture the peaks and troughs in the actual series better than the univariate or the VECM models.

The overall results show that FAVAR performs consistently better than the univariate and the VECM models. Further, accuracy of the forecasts improves at longer horizons in the case of FAVAR possibly due to the fact that interdependencies between variables play a larger role as the forecast horizon increases in a data-rich framework.

5.3.2 Out-Of-Sample Forecasts—July 2016 to January 2018: CPI Inflation

Table 6 reports the RMSE and Theil's U-statistic for CPI inflation over the forecast period for a 12-month horizon. Results in Tables 7, 8 and 9 provide the results for the Modified Diebold Mariano test.

Examination of results suggests the following:

1. RMSE suggests that forecasts generated from ARIMA-GARCH are more inaccurate than FAVAR and VECM models. Between the two multivariate models, FAVAR has lower RMSE as compared to the VECM model.
2. ARIMA-GARCH model has "U" value greater than 1. "U" statistic is less than one in case of both VECM and FAVAR models, but it is lower for FAVAR.
3. Results for DM test show that forecasts from the ARIMA-GARCH model are statistically more accurate than the multivariate VECM model at shorter horizons. Further, at longer forecast horizons, VECM model generates statistically more accurate forecasts than the ARIMA-GARCH model. Forecasts generated from FAVAR model are more accurate than the univariate ARIMA-GARCH and the VECM model at almost all horizons.
4. Fig. 2a to d in the appendix give the 3, 6, 9 and 12-month ahead forecasts made using ARIMA-GARCH, VECM and the FAVAR models. The plots show that forecasts from the FAVAR model are more accurate in predicting the actual CPI inflation. The predicted values are closer to the actual values, and the forecasts generated are able to capture the peaks and troughs in the actual series better than the univariate or the VECM models.

Results outlined above show that FAVAR performs consistently better than the univariate and the VECM model. Further, accuracy of the forecasts improves at longer horizons in the case of FAVAR as the model takes into account larger number of interdependencies among variables in a framework that employs a richer dataset.

Table 6 Out-of-sample forecast accuracy (July 2016 to January 2018): CPI inflation

	N	ARIMA-GARCH				VECM				FAVAR			
Summary		RMSPE	RMSE	Theil's U	**3-month Average U**	RMSPE	RMSE	Theil's U	**3-month Average U**	RMSPE	RMSE	Theil's U	**3-month Average U**
1 M ahead	19	0.18	0.53	0.78		0.44	0.84	1.25		0.54	1.17	1.73	
2 M ahead	18	0.38	1.03	0.89		0.77	1.35	1.16		0.35	0.90	0.77	
3 M ahead	17	0.60	1.48	0.93	**0.86**	0.92	1.81	1.14	**1.18**	0.41	1.02	0.64	**1.05**
4 M ahead	16	0.80	1.90	1.00		0.60	1.91	1.01		0.39	0.87	0.46	
5 M ahead	15	1.06	2.33	1.09		0.74	2.10	0.99		0.37	0.84	0.40	
6 M ahead	14	1.34	2.71	1.18	**1.09**	0.84	2.21	0.96	**0.98**	0.28	0.84	0.36	**0.41**
7 M ahead	13	1.60	3.07	1.28		0.86	2.45	1.02		0.44	0.76	0.32	
8 M ahead	12	1.74	3.38	1.40		0.77	2.50	1.04		0.31	0.76	0.32	
9 M ahead	11	2.12	3.74	1.49	**1.39**	0.70	2.22	0.88	**0.98**	0.30	0.74	0.29	**0.31**
10 M ahead	10	2.73	4.16	1.51		0.74	2.32	0.84		0.36	0.79	0.29	
11 M ahead	9	3.40	4.62	1.57		0.58	1.57	0.53		0.37	0.74	0.25	
12 M ahead	8	4.50	5.11	1.76	**1.61**	4.50	1.61	0.55	**0.64**	4.50	0.72	0.25	**0.26**
Average		**1.71**	**2.84**	**1.24**		**1.04**	**1.91**	**0.95**		**0.72**	**0.85**	**0.51**	

Bold in the column are 3-month averages and bold in the row are annual average

Table 7 DM test for VECM vs ARIMA-GARCH Out-of-sample period: July 2016 to January 2018

Measure of inflation	WPI inflation	CPI inflation
Month ahead	VECM versus ARIMA-GARCH	
1	ARIMA-GARCH better than VECM[e]	ARIMA-GARCH better than VECM[b]
2	ARIMA-GARCH better than VECM[e]	ARIMA-GARCH better than VECM[d]
3	Indifferent	ARIMA-GARCH better than VECM[d]
4	ARIMA-GARCH better than VECM[d]	Indifferent
5	ARIMA-GARCH better than VECM[d]	Indifferent
6	Indifferent	Indifferent
7	Indifferent	Indifferent
8	Indifferent	VECM better than ARIMA-GARCH[d]
9	VECM better than ARIMA-GARCH[d]	Indifferent
10	VECM better than ARIMA-GARCH[d]	VECM better than ARIMA-GARCH[b]
11	VECM better than ARIMA-GARCH[d]	VECM better than ARIMA-GARCH[a]
12	VECM better than ARIMA-GARCH[a]	VECM better than ARIMA-GARCH[a]

a: significant at 1%; b: significant at 5%; c: significant at 10%; d: significant at 15%; e: significant at 20%

6 Conclusion

In this study, we generate forecasts for WPI and CPI inflation in India in a FAVAR framework. These forecasts are then compared with alternative models to test for their accuracy and select the best performing model. The models under consideration are ARIMA-GARCH and VECM. Firstly, determinants of inflation were identified in a cointegrating VAR framework. It was found that there is a long-run relationship between inflation and its determinants, namely inflation expectations, output gap, rate of growth of money supply, interest rate, exchange rate, global oil inflation, minimum support price inflation, fiscal deficit and deviation of actual rainfall from normal. Based on the cointegrating framework, we categorize variables into broad categories, construct factors and then estimate Factor-Augmented VAR (FAVAR). Models are estimated for the period 2001:05 to 2016:06, and out-of-sample recursive forecasts are generated for the time period 2016:07 to 2018:01 by continuously re-estimating the model and adding an observation to it each time.

Table 8 DM test for FAVAR versus ARIMA-GARCH Out-of-sample period: July 2016 to January 2018

Measure of inflation	WPI inflation	CPI inflation
Month ahead	VECM versus ARIMA-GARCH	
1	Indifferent	FAVAR better than ARIMA-GARCH[a]
2	FAVAR better than ARIMA-GARCH[d]	Indifferent
3	FAVAR better than ARIMA-GARCH[b]	FAVAR better than ARIMA-GARCH[c]
4	FAVAR better than ARIMA-GARCH[a]	FAVAR better than ARIMA-GARCH[d]
5	FAVAR better than ARIMA-GARCH[a]	FAVAR better than ARIMA-GARCH[a]
6	FAVAR better than ARIMA-GARCH[a]	FAVAR better than ARIMA-GARCH[a]
7	FAVAR better than ARIMA-GARCH[a]	FAVAR better than ARIMA-GARCH[a]
8	FAVAR better than ARIMA-GARCH[a]	FAVAR better than ARIMA-GARCH[a]
9	FAVAR better than ARIMA-GARCH[a]	FAVAR better than ARIMA-GARCH[a]
10	FAVAR better than ARIMA-GARCH[a]	FAVAR better than ARIMA-GARCH[a]
11	FAVAR better than ARIMA-GARCH[a]	FAVAR better than ARIMA-GARCH[a]
12	FAVAR better than ARIMA-GARCH[a]	FAVAR better than ARIMA-GARCH[a]

a: significant at 1%; b: significant at 5%; c: significant at 10%; d: significant at 15%; e: significant at 20%

The FAVAR model for both measures of inflation suggests that in terms of normalized generalized variance decompositions, maximum variation in WPI inflation in India is explained by exchange rate factor, followed by MSP inflation and then by inflation expectations, whereas maximum variation in CPI inflation is explained by expected inflation followed by monetary and credit factor, fiscal factors and finally by output factors.

The main findings of our study are that for both WPI and CPI inflation, multivariate models produce more accurate forecasts than univariate model over longer forecast horizons. This is because the interactions and dependencies between variables become stronger over longer horizons. In other words, for shorter horizons, predictions that are dependent on past history may yield better results.

Among the multivariate models, FAVAR produces more accurate forecasts over all horizons. The Modified Diebold Mariano test suggests that the forecasts from the multivariate FAVAR model are significantly more accurate than the VECM

Table 9 DM test for FAVAR versus VECM Out-of-sample period: July 2016 to January 2018

Measure of inflation	WPI inflation	CPI inflation
Month ahead	VECM versus ARIMA-GARCH	
1	Indifferent	VECM better than FAVAR[b]
2	FAVAR better than VECM[b]	FAVAR better than VECM[a]
3	FAVAR better than VECM[b]	FAVAR better than VECM[a]
4	FAVAR better than VECM[b]	FAVAR better than VECM[a]
5	FAVAR better than VECM[b]	FAVAR better than VECM[a]
6	FAVAR better than VECM[a]	FAVAR better than VECM[a]
7	FAVAR better than VECM[a]	FAVAR better than VECM[a]
8	FAVAR better than VECM[a]	FAVAR better than VECM[b]
9	FAVAR better than VECM[a]	FAVAR better than VECM[b]
10	FAVAR better than VECM[a]	FAVAR better than VECM[c]
11	FAVAR better than VECM[a]	FAVAR better than VECM[a]
12	FAVAR better than VECM[a]	FAVAR better than VECM[b]

a: significant at 1%; b: significant at 5%; c: significant at 10%; d: significant at 15%; e: significant at 20%

model and the univariate ARIMA-GARCH model. Theil's U-statistic and RMSE also indicate that FAVAR model results in more accurate forecasts as compared to univariate ARIMA-GARCH and multivariate VECM model. Forecast accuracy in case of FAVAR increases as the forecast horizon widens. This is true for both the measures of inflation. This may be true as FAVAR model encompasses more information about the economy and takes into account a larger number of interdependencies among variables.

Forecasts from the ARIMA-GARCH model are significantly more accurate than the multivariate VECM model only for shorter forecast horizons. At longer horizons, forecasts from the VECM model are significantly more accurate than the ARIMA-GARCH model. This is true for both measures of inflation. Normally, multivariate models are expected to produce more accurate forecasts because of a larger information set. In the case of VECM, since cointegration is a long-run phenomenon, an inclusion of an error correction term is expected to improve the predictive ability of the model at longer horizons if the variables are indeed cointegrated.

Thus, we can infer that availability of large amount of information on macroeconomic variables in the economy can lead to a more informed view on the future course of inflation in the economy, which may permit the policymakers to plan their actions in advance. This would further help them to achieve the objective of price stability and hence growth in the economy. This study further becomes relevant in the light of the flexible inflation targeting regime recently adopted by the RBI whereby inflation dynamics can be managed in a wider context.

Appendix

See Table 10, Figs. 1 and 2

Questions to Think About

1. Multivariate forecasting can improve the predictive power by including other predictors and sharing information across forecasts. In the light of the above statement, compare the multivariate and univariate methods of forecasting inflation.

   Hint: ARIMA, ARIMA-GARCH, VAR. Refer: Dua et al. (2003).
2. What are the key drivers of inflation in developed and developing economies? Are there significant differences between the two?

   Hint: Use IMF and World Bank databases to analyse inflation in developed and developing economies. Refer: Dua and Gaur (2010).
3. a) How does principal component analysis relate to FAVAR?

   Hint: Refer Liu and Jansen (2007), Lutkepohl (2014).

   b) Estimation of FAVAR model is traditionally employed to study the dynamic effects of innovations to monetary policy on a variety of key macroeconomic variables. Using the database described in the chapter, apply the FAVAR methodology to examine the evidence of the effect of monetary policy innovations on key macroeconomic indicators.

   Hint: Refer Bernanke et al., (2005, QJE).

Table 10 Data definitions and sources

	Name of the series	Transformation	Remarks	Data sources
1	WPI all commodities inflation	First difference	Natural log of the variable is used to arrive at year-on-year inflation	www.mospi.nic.in
2	CPI general index inflation	First difference	We use natural log of the variable in each case, de-seasonalize the series and calculate year-on-year inflation	
Real economic activity (2004–2005 = 100)				
	Name of the series	Transformation	Remarks	
1	IIP General	First difference	We use natural log of the variable in each case, de-seasonalize the series and apply Christiano-Fitzgerald filter to obtain output gap which is used as an indicator of real economic activity	www.mospi.nic.in
2	IIP Electric			
3	IIP Manufacturing			
4	IIP Mining			
5	IIP Basic Goods			
6	IIP Capital Goods			
7	IIP Intermediate Goods			
8	IIP Consumer Goods			
9	Index of Electricity			
10	Index of Coal			
11	Index of Crude Oil			
12	Index of Refinery			
13	Index of Steel			
14	Index of Cement			
15	Index of Overall Core Infrastructure Industry (2004–05 = 100)			
Interest rate factor				
1	Treasury Bill Rate 15–91 Days	First difference	Variables are used in levels as they are already in % terms	www.rbi.org.in
2	Govt. Security 1 Year			
3	Govt. Security 5 Years			
4	Govt. Security 10 Years			
5	Repo Rate			
6	Prime Lending Rate			

(continued)

Table 10 (continued)

	Name of the series	Transformation	Remarks	Data sources
Monetary and credit factors				
7	Growth of Money Supply (M0)	First difference	All variables are converted in natural logs to arrive at stationary series except bank credit to commercial sector and net bank credit to the government: RBI as they contain negative values	www.rbi.org.in
8	Growth of Money Supply (M1)			
9	Growth of Money Supply (M2)			
10	Growth of Money Supply (M3)			
11	Growth of Money Supply (M4)			
12	Bank Credit to the Commercial Sector			
13	Bank Credit to the Commercial Sector: RBI			
14	Net Bank Credit to the Government			
15	Net Bank Credit to the Government: RBI			
Exchange rate factor				
1	Exchange Rate (USD)	First difference	All variables are first converted into natural logs and then first difference is taken to arrive at stationary series	www.rbi.org.in
2	Exchange Rate (POUND)			
3	Exchange Rate (SDR)			
4	Exchange Rate (EURO)			
5	Exchange Rate (YEN)			
6	NEER Trade Based (36 countries)			
7	NEER Export Based (36 countries)			
External inflation factor				
8	World Commodity Price Index	First difference	All variables are first converted into natural logs. Then, year-on-year inflation is calculated and then first difference is taken to arrive at stationary series	www.imf.org
9	World Food Prices			
10	World Food and Beverage Prices			
11	World Beverage Prices			
12	World Oil Prices			
13	World Energy Prices			
14	World Industrial Input Prices			

(continued)

Table 10 (continued)

	Name of the series	Transformation	Remarks	Data sources
15	World Agriculture Raw Material Prices			
16	World Metal Prices			
Fiscal factors				
1	Total Government Expenditure	First difference	All variables are first converted into natural logs except the deficit indicators as these contain negative values	www.cga.nic.in
2	Total Government Revenue			
3	Fiscal Deficit			
4	Revenue Deficit			
5	Primary Deficit			
MSP inflation factor				
1	MSP of Paddy	First difference	All variables are first converted into natural logs. Then, year-on-year inflation is calculated and then first difference is taken to arrive at stationary series	www.agricoop.nic.in
2	MSP of Coarse Cereal			
3	MSP of Wheat			
4	MSP of Gram			
5	MSP of Arhar			
6	MSP of Moong			
7	MSP of Urad			
8	MSP of Sugarcane			
9	MSP of Cotton			
10	MSP of Jute			
11	MSP of Groundnut			
12	MSP of Soyabeen Black			
13	MSP of Soyabeen Yellow			
14	MSP of Sunflower			
15	MSP of Rapeseed/Mustard			
WPI food inflation factors				
1	WPI Food	First difference	All variables are first converted into natural logs. Then, year-on-year inflation is calculated and then first difference is taken to arrive at stationary series	www.mospi.nic.in
2	WPI Manufacturing Food			
3	WPI Food Grain			
4	WPI Cereal			
5	WPI Pulses			
6	WPI Vegetables			
7	WPI Fruits			

(continued)

Table 10 (continued)

	Name of the series	Transformation	Remarks	Data sources
8	WPI Milk			
9	WPI Egg, Meat, etc			
10	WPI Spices			
11	WPI Manufacturing Dairy Products			
12	WPI Processing			
13	WPI Grain Mill			
14	WPI Sugar Salt			
15	WPI Confectionary			
16	WPI Edible Oil			
17	WPI Tea			
18	WPI Coffee			
19	WPI Bakery Product			
20	WPI Tea Processing			
21	WPI Other Food Articles			
22	WPI Beverages			
WPI input inflation factor				
1	WPI Fuel And Power	First difference	All variables are first converted into natural logs. Then, year-on-year inflation is calculated and then first difference is taken to arrive at stationary series	www.mospi.nic.in
2	WPI Coal			
3	WPI Cooking Coal			
4	WPI Mineral Oil			
5	WPI LPG			
6	WPI Petrol			
7	WPI Kerosene			
8	WPI Heavy Diesel Oil	No		
9	WPI Electricity			
10	WPI Agricultural Electricity	First difference		
11	WPI Fertilizers and Pesticides			
12	WPI Fertilizers			
13	WPI Pesticides			
Rainfall				
1	Rainfall seasonalized	No	Variables are de-seasonalized, and they are stationary in levels	www.imd.gov.in
2	% deviation seasonalized			

(continued)

Table 10 (continued)

	Name of the series	Transformation	Remarks	Data sources
CPI food inflation factor				
1	CPI Cereals and Products	First difference	All variables are first converted into natural logs. Then, year-on-year inflation is calculated and then first difference is taken to arrive at stationary series	www.mospi.nic.in
2	CPI Meat and Fish			
3	CPI Egg			
4	CPI Milk and Products			
5	CPI Oils and Fats			
6	CPI Fruits			
7	CPI Vegetables			
8	CPI Pulses and Products			
9	CPI Sugar and Confectionery			
10	CPI Spices			
11	CPI Other Food			
CPI input inflation				
1	CPI Fuel and Light	First difference	All variables are first converted into natural logs. Then, year-on-year inflation is calculated and then first difference is taken to arrive at stationary series	www.mospi.nic.in

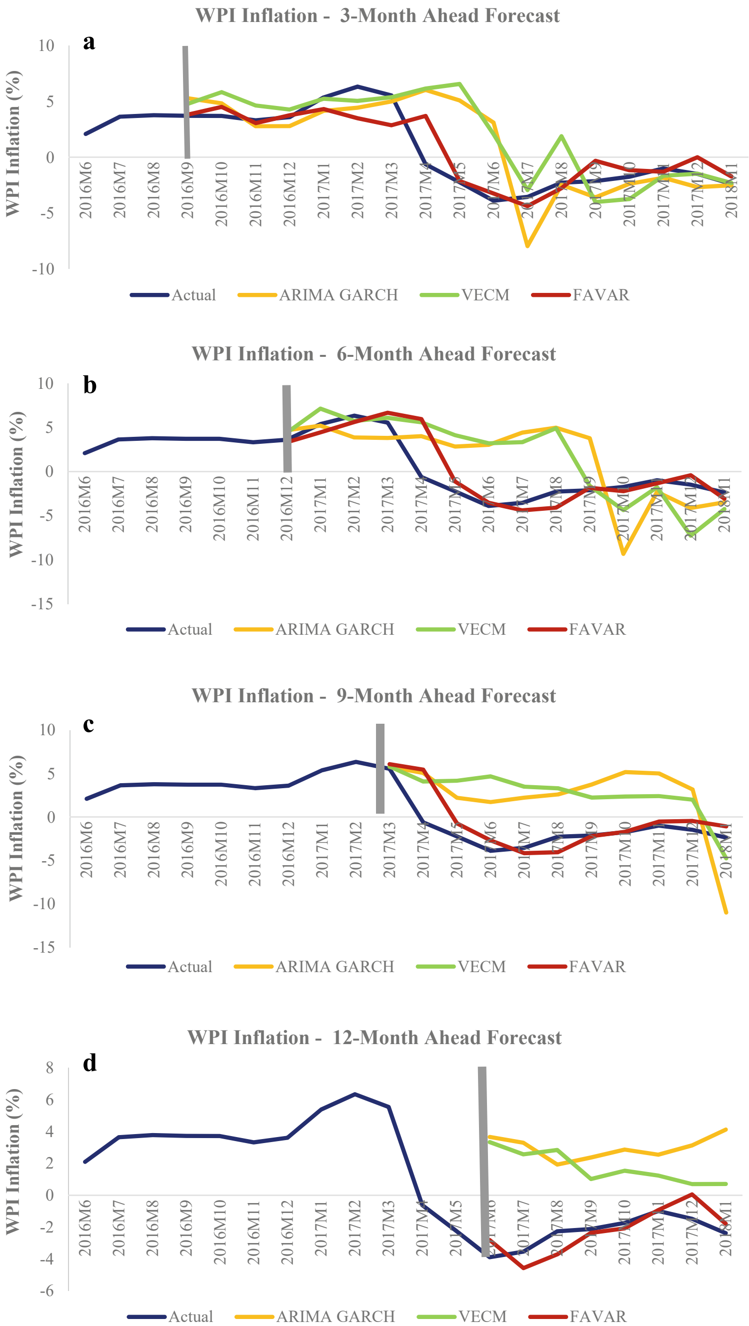


Fig. 1 Out-of-sample Forecasts for WPI inflation **a** 3-month ahead forecast,**b** 6-month ahead forecast,**c** 9-month ahead forecast, **d** 12-month ahead forecast

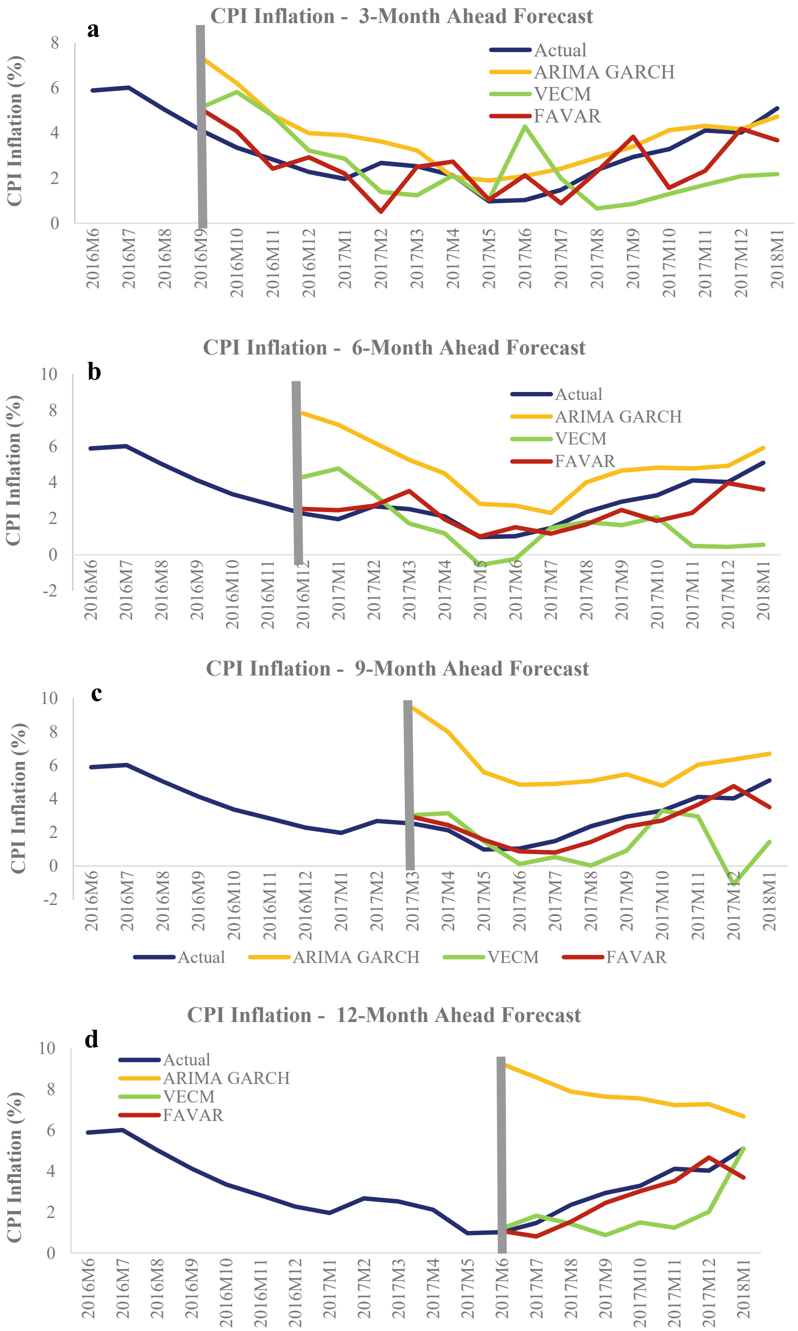


Fig. 2 Out-of-sample forecasts for CPI inflation **a** 3-month ahead forecast, **b** 6-month ahead forecast, **c** 9-month ahead forecast, **d** 12-month ahead forecast

References

Almeida, V., & Félix, R. (2006). *Computing potential output and the output-gap for the Portuguese economy*. Economics and Research Department, Banco de Portugal.

Atta-Mensah, J., & Bawumia, M. (2003). *A simple vector error correction forecasting model for Ghana, WP 01*. Bank of Ghana.

Aye, G. C., Dua, P., & Gupta, R. (2015). Forecasting Indian macroeconomic variables using medium-scale VAR models. *Current Trends in Bayesian Methodology with Applications, 2*, 37–59.

Bagliano, F. C., & Morana, C. (2009). International macroeconomic dynamics: A factor vector autoregressive approach. *Economic Modelling, 26*(2), 432–444.

Bai, J., & Ng, S. (2002). Determining the number of factors in approximate factor models. *Econometrica, 70*(1), 191–221.

Bai, J., & Wang, P. (2015). Identification and Bayesian estimation of dynamic factor models. *Journal of Business & Economic Statistics, 33*(2), 221–240.

Banbura, M., & Mirza, H. (2013). *Forecasting euro area inflation with the Phillips curve*. Manuscript, European Central Bank.

Baştürk, N., Çakmakli, C., Ceyhan, S. P., & Van Dijk, H. K. Posterior-predictive evidence on us inflation using extended new Keynesian Phillips curve models with non-filtered data. *Journal of Applied Econometrics*, *29*, 1164–1182.

Belviso, F., & Milani, F. (2005). Structural factor-augmented VAR (SFAVAR) and the effects of monetary policy. *SSRN 695483.*

Bernanke, B. S., & Boivin, J. (2003). Monetary policy in a data-rich environment. *Journal of Monetary Economics, 50*(3), 525–546.

Bernanke, B. S., Boivin, J., & Eliasz, P. (2005). Measuring the effects of monetary policy: A factor-augmented vector autoregressive (FAVAR) approach. *The Quarterly Journal of Economics, 120*(1), 387–422.

Biswas, D., Singh, S. & Sinha, A. (2010). Forecasting inflation and IIP growth: Bayesian vector autoregressive model. *Occasional Papers*, *31*(2), 31–48. RBI.

Bordoloi, S., Biswas, D., Singh, S., Manna, U. K., & Saggar, S. (2010). Macroeconomic forecasting using dynamic factor models. *Occasional Papers*, *31*(2), 69–83. RBI.

Calvo, G. A. (1983). Staggered prices in a utility-maximizing framework. *Journal of monetary Economics, 12*(3), 383–398.

Callen, T., & Dongkoo, C. (1999). *Modelling and forecasting inflation in India, WP 99–119*. IMF.

Christiano, L. J., & Fitzgerald, T. J. (2003). The band pass filter. *International Economic Review, 44*(2), 435–465.

Ciccarelli, M., & Mojon, B. (2010). Global inflation. *The Review of Economics and Statistics, 92*(3), 524–535.

Clark, T. E., & McCracken, M. W. (2010). Averaging forecasts from VARs with uncertain instabilities. *Journal of Applied Econometrics, 25*(1), 5–29.

DeJong, D., Nankervis, J., Savin, N. & Whiteman, C. (1988). *Integration versus trend-stationarity in macroeconomic time series, WP 88–27*. Department of Economics, University of Iowa

Dholakia, R. H., & Kadiyala, V. S. (2018). Changing dynamics of inflation in India. *Economic & Political Weekly, 53*(9), 65.

Diebold, F. X., & Mariano, R. S. (1995). Comparing predictive accuracy. *Journal of Business & Economic Statistics, 13*, 253–263.

Doz, C., Giannone, D., & Reichlin, L. (2011). A two-step estimator for large approximate dynamic factor models based on kalman filtering. *Journal of Econometrics, 164*(1), 188–205.

Doz, C., Giannone, D., & Reichlin, L. (2012). A quasi-maximum likelihood approach for large, approximate dynamic factor models. *Review of Economics and Statistics, 94*(4), 1014–1024.

Dua, P., & Mishra, T. (1999). Presence of persistence in industrial production: The case of India. *Indian Economic Review*, 23–38.

Dua, P., & Gaur, U. (2010). Determination of inflation in an open economy Phillips curve framework: The case of developed and developing Asian countries. *Macroeconomics and Finance in Emerging Market Economies, 3*(1), 33–51.

Dua, P., & Suri, R. (2019). Interlinkages between USD–INR, EUR–INR, GBP–INR and JPY–INR exchange rate markets and the impact of RBI intervention. *Journal of Emerging Market Finance, 18*(1_suppl), S102–S136.

Dua, P., & Goel, D. (2021). Determinants of inflation in India. *The Journal of Developing Areas, 55*(2).

Dua, P., Raje, N., & Sahoo, S. (2003). *Interest rate modelling and forecasting in India*. Department of Economic Analysis and Policy, RBI.

Eickmeier, S., & Ziegler, C. (2006). *How good are dynamic factor models at forecasting output and inflation? A meta-analytic approach, WP 42*. Deutsche Bundesbank.

Faust, J., & Wright, J. H. (2013). Forecasting inflation. *Handbook of Economic Forecasting, 2*, 2–56.

Fernald, J. G., Spiegel, M. M., & Swanson, E. T. (2014). Monetary policy effectiveness in China: Evidence from a FAVAR model. *Journal of International Money and Finance, 49*, 83–103.

Figueiredo, F. M. R. (2010). *Forecasting Brazilian inflation using a large data set, WP 228*. Central Bank of Brazil.

Forni, M., Hallin, M., Lippi, M., & Reichlin, L. (2003). Do financial variables help forecasting inflation and real activity in the euro area? *Journal of Monetary Economics, 50*(6), 1243–1255.

Forni, M., Hallin, M., Lippi, M., & Reichlin, L. (2005). The generalized dynamic factor model: One-sided estimation and forecasting. *Journal of the American Statistical Association, 100*(471), 830–840.

Gavin, W. T., & Kliesen, K. L. (2008). Forecasting inflation and output: Comparing data-rich models with simple rules. *Federal Reserve Bank of St. Louis Review*, *90*(3 Part 1), 175–92.

Gerdesmeier, D., Roffia, B., & Reimers, H. E. (2017). Forecasting euro area inflation using single-equation and multivariate VAR–models. *Oeconomica Stetinensia, 17*(2), 19–34.

Gosselin, M. A., & Tkacz, G. (2001). *Evaluating factor models: An application to forecasting inflation in Canada, WP 18*. Bank of Canada.

Harvey, D., Leybourne, S., & Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting, 13*(2), 281–291.

Hoa, T. T. (2017). *Forecasting inflation in Vietnam with univariate and vector autoregressive models, WP 05*. Graduate Institute of International and Development Studies.

Hubrich, K. (2005). Forecasting euro area inflation: Does aggregating forecasts by HICP component improve forecast accuracy? *International Journal of Forecasting, 21*(1), 119–136.

Hulagu, T., & Sahinoz, S. (2012). Is Disagreement a Good Proxy for Inflation Uncertainty? Evidence from Turkey. *Central Bank Review, 12*(1), 53–62.

Huseynov, S., Ahmadov, V., & Adigozalov, S. (2014). *Beating a random walk: "Hard times" for forecasting inflation in post-oil boom years?, MPRA Paper 63515*. University Library of Munich.

Ibarra-Ramírez, R. (2010). *Forecasting inflation in Mexico using factor models: Do disaggregated CPI data improve forecast accuracy, WP 01*.

Kavtaradze, L., & Mokhtari, M. (2018). Factor models and time-varying parameter framework for forecasting exchange rates and inflation: A survey. *Journal of Economic Surveys, 32*(2), 302–334.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics, 74*(1), 119–147.

Le Bihan, H., & Sedillot, F. (2000). Do core inflation measures help forecast inflation?: Out-of-sample evidence from French data. *Economics Letters, 69*(3), 261–266.

Liu, D., & Jansen, D. W. (2007). Macroeconomic forecasting using structural factor analysis. *International Journal of Forecasting, 23*(4), 655–677.

Liu, D., & Jansen, D. W. (2011). Does a factor Phillips Curve help? An evaluation of the predictive power for US inflation. *Empirical Economics, 40*(3), 807–826.

Lombardi, M. J., Osbat, C., & Schnatz, B. (2012). Global commodity cycles and linkages: A FAVAR approach. *Empirical Economics, 43*(2), 651–670.

Lutkepohl, H. (2014). *Structural vector autoregressive analysis in a data rich environment: A survey, SFB 649 Discussion Paper*. Humboldt University.

Mandalinci, Z. (2017). Forecasting inflation in emerging markets: An evaluation of alternative models. *International Journal of Forecasting, 33*(4), 1082–1104.

Mariano, R. S., Dakila, F. G., Jr., & Claveria, R. A. (2010). The bangko sentral's structural long-term inflation forecasting model for the Philippines. *Philippine Review of Economics, 40*(1), 58–72.

Moser, G., Rumler, F., & Scharler, J. (2007). Forecasting Austrian inflation. *Economic Modelling, 24*(3), 470–480.

Nadal De Simone, F. (2000). *Forecasting inflation in Chile using state-space and regime-switching models, WP 162*. IMF.

Önder, A. Ö. (2004). Forecasting inflation in emerging markets by using the Phillips Curve and alternative time series models. *Emerging Markets Finance and Trade, 40*(2), 71–82.

Paul, S., Rather, S. R., & Ramachandran, M. (2015). *Money and inflation: Evidence from P-Star model, WP 115*. Madras School of Economics.

Pesaran, H. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters, 58*(1), 17–29.

Petrovska, M., Ramadani, G., Naumovski, N., & Jovanovic, B. (2017). *Forecasting Macedonian inflation: Evaluation of different models for short-term forecasting, WP 06*. National Bank of the Republic of North Macedonia.

Ramakrishnan, U., & Vamvakidis, A. (2002). *Forecasting inflation in Indonesia, WP 111*. IMF.

Reserve Bank of India. (2014). *Report of the expert committee to revise and strengthen the monetary policy framework* (Chairman: Dr. Urjit R. Patel), Mumbai.

Rubio-Ramirez, J. F., Waggoner, D. F., & Zha, T. (2010). Structural vector autoregressions: Theory of identification and algorithms for inference. *The Review of Economic Studies, 77*(2), 665–696.

Rumler, F., & Valderrama, M. T. (2010). Comparing the New Keynesian Phillips Curve with time series models to forecast inflation. *The North American Journal of Economics and Finance, 21*(2), 126–144.

Sims, C. A. (1988). Bayesian skepticism on unit root econometrics. *Journal of Economic Dynamics and Control, 12*(2–3), 463–474.

Stock, J. H., & Watson, M. W. (1999). Forecasting inflation. *Journal of Monetary Economics, 44*(2), 293–335.

Stock, J. H., & Watson, M. W. (2002). Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association, 97*(460), 1167–1179.

Stock, J. H., & Watson, M. W. (2005). *Implications of dynamic factor models for VAR analysis, WP 11467*. National Bureau of Economic Research.

Stock, J. H., & Watson, M. W. (2006). Forecasting with many predictors. *Handbook of Economic Forecasting, 1*, 515–554.

Stock, J. H., & Watson, M. W. (2016). Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. *Handbook of Macroeconomics, 2*, 415–525.

Sun, T. (2004). *Forecasting Thailand's core inflation, WP 090*. IMF.

Taylor, J. B. (1980). *Aggregate dynamics and staggered contracts. Journal of political economy, 88*(1), 1–23

Theil, H. (1966). *Applied economic forecasting*. Amsterdam North-Holland Pub.

Thomakos, D. D., & Bhattacharya, P. S. (2005). Forecasting inflation, industrial output and exchange rates: A template study for India. *Indian Economic Review, 40*(2), 145–165.

Walsh, M. J. P. (2011). Reconsidering the role of food prices in inflation. *International Monetary Fund*.

Younus, S., & Roy, A. (2016). *Forecasting inflation and output in Bangladesh: Evidence from a VAR model*. Bangladesh Bank: Research Department and Monetary Policy Department.

Chapter 10
A Structural Macroeconometric Model for India

Pami Dua and Hema Kapur

Abstract This study builds a small empirical structural macroeconometric model using quarterly data for India. The model has five sectors: real, fiscal, monetary, price and external sector and 14 behavioural equations (and five identities) which are estimated using two stage least squares from 1996 Q2 to 2010 Q4. The observations from 2011 Q1 to 2013 Q2 are used for out-of-sample forecasting performance. The model is a modified and extended version of the SMEM developed by Haque et al. (IMF Staff Papers 37:537–559, 1990) and also accommodates sectoral shifts, real and financial sector linkages and open macroeconomy linkages. Both *in-sample* and *out-of-sample* forecasting performance of the model indicate that the RMPSE for all variables is within the acceptable range. The paper also quantifies the economic impact of the following six alternative scenarios on key macroeconomic variables: tight monetary policy; fiscal profligacy; mixed liberal policy; weather shock; external price shock (hike) and a global shock. The main results of the baseline scenario and impact analysis are plausible and as expected. The weather shock has a significant but temporary effect in decreasing GDP growth rate. The external price shock has a strong adverse impact on economic activity and inflation. Amongst all, the global shock is the most severe in reducing GDP growth rate. Policy shocks/measures, such as fiscal policy in the form of higher government borrowings and spending and/or monetary policy in the form of a decline in Repo or CRR positively impact output growth.

Keywords Macroeconometric model · Policy simulation · Propagation mechanism

JEL Classification E27 · E44 · F30

P. Dua
Department of Economics, Delhi School of Economics, University of Delhi, Delhi, India
e-mail: dua@econdse.org

H. Kapur (✉)
Department of Economics, Hansraj College, University of Delhi, Delhi, India
e-mail: hm.kapur@gmail.com

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_10

1 Introduction

Structural macroeconometric models (SMEMs) provide a theoretical basis, a framework and a conduit for empirical quantification of how the economy has behaved in the past on average and also of the extent to which its current or prospective behaviour might differ. These models enable policymakers, central banks, institutions and academic researchers to forecast the impact of shocks on the economy. Given the persistent economic issues in an economy such as inflation, deficits and debt burdens coupled with the uncertainty around policy decision-making, the canvas of macroeconomic modelling provides a consistent framework for analysis of the current economic situation (to examine the major determinants of the main endogenous macroeconomic variables) and policy purposes (to forecast the evolution of the key macroeconomic variables).

In this study, we develop an empirical SMEM using quarterly data for the Indian economy from 1996 Q2 to 2010 Q4. The observations beyond 2010 Q4 are used for out-of-sample forecasting performance. The estimated model is then used for policy analysis and simulation experiments, which in turn are used to create baseline scenarios and six alternative macroeconomic scenarios.

The main strength of the model is that while it is a small empirical economy-wide structural model based on quarterly data, it contains sufficient policy levers and channels of transmission mechanism to conduct simulation experiments. The relatively small size of the model makes it easy to interpret simulation results, identify specific transmission channels, and thus provide a simple and effective operational tool for economic analysis.

The study modifies and extends the Haque et al. (1990) model to incorporate some new variables and features in line with empirical investigation of behavioural equations. The model captures the stock market impact on the real economy directly through the wealth effect on consumers and indirectly through the credit channel effect and business confidence. The model also incorporates the 'covered interest parity' in the money block which enables us to validate the augmented version of the Fisher's hypothesis by introducing external factors[1] in the determination of the domestic nominal interest rate, as is expected in an integrated open economy with globalization and liberalization.

The Indian economy is now much more integrated with the rest of the world, and adverse developments in other countries/regions have repercussions on the domestic economy. The East Asian crisis in 1997–98, global price shocks[2] in 2008 and the global financial crisis (GFC) in 2007–09 are good examples where the impact was felt to varying degrees. The main usefulness of the model, therefore, lies in providing a conduit that helps ensure internal consistency while studying the different inter-linkages within the economy given its connections with the rest of the world. Thus,

[1] The external factors (such as foreign interest rate and forward premium) allow for propagation of international financial impulses to be transmitted to the Indian financial system.

[2] Such as the sharp rise in global food and global crude oil prices in the first half of 2008.

it can be used to conduct simulations and quantify the impact of various external shocks and policy actions on the domestic economy.

The paper is organized as follows: Section 2 provides a review of macroeconomic modelling in the Indian context. Section 3 outlines the theoretical base model, while Section 4 describes the empirical model. Section 5 presents the estimation methodology. Section 6 discusses the estimation results. Section 7 illustrates simulation experiments, and the final section concludes the paper.

2 Macroeconomic Modelling in India

There already exist a large number of MEMs in the Indian context which have contributed to the extensive rich literature. The contribution of each of these models is distinct in terms of their objectives, level of disaggregation, theoretical and empirical methodology, data coverage and frequency, variables used and the applications. Majority of these models are based on annual data[3] (Krishnamurty, 2008), while recently with the availability of higher frequency data,[4] and small structural models have been estimated using quarterly data such as Bhanumurthy and Kumawat (2009) and Srivastava (2013).

There are also some live projects of institutions which have been consistently updated, revised and estimated by reputed research institutions and authorities. These include INDIA-LINK project (quarterly frequency) by Dua, Bhanumurthy and Kumawat based on Bhanumurthy and Kumawat (2009); Perspective Planning Division In-House Model (PPDIHM) by Ghosh and Sachdeva (2009); VAR/VEC Model from ISI, Bangalore, by Ghosh and Narayana (2009); CGE Model from IGIDR, Mumbai, by Kumar and Panda (2009); SMEM from IEG, Delhi, by Kar and Pradhan (2009); MEM of NCAER, Delhi, by Bhide and Parida (2009) and the RBI-MSE Macro-Modelling Project given in Srivastava (2013).

Table 1 sketches a comparison of recent (published) SMEMs based on quarterly data in India to bring out the differences in terms of size and structure of the model, estimation methodology, choice of variables and objective of the study. These include Bhanumurthy and Kumawat (2009), (RBI-MSE) model in Srivastava (2013) and the model estimated in this paper. The highlights of the present model include relatively small size,[5] addition of new variables and features (such as stock market impact on real consumption spending, investment multiplier impact on real exports and CIP condition in interest rate determination) and robust diagnostic testing using instrumental variable estimation (IVE) technique.

[3] See, e.g. Ahluwalia and Rangarajan (1986); Anjaneyulu (1993); Bhattacharya (1984); Bhattacharya and Rao (1986); Chakrabarty (1987); Goyal (1994); Krishnamurty et al., (1989); Krishnamurty et al., (2004); Mallick (2004); Klein and Palanivel (1999); Mehta and Panchamukhi (1991); Pandit (1986); Pani (1977, 1984).

[4] Quarterly data on GDP and its components has become available since 1996 Q2 onwards.

[5] The model has fewer stochastic equations compared to the other published SMEMs based on quarterly data in the Indian context.

Table 1 Comparison of recent SMEMs based on quarterly data in India

Variable	B&K (2009)[a]	RBI-MSE (2013)[b]	Present Model
Sample period	1996 Q2–2008 Q4	1997–98 Q1 to 2012–13 Q2	1996 Q2–2013 Q2
Total no. of equations	27	81	19
Size of the model/no. of stochastic equations	24	46	14
Estimation method	ARDL	2SLS in co-integrating framework in two layers	2SLS IVE based on Hsiao (1997a, 1997b)
Objective	Simulation	Forecasting	Simulation and policy analysis
Economy classification	Five sectors—real, price, monetary, fiscal and trade	Four sectors—real, fiscal, monetary & financial and external	Five sectors—real, price, money, fiscal and external
Real sector	Two blocks—aggregate demand (AD) and aggregate supply (AS)	Three blocks—AD, aggregate output, capital stock and investment	Two blocks—AD and AS
Aggregate supply/output	Three subsectors' classification—agriculture, industry and services	Eight subsectors' classification—agriculture and allied activities; mining and quarrying; manufacturing; electricity, gas and water supply; construction; trade, hotels, transport, storage, and communications; finance, insurance, real estate and business services and community, social and personal services	Three subsectors' classification—agriculture, industry and services
Fiscal sector	Three endogenous variables—tax revenue, non-tax revenue and government expenditure	Six endogenous variables—personal income taxes, corporate, union excise duties, service tax and other central taxes, revenue and K expenditure	Both govt. revenue and expenditure exogenous
Monetary sector	Ms endogenous	Ms endogenous	Ms exogenous
Monetary measure	M_2	M_0, M_3, L_1 and L_3	M_3
Nominal interest measure	Prime lending rate (PLR)	Deposit rate, PLR and call money rate	TB-91 rate
Price block	Three price indices—GDP price deflator, WPI and CPI	Three price indices—GDP deflator, WPI (and its subcomponents) and selected CPI	Two price indices—GDP price deflator and WPI

(continued)

Table 1 (continued)

Variable	B&K (2009)[a]	RBI-MSE (2013)[b]	Present Model
External sector	Exchange rate endogenous; oil and non-oil exports and oil and non-oil imports disaggregation	Exchange rate exogenous; oil and non-oil exports and oil and non-oil imports disaggregation	Exchange rate endogenous; aggregate exports and aggregate imports are modelled

Notes
1. [a]B&K (2009) denotes Bhanumurthy and Kumawat (2009).
2. [b]RBI-MSE (2013) denotes Srivastava (2013)

3 The Base Model

The structure of the model is based on a stylized structure of MEM for a small open developing economy as a flexible price variant of the Mundell Fleming model, in Haque et al. (1990).[6] The base model has four sectors—aggregate demand, aggregate supply, monetary and government sector with seven behavioural equations. The essence of the model is briefly presented below.

3.1 Aggregate Demand

Aggregate spending in real terms (Y_t) is described as the sum of consumption (C), investment (I), government expenditure (G) and the trade balance [exports (X) – imports (Z)].

$$Y_t = C_t + I_t + G_t + X_t - Z_t \tag{1}$$

The consumption function is determined by the real interest rate (r_t) and disposable income $\left(Y_t^d\right)$:

$$C_t = f\left(Y_t^d(+), r_t(-)\right) \tag{2}$$

Investment depends on real output and real interest rate:

$$I_t = f(Y_t(+), r_t(-)) \tag{3}$$

Exports are assumed to depend on the real exchange rate[7] (re_t) and the real output abroad (Yt*):

[6] Kannapiran (2003) also follows a similar theoretical framework.

[7] Real exchange rate is defined as the nominal exchange rate (e_t, , price of foreign currency in domestic currency terms) multiplied by the relative prices given by ratio of the domestic and foreign prices, i.e. $re_t = e_t * \left(P_t/P_t^*\right)$.

$$X_t = f\left(re_t(+), Y_t^*(+)\right) \tag{4}$$

Real imports respond negatively to the real exchange rate and positively to real domestic output. Since restricted availability of foreign exchange reserves (R_t) frequently leads to the imposition of import controls and foreign exchange rationing and thereby acts as a constraint on imports in developing countries, the reserve–import ratio has also been included in the import equation:

$$Z_t = f(re_t(-), Y_t(+), R_t/Z_t(+)). \tag{5}$$

3.2 Aggregate Supply

The supply side is characterized by a Cobb–Douglas production function, where output is dependent on labour (L) and capital (K):

$$Y_t = \theta_0 K^{\theta_1} L^{\theta_2} \tag{6}$$

3.3 Money Market

The money supply (M) in the economy has two components—reserves in foreign currency (R) and domestic credit (DC):

$$M_t = e_t R_t + DC_t \tag{7}$$

where domestic credit is a policy variable.

$$DC_t = DC_{P,t} + DC_{G,t} \tag{8}$$

where $DC_{P,t}$ and $DC_{G,t}$ denote domestic credit availability to private and public sectors, respectively.

Money demand depends on the nominal rate of interest and the level of income:

$$M_t/P_t = f(i_t(-), Y_t(+)) \tag{9}$$

The nominal interest rate (i_t) is determined by the 'uncovered interest parity' condition (UIP) in case of an open economy and by money supply along with the domestic demand for a closed economy:

$$i_t = f(UIP, M_t, Y_t) \tag{10}$$

3.4 Government

This sector is specified by a budget constraint by combining both revenue and expenditures. The seven behavioural equations, given by Eqs. (2), (3), (4), (5), (6), (9) and (10), are estimated from the theoretical base model.

4 The Empirical Model

The empirical model is derived from the stylized base model described above, customized and expanded to address the theme of the study. We follow an eclectic approach using various strands of economic theory and empirical literature in modelling the macroeconomic variables to take into account contemporary linkages and recent developments in the economy, at both the domestic and international levels.

Thus, the model incorporates recent structural changes (such as sectoral transformation), global transmission channels (impact of sharp rise in global food and crude oil prices, net foreign inflows into the economy, global financial crisis and a significant role of external factors like foreign interest rate and forward premia) and changes in policy regime (since exchange rate is now largely market determined and domestic nominal interest rate is deregulated) in the economy. Our choice of variables, level of disaggregation and frequency of the sample data in this modelling exercise are primarily guided by the availability of data and objective of the study.

Accordingly, the model also includes various additional variables that might influence the behaviour of endogenous variables in the model in the light of the recent empirical investigation of behavioural equations. The empirical model has 14 stochastic equations, and the rest are definitions or identities. The model is classified into five parts—real sector with aggregate demand and production block, fiscal sector, monetary sector, price block and the external sector—and is outlined below.

The expected signs of the coefficients of the variables in the equation are indicated in parentheses according to economic theory. Table 2 indicates definition, empirical measures and sources of various data variables.

Table 2 Data variables, definitions and sources

Variable	Definition	Source
BC^G	Bank credit to the government (Rs billion)	www.rbi.org
BC^P	Bank credit to the private sector (Rs billion)	www.rbi.org
Business Confidence	BSE SENSEX and FII denoting Foreign Institutional Investment flows (Rs billion)	www.rbi.org
CAB	Current account balance (Rs billion)	www.rbi.org
CALL	Call money rate (%), quarterly average interest rate in the call money market	www.rbi.org
C	Real private final consumption expenditure (Rs billion)	www.rbi.org
CRR	Cash reserve ratio (%) is the amount of funds that the banks are required to keep with the RBI	www.rbi.org
DC^G	Real bank credit to the government, BC^G deflated by GDP price deflator	
DC^P	Real bank credit to the private sector, BC^P deflated by GDP price deflator	
e	Exchange rate (Rs per US $)	www.rbi.org
E	Real government revenue, nominal govt. revenue deflated by GDP price deflator	
FD	Real government fiscal deficit, GFD deflated by GDP price deflator	
FII	Net Foreign Institutional Investment flows (Rs billion)	www.rbi.org
FPI	Net Foreign Portfolio Investment flows, (Rs billion)	www.rbi.org
FUEL	Fuel price index	www.rbi.org
G	Real public consumption expenditure (Rs billion)	www.rbi.org
i	Nominal interest rate given by TB 91 day yield rate	www.rbi.org
$\bar{i}$	Policy rate (repo rate) (%) is the rate at which the RBI lends to commercial banks against eligible securities in order to meet their daily liquidity requirements	www.rbi.org

(continued)

Table 2 (continued)

Variable	Definition	Source
π	Annualized inflation calculated as $((P_t - P_{t-1})/P_{t-1}*100)$ using GDP price deflator	
I	Real gross fixed capital formation (Rs billion)	www.rbi.org
LIBOR	3-month London Inter-Bank Offered Rate is the average interest rate at which leading banks borrow funds of a sizeable amount from other banks in the London market. LIBOR is the most widely used 'benchmark' or reference rate for short-term interest rates	www.imf.org, IFS
M	Nominal broad money, M3	www.rbi.org
P	GDP price deflator	www.mospi.nic.in
P^{AGR}	Price deflator for agriculture	www.mospi.nic.in
PG	Total quarterly power generation measured in billion kwh (sum of thermal and nuclear power generation and hydel power generation)	CMIE, monthly review of the Indian economy
P^{IND}	Price deflator for industry	www.mospi.nic.in
r	Real rate of interest given by Fisher's equation as the difference between nominal interest rate and the rate of inflation ($=i - \pi$)	
RAIN	Total quarterly rainfall (mm)	CMIE, monthly review of the Indian economy
R	Real government revenue, nominal government revenue deflated by GDP price deflator	
RM	Real money supply, M3 deflated by GDP price deflator	
S	BSE SENSEX	www.rbi.org
USD	US discount rate (% per annum)	www.imf.org, IFS
WCPI	World CPI (2005 = 100)	www.imf.org, IFS
W^{OIL}	World crude oil (petroleum) index(2005 = 100)	www.imf.org, IFS
W^F	World food price index (2005 = 100)	www.imf.org, IFS
π^W	World inflation, per cent change over corresponding period of previous year	www.imf.org, IFS
X	Real exports (Rs billion)	www.rbi.org

(continued)

Table 2 (continued)

Variable	Definition	Source
Y	Real GDP at factor cost (2004–05)	www.mospi.nic.in
Y^{AGR}	Real GDP agriculture (2004–05)	www.mospi.nic.in
Y^{IND}	Real GDP industry (2004–05)	www.mospi.nic.in
Y^{SER}	Real GDP services (2004–05)	www.mospi.nic.in
Y^{W}	OECD real GDP (Rs billion)	Stats.OECD
Z	Real imports (Rs billion)	www.rbi.org

4.1 Real Sector

4.1.1 Aggregate Demand Block

The national income accounting identity defining[8] the real aggregate demand for domestic output (Y_t) as the sum of domestic absorption (A_t) and trade balance ($X_t - Z_t$) is specified below:

$$Y_t = A_t + (X_t - Z_t) \quad \text{or} \quad Y_t^{MP} = C_t + I_t + G_t + X_t - Z_t \tag{11}$$

4.1.2 Private Consumption Function

The empirically estimated private consumption function is determined by the current income,[9] real interest rate,[10] a proxy for wealth as broad money and stock prices:

$$C_t = C(Y_t(+), r_t(-), RM_t(+), S_t(+)) \tag{12}$$

In the empirical model, the stock market index is also considered as a determinant of consumption spending, since the stock market may also influence spending directly via the wealth effect on consumers or indirectly via the credit channel effect[11] through

[8] The empirical equation is similar in most models of developing economies, e.g. Bhanumurthy and Kumawat (2009); Bier (1992); Hanif et al (2011); Haque et al (1990); Hudson and Dymiotou-Jensen (1989); Kannapiran (2003); Krishnamurty et al (2004); and World Bank (1995a,b).

[9] In the empirical model, we use current total real income measured by the real GDP at market prices as a measure of disposable income because all the taxes and transfer components needed to calculate the disposable income are not available on a quarterly basis.

[10] Regarding real interest rate $\left(r_t = i_t - \pi_t^e\right)$, we assume perfect foresight and use actual/future rate of inflation, while studies like Haque et al (1990) and Taylor (1988) consider rational expectations, where $\pi_t^e = \frac{E_t P_{t+1} - P_t}{P_t}$ and Kannapiran (2003) considers naive expectations and takes actual rate of inflation into account.

[11] The credit channel effect is defined as the impact of stock market on the borrowing capacity of consumers and investors, determining the value of capital in place relative to replacement costs.

its impact on the borrowing capacity of consumers and investors. Gauthier and Li (2006)[12] examine the link between the real economy and stock market in their BEAM model for Canada. Other studies such as Dhar et al. (2000) for the USA and Cassola and Morana (2002) for the UK also consider the stock market nexus with the real economy.

4.1.3 Investment Function

The empirically estimated investment function[13] is expressed as follows:

$$I_t = I(Y_t(+), r_t(-), DC_t(+), \text{Business confidence}(+)) \quad \text{or}$$
$$I_t = I\left(Y_t(+), r_t(-), DC_t^P(+), DC_t^G(+/-), E_t(+), S_t(+), FII_t(+)\right) \tag{13}$$

where business confidence[14] and public (total) consumption expenditure and real bank credit to public sector[15] to capture the crowding in and crowding out effects, respectively, have also been added to the model.

4.1.4 Public Consumption Function

Unlike private consumption expenditure, the public provision of goods and services is not freely chosen but established a priori by the government mainly governed by social welfare and political conditions in the economy, Haque et al. (1990) and Kannapiran (2003).

Accordingly, the public/government final consumption expenditure is assumed to be exogenous and is specified as follows:

$$G_t = \overline{G} \tag{14}$$

[12] Gauthier and Li (2006) consider two determinants of consumption spending—stock market and current income in their BEAM model for Canada.

[13] The investment function is specified as positively correlated to real output, financial/liquidity situation of the private sector (i.e. availability of external financing (DC_t)) and negatively to the real interest rate.

[14] Business confidence in the economy is expected to capture firm's expected profitability (as per Tobin's q theory) in the recent scenario better.

[15] In general, the impact of bank credit availability to public sector can be positive or negative indicating crowding in and crowding out effect, respectively. Theoretically, public investment spending is expected to enhance and strengthen infrastructures (as a critical input) needed for private production, which in turn stimulates the productivity of private investment. This is captured rightly by the total real public expenditure with positive sign indicating that public sector expenditure complements private sector investment. On the other hand, net domestic borrowings by public sector crowd out the available savings in the economy available for private investment. Refer Bhanumurthy and Kumawat (2009) and Krishnamurty et al (2004).

4.1.5 Production Block

Estimation of the aggregate supply by using a neoclassical production function (Haque et al., 1990) is hampered by unavailability of data on capital stock as well as on employment on quarterly basis. Thus, an empirical measure of production block specified here is in the same spirit of recent models using quarterly data for the Indian economy [Bhanumurthy and Kumawat, (2009), with three sector disaggregation; Srivastava (2013) with eight sector classification]. The production block is subdivided into three major parts: agriculture, industry and services. Production for agriculture sector $\left(Y_t^{\mathrm{AGR}}\right)$ is specified as a function of fairly standard variables capturing supply side (rain and investment) and demand side (price of agriculture goods) factors:

$$\begin{aligned} Y_t^{\mathrm{AGR}} &= Y^{\mathrm{AGR}}(\text{supply side factors, demand side factors})\text{or} \\ Y_t^{\mathrm{AGR}} &= Y^{\mathrm{AGR}}\left(\mathrm{Rain}(+),\, I_t(+),\, P_t^{\mathrm{AGR}}(+)\right) \end{aligned} \tag{15}$$

Further, production for industry $\left(Y_t^{\mathrm{IND}}\right)$ is specified as a function of domestic demand (captured by non-industrial output $\left(Y_t^{\mathrm{AGR}} + Y_t^{\mathrm{SER}}\right)$ and investment), external demand (captured by exports and exchange rate) and stance of the monetary policy (as availability of real bank credit and the nominal interest rate):

$$\begin{aligned} Y_t^{\mathrm{IND}} &= Y^{\mathrm{IND}}(\text{domestic demand, external demand, stance of monetary policy})\text{or} \\ Y_t^{\mathrm{IND}} &= Y^{\mathrm{IND}}\left(\left(Y_t^{\mathrm{AGR}} + Y_t^{\mathrm{SER}}\right)(+),\, I_t(+),\, X_t(+),\, e_t(+),\, DC_t(+),\, i_t(-)\right) \end{aligned} \tag{16}$$

Similarly, production for services $\left(Y_t^{\mathrm{SER}}\right)$ is modelled as determined by the domestic demand $\left((Y_t^{\mathrm{AGR}} + Y_t^{\mathrm{IND}}\right)$, investment (I_t) and external demand captured by world GDP $\left(Y_t^w\right)$ and exchange rate (e_t):

$$\begin{aligned} Y_t^{\mathrm{SER}} &= Y^{\mathrm{SER}}(\text{domestic demand, external demand) or} \\ Y_t^{\mathrm{SER}} &= Y^{\mathrm{SER}}\left(\left(Y_t^{\mathrm{AGR}} + Y_t^{\mathrm{IND}}\right)(+),\, I_t(+),\, Y_t^w(+),\, e_t(+)\right) \end{aligned} \tag{17}$$

Now the aggregate supply side (as given by the real output) can be defined as the sum of the production of agriculture, industry and services which is an identity:

$$Y_t = Y_t^{\mathrm{AGR}} + Y_t^{\mathrm{IND}} + Y_t^{\mathrm{SER}} \tag{18}$$

4.2 Fiscal Sector

In the fiscal sector, the fiscal identity is specified as Eq. (19), where fiscal deficit or balance is defined as total government expenditure (E_t) minus total government revenue (R_t). All these variables are exogenous and expressed in real terms.

$$FD_t = E_t - R_t \tag{19}$$

4.3 Monetary Sector

In the monetary block, the determination of monetary aggregate and nominal interest rate is formulated. Money market equilibrium is defined as an identity where supply for real balances equals demand for real balances.

$$M_t^s = M_t^d \tag{20}$$

Supply of money is given by net foreign assets (NFA_t) plus domestic credit (DC_t) minus net non-monetary liabilities ($NNML_t$). DC_t includes both credit to the private and public sector (net) and is assumed to be an exogenous variable which is determined by the credit, interest rate and other related policies of banks and monetary and fiscal policies of the government (Haque et al., 1990; Kannapiran, 2003).

$$M_t^s = NFA_t + DC_t - NNML_t \tag{21}$$

Demand for money is specified as positively correlated to real income and negatively correlated to the nominal interest rate (Haque et al., 1990; Kannapiran, 2003). In Eq. (22), real income (Y_t) and nominal interest rate (i_t) are determined as endogenous variables.

$$M_t^d = M(Y_t(+), i_t(-)) \tag{22}$$

The nominal interest rate is determined as an endogenous variable by solving Eq. (22) for i_t[16]:

$$i_t = i\left(M_t^d(-), Y_t(+)\right) \tag{23}$$

This model differs from Haque et al. (1990) with respect to the interest parity condition. Since we are considering India as an open economy with capital mobility, domestic and foreign financial assets are not assumed to be perfect substitutes, because of the presence of various types of risk. In such a situation, the existence of a forward market provides a mechanism for getting a forward cover for the anticipated component of exchange risk. Thus, the nominal interest rate is determined by a 'covered interest parity' (CIP) condition, similar to Dua and Pandit (2002). CIP implies that the interest rate differential between two sovereigns is determined by

[16] Similar theoretical framework has been followed by Ramanathan (1992) and Kannapiran (2003).

the exchange rate forward premium,[17] due to arbitrage. Given this, a CIP condition would hold if:

$$i_t = i_t^* + FP_t \tag{24}$$

Accordingly, the empirically estimated equation, following Bhattacharya et al. (2008), Dua and Pandit (2002), and Dua and Raje (2013), considers various reduced form determinants of the interest rate such as broad money (M_t), , policy rate (repo $(\bar{i}_t)$), foreign interest rate (i_t^*), , forward premium (FP_t) and public final spending (G_t) as specified below:

$$i_t = i\big(M_t(+/-), \pi_t(+), \bar{i}_t(+), i_t^*(+), FP_t(+), G_t(+)\big) \tag{25}$$

The impact of the monetary measure on the interest rate can be negative or positive depending on the liquidity effect and the latter as the inflation expectation effect. The inflation rate is also expected to have a positive impact on the interest rate. However, as the economy moves towards liberalization and gradually integrates with the world economy, the international inter-dependencies in the financial markets become important in the determination of interest rate. Thus, international variables also play a prominent role in the determination of interest rate.[18]

4.4 Price Block

Since we are considering the supply side with three sector disaggregation, the GDP price deflator is estimated for each of the three sectors separately. Then the aggregate GDP deflator is derived as a weighted average of the sectoral price deflators with weights given by the GDP sectoral shares.

The price deflator for agriculture sector is modelled as a function of demand side factors such as money supply, supply side factors such as output, input costs such as fuel prices and government intervention given by administered prices/minimum support prices:

$$P_t^{\text{AGR}} = \text{(demand side factors, supply side factors, government intervention)or}$$
$$P_t^{\text{AGR}} = P^{\text{AGR}}\big(M_t(+), Y_t^{\text{AGR}}(-), FUEL_t(+), MSP_t(+)\big) \tag{26}$$

Similarly, the price deflator for industry is also determined by demand (e.g. money supply and non-industrial output), supply and cost side (fuel) variables:

[17] Forward premium (FP_t) is defined as forward foreign exchange rate (F_t) minus spot exchange rate (S_t).

[18] For details on various correlates of interest rate function, refer Dua and Raje (2013).

$$P_t^{\text{IND}} = P^{\text{IND}}(\text{demand side factors, supply/cost side factors})\text{or}$$
$$P_t^{\text{IND}} = P^{\text{IND}}\big(M_t(+), \big(Y_t - Y_t^{\text{IND}}\big)(+), FUEL_t\ (+)W_t^F(+)\big) \tag{27}$$

Finally, the price deflator for services is determined by demand, supply and cost side variables:

$$P_t^{\text{SER}} = P^{\text{SER}}(\text{demand side facors, supply/cost side factors})\text{or}$$
$$P_t^{\text{SER}} = P^{\text{SER}}\big(M_t(+), Y_t^{\text{SER}}(-), FUEL(+), W_t^F(+)\big) \tag{28}$$

Then the aggregate GDP deflator (P_t) is given by the following identity where w_{AGR}, w_{IND} and w_{SER} denote the sectoral shares of agriculture, industry and services, respectively, in the GDP:

$$P_t = w_{\text{AGR}} P_t^{\text{AGR}} + w_{\text{IND}} P_t^{\text{IND}} + w_{\text{SER}} P_t^{\text{SER}} \tag{29}$$

We also consider another price variable, viz. wholesale price index (WPI)[19] in addition to the GDP deflator. The empirically estimated WPI function[20] is determined by GDP deflator (P_t), fuel prices $(FUEL_t)$ and world food prices $\big(W_t^F\big)$:

$$\text{WPI}_t = \text{WPI}(P_t(+), FUEL_t(+), W_t^F(+) \tag{30}$$

4.5 External Sector

External sector is classified into two parts: trade and exchange rate determination. We are considering India as a small open economy and assume it to be a price taker in the world market. Hence, we take world food prices, world crude petroleum/oil prices, important minerals and metal prices to be exogenously given.

---

[19] Bhanumurthy and Kumawat (2009); Krishnamurty et al. (2004) and Srivastava (2013) also considered the consumer price index (CPI). Mohanty (2010) notes, ‘The WPI is considered as the headline inflation measure because of its availability at high frequency, until recently, national coverage and availability of disaggregated data which facilitate better analysis of inflation’.

[20] Various determinants of WPI inflation considered in Dua and Gaur (2010) have also been tried, and the final results are reported here.

4.6 Trade Block

4.6.1 Export Function

In the light of recent empirical evidence,[21] additional variables have been tried to widen the domain of base model to capture exports dynamics better in an integrated economy. Panagiotidis and Sharma (2005) consider causality between real GDP, gross fixed capital formation and exports for India. Devi and Dhananjayan (1997); Kruegar (1978); Salvatore and Hatcher (1991), find significant correlation between exports and domestic economic growth, while Ghatak and Price (1997) and Kemal et al (2002); Rehman and Mustafa (1997) find an evidence for growth-driven exports. Asafu-Adjaye and Chakraborty (1999) and Konya and Singh (2006) do not find any support for growth-driven exports hypothesis for India. Thus, with globalization and liberalization, and its consequences such as freeing of trade, capital account convertibility, we have a strong case for India being well integrated with rest of the world economy. Given this, the impact of domestic investment on exports is expected to be positive. This is because any increase in investment resulting in greater output is now not confined to just domestic boundaries but faces a larger global market. Accordingly, the empirical export function is specified as a function of world GDP, foreign and domestic inflation, exchange rate and investment:

$$X_t = X\left(Y_t^w(+), \pi_t^w(+), \pi_t(-), e_t(+), I_t(+)\right) \tag{31}$$

4.6.2 Import Function

Since oil imports constitute around 80% of our total imports, the real imports equation[22] is specified as a function of domestic demand (real output), real exchange rate and competitiveness as measured by relative import/world prices and world prices of crude petroleum as below:

$$Z_t = Z\left(Y_t(+), e_t(-), P_t^W(-), W_t^{\mathrm{OIL}}(+)\right) \tag{32}$$

[21] Refer Di Mauro and Forster (2008), Dieppe et al (2012), Fagan et al., (2001, 2005) and Hanif et al (2011).

[22] For modelling of import function and its various correlates, refer Aghevli and Sassanpour (1982); Bhanumurthy and Kumawat (2009); Carone (1996); Dutta and Ahmed (2006); Emran and Shilpi (2010); Ginman and Murray (1976); Goldstein and Khan(1985); Haque et al (1990); Houthakker and Magee (1969); Leamer and Stern (1970); Lopez and Thomas (1990); Mallick (2004); Kannapiran (2003); Khan and Knight (1988) and Ziramba and Bbuku (2013).

4.6.3 Exchange Rate Function

The exchange rate is determined endogenously in the model by fairly standard variables, following Dua and Sen (2011) and Dua and Ranjan (2012) as a function of domestic and foreign interest rate, domestic and world output, domestic money supply along with certain other variables that explain the capital flows (such as net FII inflow and stock prices).

$$e_t = e\big(i_t(+), i_t^*(-), Y_t(-), Y_t^w(+), M_t(+), FII_t(-), S_t(-)\big) \quad (33)$$

The behavioural/stochastic equations and the identities/definitions summarizing the empirical model are given together in Tables 3 and 4, respectively, followed by a flow chart describing the direct transmission effects of the shocks and policy changes to the system.

Table 3 Behavioural/stochastic equations of the empirical model

Sector	Block	Equations
Real	Aggregate demand	$C_t = C(Y_t(+), r_t(-), RM_t(+), S_t(+))$
		$I_t = I\big(Y_t(+), r_t(-), DC_t^P(+), DC_t^G(-), E_t(+), S_t(+), FII_t(+)\big)$
	Aggregate supply	$Y_t^{\text{AGR}} = Y^{\text{AGR}}\big(\text{Rain}(+), I_t(+), P_t^{\text{AGR}}(+)\big)$
		$Y_t^{\text{IND}} = Y^{\text{IND}}\big((Y_t^{\text{AGR}} + Y_t^{\text{SER}})(+), I_t(+), X_t(+), e_t(+), DC_t(+), i_t(-)\big)$
		$Y_t^{\text{SER}} = Y^{\text{SER}}\big((Y_t^{\text{AGR}} + Y_t^{\text{IND}})(+), I_t(+), Y_t^w(+), e_t(+)\big)$
Monetary		$M_t^d = M(Y_t(+), i_t(-))$
		$i_t = i\big(M_t(+/-), \pi_t(+), \bar{i}_t(+), i_t^*(+), FP_t(+), G_t(+)\big)$
Price		$P_t^{\text{AGR}} = P^{\text{AGR}}\big(M_t(+), Y_t^{\text{AGR}}(-), FUEL_t(+), MSP_t(+)\big)$
		$P_t^{\text{IND}} = P^{\text{IND}}\big(M_t(+), (Y_t - Y_t^{\text{IND}})(+), FUEL_t(+), P_Z(+)\big)$
		$P_t^{\text{SER}} = P^{\text{SER}}\big(M_t(+), Y_t^{\text{SER}}(-), FUEL(+), P_Z(+)\big)$
		$\text{WPI}_t = \text{WPI}(P_t(+), FUEL_t(+), W_t^F(+)$
External	Trade	$X_t = X\big(Y_t^w(+), \pi_t^w(+), \pi_t(-), e_t(+), I_t(+)\big)$
		$Z_t = Z\big(Y_t(+), e_t(-), P_t^W(-), W_t^{OIL}(+)\big)$
	Exchange rate	$e_t = e\big(i_t(+), i_t^*(-), Y_t(-), Y_t^w(+), M_t(+), FII_t(-), S_t(-)\big)$

Table 4 Identities/definitions of the empirical model

National income accounting identity	$Y_t = C_t + I_t + G_t + X_t - Z_t$
Aggregate supply identity	$Y_t = Y_t^{\mathrm{AGR}} + Y_t^{\mathrm{IND}} + Y_t^{\mathrm{SER}}$
Fiscal identity	$FD_t = E_t - R_t$
Money market equilibrium	$M_t^d = M_t^s$
Aggregate price identity	$P_t = w_{\mathrm{AGR}} P_t^{\mathrm{AGR}} + w_{\mathrm{IND}} P_t^{\mathrm{IND}} + w_{\mathrm{SER}} P_t^{\mathrm{SER}}$

5 Estimation Methodology

Since the study estimates a structural model which is a simultaneous equation system, there is an inherent problem of endogeneity of the regressors.[23] Hence, the traditional methods of estimations such as ordinary least squares (OLS) and weighted LS may yield biased and inconsistent estimates. Furthermore, since most of the economic time series are non-stationary, OLS or generalized LS estimation may lead to the problem of what Granger and Newbold (1974) refer to as 'spurious regression'.

Regarding estimation, Hsiao (1997a, 1997b)[24] has shown that, 'even if the variables are non-stationary (as is expected in the present time series analysis), the standard IVE methods and testing procedures can still be applied, provided the variables are co-integrated. If endogenous variables are treated as those determined by the model and exogenous variables as independently determined, then presence/absence of co-integration is presumed from the way a structural model is set up'.

Thus in order to estimate the SMEM with simultaneous relationships between the main macroeconomic variables in India for the time period 1996 Q2 and 2013 Q2, we follow Hsiao (1997a, 1997b). We employ various tests and techniques, in the study, in the following order of their implementation in the analysis.

- Test for non-stationarity of the series
- Check identification property of the simultaneous equation model
- Conduct robust diagnostic testing in IVE using Hausman (1978) test for endogeneity of regressors, the test of overidentification of restrictions (OIR) in Sargan (1964), and both Cumby and Huizinga (1992) CH test[25] as well as modified LM test (1981)[26] for serial correlation in IVE set-up

[23] This is because of the presence of endogenously determined variables on the right-hand side of the equations which may be correlated with the disturbances.

[24] Hsiao (1997a, b), in his influential work, presented an improvement to the Cowles Commission's structural approach by incorporating the advances in time series regression analysis with integrated regressors that take into account non-stationarity and co-integration.

[25] For details, refer Cumby and Huizinga (1992).

[26] The modified LM test for serial correlation in IVE set-up takes care of the presence of endogenous regressors and is explained in Bean (1981) and Gugnani (1985). This test assumes error term to be independently distributed with zero mean and homoscedastic.

- Employ the standard IVE after all the diagnostics are done and econometric problems are taken care of and estimate all behavioural equations using two stage least square (2SLS)
- Use general to specific approach advocated by Hendry et al. (1978, 1980)
- Check if signs of all coefficients in the estimated equations are consistent with the economic theory intuition and
- Undertake model validation using simulation technique.

Some of the tests are briefly described below:

5.1 *Testing For Non-Stationarity*

First, we test for the non-stationarity of the series, i.e. whether they contain a unit root or not. In this study, we employ the DF-GLS test, Elliot et al. (1996), which is a variant of the standard augmented Dickey–Fuller test (Dickey and Fuller (1979, 1981)). We also employ the Ng–Perron test, Ng and Perron (2001), based on their own work, Perron and Ng (1996), and with detrended data, Elliott et al. (1996).

5.2 *Testing for Serial Correlation*

To test for serial correlation in the IVE set-up, we conduct the CH test, Cumby and Huizinga (1992), and modified Lagrange multiplier (LM) test, Bean (1981) and Gugnani (1985)[27] with the null hypothesis of no serial correlation against the alternative of up to pth order autocorrelation. Both the statistics are asymptotically distributed as χ^2 statistic with n–k–p degree of freedom. However, the CH test allows for a more general null that the regression error is a moving average of known order $p \geq 0$ against the general alternative that autocorrelations of regression error are nonzero at lags greater than p and also takes into account the presence of conditional heteroscedasticity of the error term. The CH test[28] is shown to be a more general and improved version of standard Q test in Box and Pierce (1970) and Box and Ljung (1978), h test in Durbin (1970), and LM test in Breusch (1978), in three situations listed below, where the above-stated conventional tests cannot be applied:

- The model contains endogenous regressors and is thus estimated by IVE or generalized methods of moments.
- The error term is conditionally heteroscedastic.
- The model uses overlapping data, mostly in context of financial markets studies.

---

[27] The modified LM test takes care of the presence of endogenous regressors and is explained in Bean (1981) and Gugnani (1985). This test assumes error term to be independently distributed with zero mean and homoscedastic.

[28] For details, refer Cumby and Huizinga (1992).

5.3 Model Validation Using Model Simulation Technique

Validation of a simultaneous equation system is a crucial exercise since it is possible that in a multiple equation model each individual equation may have a good statistical fit, but the model as a whole may do a poor job of reproducing the historical data. This may be because the model as a whole will have a dynamic structure, which is much richer than that of anyone of its individual equations. We examine model validation using the model simulation technique. A widely used simulation error statistic is the root mean square per cent Eerror (RMSPE), which is defined as follows:

$$\text{RMSPE} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{Y_t^s - Y_t^a}{Y_t^a}\right)^2} * 100$$

Both historical/in-sample simulation and an ex-ante/out-of-sample forecast/simulation may be performed to evaluate the model's ability to replicate the actual data. For each experiment, the RMPSE is calculated to evaluate the accuracy of the model's predicted values for each endogenous variable.

6 Estimation Results

6.1 Estimation of Behavioural Equations

First of all, the variables are tested for the presence of a unit root using two tests: DFGLS and Ng–Perron over the sample period 1996 Q2–2010 Q4. Both the tests suggest that all the series under consideration contain unit root and are non-stationary.[29] Then, following Hsiao (1997a, 1997b), we use IVE where the additional instruments considered in our analysis include lagged variables of all endogenous variables and other exogenous variables.

Given the complete specification of the empirical model in Table 3, each equation is identified as the number of excluded predetermined variables from any given equation far exceeds the number of endogenous variables included. Then, we have conducted various diagnostic tests which include the Hausman test, Sargan test and both modified LM and CH test[30] in IVE set-up. All behavioural equations are individually estimated by the OLS[31] and 2SLS method. We have also optimized on

[29] The unit root results have not been reported for brevity and are available on request.

[30] The modified LM test in IVE set-up for serial correlation $\left(\sim \chi^2(1)\right)$ yielded the same result of non-rejection of null of no serial correlation. However, the results are not reported here but are available on request.

[31] OLS estimation results have also been undertaken but are not reported. These are available on request.

lag structure of each equation and used Hendry 'general to specific' modelling procedure.[32]

All the diagnostic tests and estimation results are satisfactory in accordance with theory. Tables 5, 6 and 7 presents the results on 14 estimated behavioural equations of the model. The coefficients of the relevant variables are significant and have the right signs as expected by economic theory. Overall, all the summary measures suggest that the equations fit the data reasonably well for the sample period.

6.2 Model Simulation

All the behavioural equations are estimated by using both OLS and 2SLS as indicated in the above section where the estimated parameters show robustness on the basis of SE of the regression, *t*-test, Hausman test, Sargan test, CH test and modified LM test. However, the OLS estimates in many cases yield wrong signs of coefficients for some of the variables (i.e. not as expected by theory), suffer from serial correlation (implied by the LM statistic) and are not consistent (indicated by the Hausman statistic). Hence, the use of 2SLS (on economic and/or statistical grounds) should reduce the possibility of inconsistency introduced by the model's simultaneity. These equations look reasonable, and the estimates are by and large, consistent.

Accordingly, a simulation model is formed by a set of 14 behavioural equations estimated by 2SLS along with five definitions/identities (as a complete system) which is solved simultaneously, through time. Before using the model to conduct simulation experiments and obtain policy implications, we determine the effectiveness of the model by validating the model.

6.3 Model Validation

For model validation, we perform both in-sample/historical and out-of-sample simulation as a mode of simulation to evaluate the model's ability to replicate the actual data using dynamic simulation. In this method, model is simulated over the entire or a part of the sample period for which the model is estimated and also beyond that. Then, a comparison of the original data series with the simulated series for each endogenous variable is done using conventional criterion of RMPSE. Tables 8 and 9 present the in-sample and out-of-sample results for RMPSE and its analysis.

Furthermore, Fig. 2 shows a negligible difference between the actual and simulated values of the real GDP, indicating that the error is low and unbiased. The base line scenario is the same as the solution of the model. It comprises simulated values which

---

[32] Hendry and others (Davidson et al., 1978; Hendry and Mizon, 1978; Hendry and Srba, 1980) have advocated an approach based on a sequential testing procedure to select a parsimonious representation of a model.

Table 5 Estimated behavioural equations of the model—*real sector*

	Variables															Diagnostic tests			
1	C_t	Constant	C_{t-1}		C_{t-4}	Y_t^{MP}		r_t	RM_t	S_t		DC1		DC2		SE	Z	CH	Z1
		763.791 (0.000)	−0.248 (0.000)		0.715 (0.000)	0.139 (0.005)		−4.721 (0.655)	3.732 (0.002)	0.019 (0.008)		−184.112 (0.135)		−301.329 (0.027)		104.757	5.259 (0.153) [3]	0.041 (0.837)	2.881 (0.718) [5]
Additional instruments: Y_{t-1}^{MP}, Y_{t-2}^{MP}, Y_{t-3}^{MP}, Y_{t-4}^{MP}, $\bar{i}_t$, r_{t-1}, RM_{t-1}, RM_{t-2}																			
2	I_t	Constant	I_{t-1}	I_{t-2}	I_{t-3}	I_{t-4}	Y_t^{MP}	Y_{t-1}^{MP}	r_t	DC_t^P	DC_t^G	E_t	FII	S_{t-1}	DI	SE	Z	CH	Z1
		−77.671 (0.753)	0.041 (0.804)	0.185 (0.103)	−0.021 (0.881)	0.169 (0.302)	0.119 (0.001)	0.052 (0.253)	−19.505 (0.060)	0.628 (0.647)	−1.361 (0.068)	6.934 (0.304)	0.487 (0.001)	0.027 (0.013)	−234.918 (0.054)	81.993	16.673 (0.000) [2]	0.144 (0.704)	0.426 (0.514) [1]
Additional instruments: Y_{t-4}^{MP}, r_{t-1}, r_{t-2}																			
3	Y_t^{AGR}	Constant	Y_{t-1}^{AGR}		Y_{t-2}^{AGR}	Y_{t-3}^{AGR}	Y_{t-4}^{AGR}	Y_{t-5}^{AGR}	I_t	DY^{AGR1}	DY^{AGR2}	DY^{AGR3}	DY^{AGR4}	$RAIN_{t-1}-RAIN_{t-2}$		SE	Z	CH	Z1
		821.363 (0.001)	0.445 (0.000)		−0.268 (0.000)	−0.310 (0.000)	0.766 (0.000)	−0.394 (0.000)	0.117 (0.000)	−154.076 (0.007)	−114.177 (0.042)	82.550 (0.123)	−79.100 (0.146)	0.265 (0.003)		49.094	0.054 (0.815) [1]	0.027 (0.868)	5.346 (0.253) [4]
Additional instruments: I_{t-1}, I_{t-2}, Y_{t-1}^{MP}, FII_t, S_t																			
4	Y_t^{IND}	Constant	Y_{t-1}^{IND}		Y_{t-2}^{IND}	Y_{t-3}^{IND}	Y_{t-4}^{IND}	Y_{t-1}^{AGR}	Y_t^{SER}	I_t	I_{t-1}	DC_{t-1}^P	DY^{IND}	DY^{IND1}		SE	Z	CH	Z1
		362.905 (0.011)	0.396 (0.003)		−0.253 (0.002)	0.198 (0.173)	−0.131 (0.417)	0.037 (0.255)	0.058 (0.095)	0.285 (0.000)	−0.147 (0.006)	0.553 (0.047)	−27.566 (0.494)	−43.226 (0.089)		23.374	15.986 (0.000) [2]	4.77E−05 (0.9945)	2.203 (0.531) [3]
Additional instruments: Y_{t-1}^{SER}, Y_{t-2}^{SER}, Y_{t-1}^{MP}, FII_t, S_t																			
5	Y_t^{SER}	Constant	Y_{t-1}^{SER}		Y_{t-2}^{SER}	Y_{t-3}^{SER}	Y_{t-4}^{SER}	Y_{t-1}^{AGR}	I_t	I_{t-1}	i_{t-1}	X_t		DY^{SER}		SE	Z	CH	Z1
		102.737 (0.543)	−0.078 (0.259)		0.008 (0.847)	0.076 (0.516)	0.898 (0.000)	0.092 (0.389)	0.088 (0.510)	0.110 (0.453)	−17.400 (0.000)	0.059 (0.424)		−148.140 (0.083)		50.263	6.595 (0.036) [2]	2.367 (0.123)	2.323 (0.676) [4]

(continued)

Table 5 (continued)

Variables	Diagnostic tests
Additional instruments: Y_{t-1}^{MP}, FII_t, S_t, X_{t-1}, Y_t^W, e_{t-1}	

Notes

1. The first column of Table 9A indicates the equation number and SE is the equation standard error
2. The values in () parenthesis denote the p-values, and [] parenthesis denotes the degrees of freedom
3. Z is Wu–Hausman statistic $\left(\sim \chi^2(p)\right)$ for endogeniety of regressors, with p degrees of freedom
4. CH is the Cumby–Huzinga test in IVE set-up for serial correlation $\left(\sim \chi^2(1)\right)$
5. Z1 is the Sargan's test $\left(\sim \chi^2(q)\right)$ for over identifying restrictions, with q degrees of freedom
6. Equation (1): DC1 = 1 for 1998 Q4 and 0 otherwise and DC 2 = 1 for 2010 Q1 and 0 otherwise
7. Equation (2): DI = 1 for 2009 Q1 and 0 otherwise
8. Equation (3): DY^{AGR1} = 1 for 2002 Q4 and 0 otherwise; DY^{AGR2} = 1 for 2004 Q4 and 0 otherwise; DY^{AGR3} = 1 for 2007 Q4 and 0 otherwise and DY^{AGR4} = 1 for 2009 Q4 and 0 otherwise
9. Equation (4): DY^{IND} = 1 for 2009 Q1 and 0 otherwise and DY^{IND1} = 1 for 2004 Q2 and 0 otherwise
10. Equation (5): DY^{SER} = 1 for 2009 Q1 and 0 otherwise

Table 6 (Part 1) Estimated behavioural equations of the model—*monetary sector*

		Variables														Diagnostic tests			
6	RM_t	Constant	RM_{t-1}	RM_{t-2}	RM_{t-4}	Y_t^{MP}	i_t	DRM								SE	Z	CH	Z1
		−14.936 (0.000)	1.238 (0.000)	−0.567 (0.000)	0.201 (0.009)	0.006 (0.000)	−0.057 (0.888)	−11.014 (0.010)								3.767	21.244 (0.000) [2]	0.285 (0.593)	1.988 (0.737) [4]
Additional instruments: $Y_{t-1}^{MP}\ Y_{t-2}^{MP}\ Y_{t-3}^{MP}\ Y_{t-4}^{MP}\ \pi_{t-1},\ \bar{i}_t$																			
7	i_t	Constant	i_{t-1}	i_{t-2}	i_{t-3}	M_t	$\bar{i}_t$	$\bar{i}_{t-1}$	i_t^*	i_{t-1}^*	FP_t	FP_{t-1}	G_t	Di	Di1	SE	Z	CH	Z1
		0.192 (0.832)	0.656 (0.000)	0.009 (0.927)	0.072 (0.450)	1.74×10^{-6} (0.862)	0.242 (0.006)	−0.204 (0.008)	0.593 (0.008)	−0.414 (0.080)	0.382 (0.000)	−0.274 (0.000)	0.0003 (0.576)	−1.556 (0.032)	0.428 (0.551)	0.583	0.568 (0.450) [1]	0.907 (0.340)	2.434 (0.296) [2]
Additional instruments: $M_{t-1}\ Y_{t-1}^{MP}\ Y_{t-4}^{MP}$																			
(Part 2) Estimated behavioural equations of the model—price sector																			
8	P_t^{AGR}	Constant	P_{t-1}^{AGR}	P_{t-2}^{AGR}	P_{t-3}^{AGR}	Y_{t-1}^{AGR}	MSP_t	M_t	DP^{AGR}							SE	Z	CH	Z1
		19.218 (0.012)	0.716 (0.000)	−0.353 (0.022)	0.386 (0.001)	−0.004 (0.004)	0.002 (0.690)	0.0006 (0.004)	−4.670 (0.053)							2.262	0.014 (0.903) [1]	2.258 (0.132)	0.579 (0.446) [1]
Additional instruments: $M_{t-1}\ Y_{t-1}^{MP}$																			
9	P_t^{IND}	Constant	P_{t-1}^{IND}	P_{t-2}^{IND}	$FUEL_t$	M_t	$Y_{t-1}^{MP} - Y_{t-1}^{IND}$	$Y_{t-2}^{MP}–Y_{t-3}^{IND}$	W_t^f	DP^{IND}						SE	Z	CH	Z1
		12.859 (0.001)	0.793 (0.000)	−0.144 (0.231)	0.066 (0.015)	0.0001 (0.086)	0.001 (0.000)	0.001 (0.008)	0.016 (0.087)	−1.901 (0.078)						0.895	0.076 (0.781) [1]	0.506 (0.476)	2.786 (0.248) [2]
Additional instruments: $Y_{t-1}^{MP},\ M_{t-1},\ CRR_t$																			
10	P_t^{SER}	Constant	P_{t-1}^{SER}	P_{t-2}^{SER}	P_{t-3}^{SER}	P_{t-4}^{SER}	M_t	Y_t^{SER}	Y_{t-1}^{SER}	$FUEL_t$	W_t^f	DP^{SER}				SE	Z	CH	Z1

(continued)

Table 6 (continued)

		Variables												Diagnostic tests			
		8.372 (0.176)	0.842 (0.000)	−0.282 (0.058)	0.169 (0.200)	0.132 (0.197)	0.0002 (0.096)	−0.002 (0.008)	0.001 (0.047)	0.022 (0.445)		0.026 (0.054)	−4.258 (0.000)	0.894	2.908 (0.233) [1]	0.804 (0.369)	0.166 (0.761) [1]
Additional instruments: $Y_{t-1}^{\mathrm{MP}}\ Y_{t-2}^{\mathrm{MP}}\ M_{t-1}\ Y_{t-2}^{\mathrm{ser}}$																	
11	WPI_t	Constant	WPI_{t-1}		WPI_{t-2}	P_t	P_{t-1}	$FUEL_t$	$FUEL_{t-1}$		W_t^f		DWPI	SE	Z	CH	Z1
		1.348 (0.094)	0.746 (0.000)		−0.014 (0.750)	0.508 (0.000)	−0.322 (0.016)	0.174 (0.000)	−0.116 (0.013)		0.0123 (0.054)		−0.913 (0.079)	0.378	3.056 (0.080) [1]	1.324 (0.249)	0.000 **
Additional Instruments: M_{t-1}																	

Notes
1. See Notes 1 to 5 of Table 9A
2. Equation (6): DRM = 1 for 2008 Q2 and 0 otherwise
3. Equation (7): DTB = 1 for 2009 Q2 and 0 otherwise and DTB1 = 1 for 2008 Q3 and 0 otherwise
4. Equation (8): $DP^{\mathrm{AGR}} = 1$ for2005 Q1 and 0 otherwise
5. Equation (9): $DP^{\mathrm{IND}} = 1$ for 2009 Q1 and 0 otherwise
6. Equation (10): $DP^{\mathrm{SER}} = 1$ for 2009 Q1 and 0 otherwise
7. Equation (11): DWPI = 1 for 2008 Q3 and 0 otherwise
8. **: Equation exactly identified

Table 7 Estimated behavioural equations of the model—*external sector*

		Variables											Diagnostic tests			
12	X_t	Constant	X_{t-1}	X_{t-4}	e_t		Y_t^W	π_{t-1}	π_t^W	$I_t I_t$		DX	SE	Z	CH	Z1
		−1113.499 (0.037)	0.222 (0.347)	0.204 (0.116)	2.091 (0.969)		0.0004 (0.788)	−15.123 (0.398)	66.075 (0.004)	0.454 (0.000)		−321.478 (0.056)	108.026	2.000 (0.367) [2]	1.409 (0.235)	0.195 (0.754) [3]
Additional instruments: Y_{t-1}^{MP} I_{t-1} FII_t S_t i_{t-1}^*																
13	Z_t	Constant	Z_{t-1}	Z_{t-2}	Z_{t-3}		Z_{t-4}	Y_t^{MP}	e_t	W_t^{OIL}		DZ	SE	Z	CH	Z1
		−34.594 (0.866)	0.571 (0.000)	0.349 (0.025)	−0.290 (0.043)		0.204 (0.039)	0.030 (0.369)	−2.228 (0.663)	3.290 (0.000)		−529.889 (0.000)	91.564	2.036 (0.361) [2]	0.641 (0.423)	0.368 (0.831) [2]
Additional instruments: Y_{t-1}^{MP} Y_{t-2}^{MP} C_{t-1} e_{t-1}																
14	e_t	Constant	e_{t-1}	e_{t-4}	i_t	i_t^*	Y_t^{MP}	Y_t^W	FII_t	S_t	M_t	De	SE	Z	CH	Z1
		9.608 (0.000)	0.451 (0.000)	0.451 (0.000)	0.483 (0.000)	−0.196 (0.149)	−0.0001 (0.655)	1.12×10^{-5} (0.000)	−0.0002 (0.872)	−0.0004 (0.000)	7.93×10^{-5} (0.060)	−0.660 (0.483)	0.691	23.271 (0.000) [3]	0.488 (0.484)	7.995 (0.156) [5]
Additional instruments: i_{t-1} i_{t-2} i_{t-3} Y_{t-1}^{MP} Y_{t-2}^{MP} C_{t-1} M_{t-1} M_{t-2}																

Notes
1. See Notes 1 to 5 of Table 9A
2. Equation (12): DX = 1 for 2009 Q3 and 0 otherwise
3. Equation (13): DZ = 1 for 2009 Q1 and 0 otherwise
Equation (14): De = 1 for 2009 Q1 and 0 otherwise

Table 8 In-sample and out-of-sample RMPSE for various variables

Sector	Endogenous variables	2006 Q1–2010 Q4 (STATIC) RMPSE	2011 Q1–2013 Q2 (DYNAMIC) RMPSE
Real	C I Y^{AGR} Y^{IND} Y^{SER} Y	1.665 3.770 2.447 1.760 0.747 0.918	4.055 4.816 4.550 4.803 0.938 1.552
Monetary	i RM	12.494 1.836	14.082 0.566
Price	P^{AGR} P^{IND} P^{SER} P WPI	1.797 0.670 0.713 0.744 0.522	2.038 1.991 1.487 1.008 1.438
External	X Z e	6.324 3.035 1.621	7.425 5.285 4.875
For complete model	Average RMPSE	1.689	2.705

Notes
1. In-sample period (2006 Q1–2010 Q4) covers observations till the estimation period of all behavioural equations.
2. Out-of-sample period (2011 Q1–2013 Q2) covers observations beyond estimation period using dynamic simulation.

Table 9 RMPSE analyses

Sector	0–5%	5–10%	Between 10 and 15%
2006 Q1–2010 Q4			
Real	$C, I, Y^{AGR}, Y^{IND}, Y^{SER}, Y$		
Monetary	RM		i
Price	$P^{AGR}, P^{IND}, P^{SER}, P$, WPI		
External	Z, e	X	
All sectors	Average RMPSE		
2011 Q1–2013 Q2			
Real	$C, I, Y^{AGR}, Y^{IND}, Y^{SER}, Y$		
Monetary	RM		i
Price	$P^{AGR}, P^{IND}, P^{SER}, P$, WPI		
External	e	X, Z	
All sectors	Average RMPSE		

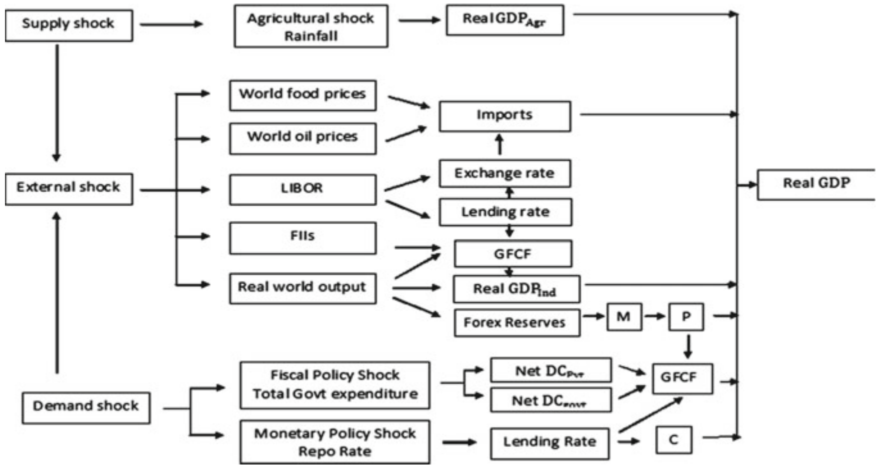


Fig. 1 Flow chart: direct transmission effects of the external shocks and policy changes

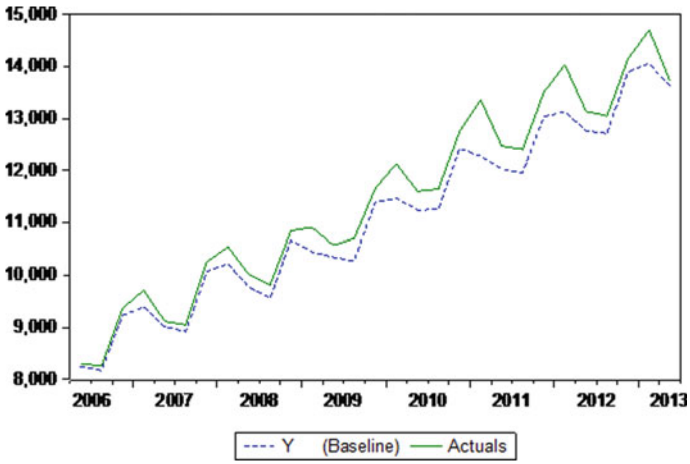


Fig. 2 In-sample RMPSE(Y) = 0.918, out-of-sample RMPSE(Y) = 1.552

are representative of equilibrium values generated on the basis of actual time paths (based on realized values) of exogenous variables (Fig. 1).

7 Simulation Experiments

Using exogenous shocks, both at domestic (policy and weather shock) and external level (world food prices, oil price shock and a global financial shock), six alternative

Table 10 Summary statistics of selected variables: sample period 1996 Q2–2013 Q2

Variable	Mean	Maximum	Minimum	Standard deviation
BSE	9297.198	20,101.23 (2010 Q4)	2908.310 (1998 Q4)	6165.155
FII	94.749	569.220 (2010 Q3)	-138.610 (2008 Q4)	154.201
G	1029.167	1821.980 (2012 Q4)	441.472 (1996 Q3)	379.363
RAIN	257.947	765.20 (2010 Q3)	19.7 (2001 Q1)	244.703
REPO	7.04	12.0 (1996 Q2)	3.85 (1997 Q3)	1.75
W^{OIL}	97.462	226.998 (2008 Q2)	21.822 (1999 Q1)	61.794
W^{F}	116.847	187.9 (2011 Q2)	77.50 (2001 Q4)	35.209
Y^{W}	1,571,567	2,212,773 (2013 Q2)	974,707.6 (1996 Q2)	280,736.6

scenarios are constructed and their potential impact on selected endogenous variables is examined. In case of policy shock, and we have conducted both impulse (one time) shock and the step/permanent (sustained) shock. The main difference observed in impulse and the step shock is that the latter is more pronounced, lingers and takes much longer to peter out. Table 10 spells out a summary of the statistics of selected exogenous variables on the basis of which alternative scenarios have been formulated historically.

In all exercises, the base year for policy (both impulse and step) and other exogenous shocks is kept same. A summary of these six alternative shocks is listed in Table 11 outlining variations in various factors in impact analysis and is stated below. Table 12 presents a scenario analysis for economy's growth rate. All comparisons of the alternative scenarios are done by referring to baseline scenario.

7.1 Alternative Scenarios

7.1.1 Monetary Policy Shock

A contractionary monetary policy shock as represented by a hike in policy repo rate shock is examined. In this, the policy (repo) rate of the RBI is first hiked to its maximum level observed in sample period for only one time period (two quarters at a stretch, 2011 Q1 and 2011 Q2), an impulse shock and then for the entire forecast period (2011 Q1 to 2013 Q2), a step shock. The impact of interest rate shock on real GDP is shown in Fig. 3a, b and Table 12.

Table 11 Variations in various factors in impact Analysis

Policy shock		
Alternative scenario	Maximum	Minimum
Monetary policy: $\bar{i}\uparrow$ (Scenario 1) impulse shock Step shock	12% for 2011 Q1–Q2 and 12% for 2011 Q1–2013 Q2	
Fiscal policy: $G\uparrow$ (Scenario 2) impulse shock Step shock	1821.98 for 2011 Q1–Q2 and 1821.98 2011 Q1–2013 Q2	
Mixed policy: $\bar{i}\downarrow$ & G $\uparrow$ (Scenario 3) impulse shock Step shock	$G=$ 1821.98 for 2011 Q1–Q2 and 1821.980 2011 Q1–2013 Q2	$\bar{i}=$ 3.85% for 2011 Q1–Q2 and 3.85% 2011 Q1–2013 Q2
Weather shock: rain $\downarrow$ (Scenario 4)		19.7 for 2011 Q1–Q2
External price shock: (Scenario 5) W_t^F and $W_t^{\mathrm{OIL}}\uparrow$	W_t^F 187.9 W_t^{OIL} 226.998 For 2011 Q1–Q2	
Global Shock: (Scenario 6) S, FII and $Y_t^W\downarrow$	S 9177.97, FII −138.610, Y_t^W 1,696,436 For 2011 Q1–Q4	
Baseline	Same as model solution	

Table 12 Scenario analysis for real GDP growth rate (%)

Year	Baseline	Monetary policy (1)	Fiscal policy/Profligacy (2)	Mixed policy shock (3)	Weather shock (4)	External price shock (5)	Global shock (6)
2009–10	8.22	8.22	8.22	8.22	8.22	8.22	8.22
2010–11	8.13	Impulse 7.91 Step 7.91	Impulse 8.26 Step 8.26	Impulse 8.38 Step 8.38	8.11	8.05	7.38
2011–12	6.06	Impulse 6.09 Step 5.78	Impulse 6.11 Step 6.36	Impulse 6.11 Step 6.72	6.15	5.90	3,90
2012–13	6.67	Impulse 6.69 Step 6.40	Impulse 6.67 Step 6.83	Impulse 6.65 Step 7.06	6.62	6.58	6.86

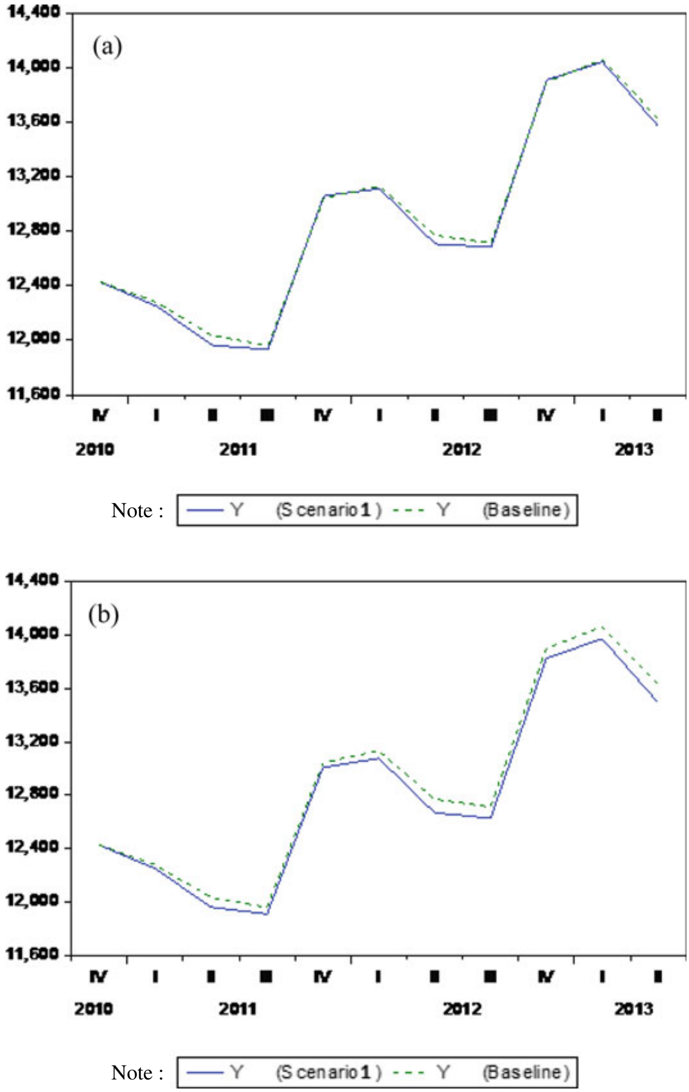
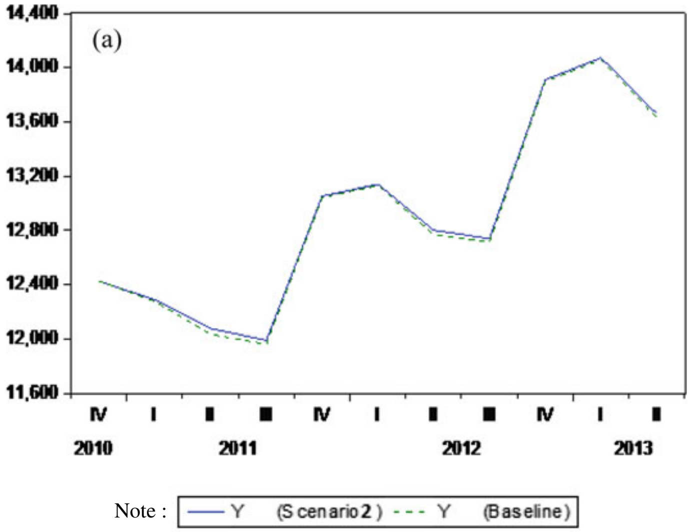


Fig. 3 **a** Scenario 1-impact of impulse monetary policy shock on GDP(Y) (Rs Billion). **b** Scenario 1-impact of step monetary policy shock on GDP(Y) (Rs Billion)

7.2 Fiscal Policy Shock

A liberal fiscal policy shock as represented by an increase in government final consumption expenditure is examined, first for only one time period (impulse, two quarters, 2011 Q1 and 2011 Q2) and then for the entire forecast period (step) 2011 Q1 to 2013 Q2. An important issue in this case pertains to the financing of increased government expenditure, for which we assume increased bank credit borrowings by the public sector. The impact of fiscal profligacy on real GDP is shown in Fig. 4a, b and Table 12.



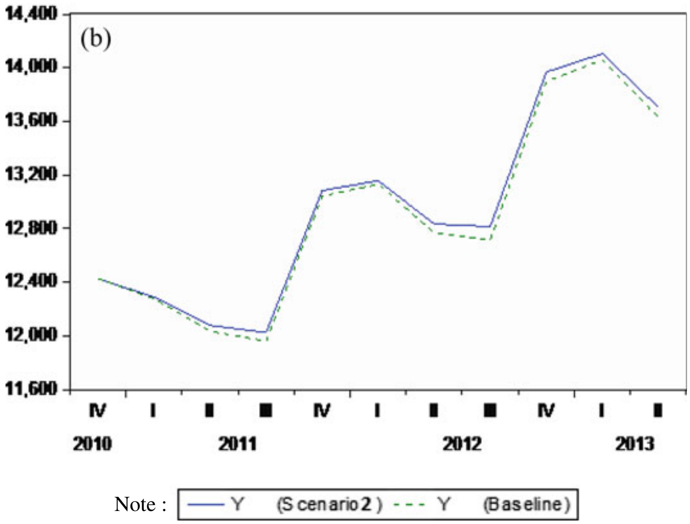


Fig. 4 **a** Scenario 2-impact of impulse fiscal policy shock on GDP(Y) (Rs Billion) **b** Scenario 2-impact of step fiscal policy shock on GDP(Y) (Rs Billion)

7.3 *Mixed Policy Shock*

This exercise combines monetary and fiscal policy measures such as the ones used in post global crisis period, to mitigate the adverse impacts of exogenous external shocks. Thus, it provides us with a mechanism to ascertain the effectiveness and repercussions of a liberal policy. It includes a decline in repo and an increase in public final expenditure. An impulse and a step shock (Fig. 5a, b) are given similar to scenario 1 and 2.

7.4 *Weather Shock*

Here the rainfall level is reduced to a minimum level observed historically for two quarters successively (2011 Q1 and Q2). We examine its impact on real GDP (Fig. 6), agricultural output and prices.

7.5 *External Price Shock*

In this exercise, the world crude oil price index and world food price index (2005 = 100) are increased to (their highest levels attained in the first half of 2008), respectively, for 2 quarters (2011 Q1 and Q2), and its impact on real GDP is examined (Fig. 7).

7.6 *Global Shock (GS)*

This shock is characterized by juxtaposing certain recessionary world conditions which are expected to transmit their impact on the domestic economy through two channels, viz. financial linkages (through stock market and net foreign inflows) and trade channel, via falling exports, consumption, investments and depreciation of the exchange rate. Thus, impact of GFS on real GDP (Fig. 8) is examined by stressing various exogenously affected variables for four quarters successively (2011 Q1–Q4) to their GFC levels historically (between December 2007 and June 2009).

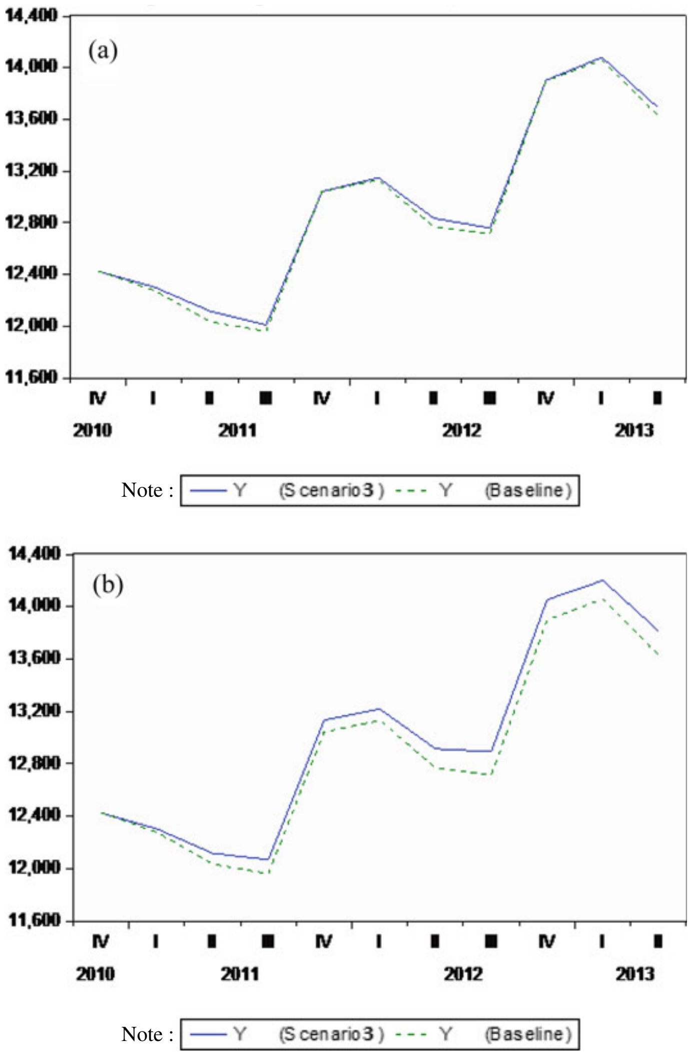


Fig. 5 **a** Scenario 3-impact of impulse mixed policy shock on GDP(Y) (Rs Billion) **b** Scenario 3-impact of step mixed policy shock on GDP(Y) (Rs Billion)

7.7 Propagation Mechanism

Given the set of estimated behavioural equations listed in Table 5, 6 and 7 along with the accounting identities, a propagation mechanism depicting first-round effects[33] due to the above six exercises is described below with the help of flow charts.

[33] In the first-round effects, we capture a brief description of the linkages in the different behavioural equations in each block.

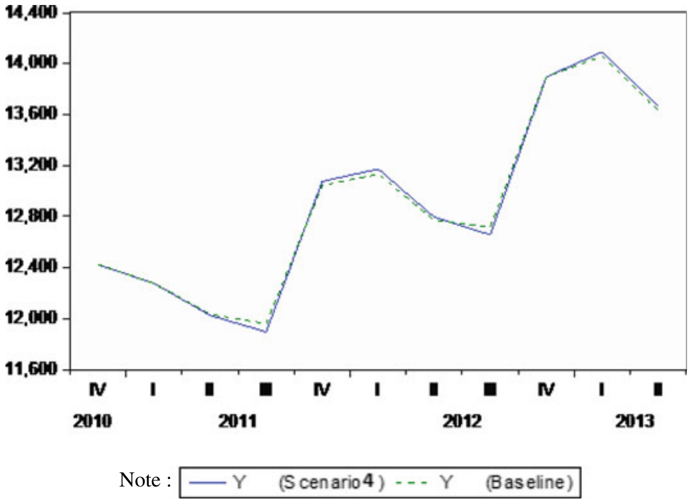


Fig. 6 Scenario 4-impact of weather shock on GDP(Y) (Rs Billion)

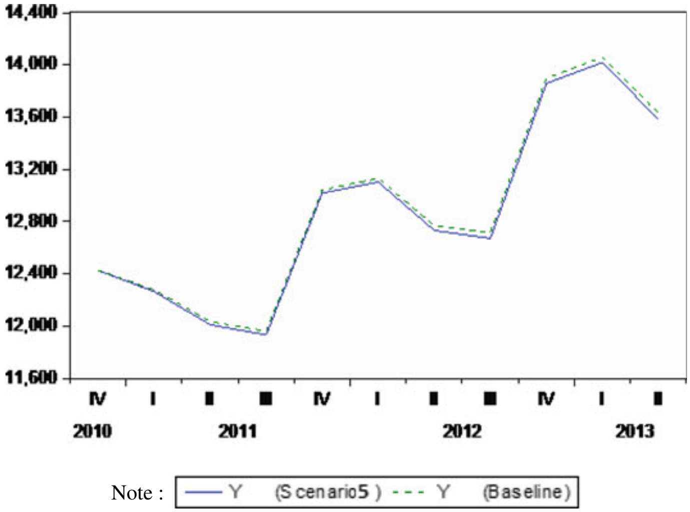


Fig. 7 Scenario 5-impact of external price shock on GDP(Y) (Rs Billion)

However, the actual process is much more complex than what appears from the behavioural relationships in terms of first-round effects. This is because the first-round effects are followed by significant feedback and lagged effects overtime and across the blocks of equations. This is an indication of significant degree of simultaneity in the model.

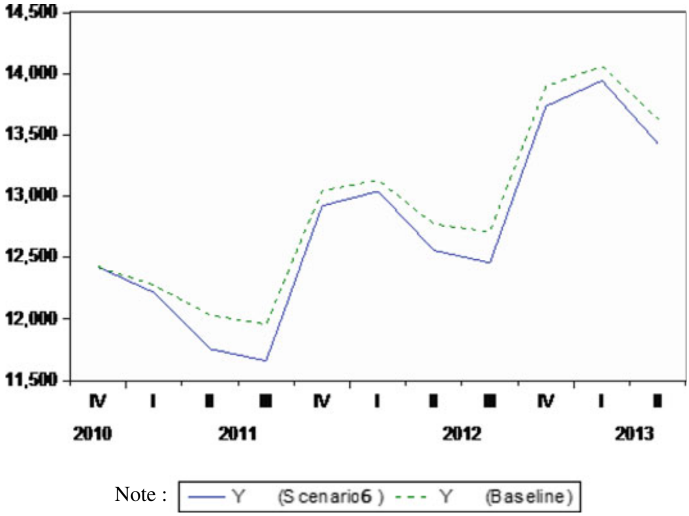
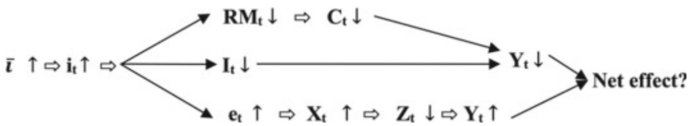


Fig. 8 Scenario 6-impact of a global shock on GDP(Y) (Rs Billion)

7.7.1 Monetary Policy Shock



The monetary policy shock is a demand side shock which is expected to be quite effective in India, as the money market in India is policy driven and responds immediately to any change in the policy rate. The impact of the monetary shock on economy can be decomposed into the interest rate and the exchange rate channels. The former operates through real block, while the latter operates through trade block via its impact on tradable sector's price competitiveness. A repo rate hike, in the first round, affects the domestic nominal interest rate directly and various other endogenous variables indirectly in the following manner:

1. The investment in economy is affected adversely through the increase in users' cost of capital.
2. Private consumption and investment are affected indirectly by a drop in credit demand that follows the rise in interest rates. Private consumption is also negatively affected by a drop in households' real money balances/wealth.
3. The hike in policy rate, under flexible prices assumption, causes a depreciation of exchange rate via higher inflation impacting exports positively and imports negatively.

However, the process of net effect on real GDP gets somewhat more complex, and eventually, a fall in GDP is mainly attributable to the interest rate channel which is expected to more than offset the exchange rate effect. Thus in case of impulse shock, the real GDP growth rate initially declines in 2010–11 to 7.91% as compared to baseline scenario at 8.13% and then increases relative to baseline to sustain the growth rate to the levels prior to the shocks in around two years (Table 12).

Overall monetary policy shock is expected to have a relatively weak effect on domestic output and prices, due to various reasons such as the policy rate may be less than fully transmitted to the retail interest rates, which ultimately affect the saving and investment decisions of economic agents. Furthermore dependence on credit to finance consumption and investment may be more limited. On the other hand, a permanent hike is expected to be more effective in straining the growth rate in the economy.

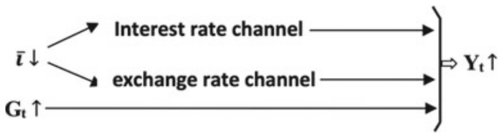
7.7.2 Fiscal Policy Shock/Fiscal Profligacy

$$G_t \uparrow \Rightarrow \; Y_t \uparrow$$

Fiscal policy also impacts demand side and positively affects the real GDP through multiplier effect. Here also, both impulse and step shock for fiscal profligacy are considered to examine the extent to which fiscal policy can be expansionary and can be used as a tool to mitigate some of the existing adverse situations.

A one-time government final expenditure increase may cause only a temporary rise in real GDP in short run, and the influence of the shock may disappear from the economy after the expenditures move back to the initial level. Table 12 indicates that the annual growth rate of real GDP remains unaffected in two year horizon as compared to baseline scenario at 6.67% in 2012–13. On the other hand, a permanent shock is expected to supply an increase in the GDP growth rate, assuming there is no additional funding by tax increase or expenditure cutting from other fields.[34]

7.7.3 Mixed Policy Shock



[34] Since this underlying assumption of conducting a step shock is untenable, such a situation is hardly executable in real-world conditions.

In this scenario, a mix of fiscal and monetary policy measures is employed by the authorities. The experiment contains a liberal policy toolbox in which the public final consumption is increased, and the policy rate is reduced simultaneously.

In the first round, an increase in $\boldsymbol{G_t}$ is expected to have a direct impact on aggregate demand in the economy and thereby on real GDP (directly and through the multiplier effect). Furthermore, it may also impact positively the domestic nominal interest rate. On the other hand, an expansionary monetary policy, through a decline in the policy repo rate, is expected to cause a significant decline in the domestic nominal interest rate via both interest rate and exchange rate channel in the present model. Consequently, the monetary policy may more than neutralize the impact of fiscal policy on the interest rates. This may, in turn, lead to a rise in investment and thereby industrial output in the economy due to the interest rate effect, whereas exports are expected to fall and imports rise due to exchange rate appreciation. The net effect on real GDP is positive (provided interest channel impact is greater than exchange rate channel) and significant in the first round; however in the second round, the dynamic interactions overtime and significant feedback effects fade out the net increase in GDP.

7.7.4 Weather Shock

$$\text{Rain} \downarrow \Rightarrow \mathrm{Y}_t^{\mathrm{AGR}} \downarrow \rightarrow Y_t \downarrow (\& \; P \; \uparrow)$$

Weather shock is a supply side adverse shock with a negative impact on economic activity and prices. A decline in rainfall may severely affect the agricultural output[35] and hence the overall GDP growth, given inter-sectoral demand and supply linkages. However, given the share of agriculture in total real GDP declining[36] over the years (from 26% in 1996 Q2 to 13% in 2013 Q2) combined with the increasing openness of the economy, the impact of one period rainfall deficiency is expected to peter out to a great extent.

7.7.5 External Price Shock

$$\mathbf{W_t^f} \uparrow \& \; \mathbf{W_t^{oil}} \uparrow \begin{cases} \nearrow \; \mathbf{P_t} \uparrow \\ \searrow \; \mathbf{Z_t} \uparrow \end{cases} \Rightarrow \mathbf{Y_t} \downarrow$$

---

[35] This is more likely for oilseeds, pulses and cotton grown in central and western parts of the country, which is less irrigated and hence more dependent on rains.

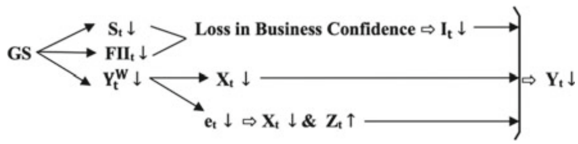
[36] Another reason may be that any damage to kharif crops due to scanty monsoon is offset by a bumper rabi crop, given that there is sufficient soil moisture and surplus water in reservoirs.

We consider a steep hike in world crude oil price and food prices (Table 11) under the head external price shock. Its impact is similar to an adverse supply shock, with a negative impact on economic activity and an increase in prices.

Since India is 80% dependent on oil imports, the impact of oil shock on economic activity and inflation is expected to be relatively strong, reflecting India's high degree of dependence on oil to generate energy. Higher oil prices significantly influence all domestic prices both directly, through higher import prices and indirectly, via second-round effects. The latter feeds into domestic prices through the increase in transportation, fuel and unit production costs. In addition, an oil price shock may also cause a persistent deterioration in terms of trade and worsens the trade balance. However, this adverse impact may be partly offset by the growing importance of the services sector which is less energy intensive.

The overall impact of an external price shock on the economy's growth rate comes out to be significant in the model simulation and takes the longest (beyond 10 quarters) to peter out. Table 12 indicates that external price shock causes a decline in growth rate (compared to base line scenario) which continues and does not peter out completely in the sample period taken for the study. The growth rate of the economy falls to 6.58% (against 6.67% for the base line scenario).

7.7.6 Global Shock



A GS is constructed by juxtaposing the conditions characterizing the world economy in the time period February 2007 to January 2009 due to GFC. Due to interlinkages between the international financial markets, huge volatility in net FII and recessionary conditions in the world economy, the impact of GS on Indian economy is found to be quite adverse and pronounced in simulation results.

In the model, a decline in BSE index combined with the negative net FII is expected to thwart consumer and business confidence in the economy. This may cause a decline in the private consumption and investment spending. On the other hand, the direct impact of depressed global demand is observed in an immediate decline in export volumes. The latter is then expected to reduce employment/ output, incomes and thereby demand in the economy. In the next round, private consumption and investment decline further with the declining economic activity. The additional impact on real GDP may be realized through the exchange rate channel which may appreciate due to a fall in world demand causing a fall in exports and a rise in imports aggravating the dismal decline in real GDP.

8 Conclusion

The main objective of this study is to develop an empirical economy-wide SMEM with broad disaggregation using quarterly data. The model is estimated from 1996 Q2 to 2010 Q4, and out-of-sample forecasting performance is evaluated from 2011 Q1 to 2013 Q2. The model is fairly dynamic with strong linkages overtime, across and within different blocks and sectors to analyse the current economic situation of Indian economy. This model incorporates the recent structural changes (such as sectoral transformation), global transmission channels (through significant impact of external shocks such as sharp rise in global food and fuel prices, global financial shock impact via stock market, net foreign inflows and trade channel and external factors like foreign interest rate and forward premium) and changes in the policy regimes (since exchange rate is now market determined and domestic interest rate is deregulated) in the economy. Thereby, it enables us to examine the major determinants of key macroeconomic variables and predict the current behaviour of the economy in the recent time period.

The model provides a positive and significant nexus between the real sector and stock market directly via wealth effect and indirectly via credit channel effect on consumption and investment in the economy, as evident from the estimated equations. The foreign interest rate and forward premium are found to be positively related to the domestic rate of interest, and both are significantly away from zero.

Two main findings emerge on the basis of the estimation results of the 14 behavioural equations:

1. Policy measures are effective. In particular, monetary policy has a significant impact on all the key macroeconomic variables: consumption, investment, interest rate, prices and real GDP.
2. Indian economy is well integrated with the rest of the world. Global transmission channels, through trade and financial linkages, are found to be significant (in the estimated behavioural equations) in transmitting the impact of global developments on domestic economy in impacting consumption, investment, prices, exports, imports and exchange rate.

The above two observations are also confirmed by the solution of the model, when all 14 estimated equations and a set of identities are solved simultaneously. Model simulation exercise and experiments yield the following results:

1. The model performs well over the in-sample and out-of-sample period, as RMPSE is less than 10% for all variables (except interest rate for which it is less than 15%). This result implies that the model is dynamically stable.
2. Estimated model is used to construct baseline scenario which is the same as the solution to the model beyond the sample period, for which the behavioural equations have been estimated.
3. The model has been subjected to both impulse and step policy shock of the same magnitude and the same initial period. In nearly all the cases, the disturbances resulting from impulse policy shock peter out in 6 to 8 quarters. However, mixed

policy step shock is found to be more effective than a single policy impulse or step shock.

4. Weather shock in terms of one time rainfall deficiency (for two quarters at a stretch) has a significant but temporary effect in declining real GDP growth rate.
5. External price shock also has a significant adverse impact on growth rate and takes the longest (beyond 10 quarters) to peter out.
6. Amongst all, it is the GS which is the most severe and significant in dropping GDP growth rate but peters out in 6 to 8 quarters.

The simulation experiments with exogenous and policy shocks highlight the complexity of the Indian economy. The fact that the effects of all exogenous shocks mostly peter out in 8 quarters indicates inherent stability of the model. The major policy implications of this modelling exercise are that the policy shocks/measures in Indian economy in the form of monetary (say, through decline in repo or CRR) and/or fiscal (say, through higher government borrowings and spending) policy during a strained/shock/crisis period are effective in the recovery of growth but may not be able to sustain high growth.

Questions to Think About

1. Suggest alternative methodologies to estimate equations in the macroeconomic model given in the chapter. How is a structural model different from a VAR model? Examine and explain.

   Hint: VAR, co-integration, ARDL, OLS, simultaneous equations model

   Refer: Dua (2017) and references in chapter
2. Based on the model described in the chapter, explain how you would implement the following simulations:

   (i) Increase in minimum support prices
   (ii) Increase in fuel prices (domestic/external)

   Hint: In Sect. 4, consider the empirical model for price block and the relevant channel of intervention as below:

   (ii) For increase in minimum support prices—use Eq. (26) to provide a shock.
   (iii) For increase in fuel prices (domestic/external)—use Eq. (27) to provide a shock.

   The construction of these shocks can be designed as described in Sect. 7.
3. The macroeconomic model described in this chapter is constructed and estimated for an emerging economy, India. Explain the features that are specific to a developing economy.

   Hint: Section 1 describes India as an integrated and open economy. For features specific to a developing economy, refer to Sect. 3 for the base model and Sect. 4 for a customized and expanded empirical model for an emerging economy.

   Refer: Dua and Pandit (2002); Dua and Raje (2013); Haque et al. (1990)

Acknowledgements The authors are grateful to N. R. Bhanumurthy and Lokendra Kumawat for their constructive suggestions.

References

Aghevli, B. B., & Sassanpour, C. (1982). Prices, output and the trade balance in Iran. *World Development, 10*, 791–800.

Ahluwalia, I. J., & Rangarajan, C. (1986). A study of linkages between agriculture and industry: The Indian experience. In *Proceedings of the eighth world congress of the international economic association.*

Anjaneyulu, D. (1993). *Macroeconometric linkages in the Indian economy: Interlinks between imports, output, exchange rate and external debt*, RBI Occasional Papers (Vol. 14, pp. 297–318).

Asafu-Adiaye, J., & Chakraborty, D. (1999). Export-led growth and import compression: further time series evidence from LDCs. *Australian Economic Papers, 38*, 164–175.

Bean, C. R. (1981). *Essays in unemployment and unanticipated inflation in post war Britain*, Unpublished Ph.D. Thesis, Massachusetts Institute of Technology.

Bhanumurthy, N. R., & Kumawat, L. (2009). External shocks and the Indian economy: Analyzing through a small, structural quarterly macroeconometric model, WP 19776, Munich Personal RePEc Archive.

Bhanumurthy, N. R., Bhattacharya, B. B., & Mallick, H. (2008). Modeling interest rate cycles in India. *Journal of Policy Modeling, 30*, 899–915.

Bhattacharya, B. B. (1984). Public expenditure, inflation and growth: A macroeconomic analysis for India. *OUP.*

Bhattacharya, B. B., & Rao, C. H. (1986). Agriculture-industry interrelations: Issues of relative growth in the context of public investment. In *VIII world congress of the international economic association.*

Bhide, S., & Parida, P. C. (2009). Impact of external economic environment: An assessment using a macroeconometric model. In K. S. Parikh (Eds.), *Macro-modelling for the eleventh five year plan of India.* Academic Foundation.

Bier, W. (1992). Macroeconomic models for the PC+L862, WP 92, International Monetary Fund Working Papers.

Box, G. E. P., & Ljung, G. M. (1978). On a measure of lack of fit in time series models. *Biometrika, 65*, 297–303.

Box, G. E. P., & Pierce, D. A. (1970). Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. *Journal of the American Statistical Association, 65*, 1509–1526.

Breusch, T. S. (1978). Testing for autocorrelation in dynamic linear models. *Australian Economic Papers, 17*, 334–355.

Carone, G. (1996). Modeling the US demand for imports through cointegration and error correction. *Journal of Policy Modeling, 18*, 1–48.

Cassola, N., & Morana, C. (2002). Monetary policy and the stock market in the Euro area, WP 119, European Central Bank Working Papers.

Chakrabarty, T. K. (1987). Macroeconometric model of the Indian economy. *RBI Occasional Papers, 8*, 191–263.

Cumby, R. E., & Huizinga, J. (1992). Testing the autocorrelation structure of disturbances in ordinary least squares and instrumental variables regressions. *Econometrica, 60*, 185–195.

Davidson, J. E., Hendry, D. F., Srba, F., & Yeo, S. (1978). Econometric modelling of the aggregate time-series relationship between consumers' expenditure and income in the United Kingdom. *The Economic Journal, 88*, 661–692.

Devi, N. S., & Dhananjayan, R. S. (1997). Exports and economic growth: A study of select nations in Asia and Europe during 1980/81 to 1993/94. *Indian Journal of Applied Economics, 6*, 41–63.

Dhar, S., Pain, D., & Thomas, R. (2000). A small structural empirical model of the UK monetary transmission mechanism, WP 113, Bank of England Working Papers Series.

Di Mauro, F., & Forster, K. (2008). Globalisation and the competitiveness of the Euro area, ECB Occasional Paper, No. 97.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*, 427–431.

Dickey, D. A., & Fuller, W. A. (1981). Likelihood ratio statistics for autoregressive time series with a unit root. *Econometrica, 49*, 1057–1072.

Dieppe, A., Dees, S., Jacquinot, P., Karlsson, T., Osbat, C., Ozyurt, S., & Vyskrabka, M. (2012). Competitiveness and external imbalances within the Euro area, ECB Occasional Paper, No. 139.

Dua, P., & Raje, N. (2013). Determinants of yields on government securities in India. *Margin: Journal of Applied Economic Research, 8*, 375–400.

Dua, P., & Gaur, U. (2010). Determination of inflation in an open economy Phillips curve framework: The case of developed and developing Asian countries. *Macroeconomics and Finance in Emerging Market Economies, 3*, 33–51.

Dua, P., & Pandit, B. L. (2002). Interest rate determination in India: domestic and external factors. *Journal of Policy Modelling, 24*, 853–875.

Dua, P., & Ranjan, R. (2012). *Exchange rate policy and modelling in India.* Oxford University Press.

Dua, P., & Sen, P. (2011). Capital flows and exchange rates in India. *Indian Economic Review, 48*, 189–220.

Durbin, J. (1970). The small-sample power of Durbin's h test. *Econometrica, 38*, 410–421.

Dutta, D., & Ahmed, N. (2006). An aggregate import demand function for India: A cointegration analysis. *Applied Economics Letters, 11*, 607–613.

Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica, 64*, 813–836.

Emran, M. S., & Shilpi, F. (2010). Estimating an import demand function in developing countries: A structural econometric approach with applications to India and Sri Lanka. *Review of International Economics, 18*, 307–319.

Fagan, G., Henry, J., & Mestre, R. (2001). An area-wide model (AWM) for the Euro area, WP 42, European Central Bank.

Fagan, G., Henry, J., & Mestre, R. (2005). An area-wide model for the Euro area. *Economic Modelling, 22*, 39–59.

Gauthier, C., & Li, F. C. (2006). Linking real activity and financial markets: The bonds, equity and money (BEAM) model for Canada, WP 42, Bank of Canada.

Ghatak, S., & Price, S. W. (1997). Exports—Composition and economic growth: Cointegration and causality evidence for India. *Review of World Economics, 133*, 538–553.

Ghosh, P. P., & Narayana, N. S. S. (2009). Macroeconomic simulations based on VEC models. In K. S. Parikh (Ed.), *Macro-modelling for the eleventh five year plan of India.* Academic Foundation.

Ghosh, P. P., & Sachdeva, A. S. (2009). A macro consistency planning model. In K. S. Parikh (Ed.), *Macro-modelling for the eleventh five year plan of India.* Academic Foundation.

Ginman, P. J., & Murray, T. (1976). An empirical examination of the traditional aggregate import demand model. *The Review of Economics and Statistics*, 75–80.

Goldstein, M., & Khan, M. S. (1985). Income and price effects in foreign trade. *Handbook of International Economics, 2*, 1041–1105.

Goyal, A. (1994). Growth dynamics in a general equilibrium macroeconomic model for India. *Journal of Policy Modeling, 16*, 265–289.

Granger, C. W. J., & Newbold, P. (1974). Spurious regressions in econometrics. *Journal of Econometrics, 2*, 111–120.

Gugnani, P. (1985). *An investigation into the recent behaviour of nominal and real interest rates in the U.K.*, Unpublished Ph.D. Thesis, London School of Economics.

Hanif, et al. (2011). A small-size macroeconometric model for Pakistan economy. *Technology and Investment*, *2*, 65–80.

Haque, N. U., Lahiri, K., & Montiel, P. J. (1990). A macroeconometric model for developing countries. *IMF Staff Papers, 37*, 537–559.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica, 46*, 1251–1272.

Hendry, D. F., & Mizon, G. E. (1978). Serial correlation as a convenient simplification, not a nuisance: A comment on a study of the demand for money. *Bank of England Economic Journal, 88*, 549–563.

Hendry, D. F., & Srba, F. (1980). AUTOREG: A computer program library for dynamic econometric models with autoregressive errors. *Journal of Econometrics, 9*, 85–102.

Houthakker, H. S., & Magee, S. P. (1969). Income and price elasticities in world trade. *The Review of Economics and Statistics*, 111–125.

Hsiao, C. (1997a). Cointegration and dynamic simultaneous equations models. *Econometrica, 65*, 647–670.

Hsiao, C. (1997b). Statistical properties of the two stage least squares estimator under cointegration. *Review of Economic Studies, 64*, 385–398.

Hudson, J., & Dymiotou-Jensen, M. (1989). *Modelling a developing country.* Gower Publishing Company.

Kannapiran, C. (2003). A macroeconometric model of a developing economy. *Journal of the Asia Pacific Economy, 8*, 41–56.

Kar, S., & Pradhan, B. K. (2009). Shocks, meltdowns, policy responses and feasibility of high growth in the Indian economy: A macroeconometric approach. In K. S. Parikh (Ed.), *Macro-modelling for the eleventh five year plan of India.* Academic Foundation.

Kemal, A. R., Din, M., Qadir, U., Fernando, L., & Colombage, S. S. (2002). *Export and economic growth in South Asia.* South Asia Network of Economic Research Institutes.

Khan, M. S., & Knight, M. D. (1988). Import compression and export performance in developing countries. *Review of Economics and Statistics, 70*, 315–321.

Klein, L. R., & Palanivel, T. (1999). An econometric model for India with emphasis on the monetary sector. *The Developing Economies*, 275–327.

Konya, L., & Singh, J. P. (2006). Exports, imports and economic growth in India, WP No. A06.06, School of Economics La Trobe University.

Krishnamurty, K. (2008). Macroeconometric models for India: Past, present and future. In V. Pandit & K. R. Shanmugam (Eds.), *Theory, measurement and policy: Evolving themes in quantitative economics.* Academic Foundation.

Krishnamurty, K., Pandit, V., & Mohanty, G. (2004). Policies for stability and growth experiments with a large and comprehensive structural model for India. In V. Pandit & K. Krishnamurthy (Eds.), *Economic policy modeling for India.* Oxford University Press.

Krishnamurty, K., Pandit, V., & Sharma, P. D. (1989). Parameters of growth in a developing mixed economy: The Indian experience. *Journal of Quantitative Economics, 5*, 295–325.

Kruegar, A. O. (1978). Alternative trade strategies and employment in LDCs. *American Economic Review, 68*(2), 270–274.

Kumar, A. G., & Panda, M. (2009). Global economic shocks and Indian policy response: An analysis using a CGE model. In K. S. Parikh (Ed.), *Macro-modelling for the eleventh five year plan of India.* Academic Foundation.

Leamer, E. E., & Stern, R. M. (1970). Constant-market-share analysis of export growth. *Quantitative International Economics*, 171–183.

Lopez, R. E., & Thomas, V. (1990). Import dependency and structural adjustment in sub-Saharan Africa. *The World Bank Economic Review, 4*, 195–207.

Mallick, S. K. (2004). A dynamic macroeconometric model for short-run stabilization in India. *Applied Economics, 36*, 261–276.

Mehta, R., & Panchamukhi, V. R. (1991). Econometric modelling of trade in South Asia. *Econometric Modelling and Forecasting in Asia.*

Mohanty, D. (2010). *Measures of inflation in India—Issues and perspectives, conference of Indian association for research in national income and wealth (IARNIW).* Centre for Development Studies (CDS).

Ng, P., & Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica, 69*, 1519–1554.

Panagiotidis, T., & Sharma, A. (2005). An analysis of exports and growth in India: Cointegration and causality evidence (1971–2001). *Review of Development Economics, 9*, 232–248.

Pandit, V. (1986). A note of the structural macroeconomic model of India. *Mimeo.* Delhi School of Economics.

Pani, P. K. (1977). A macroeconomic model of the Indian economy. *Macmillan Company of India.*

Pani, P. K. (1984). A macro model of Indian economy with special reference to output, demand and prices: 1969–70 to 1981–82, No. 2, RBI Occasional Papers.

Perron, P., & Ng, S. (1996). Useful modifications to unit root tests with dependent errors and their local asymptotic properties. *Review of Economic Studies, 63*, 435–465.

Ramanathan, R. (1992). *Introductory econometrics with applications* (2nd ed.). Harcourt Brace Jovanovich.

Salvatore, D., & Hatcher, T. (1991). Inward and outward oriented trade strategies. *Journal of Developing Studies, 27*, 7–25.

Sargan, J. D. (1964). Wages and prices in the United Kingdom: A study in econometric methodology. In P. E. Hart, G. Mills & J. K. Whitaker (Eds.),*Econometric analysis for national economic planning*. Butterworths.

Srivastava, D. K. (2013). Macro-econometric model of the Indian economy based on quarterly data. *RBI-MSE macro-modelling project*.

Taylor, J. B. (1988). A summary of the empirical and analytical results and the implications for international monetary policy. In Y. Suzuki, & O. Mitsuaki Okabe (Eds.), *Toward a world of economic stability: Optimal monetary framework and policy*, (pp. 17–34). University of Tokyo Press.

World Bank. (1995a). *Country assistance strategy: Independent state of PNG.* World Bank.

World Bank. (1995b). Macroeconomic data team model building RMSM-X reference guide. In *World bank international economics department development data group.* World Bank.

Ziramba, E., & Bbuku, M. (2013). An empirical analysis of aggregate import demand and expenditure components in Namibia. *International Journal of Economics and Research, 1*, 39–50.

Part III
Business Cycles and Global Crises

Chapter 11
International Synchronization of Growth Rate Cycles: An Analysis in Frequency Domain

Pami Dua and Vineeta Sharma

Abstract This study examines international synchronization of growth rate cycles using spectral techniques in the frequency domain. In particular, we look at synchronization of growth rate cycles between bilateral country pairs, US, UK, Germany, Japan and India over the period from January 1974 to December 2018. We examine two aspects of the synchronization process—one, strength of co-movement across countries' growth rate cycles, and two, sequencing in terms of leads and lags of these cycles vis-à-vis each other. The strength of co-movements is analyzed using coherences of growth rate cycles between bilateral country pairs across frequency bands and over time. The lead–lag structure between growth rate cycles of countries is obtained from the spectral phase shift parameter. This is evaluated against the lead–lag structure in the time domain, as inferred from the reference chronology given by the Economic Cycle Research Institute (ECRI). Based on the growth rate of the coincident index obtained from ECRI, we infer the sequencing of growth rate cycles in one country vis-à-vis the other in terms of the relative timing of their peaks and troughs. This comparative analysis across the time and frequency domains highlights both the pattern of lead–lag in terms of timing of peaks and troughs (time domain) as well as the lead–lag in terms of all phases of the cycle (frequency domain). For analyzing these patterns over time, we undertake the exercise over two subsamples: January 1974–December 1990 and January 1991–December 2018. We find that the coherence between developed country pairs is, in general, higher than that between developed–emerging economy pairs. We also find evidence of greater co-movement of country cycles post-1990, as compared with that in 1974–1990. The magnitude of leads–lags shows that the synchronization process is faster in the latter time period. The leads–lags obtained from the spectral phase shift estimates are found to be in line with those inferred from economic indicator analysis (EIA).

Keywords Growth rate cycles · Co-movements · Spectral analysis

P. Dua
Department of Economics, Delhi School of Economics, University of Delhi, Delhi 110007, India
e-mail: dua@econdse.org

V. Sharma (✉)
Department of Economics, Kirori Mal College, University of Delhi, Delhi 110007, India
e-mail: vineetasharma@kmc.du.ac.in

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_11

JEL Classification C22 · E32

1 Introduction

In the global world order, with international linkages through trade, capital and financial flows, economic circumstances in one country are not independent of happenings in the rest of the world. World economic history bears testimony to this; from the intensification of the globalization phase in the early 1990s to the 2007–09 global recession, the world economy is dotted with episodes where economic circumstances in one country have moved systematically in tandem with those in others. While synchronization of recessions has been a persistent historical feature of cyclical processes, the proportion of economies observed to be simultaneously in a recessionary phase has been significantly larger during the past few recessions.

The question of synchronization of cycles across countries has been an important one in the context of coordination of trade policy, smooth functioning of currency and monetary unions (Campos et al., 2019; Saiki, 2018) which requires knowledge of how far cyclical conditions across countries are coordinated. Inferences based on empirical analysis of cycle synchronization, however, far elude consensus in cycle literature. This, often referred to as the recoupling/decoupling debate, requires a more nuanced view of both the methods used as well as the underlying data. More recent empirical literature on business cycles focuses on methods that distinguish between different phases of the cycle. Using such techniques, it has been shown that business cycles strongly co-move during recessions, but are largely independent during non-recessionary periods, as seen in IMF WEO, (2013); Yetman, (2011); Bordo and Hebling, (2003); Bayoumi and Helbling, (2003); Canova et al., 2007). Harding and Pagan, (2006), Dufrénot and Keddad, (2014), Filardo and Gordon, (1994), using Markov switching methods, have reiterated that the degree of co-movement is asymmetric across phases of the business cycles. Among other important methodologies that make a distinction between phases of the cycle is the economic indicator analysis (EIA). The synchronization between cycles is viewed in terms of turning points occurring either roughly at the same points in time or differing by intervals that are roughly constant.

While the methodology used by the Economic Cycle Research Institute (ECRI) employing the EIA defines leads and lags in terms of peaks and troughs only, spectral analysis in the frequency domain defines leads and lags in terms of all time points. In the specific context of stabilization policies for phases of the business cycle, the peak and trough dates are important for the timing of stabilization policy. However, when the effect of a policy is to be seen in continuity, it is important to have the lead–lag relationship over all phases of the cycle, for all time points, e.g., a policy to slow down a boom without turning it into a depression (Granger and Hatanaka, 1964). Thus, a comparison of the two provides a more complete picture and brings forward patterns between lead–lag in terms of peaks and troughs and the lead–lag in terms of all phases of the cycle.

In this study, we undertake a comparative analysis of synchronization of growth rate cycles[1] in the time and frequency domains. International synchronization of growth rate cycles in the frequency domain is examined by addressing two aspects of the issue—one of examining co-movement across countries' cycles, and second, sequencing in terms of leads and lags of these cycles vis-à-vis each other. The pattern of co-movement of growth rate cycles across countries is analyzed using spectral estimates across frequency bands and overtime. We study these parameters across three frequency bands, viz. growth rate cycle frequency (cycles between 12 months and 8 years), low frequency (cycles of duration more than 8 years) and high frequency (cycles of less than 12 months duration).

In the time domain, we use reference chronologies of the growth rate cycle obtained from ECRI to infer the sequencing of growth rate cycles in one country vis-à-vis the other in terms of the relative timing of their peaks and troughs. We then compare our estimates with those obtained using spectral techniques in the frequency domain. Such an analysis gives us additional insights and a broader picture of the process of synchronization.

We base our analysis on the growth rate of the coincident composite index of economic activity for the set of five countries—US, UK, Germany, Japan and India, obtained from ECRI. To further examine whether there has been a change overtime in the pattern of co-movements of cycles, we divide the sample into two periods, January 1974–December 1990 and January 1991–December 2018 and look at the patterns of coherences that emerge.

This study is organized along the following lines. Section 2 gives a brief background of literature and discusses various methodologies that have been used to measure and characterize the synchronization process. Section 3 deals with the methodology followed in the paper. Section 4 describes the data. This is followed by a discussion of empirical results and their analysis in Sect. 5. Section 6 concludes.

2 International Synchronization of Cycles: Literature Review

It has been a question of interest to examine if business cycles move together internationally in some analyzable pattern. The empirical dimension of the question of measurement of international synchronization of cycles has been addressed

[1] To gain insight into the cyclical process of growth, it is important to understand the difference between business cycles and growth rate cycles and their relationship. A business cycle measures ups and downs in economic activity. Growth rate cycles, on the other hand, are cyclical upswings and downswings in the growth rate of economic activity. The reference chronology method (based on the economic indicator analysis) of dating cycles defines peaks and troughs in the cycle. A movement from a peak to a trough is said to constitute a contraction (slowdown) while that from a trough to a peak an expansion (pickup). A slowdown, a milder counterpart of a recession, is a downshift in the pace of growth in economic activity. Economic slowdowns begin with reduced but still positive growth rates, which may eventually develop into recessions.

in time domain using a variety of techniques. Backus et al., (1992), Zimmerman, (1997) and Baxter, (1995) use model calibration techniques. Diebold and Yilmaz, (2009) spillover index uses VAR and VECMs. Various formulations of the Engle and Kozicki, (1993) and Engle and Vahid, (1993) framework have been followed by Cubadda and Hecq, (2001), Hecq, (2009) and Candelon and Hecq, (2000). The latter strand examines if the co-movements are "common cycles" (see Engle and Kozicki, (1993), Engle and Vahid, (1993), Cubadda and Hecq, (2001), Hecq, (2009) and Candelon and Hecq, (2000)). There has not emerged a consensus on whether the synchronizations have increased or declined overtime. For example, Cakir and Kabundi, (2013), Antonakakis, (2012) and Kim and Saiki, (2014) find evidence of increased synchronization overtime, while Artis, (2003) finds evidence of decoupling. The differences could be attributed to the use of different data and to issues of measurement.

Hamilton, (2005) argued that recessions are fundamentally different from "normal" times, i.e., degree of co-movement of country business cycles is asymmetric across phases of the business cycles. Yetman, (2011) infers the degree of synchronization by constructing a dynamic Pearson correlation coefficient and finds that the bilateral and average bilateral correlations show a spike during periods of recessions. Concordance index, introduced by Harding and Pagan, (2006) and also employed by Artis et al., (1997) and Medhioub, (2010), finds that recessions are qualitatively different from other times. In the context of such asymmetries, an important class of nonlinear specification models used is the autoregressive threshold models by Tiao and Tsay, (1994), the SETAR models by Anderson and Terasvirta, (1992) and dynamic factor analysis and the regime switching models by Hamilton, (1989) and Filardo and Gordon, (1994).

Other nonparametric methods include frequency domain methods, involving the use of spectral and cross-spectral estimates. Granger, (1969) discussed the use of spectral and cross-spectral techniques for business cycle analysis.[2] Such methods have been employed by Maršálek and Pomënková, (2010, 2011) and Kapounek and Pomënková, (2010), among others.

Business cycle synchronization studied in the frequency domain has some desirable features of nonlinear models and can be used to study correlation and a lead–lag sequencing of the correlation between two series. By invoking a frequency-wise break-up of how cycles move together, one may be able to get better insight into the details of the process of synchronization. Dynamic correlation in frequency domain was proposed by Croux et al., (1999) to analyze synchronization between cycles. Jensen and Selover, (1999), Pakko, (2004), Canova and Dellas, (1993), Canova, (1998) and Camba-Mendez et al., (2001) constitute important studies measuring international synchronization of cycles using spectral methods. Breitung and Candelon, (2001) use a frequency domain common cycle test to analyze synchronization at different business cycle frequencies. Allegret and Essaadi, (2011) base their inferences on a time-varying coherence function. Owens and Sarte, (2005)

[2] More detailed discussion of spectral analysis are provided by Priestley, (1981), Fuller, (1976), Harvey, (1993), Hamilton, (1994), Chatfield, (1996), Hatanaka, (1996) and others.

examine whether the diffusion indexes, for which they estimate the power spectra, can be tied to the business cycle.

Hughes-Hallett and Richter, (2004, 2008) use spectral approach to analyze business cycles of European emerging countries. Bátorová, (2007) uses dynamic correlation, cohesion and cross-cohesion to assess the degree of synchronization of the CEECs business cycle with the euro area. Bátorová et al., (2008, 2009, 2011) apply cross-spectral analysis to examine the influence of the Chinese economy on business cycles in the developed OECD countries. Bátorová et al., (2013) analyze globalization and business cycles in China and selected OECD countries using dynamic correlation analysis. Aloui and Hkiri, (2014) examine the short-term and long-term dependencies between stock market returns for the Gulf Cooperation Council Countries during the period 2005–2010. They also show changes in the pattern of co-movements after 2007 at relatively higher frequencies. Berdiev and Chang, (2015) investigate the synchronization of growth cycles between China, Japan, the US and other Asia–Pacific countries using wavelet analysis, emphasizing the importance of examining the strength of business cycle synchronization using a time–frequency framework.

Wavelet spectrum analysis to study globalization and business cycles allows for a simultaneous time–frequency analysis. Aguiar-Conraria and Soares, (2011) use wavelet analysis to study business cycle synchronization across the EU-15 and the Euro-12 countries. Fidrmuc et al., (2014) and Hanus and Vacha, (2015) employ a wavelet spectrum analysis to study globalization and business cycles in China and G7 countries.

An alternative way of capturing international transmission is the economic indicator analysis, used to date peaks and troughs in business cycles. Boehm, (2001) looks at international transmission of business cycles by using the economic indicator analysis which acknowledges the extent to which growth cycle peaks and troughs in one country lag corresponding turns in the other country. Banerji and Hiris, (2001) apply the classical indicator approach within a multidimensional framework and an international extension of this framework for comparison across major economies. Banerji and Dua, (2010) examine various measures of synchronization of recessions, including clustering of the onset of recessions across economies, proportion of economies in expansion and the diffusion index of international coincident indexes; see also Banerji and Dua, (2011).

We use frequency domain methods to infer international synchronization, measuring co-movements using coherences, and lead–lag sequencing determined from the phase shift parameters. We then comparatively place together spectral estimates with results obtained from the reference chronology given by ECRI based on the NBER methodology.

3 Methodology

3.1 Relationship Between Time and Frequency Domains

Dynamics of time series obtained from time domain analysis may be usefully supplemented by frequency domain approach. Frequency domain methods study time series in terms of repetitive cycles, as against the traditional time domain methods, which are associated with models involving time functions.

Since cyclical phenomena resemble a wave, we can imagine a sine (or a cosine) wave as a close approximation to a hypothetical cycle, as depicted in Fig. 1. The horizontal axis represents the time or distance that the wave travels, depicted in terms of π. The period of a wave is the time the wave takes to repeat itself or starts the next iteration. The period is 2π as shown in Fig. 1.

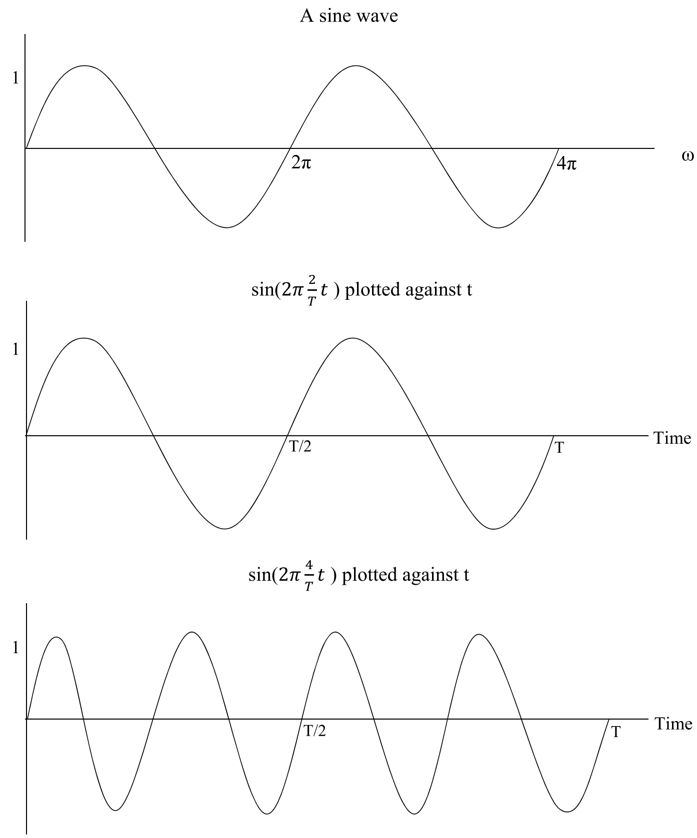


Fig. 1 Sine wave associated with different frequencies plotted against time

A closely related property of the period is the frequency. Frequency is defined as the number of times an event occurs over a given time horizon, i.e., the inverse of the time it takes to complete one cycle. Thus, the time period between two peaks or two troughs over a given length of time can be converted into its corresponding frequency. The longer it takes to reach the next turning point, the lower will be the frequency. In particular, the inverse of the period T is defined as the frequency, $f = 1/T$ of the process. Similarly, period is the inverse of frequency, $T = 1/f$.

Within a given time interval, frequency is the number of repetitions of a function g in that time, measured as cycles per unit time. Since 2π radians make up one complete cycle, the angular frequency ω radians per unit time can be translated into f cycles per unit time.

$$\omega = 2\pi f \text{ or } f = \omega/2\pi$$

The period is then $2\pi/\omega$. Thus, time durations of cycles can be converted into corresponding frequency bands and vice versa.[3]

Given this, the sine wave defined on $[-n\pi, n\pi]$ can be translated into a sine wave defined on the time period $[0, T]$. The relationship depicted above can be summarized in the lower panels of Fig. 1. Suppose a process completes two cycles within the period T. The second panel of Fig. 1 shows such a process which corresponds to $\sin[2\pi(2/T)t]$. Similarly, we can plot $\sin[2\pi(k/T)t]$ which will have k cycles within the time interval T. The lower panel of Fig. 1 depicts a process that has four complete cycles during period T.

3.1.1 Translation from the Time Domain to the Frequency Domain

The first panel of Fig. 2 shows two sine waves, with different frequencies. One wave completes four cycles during the given time horizon T (frequency four), and the other completes seven cycles (frequency seven). They are accordingly labeled low frequency and high frequency, respectively.

To see the translation of the time domain into the frequency domain, we can refer to the lower panel in Fig. 2. The same sine wave in the frequency domain is plotted with frequency on the X-axis, using the inverse rule. A complete sine wave in the time domain can be represented by one single spike in the frequency domain. Two such waves are shown in Fig. 2: first in the time domain and then correspondingly in the frequency domain.

[3] For illustration, we use the relationship to the numbers used in Fig. 3. Over a period of 10 years, the high-frequency component corresponding to T = 12 months is equivalent to $\omega = 2\pi f = 2\pi/T = \pi/6$. Similarly, the business cycle frequencies for T = 48 work out to be associated with $\omega = \pi/24$, and a low frequency corresponding to $T = 108$ has $\omega = \pi/54$.

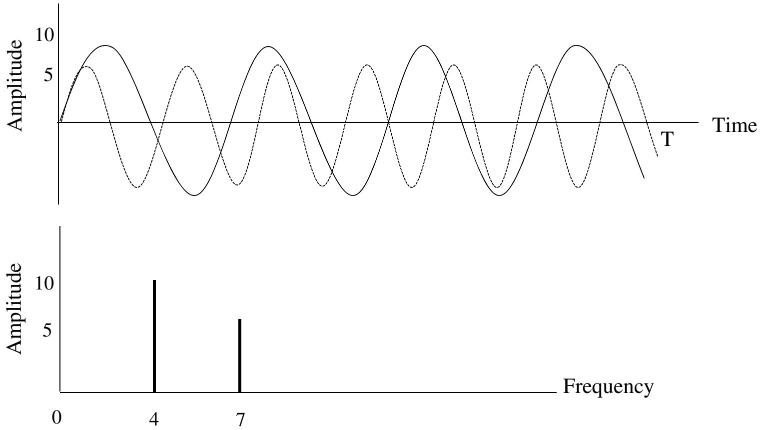


Fig. 2 Representation of a sine wave in the time and frequency domains. *Notes* (1) A sine wave with a different amplitude and frequency in the time domain can be represented by different spikes in the frequency domain

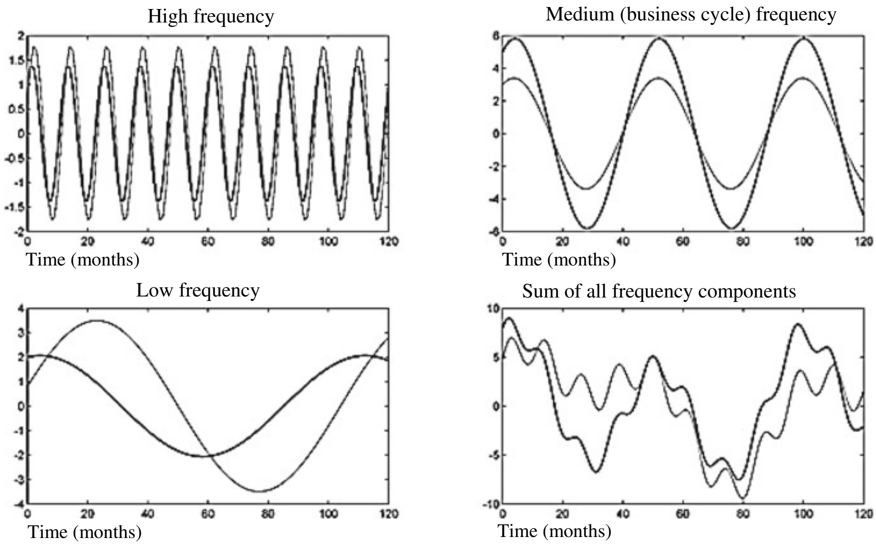


Fig. 3 Frequency components of a time series. *Source Bátorová, (2012).* Notes (1) The first plot represents high-frequency components with frequency f = 1/12 which corresponds to short-run time period of 12 months. The second plot illustrates medium frequency components with frequency 1/48 corresponding to the business cycle time horizon, equivalent to a period of 48 months. Components in low frequencies corresponding to the long-run time horizon are presented in the third plot. Low-frequency component created with f = 1/108, corresponds to T = 108 months. The sum of these components creates a final time series illustrated in the last plot of the figure. A time series, composed of an infinite sum of such components, can be isolated through spectral analysis

3.1.2 Time Series as a sum of Different Frequencies

While for expository purpose, it is usual to depict the cycle with a sine wave, real cyclical phenomena do not have the regularity shown by a single sine wave. In the empirical study of cycles, a perfect regularity in fluctuations as implied by a single sine wave has not been suggested. As Gordon, (1961) put it

> "*Although business cycles represent recurring alternations of prosperity and depression, virtually all authorities agree that there is nothing periodic about these movements. There is no evidence that business cycles tend to occur over and over again in virtually the same form with the same duration, and the same amplitude of movement.*
>
> *Some cycles are mild and others severe…*"

Thus, a time series can be thought of as a process consisting of different sine (or cosine) waves of different frequencies (representing different durations) and different amplitudes (representing different severity) that cumulate together. Figure 3 illustrates this for two processes. The figure shows two series over a time period of 120 months (10 years). The first plot represents high-frequency components with $f = 1/12$ which corresponds to short cycle with period of 12 months (1 year). The second plot illustrates medium frequency components with frequency 1/48, equivalent to a period of 48 months (4 years). Components in the low frequencies corresponding to the long-run time horizon are presented in the third plot. Long-run time series created with the frequency $f = 1/108$ corresponds to 108 months (9 years). The sum of these components creates a final time series illustrated in the last plot of the figure.

The underlying intuition of spectral analysis is to be able to separate the different components of a time series associated with different frequencies. A time series, thus, consisting of components of different frequencies can be broken down and picked up by spectral methods like a signal extraction exercise. Conversely, it implies that a time series, composed of an infinite sum of such components, can be isolated through the spectral analysis. It is the mixture of regularity and non-regularity that makes spectral analysis mathematically suited to model these fluctuations, as seen in Gordon, (1961).

3.2 The Frequency Domain: Spectral Analysis

Spectral techniques are powerful instruments to study business cycle properties. The approach is based on determining the periodic components embedded in a time series by computing the associated periods, amplitudes and phases.

Spectrum analysis explores cyclical patterns of data. Since cyclical phenomena resemble and have wave like characteristics, it is possible to represent any real-valued, covariance stationary process as a weighted sum of orthogonal periodic components, also known as the *spectral representation theorem* by Janacek and

Swift, (1993). Correspondingly, spectral techniques[4] decompose the original time series with cyclical components into underlying sinusoidal (sine and cosine) functions, each having a different frequency ω ranging between 0 and π. Any covariance stationary process $\{X_t\}_{t=-\infty}^{\infty}$ can be expressed as

$$X_t = \int_0^{\pi} \alpha(\omega)\cos(\omega t)d\omega + \int_0^{\pi} \beta(\omega)\sin(\omega t)d\omega$$

where each frequency ω corresponds to a unique time horizon *T*, such that $T = 2\pi/\omega$, and weights $\alpha(\omega)$ and $\beta(\omega)$ are random variables with zero mean. It means that the process X_t is a periodic function with frequency ω or with period *T*.

Such a transformation represents a periodic function (see Fig. 1) defined on an interval [-*R*,*R*] as a linear combination of cosine and sine functions defined on (-π, π).

The spectral transformation (sometimes known as the *Fourier transform*) is then used to construct estimates of the parameters that define the cyclical properties of the series. These include spectra and co-spectra from which the coherence and the phase shift are derived. We discuss these concepts in the following subsections.

3.2.1 Application of Spectral Methods to Business Cycle Analysis

The various concepts used in spectral analysis closely explain characteristics of business cycles. The following section explains these.

1.1 ***The Spectrum***

The variance of a process can be decomposed into contributions tied to a set of distinct frequencies, i.e., the sample variance of a fragment of a series can be decomposed into components attached to different frequencies. The spectrum may be interpreted as the contribution of a given frequency to the variance of the process at that frequency. The area under the spectrum is the total variance of the series. Thus, an examination of the spectrum enables us to infer proportion of the variance explained by the cycle frequencies.

Given X_{it} and X_{jt} growth rate cycle indicators for country *i* and *j*, respectively, the spectrum which corresponds to their *kth* order auto-covariance matrix Γ_k incorporates all information about the variance–covariance structure.

Following Priestley, (1981), for a real-valued weakly stationary discrete stochastic process $\{X_t; t = \ldots, -2, -1, 0, 1, 2, \ldots\}$ with zero mean and covariance function

[4] We employ non-evolutionary spectral techniques, which requires that the time series be stationary. For examining the stationarity status of series, we conducted unit root tests, focusing on the DF-GLS (Elliot et al., 1996) and the KPSS test proposed by Kwiatkowski et al., (1992).

$R(s) = E\left[X_t X_{t-s}\right] = R(-s)$, the spectral density function (or power spectrum) is the Fourier transform of the covariance function $\hat{h}(\omega) = \frac{1}{2\pi} \sum_{s=-(N-1)}^{(N-1)} \widehat{R}(s) e^{-i\omega s}$.

The so estimated spectral density function although unbiased is an inconsistent estimate of the spectrum.[5] Smoothing procedures, using windows, give a consistent estimator of the spectrum.[6]

1.2 *Cross-Spectral Estimates*

Cross-spectral analysis provides an extension of spectral analysis to the bivariate case. The objective of cross-spectral analysis is to determine the relationship between two time series as a function of frequencies. While univariate spectral analysis allows detection of movements for a single series, it is possible to describe pairs of time series in frequency domain using cross-spectral analysis by decomposing their covariance by frequency components. An important appeal of cross-spectral analysis lies in the fact that it permits the characterizations of the cyclical relationship which may be difficult to model in the time domain. Cyclical co-movements studied in the frequency domain retain some desirable features of nonlinear models.

In characterizing the process of synchronization of cycles across countries, we use some statistics derived from spectra and cross-spectra, i.e., coherence and phase difference.

1.3 *Coherence*

Coherence measures the strength of relationships between corresponding frequency components of the two series in the same way as a correlation coefficient. Thus, it allows a comparison of how country cycles may have associations that are varying across frequencies. In particular, we can infer if country cycles are more tied at low frequencies (long cycles), growth rate cycle frequencies or high frequencies (short cycles).

For a bivariate case, with a stationary series $X_t = \left(X_{it}, X_{jt}\right)^T$ coherency spectrum[7] is given by (Priestley, 1981)

$$\left|\hat{w}_{ij}(\omega)\right| = \frac{\left|\hat{h}_{ij}(\omega)\right|}{\left\{\hat{h}_{ii}(\omega)\hat{h}_{jj}(\omega)\right\}^{1/2}} = \left\{\frac{\hat{c}_{ij}^2(\omega) + \hat{q}_{ij}^2}{\hat{h}_{ii}(\omega)\hat{h}_{jj}(\omega)}\right\}^{1/2}$$

where $\hat{h}_{ii}(\omega)$ and $\hat{h}_{jj}(\omega)$ are the auto-spectra of $\{X_{it}\}$ and $\left\{X_{jt}\right\}$, respectively, and $\hat{h}_{ij}(\omega)$ is the cross-spectrum of $\{X_{it}\}$ and $\left\{X_{jt}\right\}$, while $\hat{c}_{ij}^2(\omega)$, $\hat{q}_{ij}^2(\omega)$ are the co-spectrum and the quadrature spectrum derived from the polar form of $\hat{h}_{ij}(\omega)$.[8]

---

[5] See Granger and Hatanaka, (1964) or Priestley, (1981) for proof.

[6] For details, see Priestley, (1981).

[7] Some authors refer to $\left|w_{ij}(\omega)\right|^2$ as the coherence.

[8] For the polar form $\hat{h}_{ij}(\omega) = \hat{c}_{ij}(\omega) - i\hat{q}_{ij}(\omega)$, the co-spectrum is the real part and quadrature spectrum the imaginary part.

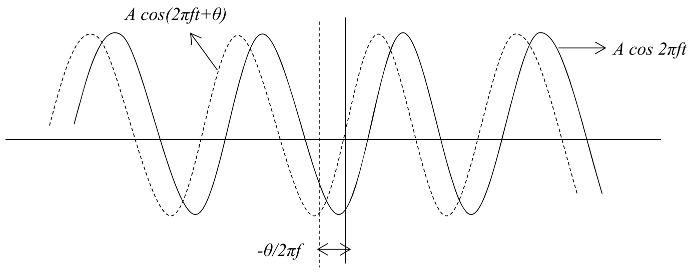


Fig. 4 Graphical representation of the phase

$w_{ij}(\omega)$ can be interpreted as the correlation coefficient between the random coefficients of the components in X_{it} and X_{jt} at frequency ω. It follows that for all ω, $0 \le |w_{ij}(\omega)| \le 1$ for any two jointly stationary processes. Thus, a value close to zero would be indicative of low linear association between the two processes, while a value close to one would mean that the two processes are closely associated.

As in the case of the spectral density estimation, the coherence estimator is an inconsistent estimator. For consistency, as discussed above, the lag window and spectral window are used.

1.4 *Phase*

The phase difference between two series measures the leads or lags between frequency components vis-à-vis each other. With reference to business cycles, it indicates the relative leads or lags between cycles across countries.

From Fig. 4, it is clear that the diagram for $A\ cos\ (2\pi ft + \theta)$ can be obtained by shifting the diagram for $A\ cos\ (2\pi ft)$, i.e., $\theta = 0$ either to the left or to the right (depending on whether $\theta > 0$ or $\theta < 0$) by $-\theta/2\pi f$. θ indicates the position of the sinusoid in relation to the origin of time by using angle. Since $1/f$ is the period of the sinusoid, $-\theta/2\pi$ indicates what portion of the period this shift amounts to.

At frequency ω, a phase lead of θ radians is equivalent to θ/ω periods, which is the number of periods by which a cycle in one country occurs ahead of a similar cycle in another. A measure of the phase difference between the frequency components of the two processes is as follows:

$\phi_{ij}(\omega) = \tan^{-1}\left(-\frac{q_{ij}(\omega}{c_{ij}(\omega)}\right)$ and the plot of $\phi_{ij}(\omega)$ against ω over $0 \le \omega \le \pi$ is the phase diagram.

A brief summary outline of the spectral estimation process is given in Fig. 5, as a series of steps in a flowchart. It discusses that the first step involved in the spectral estimation is to extract a cyclical component from the time series, followed by its conversion to its frequency counterpart using f = 1/T. As discussed above, the Fourier transform is the weighted sum of sine and cosine functions. For a univariate case, the squared Fourier transform (called the periodogram), upon smoothing gives the spectrum. For a bivariate case, the cross-periodogram is obtained from the product of the Fourier transform of one series with that of the other. Smoothing of the cross-periodogram yields the cross-spectrum, which gives the estimates of the coherence

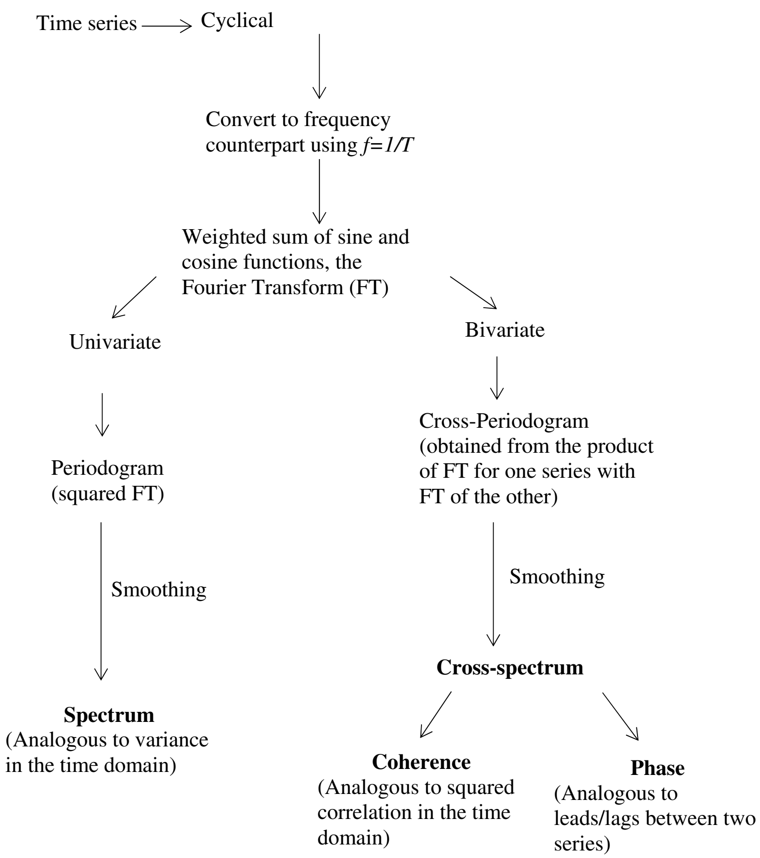


Fig. 5 Summary of the spectral estimation process

(analogous to the squared correlation in the time domain) and the phase (analogous to leads–lags between two series).

3.2.2 Economic Indicator Analysis

Economic indicator analysis defines leads–lags in growth cycle peaks and troughs in one country vis-a-vis turns in the other countries and can thus be used to infer sequencing of cycles. To determine the dating of peaks and troughs, turning point dates are selected from some coincident economic indicators which reflect economic processes such as output, income, employment and sales that comprise a composite coincident index. A set of rules (Bry and Boschan, (1971)) guides the selection of the cyclical turning points of a single indicator. The Economic Cycle Research Institute uses the NBER methodology of dating turning points of the indexes of economic activity.

The methodology used by ECRI and NBER employing the economic indicator analysis (EIA) defines leads and lags in terms of peaks and troughs only. Spectral analysis, on the other hand, defines leads and lags in terms of all time points. In the specific context of stabilization policies for phases of the business cycle, the peak and trough dates are important for the timing of stabilization policy. However, when the effect of a policy is to be seen in continuity (e.g., open market operations), it is important to have the lead–lag relationship over all phases of the cycle, for all time points, e.g., a policy to slow down a boom without turning it into a depression. Such an analysis is possible with this alternative approach, in the frequency domain.

4 Data

A measure of "aggregate economic activity" is ideal to use since it recognizes the fact that the business cycle is a consensus of cycles in many activities, which have a tendency to peak and trough around the same time. The coincident index comprises indicators that measure current economic performance such as measures of output, income, employment and sales, which help to date peaks and troughs of business cycles.

This chapter analyzes growth rate cycles, characterized by monthly growth rates of the coincident index, obtained from ECRI. We focus on the US, UK, Germany, Japan and India over a period from 1974.01 to 2018.12.

5 Results

5.1 Basic Statistics

The ECRI reference chronology for growth rate cycles based on NBER methodology gives peak (shown by upward spikes) and trough (shown as downward spikes) dates for all the five countries as shown in Fig. 6. It can be seen that the timing of peaks and that of toughs of different countries are closely in line vis-à-vis the US economy.

Correspondingly, pairwise simple correlation coefficients between country pairs were calculated and are reported in Table 1. To examine if the growth rate cycles are characteristically different across the two time periods considered, i.e., 1974–1990 versus 1991–2018, we report statistics over both periods. These indicate that during the period 1991–2018, the correlations of UK with the US have increased markedly. The correlations for India vis-à-vis all other countries in the sample have shown an increase during 1991–2018, compared to the period 1974–1990. The correlation of the Indian growth rate cycle vis-à-vis the US was 0.23 during 1974–1990 and higher at 0.40 during the latter period. For the German economy, except for the correlations with India, correlations with all other countries have registered a decline. For the

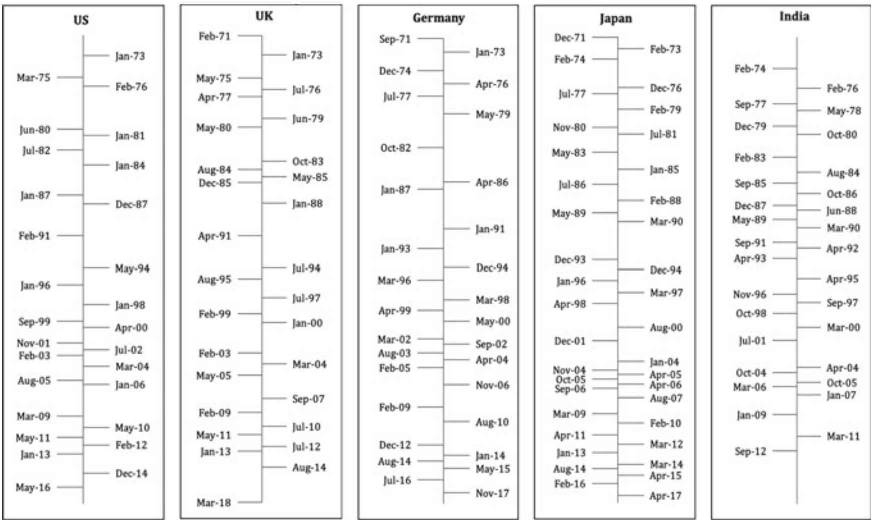


Fig. 6 Timing of peaks and troughs of growth rate cycles based on ECRI reference chronology. *Notes* (1) Marks in the right direction show peaks and left direction troughs in the respective growth rate cycles

case of Japan, the latter period shows higher correlation with India and the US, while correlations are lower with respect to the UK and Germany.

Table 1 Correlations of the coincident index growth rates across countries

1974–1990	US	UK	Germany	Japan	India
US	1				
UK	0.459	1			
Germany	0.550	0.532	1		
Japan	0.336	0.512	0.625	1	
India	0.232	0.069	0.102	0.157	1
1991–2018	*US*	*UK*	*Germany*	*Japan*	*India*
US	1				
UK	0.690	1			
Germany	0.468	0.317	1		
Japan	0.356	0.134	0.551	1	
India	0.402	0.255	0.343	0.299	1

5.2 Non-Spectral Results

We find that during the period 1991–2018, the correlations of the UK with the US have increased markedly. The correlations for India vis-à-vis all other countries in the sample have shown an increase during 1991–2018, compared to the period 1974–1990. For the German economy, except for the correlations with India, all other correlations with other countries have registered a decline. For the case of Japan, the latter period shows higher correlation with India and the US, while correlations are lower with respect to the UK and Germany.

5.3 Synchronization: Cross-Spectral Estimates

In line with the requirements of non-evolutionary spectral analysis, we conducted two unit root tests on the growth rates of the coincident index given by ECRI for each country series for determining the stationarity status of the series, the DF-GLS test and the KPSS test. Inferred from these, we found the growth rates of the coincident index to be stationary, I(0).[9]

We now delve into the frequency-wise break-up of the synchronization process. While the notion of business cycle duration and related frequency band is generally agreed upon (complying with the Burns and Mitchell, (1946) definition of 1.5 years to 8 years), we inferred growth rate cycle frequency from available data on ECRI growth rate cycle dates. For each country across all regions, we calculated durations from peak to peak and trough to trough of all growth rate cycles. Then we calculated the overall growth rate cycle duration by averaging over the peaks and troughs. We then located the minimum and maximum over all countries to obtain a band. This worked out to be between 12 and 96 months. Using $\omega = 2\pi/T$, this corresponds to a growth rate cycle frequency band of [π/48, π/6]. Low-frequency band (corresponding to cycles of duration more than 8 years) has been defined to be less than π/6, and high-frequency band (corresponding to cycles of less than 12 months duration) refers to frequencies greater than π/48.

5.3.1 Coherences

1.1 ***1974–2018***

Average coherences and phase shifts over all three frequency bands were calculated for the entire sample and are reported in Table 2. Between country pairs, for the full sample, 1974–2018, the average coherence in the low-frequency band is the highest between US and UK, standing at 0.81. US–India[10] and UK–India stand close at 0.47

[9] Results are not reported for the sake of brevity, but are available from the authors on request.

[10] Granger and Hatanaka, (1964) call a coherence value of more than 0.5 as high.

Table 2 Average coherences and phase estimates for growth rate cycles: 1974–2018

	Low frequency[a]		Growth rate cycle frequency[b]		High frequency[c]	
Country pairs	Coherence	Phase	Coherence	Phase	Coherence	Phase
US–UK	0.81	0.04	0.38	0.13	0.31	−0.05
US–Germany	0.61	0.09	0.51	0.02	0.28	−0.17
US–Japan	0.40	0.05	0.47	0.08	0.22	−0.15
US–India	0.47	0.02	0.42	−0.24	0.25	−0.09
Japan–India	0.35	−0.03	0.32	−0.14	0.23	−0.07
UK–India	0.46	−0.01	0.25	−0.17	0.25	−0.10
Germany–India	0.42	−0.04	0.31	−0.18	0.24	−0.18
UK–Japan	0.32	0.07	0.33	−0.01	0.22	0.04
Germany–Japan	0.64	−0.00	0.58	0.05	0.20	−0.03

Notes
1. [a]Average growth rate cycle duration has been calculated to be between 1 year and 8 years, which corresponds to a frequency band of (π/48, π/6)
2. [b]refers to all frequencies > π/48
3. [c]refers to all frequencies < π/6
4. (-) Phase shift is to be read as that fraction of a cycle the first country in the pair leads the other

and 0.46, respectively. For the pair US–India, it is the highest for the low-frequency band (0.47), stands at 0.42 for the growth rate cycle frequency and at 0.25 for the high-frequency band.

Spectral Results

To have a deeper insight into the changes in the pattern of co-movements, we divided the sample into two parts: 1974–1990 and 1991–2018.[11] Results for the sub-period analysis are reported in Tables 3 and 4.

1.2 ***1974–1990***

We find that over the period 1974–1990, across various frequency bands, for all country pairs, coherence is the highest in the low-frequency band, falls in the growth rate cycle frequency band and falls further in the high-frequency band. This seems to imply that for this period, long cycles are more correlated than shorter ones. Backus et al., (1992) in estimating cross-country correlations for 1970.1–1990.2 find that output correlations for the pair US–Germany stands at 0.69 (0.697 from our spectral results at low frequency), for US–Japan at 0.60 (0.70) and for US–UK at 0.55 (0.76). These are close to our estimates at low frequency during the period 1974–1990 as given in Table 3.

[11] Since the beginning of 1990s has historical significance as far as events in the international economy are concerned, this was used as a divide year for the sample.

Table 3 Average coherences and phase estimates of growth rates of the coincident index 1974–1990

	Low frequency[a]		Growth rate cycle frequency[b]		High frequency[c]	
Country pairs	Coherence	Phase	Coherence	Phase	Coherence	Phase
US–UK	0.760	0.011	0.497	0.323	0.354	−0.067
US–Germany	0.697	0.017	0.555	0.174	0.270	−0.012
US–Japan	0.702	0.010	0.504	0.230	0.224	−0.341
US–India	0.667	−0.003	0.390	−0.271	0.394	−0.144
Japan–India	0.786	−0.002	0.396	−0.436	0.316	−0.141
UK–India	0.462	−0.031	0.307	−0.384	0.275	0.102
Germany–India	0.500	−0.011	0.390	−0.487	0.334	−0.096
UK–Japan	0.735	0.009	0.362	−0.017	0.258	−0.001
Germany–Japan	0.801	−0.013	0.592	0.019	0.246	0.022

Notes
1. [a]Average growth rate cycle duration has been calculated to be between 1 year and 8 years, which corresponds to a frequency band of (π/48, π/6)
2. [b]refers to all frequencies > π/48
3. [c]refers to all frequencies < π/6

Table 4 Average coherences and phase estimates of growth rates of the coincident index 1991–2018

	Low frequency[a]		Growth rate cycle frequency[b]		High frequency[c]	
Country pairs	Coherence	Phase	Coherence	Phase	Coherence	Phase
US–UK	0.77	0.01	0.61	-0.14	0.34	−0.05
US–Germany	0.47	0.02	0.49	0.04	0.29	−0.21
US–Japan	0.22	0.01	0.51	0.04	0.27	0.10
US–India	0.39	0.03	0.46	−0.19	0.44	−0.10
Japan–India	0.33	−0.03	0.35	−0.27	0.21	−0.05
UK–India	0.48	0.00	0.37	0.11	0.30	−0.16
Germany–India	0.35	0.04	0.45	−0.07	0.24	−0.30
UK–Japan	0.06	0.46	0.34	0.25	0.35	−0.03
Germany–Japan	0.46	0.05	0.62	0.05	0.32	−0.00

Notes
1. [a]Average growth rate cycle duration has been calculated to be between 1 year and 8 years, which corresponds to a frequency band of (π/48, π/6)
2.[b]refers to all frequencies > π/48
3. [c]refers to all frequencies < π/6

1.3 *1991–2018*

The average coherences over different frequency bands during the period 1991–2018 suggest that there has been a change in the pattern of frequency band-wise coherence during this period. The country pairs (with the exception of US–UK, US–India and UK–India) show a spike in the coherence parameter at growth rate cycle frequency, with the coherence being lower at both high and low frequencies.

1.4 *Coherences for Country Pairs*

We find that the coherence for all pairs has increased in at least one of the frequency bands post-1990s period. In particular, between bilateral country pairs, it increased in the growth rate cycle frequency band, with the notable exception of pairs involving Japan, US–Japan, UK–Japan and Japan–India. This aligns well with the fact that the Japanese economy has had a period of stagnation during the 1990s, with domestic factors playing a key role in that.

Looking at Table 3, for US–India pair it emerges that the average coherence in both the time periods is the highest for the low-frequency band. During 1974–1990, the low-frequency band corresponding to cycles of long duration has a high coherence of 0.67, while all others are quite low. This seems to imply that long cycles are more correlated than shorter ones. While average coherences of the Indian growth rate cycle vis-à-vis the US during the period 1991–2018 in the growth rate cycle frequency and high-frequency band are higher than during 1974–1990, average coherence has declined for low frequency or long cycles. The increase in the high-frequency band may be related to various financial innovations that mark the 1990s period and advents in information technology. Within the growth rate cycle frequency, it is possible that the policies across countries, especially monetary policies, are strongly tied and that is a proximate reason for the observed synchronization. With respect to the UK, the coherence for India has increased over all frequency bands.

We also find that for a given country pair, across different frequency bands, coherence spikes in the growth rate cycle frequency band. It has been observed by the IMF World Economic Outlook, (2013), Yetman, (2011) among others that correlations among countries and regional groups tend to be higher during crisis periods than otherwise.

When we specifically look at US vis-à-vis other countries, we find that both during 1974–1990 and 1991–2018, the US–UK pair has the highest coherence in the long-run frequency band. During 1991–2018, only with Japan there is a spike in the growth rate cycle frequency band. While the coherence of US vis-à-vis the UK rises in the low-frequency band, it rises in both the growth rate cycle and high-frequency band vis-à-vis India and only in the high-frequency band vis-à-vis Japan.

Of Japanese coherence vis-à-vis other countries, it is observed that while in the period 1974–1990, Japan has a steadily declining coherence starting with the low-frequency band, and during 1991–2018, it has a spike in the coherence in the growth rate cycle frequency band for all countries. During 1991–2018, the coherence of

Japan vis-à-vis all countries increases only in the high-frequency band, while also increasing in the growth rate cycle frequency band vis-à-vis Germany.

For the case of India, vis-à-vis the US, coherence increases in the growth rate cycle and high-frequency bands during 1991–2018, while falling in the low-frequency band. While the coherence vis-à-vis UK increases across all three frequency bands, it falls in all frequency bands for Japan. With Germany, it rises only in the growth rate cycle frequency band.

To summarize, broadly, two main conclusions emerge. First, that over all bilateral regional and country pairs, there has been an increase in the coherence during 1991–2018 over the period 1974–1990 in at least one of the frequency bands. Second, that during the period 1991–2018, there is a remarkable spike in coherence in the growth rate cycle band. This is in line with the inferences drawn by other studies that find that the synchronization between cycles is higher during crisis periods than in "normal times".

5.3.2 Phase shifts

2.1 ***1974–2018***

In defining bilateral pairs, spectral techniques infer leads–lags from the phase shift estimate. While coherences are analogous to correlations, phase shifts have to be read more carefully. A positive value of the phase shift means that the second in the pair is the fraction of a cycle ahead of the first country. Tables 2, 3 and 4 report phase shift in terms of what fraction of a cycle is one country ahead of the other. The months equivalent of the radian fractions for the entire cycle are reported in Table 6 together with ECRI leads–lags. The convention in reference chronology uses a negative value for a lead and positive for a lag. We use the same notation for the spectral phase shifts, with a negative value implying that the first in the pair is leading.

Over both periods, we find that vis-à-vis India, the US cycle leads the Indian growth rate cycle. Also, for other bilateral pairs involving the US, the US seems to lead cycles (Table 5).

2.2 ***1974–1990***

During the early sample period, 1974–1990, estimates reported in Table 6 show that most country pairs have large lead–lag timings, showing the transmission of business cycles, putting them in the same phase. Indian growth rate cycle consistently lags that of its partner countries, and the lags are large. With Germany, the Indian growth rate cycle shows a lag of 26 months, with UK 21 months and with the US, almost 15 months. Even between two developed country pairs, the lags are large, with the US business cycle lagging UK by almost 17 months, while US lags Japan by almost 12 months.

Table 5 Direction of movement of average coherences across the period 1974–1990 and 1991–2018

	Low frequency	Cycle frequency	High frequency
US–UK	↑	↑	↓
US–Germany	↓	↓	↑
US–Japan	↓	↑	↑
US–India	↓	↑	↑
Japan–India	↓	↓	↓
UK–India	↑	↑	↑
Germany–India	↓	↑	↓
UK–Japan	↓	↓	↑
Germany–Japan	↓	↑	↑

Table 6 Comparative results: spectral phase shifts versus EIA reference chronology

	Spectral Estimates		EIA Reference Chronology	
Country Pairs	1974–1990	1991–2018	1974–1990	1991–2018
US–UK	17.44	−1.97	0.00	−2.64
US–Germany	9.40	3.42	−0.84	−5.22
US–Japan	12.42	3.86	1.38	1.74
US–India	−14.63	−5.03	−6.67	−6.15
Japan–India	−2.35	−2.08	−0.10	−3.72
UK–India	−20.74	−1.99	−6.17	−1.79
Germany–India	−26.30	−3.12	−4.38	−2.00
UK–Japan	−0.92	3.74	−2.42	1.75
Germany–Japan	1.03	3.09	2.17	2.23

Notes
1. Months equivalent of the phase shifts are those associated with the growth rate cycle frequency

2.3 ***1991–2018***

For all the country pairs in the period 1991–2018, compared to 1974–1990, the phase shifts have become significantly smaller, indicating that it takes lesser time for the growth rate cycles in one country to get transmitted to other countries. Specifically for the Indian economy, the phase shifts have reduced from 15 to 5 months vis-à-vis the US, from 26 to 3 months vis-à-vis Germany and from 21 to 2 months vis-à-vis UK. For the pairs US–Japan and US–Germany, the same pattern can be observed with the US lagging both the countries.

2.4 ***Phase Shifts across Country Pairs***

It seems evident from Table 6 that for the country pairs like US–UK, the phase shifts show lower values compared with other pairs. It is also observed that for all the country pairs, the latter time period, 1991–2018 the transmission process has been faster compared to the same pair phase shifts in the earlier time period.

In summary, we observe that the time it takes for cycle transmission is lower during the period 1991–2018 as compared to that in 1974–1990 for the growth rate cycle frequency and the high-frequency bands. Placed together with the movement in coherences in the corresponding frequency bands, it emerges that in the low-frequency band, not only have coherences fallen, the lag has become larger. Similarly, for the other two frequency bands, while coherence has increased, the time lag has also reduced. Figure 7 plots the coherence and phase shifts over different frequencies.

5.3.3 Spectral Phase shifts and ECRI/NBER Reference Chronology: A Comparison

Finally, we place together our spectral results with those of ECRI reference chronology. As noted earlier, the methodology used by ECRI employing the EIA defines leads and lags in terms of peaks and troughs only. On the other hand, spectral analysis defines leads and lags in terms of all time points. Therefore, one would not expect to get the same results using the EIA and the cross-spectrum because of the conceptual difference as to the lead–lag.[12]

It is interesting to see in Table 6 that the same direction of leads and lags is obtained across the two methodologies though magnitudes vary. The magnitude of leads by the spectral method is larger than the leads obtained from the reference chronology in the period 1974–1990, but is of similar magnitude during 1991–2018. Thus, a comparative evaluation of the spectral and EIA results indicates that they are broadly in agreement with each other directionally but magnitudes differ.

6 Conclusion

In this paper, we look at the issue of synchronization of growth rate cycles and analyze the pattern of co-movement of growth rate cycles for a set of five countries—US, UK, Germany, Japan and India. Employing spectral methods, we find evidence of co-movements in the growth rate cycles across countries during 1974–2018. In a sub-period analysis (1974–1990 and 1991–2018), broadly two main conclusions

[12] See Granger and Hatanaka, (1964).

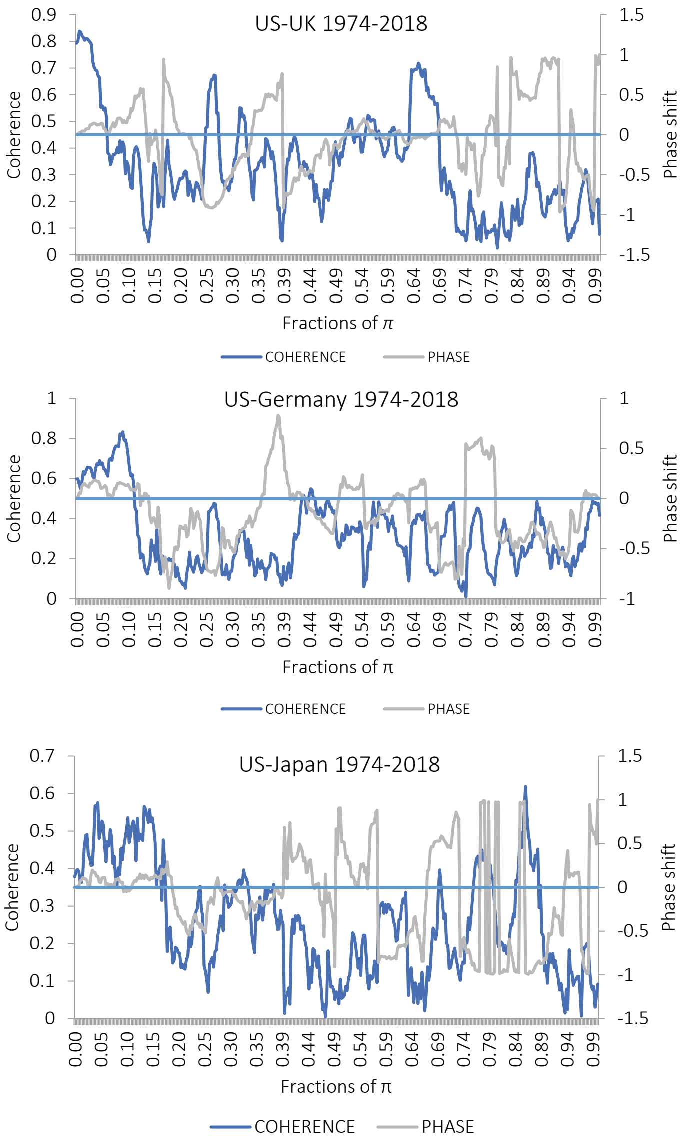


Fig. 7 Coherence and phase shifts

emerge. First, that across all bilateral country pairs, there has been an increase in the coherence during 1991–2018 over the period 1974–1990 in at least one of the frequency bands. Second, that during the period 1991–2018, there is a remarkable spike in coherence in the growth rate cycle band. This is in line with the inferences drawn by other studies that find that the synchronization between cycles is higher during crisis periods than during other times.

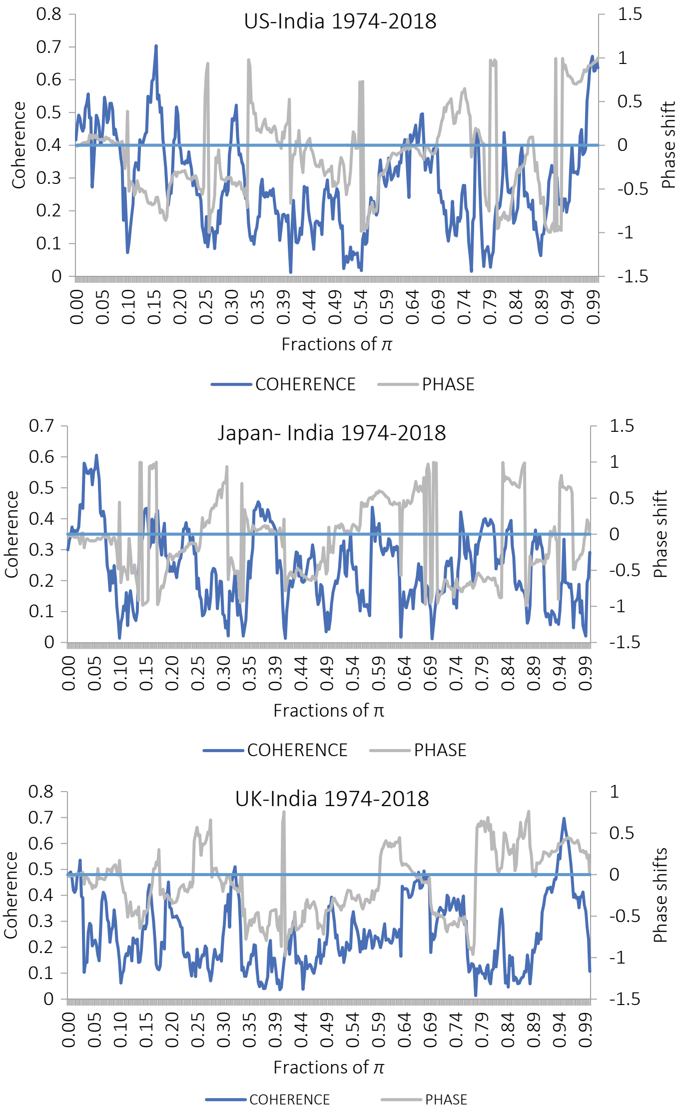
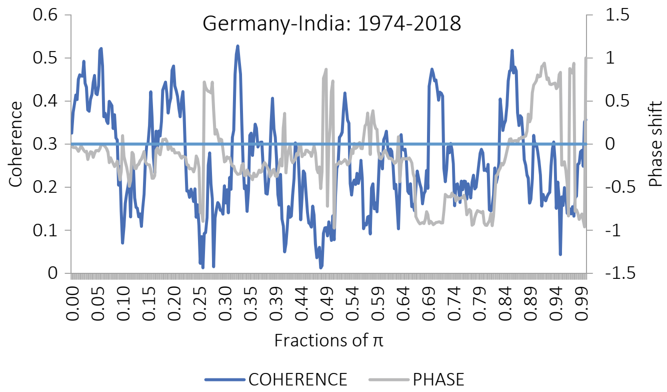
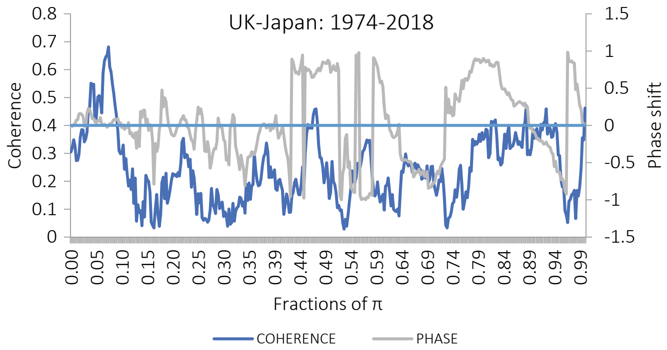


Fig. 7 (continued)

The US growth rate cycle seems to be leading cycles vis-à-vis other countries. Leads–lags, as inferred from phase shifts, have become lower when compared across the two periods 1974–1990 and 1991–2018, indicating that cycles in the two countries are not only more tied post-1990s, the leads–lags of cycles vis-à-vis each other have become smaller in two frequency bands—high frequency and growth rate cycle frequency. Placed together with the movement in coherences in the corresponding frequency bands, it emerges that in the low-frequency band (corresponding to long





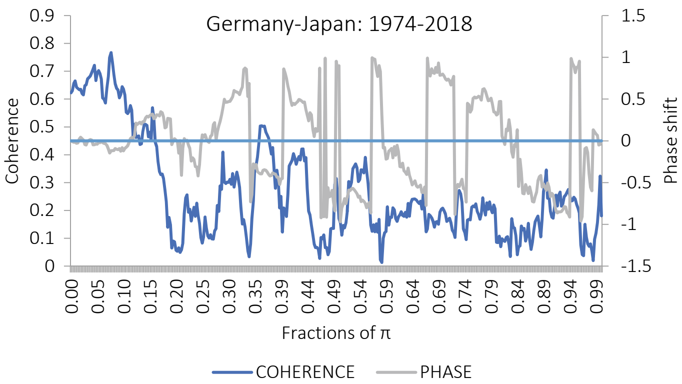


Fig. 7 (continued)

cycles), coherences have fallen, as well as the number of months of leads indicated by the phase shift has become larger. Similarly, for the other two frequency bands, while coherence has increased, the lead months have also reduced.

A comparison of the phase shifts with the reference chronology of growth rate cycles given by ECRI indicates compliance in the direction of leads–lags, while magnitudes differ. This arises expectedly from the conceptual difference between the two, but still gives interesting and significant insights from the policy perspective.

Questions To Think About

1. Explain the major differences between time and frequency domains methods.
   Hint: Compare attributes at a point of time vs those over a frequency.
   Refer Granger and Hatanaka, (1964); Janecek and Swift, (1993).
2. Average growth rate cycle duration has been calculated to be between 1 and 8 years. Calculate the corresponding frequency bands. Using IIP data of India and US, calculate coherence (analogous to frequency-wise correlation) over frequencies greater and less than cycle frequencies and compare with the correlation coefficient in the time domain.
   Hint: Frequency band of ($\pi/48$, $\pi/6$) corresponds to the growth rate cycle duration.
   Refer Poměnková et al., (2014). Calculate the average coherence in a frequency band with frequency $< \pi/48$ and $> \pi/6$. These averages can be compared with the correlation coefficient obtained.
3. List some of the variables that can influence the co-movement of financial cycles across countries.
   Hint: Degree and depth of financialization; level of development.

Acknowledgements The authors would like to thank the Economics Cycle Research Institute (ECRI), New York, for providing the data used in the study.

References

Aguiar-Conraria, L., & Soares, M. J. (2011). Business cycle synchronization and the Euro: A wavelet analysis. *Journal of Macroeconomics, 33*, 477–489.

Allegret, J. P., & Essaadi, E. (2011). Business cycle synchronization in East Asian economy: Evidence from time-varying coherence study. *Economic Modelling, 28*, 351–365.

Aloui, C., & Hkiri, B. (2014). Co-movements of GCC emerging stock markets: New evidence from wavelet coherence analysis. *Economic Modelling, 36*, 421–431.

Anderson, H. M., & Terasvirta, T. (1992). Characterizing non-linearities in business cycles using smooth transition autoregressive models. *Journal of Applied Econometrics, 7*, S119–S136.

Antonakakis, N. (2012). Business cycle synchronization during US recessions since the beginning of the 1870s. *Economics Letters, 117*, 467–472.

Artis, M. (2003). Is there a European business cycle, WP 1053, CESIFO.

Artis, M., Kontolemis, Z. G., & Osborn, D. R. (1997). Business cycles for G7 and European countries. *Journal of Business, 70*, 249–270.

Backus, D. K., Kehoe, P. J., & Kydland, F. E. (1992). International real business cycles. *Journal of Political Economy, 100*, 745–775.

Banerji, A., & Dua, P. (2010). Synchronization of recessions in major developed and emerging economies. *Margin—The Journal of Applied Economic Research*, *4*, 197–223.

Banerji, A., & Dua, P. (2011). Predicting recessions and slowdowns: A robust approach, WP 202, Centre for Development Economics

Banerji, A., & Hiris, L. (2001). A framework for measuring international business cycles. *International Journal of Forecasting, 17*, 333–348.

Bátorová, I. (2007). *Application of factor models in business cycle analysis in the enlarged EU,* Unpublished Master Thesis, Bratislava.

Bátorová, I., Fidrmuc, J., & Korhonen, I. (2008). China in the world economy: Dynamic correlation analysis of business cycles, discussion paper 7, Bank of Finland.

Bátorová, I., Fidrmuc, J., & Korhonen, I. (2009). New global players and disharmonies in the world orchestra: Cohesion analysis of business cycles of China. In*The Economic Performance of the European Union*, Palgrave Macmillan, London.

Bátorová, I., Fidrmuc, J., & Korhonen, I. (2011). From Decoupling of Asian Stock Markets to Recoupling during the Great Recession. In S. Rosefielde, M. Kuboniwa, & S. Mizobata (Eds.), *Two Asias: The emerging postcrisis divide*, World Scientific, Singapore.

Bátorová, I., Fidrmuc, J., & Korhonen, I. (2013). China in the world economy: Dynamic correlation analysis of business cycles. *Cesifo Economic Studies, 59*, 392–411.

Baxter, M. (1995). International trade and business cycles. *Handbook of International Economics, 3*, 1801–1864.

Bayoumi, T. & Helbling, T. (2003). Are they all in the same boat? The 2000–2001 Growth Slowdown and the G-7 Business Cycle Linkages, WP 46, IMF.

Berdiev, A. N., & Chang, C. P. (2015). Business cycle synchronization in Asia-Pacific: New evidence from wavelet analysis. *Journal of Asian Economics, 37*, 20–33.

Boehm, E. A. (2001). The contribution of economic indicator analysis to understanding and forecasting business cycles. *Indian Economic Review, 36*, 1–36.

Bordo, M. D. & Hebling, T. (2003). Have national business cycles become more synchronized, WP 10130, NBER.

Breitung, J., & Candelon, B. (2001). Is there a European business cycle? New insights from a frequency domain analysis. *Vierteljahrshefte Zur Wirtschaftsforschung (quarterly Journal of Economic Research), 70*, 331–338.

Bry, G. & Boschan, C. (1971). Standard Business Cycle Analysis of Economic Time Series. In G. Bry, & C. Boschan (Eds.), *Cyclical analysis of time series: Selected procedures and computer programs*, NBER.

Burns, A., & Mitchell, W. (1946). *Measuring business cycles.* New York: NBER.

Çakır, M. Y., & Kabundi, A. (2013). Trade shocks from BRIC to South Africa: A global VAR analysis. *Economic Modelling, 32*, 190–202.

Camba-Mendez, G. & Kapetanios, G. (2001). Spectral based methods to identify common trends and common cycles, WP 62, European Central Bank.

Campos, N. F., Fidrmuc, J., & Korhonen, I. (2019). Business cycle synchronisation and currency unions: A review of the econometric evidence using meta-analysis. *International Review of Financial Analysis, 61*, 274–283.

Candelon, B., & Hecq, A. (2000). Stability of Okun's law in a co-dependent system. *Applied Economic Letters, 7*, 687–693.

Canova, F. (1998). Detrending and business cycle facts. *Journal of Monetary Economics, 41*, 475–512.

Canova, F., & Dellas, H. (1993). Trade interdependence and the international business cycle. *Journal of International Economics, 34*, 23–47.

Canova, F., Ciccarelli, M., & Ortega, E. (2007). Similarities and convergence in G-7 cycles. *Journal of Monetary Economics, 54*, 850–878.

Chatfield, C. (1996). *The Analysis of Time Series: An Introduction.* London: Chapman and Hall.

Croux, C., Forni, M., & Reichlin, L. (1999). A measure of co-movement for economic variables: Theory and empirics, No. 2339, CEPR Discussion Paper.

Cubadda, G., & Hecq, A. (2001). On non-contemporaneous short-run co-movements. *Economics Letters, 73*, 389–397.

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers with applications to global equity markets. *The Economic Journal, 119*, 158–171.

Dufrénot, G., & Keddad, B. (2014). Business cycles synchronization in East Asia: A Markov-switching approach. *Economic Modelling, 42*, 186–197.

Elliot, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica, 64*, 813–836.

Engle, R. F., & Vahid, F. (1993). Common trends and common cycles. *Journal of Applied Econometrics, 8*, 341–360.

Engle, R. F., & Kozicki, S. (1993). Testing for common features. *Journal of Business and Economic Statistics, 11*, 369–395.

Fidrmuc, J., Korhonen, I., & Poměnková, J. (2014). China and the world economy: Wavelet spectrum analysis of business cycles. *Applied Economics Letters, 21*, 1309–1313.

Filardo, A. J., & Gordon, S. F. (1994). International Co-movements of Business Cycles, WP 94–11, Federal Reserve Bank of Kansas City.

Fuller, W. (1976). *Introduction to statistical time series*. New York: Wiley.

Gordon, R. A. (1961). *Business fluctuations* . New York: Harper and Row.

Granger, C. (1969). Investigating casual relations by econometric models and cross-spectral methods. *Econometrica, 37*, 424–438.

Granger, C. J., & Hatanaka, M. (1964). *Spectral Analysis of Economic Time Series*. Princeton: Princeton University Press.

Hamilton, J. (1989). A new approach to the economic analysis of non-stationary time series and business cycles. *Econometrica, 57*, 357–384.

Hamilton, J. (1994). *Time series analysis*. Princeton: Princeton University Press.

Hamilton, J. D. (2005). Oil and the macroeconomy. In S. Durlauf, & L. Blume (Eds.), *The new Palgrave dictionary of economics*, Macmillan, London.

Hanus, L. & Vacha, L. (2015). Business Cycle Synchronization of the Visegrad Four and the European Union, WP 42, Collaborative EU Project Financial Distortions and Macroeconomic Performance: Expectations, Constraints and Interaction of Agents.

Harding, D., & Pagan, A. (2006). Synchronization of Cycles. *Journal of Econometrics, 132*, 59–79.

Harvey, A. (1993). *Time series models*. Cambridge: The MIT Press.

Hatanaka, M. (1996). *Time-series-based econometrics*. New York: Oxford University Press.

Hecq, A. (2009). Asymmetric business cycle co-movements. *Applied Economics Letters, 16*, 579–584.

Hughes-Hallett, A. J., & Richter, C. (2004). A Time-Frequency Analysis of the Coherences of the US Business Cycle and the European Business Cycle, No. 4751, Centre for Economic Policy Research.

Hughes-Hallett, A. J., & Richter, C. (2008). Have the Eurozone economies converged on a common European cycle. *International Economics and Economic Policy, 5*, 71–101.

IMF. (2013). *World economic outlook*. Washington: IMF.

Janacek, G., & Swift, L. (1993). *Time Series: Forecasting, Simulation, Applications*, Ellis Horwood, New York.

Jensen, R. V., & Selover, D. (1999). Mode-locking and international business cycle transmission. *Journal of Economic Dynamics and Control, 23*, 591–618.

Kapounek, S., & Pomënková, J. (2010). Business Cycle Development in Czech And Slovak Economies, *Bulletin of the Transilvania University of Brașov*, 3.

Kim, S. H., & Saiki, A. (2014). Business cycle synchronization and vertical trade integration: A case study of the Eurozone and East Asia, WP 407, Netherlands Central Bank Working Papers.

Kwiatkowski, D., Phillips, P., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics, 54*, 159–178.

Maršálek, R., & Pomënková, J. (2010). Spectral analysis of the cyclical behaving of the Czech republic industrial production. *Forum Statisticum Slovacum, 2*, 123–128.

Maršálek, R., & Pomënková, J. (2011). Time and frequency domain in the business cycle structure, WP 7, MENDELU Working Papers in Business and Economics.

Medhioub, I. (2010). Business cycle synchronization: A mediterranean comparison, WP 527, Economic Research Forum.

Owens, R., & Sarte, P. D. (2005). How well do diffusion indexes capture business cycles? A Spectral Analysis, *Federal Reserve Bank of Richmond Economic Quarterly*, 91.

Priestley, M. B. (1981). *Spectral analysis and time series,* I and II, Academic Press.

Pakko (2004). A spectral analysis of the cross-country consumption correlation puzzle, WP 2003–023B, Federal Reserve Bank of St. Louis.

Saiki, A. (2018). Business cycle synchronization and vertical trade integration: A case study of the Eurozone and East Asia. *Global Economy Journal, 18*, 1–15.

Tiao, G. C., & Tsay, R. S. (1994). Some advances in non-linear and adaptive modelling in time-series. *Journal of Forecasting Special Issue on Time Series Advances in Economic Forecasting, 13*, 109–131.

Yetman, J. (2011). Exporting recessions: International links and the business cycle. *Economics Letters, 110*, 12–14.

Zimmermann, C. (1997). International real business cycles among heterogeneous countries. *European Economic Review, 41*, 319–356.

Chapter 12
Inter-Linkages Between Asian and U.S. Stock Market Returns: A Multivariate GARCH Analysis

Pami Dua and Divya Tuteja

Abstract This chapter investigates inter-linkages of the Asian stock markets, viz. China, Hong Kong, India, Japan and Singapore with the U.S. stock market. The objective is to discern the impact of the global financial crisis and the Eurozone debt crisis on the linkages across these equity markets. In order to identify the crisis periods, we utilize the timeline given by the respective U.S. and Eurozone specific Markov-switching vector autoregressive models. The sample under study is from June, 2000 to December, 2019, and the data is at weekly frequency. We employ multivariate GARCH (generalized autoregressive conditional heteroscedasticity) models, viz. GARCH-CCC, GARCH-DCC and GARCH-EWMA, to estimate the time-varying conditional correlation among the stock market pairs. Finally, crisis periods identified by the Markov-switching models are used as dummy variables and regressed on the conditional correlation coefficients obtained from the multivariate GARCH models to test for contagion effects. We test for the existence of contagion effects among international stock markets during both the crises by utilizing ordinary least squares (OLS). The results suggest that there were significant contagion effects among the stock markets at play during the crisis episodes.

Keywords Stock markets · Multivariate GARCH-DCC · Global financial crisis · Eurozone debt crisis · Contagion · Asia · US

JEL Classification C32 · G15

1 Introduction

The 1990s have been marked by financial sector reforms being undertaken in several developing and emerging market economies (EMEs) which, in turn, have led to

P. Dua
Department of Economics, Delhi School of Economics, Delhi, India

D. Tuteja (✉)
Economics Division, Indian Institute of Foreign Trade, New Delhi, India
e-mail: divya@iift.edu

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_12

increasing co-movement among financial markets. The deepening and broadening of these markets have changed the contours of international investment in global financial markets which are characterised by increasingly inter-related movement of capital across borders and an intensification of market integration. Moreover, in the background of several adverse news announcements during the crisis of 2008–09 in the U.S. and the subsequent Eurozone debt crisis of 2010–12 which shook the global markets, studying the inter-linkages between international financial markets assumes further significance.

The phenomenon of financial 'contagion' may be spurred through direct economic linkages like trade and financial inter-relations among two economies or due to indirect effects such as a change in global investor attitude. Contagion has been defined in several ways in the existing literature. In a study, Calvo and Reinhart (1996) differentiate between fundamentals based contagion and 'true' contagion. The former occurs when a crisis-hit economy infects other economies which are closely linked to it via trade or financial relations. On the other hand, the latter is the outcome of 'animal spirits' or investors' herding behaviour and takes place when all the common shocks and possible channels to transmission have been controlled for. Contagion could also be a result of common adverse shocks such as an increase in the world rate of interest but symmetric shocks do not seem to be a part of most definitions of contagion (Kaminsky and Reinhart, 2000). Much of the recent theoretical literature has been focussed on the role played by portfolio constraints and information asymmetry in inciting contagion across international financial markets.

In this backdrop, the present chapter attempts to unravel and explore the extent of inter-linkages among major Asian stock markets with the U.S. stock market. Specifically, we test for the impact of events that transpired during recent crises in the U.S. and Eurozone economies on the relationship between Asian and U.S. stock markets. Our objective is to test for the existence of contagion effects during these episodes of turbulent news that severely affected global stock markets.

Table 1 presents the market capitalization, share of GDP (as percentage of world GDP in PPP terms) and growth rate of GDP for major Asian economies and U.S. It is pertinent to note that the stock market capitalization of all the Asian economies, barring Singapore, has increased over the period of 2005 to 2020. From the table, we observe that the market capitalization of Hong Kong, Japan, Singapore and South Korea among the Asian countries as well as the U.S. is well above 100%. Further, the share of world GDP (in PPP terms) is highest for the Asian nations of China, India and Japan. Moreover, between 2005 and 2020, the share of world GDP doubled for both China and India. Finally, the fastest-growing Asian economies before the crises in the West included China, India, Hong Kong and Singapore. It is notable that the crises of 2008–09 and 2010–12 marred growth rates in all the economies across the board. The economic growth took a further hit in the aftermath of the COVID-19 pandemic, post 2020. We select the Asian economies of China, India, Hong Kong, Japan and Singapore for the analysis in this study.

In order to fulfil the earlier defined objective of the chapter, we follow a multi-step procedure. First, we utilize the U.S. and Eurozone economy-specific Markov-switching models to define the crisis periods, i.e. phases of the global financial

Table 1 Asian Economies and U.S.: market capitalization, GDP and growth rate of GDP

Country	Market capitalization (as % of GDP)			GDP of the economy (share of world GDP in PPP terms)			Growth rate of GDP		
	2005 (%)	2015 (%)	2020 (%)	2005 (%)	2015 (%)	2020 (%)	2005 (%)	2015 (%)	2020 (%)
China	17	74	82	9.70	17.10	18.71	11.40	6.90	2.35
India	86	72	98	4.80	7.00	7.03	9.30	7.60	−7.25
Indonesia	28	41	47	2.00	2.50	2.44	5.70	4.80	−2.07
Hong Kong	581	1029	1768	0.40	0.40	0.40	7.40	2.40	−6.08
Japan	100	118	133	5.70	4.30	3.89	1.30	0.50	−4.59
South Korea	80	89	133	1.60	1.60	1.73	3.90	2.60	−0.85
Singapore	202	218	192	0.40	0.40	0.42	7.50	2.00	−5.39
U.S	130	140	195	19.50	15.80	15.86	3.30	2.60	−3.64

Source World Development Indicators, 2021; World Economic Outlook, 2021 crisis and Eurozone debt crisis. Second, we estimate the conditional correlation coefficients across the selected stock markets. This is accomplished by employing alternative multivariate GARCH specifications, viz. GARCH-CCC, GARCH-DCC and GARCH-EWMA. Among these, the former two are correlation-based GARCH models, while the latter is a simple covariance based GARCH formulation. The CCC-GARCH-based constant conditional correlation provides a measure of the average level of co-movement among the stock market pairs over the period of study. Next, we conduct a test for the existence of contagion during the various phases of global financial crisis and Eurozone sovereign debt crisis. In order to accomplish this, the GARCH-DCC and GARCH-EWMA model estimates are used since they provide time-varying correlation coefficients. The GARCH-EWMA estimates for correlation provide the robustness check for the main results which are based on the GARCH-DCC model.

The rest of the chapter is structured as follows: Section 2 focuses on the literature for inter-linkages among Asian and other stock markets, with particular emphasis on the recent turbulent episodes in the global financial markets. The following Section 3 brings out the methodological details. Next, Section 4 discusses the empirical estimation strategy and data. Section 5 presents the results and findings of the analysis. Finally, Section 6 concludes.

2 Inter-Linkages Between Asian and U.S. Stock Markets and Impact of Crises

There are several aspects of contagion that have been highlighted in the existing literature. The present study employs data for a sample of Asian and U.S. equity markets to examine the transmission of contagion during crises in the U.S. and Euro Area. According to Dungey et al., (2005), econometric techniques which a majority of the empirical literature utilizes such as correlation breakdowns, ARCH/GARCH framework, cointegration and logit and probit models are inappropriate for the measurement of contagion since the data are plagued by heteroscedasticity, omitted variable bias and endogeneity. Other studies such as Forbes and Rigobon, (2002), Dungey et al., (2005) and Pesaran and Pick, (2007) have also questioned the efficacy and reliability of these techniques. Forbes and Rigobon, (2002) show that cross-market correlation coefficients are biased upwards (as higher volatility translates into high correlation coefficients) during periods of crisis due to the heteroscedasticity in the data. In particular, Pesaran and Pick, (2007) criticize the analyses using correlation breakdowns for selecting the crisis periods a priori. Recent work on correlation breakdowns corrects for the sample selection bias which results from arbitrary selection of crisis periods and focuses on conditional correlations instead of unconditional correlation coefficients. In this chapter, we use the Markov-switching models which are specific to the U.S. and Eurozone in order to delineate the crisis periods. We employ multivariate GARCH-based conditional correlations for our analysis.

Some of the studies investigating the phenomenon of contagion across stock markets include Forbes and Rigobon, (2002); Bae et al., (2003); Bahng and Shin, (2003); Bekaert et al., (2005); Chiang et al., (2007); Bodart and Candelon, (2009); Baur and Fry, (2009); Billio and Caporin, (2010); Dungey et al., (2010); Yiu et al., (2010), Kenourgios et al., (2011); Samarakoon, (2011); Syllignakis and Kouretas, (2011); Min and Hwang, (2012); Morales and Andreosso-O'Callaghan (2012); Ahmad et al., (2013); Kim and Ryu, (2015), Kenourgios et al. (2016), Jin (2016), Tran (2018) and Le and Tran, (2021). However, in this section, we focus mainly on the studies pertaining to the Asian stock markets.

Bae et al. (2003) proposed a new approach to study the phenomenon of financial contagion utilizing the propagation of large shocks in extreme returns across regions by employing a multinomial logistic regression. The sample under analysis consists of emerging market economies in Latin America and Asia during the 1990s. They find contagion effects in Latin American countries to be more than that in the Asian countries. Contagion effects from the former to the rest of the world are also found to be more important than those from the latter. However, the U.S. is more or less insulated from the contagion effects originating in the Asian countries. Bahng and Shin, (2003) investigate the existence of inter-linkages, asymmetric responses, causality and financial transmission in the stock price indices of China, Japan and South Korea. Further, they study whether U.S. markets exert any influence on the Asian markets. The methodology selected for the study was regression analysis and cointegration/vector autoregression (VAR). The U.S. market index significantly influences the Japanese and South Korean markets, especially during downturns. Chiang et al., (2007) test for contagion during the Asian crisis in nine Asian stock markets using GARCH-DCC model and find evidence of contagion across the markets. Baur and Fry, (2009) propose to test for contagion using a multivariate test which analyses extreme unobserved common shocks and measures the significance, both statistical and economic, of the phenomenon of contagion for a panel of stock markets during the East-Asian crisis. Hong Kong is indicated to be the key source of contagion effects during the crisis episodes which are occur in bursts and are temporary in comparison to the interdependence across the Asian equity markets. Billio and Caporin, (2010) employ a simultaneous equation model with GARCH errors to study the contemporaneous relationship and evidence of contagion between Asian and American equity markets. They identify periods of contagion transmission and flight-to-quality between June, 1995 and November, 2005 and find evidence of some contagion effects during the East-Asian crisis.

Some of the recent studies such as Yiu et al., (2010), Samarakoon, (2011), Morales & Andreosso-O'Callaghan, (2012), Ahmad et al., (2013), Jin, (2016), Tran, (2018) and Le and Tran, (2021) have examined contagion in Asian stock markets during the U.S. financial crisis. Yiu et al., (2010) study 11 Asian markets and find significant evidence of contagion from the U.S. to the Asian markets during the financial crisis of 2007 but no contagion between the markets during the Asian crisis. Samarakoon, (2011) investigates the process of transmission of shocks from the U.S. global financial crisis of 2008–09 to a set of emerging and frontier stock markets. The paper finds existence of significant contagion effects from the Asian economies to the U.S. markets and interdependence driven by U.S. shocks to the Asian emerging markets. Morales & Andreosso-O'Callaghan, (2012) utilize the Forbes and Rigobon, (2002) methodology and deduce no contagion in Asian stock markets due to the U.S. crisis. Ahmad et al., (2013) assess financial contagion across Brazil, Russia, India, Indonesia, China, South Korea and South African equity markets using GARCH-DCC framework and find that the economies were impacted by contagion during the crisis. Jin, (2016) studies the Asian stock markets during the U.S. financial crisis of 2008 to find evidence of significant financial contagion. It is noteworthy that the findings of the studies on contagion in Asian equity markets during U.S. and Eurozone crisis episodes are mixed. Tran, (2018) compares the contagion during the Mexican 'Tequila' Asian Crisis of 1997 and the U.S. subprime crisis and finds that the contagion during the U.S. crisis of 2007–08 affected the stock markets across the board. Le and Tran, (2021) compare the contagion effects during the U.S. crisis of 2007–08 with those during the COVID-19 pandemic and conclude that both the Vietnamese and Philippines economies were affected during the recent pandemic.

3 Methodology

This section elaborates the methodological aspects of the techniques that have been utilized in the present work.

3.1 Markov-Switching Models

The first step in our analysis is the identification of crisis periods for which we employ a Markov-switching VAR model. The first and second moments of returns in the EZ stock and exchange rate returns are depicted by a two-dimensional bivariate Markov-switching model with heteroscedasticity. In the case of the U.S., we utilize the stock market along with the TED spread[1] to identify the crisis periods. This framework allows us to characterize the tranquil and crisis regimes in the US and EZ markets respectively. This strategy is similar to that followed by us in Dua and Tuteja, (2016a). Data at weekly frequency for the analysis have been sourced from Federal Reserve Bank of St. Louis and Wall Street Journal's Websites. The Markov Switching Intercept Autoregressive Heteroscedasticity (MSIAH) model (Hamilton, 1989; 1990; Guidolin, 2011) has the following general form for a two-regime MSVAR (p) process

$$y_t = \mu_{S_t} + \sum_{j=1}^{p} \kappa_{j,S_t} y_{t-j} + \eta_t \tag{1}$$

[1] The TED spread is defined as the difference between the three-month LIBOR and the three-month U.S. Treasury Bill rate and measures credit risk.

where $y_t = \begin{pmatrix} s^{US(orEZ)} \\ e^{TED(or\,€)} \end{pmatrix}$ is the 2 ×1 vector of endogenous variables, i.e. returns on the US stock market s^{US} (or EZ stock market s^{EZ}) and TED spread (or Euro per dollar, i.e. $e^{€}$; μ_{S_t} is a 2 ×1 vector of regime-dependent mean returns; κ_{j,S_t} is the 2 × 2 matrix of regime-dependent VAR coefficients; $S_t = 1, 2$ is a latent-state variable driving all the parameter matrices. It is an irreducible, aperiodic and ergodic two-state Markov chain process with the transition matrix

$$P = \begin{bmatrix} p_{11}\ p_{12} \\ p_{21}\ p_{22} \end{bmatrix} \tag{2}$$

$$P\{S_t = j|S_{t-1} = i, S_{t-2} = k, \ldots, y_{t-1}, y_{t-2}, \ldots\} = P\{S_t = j|S_{t-1} = i\} = p_{ij} \tag{3}$$

Such a process will be called a two-state Markov chain with transition probabilities $\{p_{ij}\}_{i,j=1,2}$. The residuals follow a standard Gaussian distribution conditional on the state, i.e. $\eta_t \sim N(0, \Sigma_{S_t})$. The 2 × 2 matrix Σ_{S_t} represents the state factor S_t in the regime-dependent variance–covariance matrix such that

$$\Sigma_{S_t} = \begin{bmatrix} \sigma_{1,1,S_t}\ \sigma_{1,2,S_t} \\ \sigma_{2,1,S_t}\ \sigma_{2,2,S_t} \end{bmatrix} \tag{4}$$

We estimate the economy-specific models using the expectations-maximization algorithm. The smoothed probabilities derived from the MS-VAR model encompassing the US stock market returns and TED market spreads are utilized to select the time periods for GFC. In the same vein, smoothed probabilities calculated from the MS-VAR model consisting of EZ stock market returns and currency market returns are employed to specify the periods for EZDC.

3.2 Univariate ARCH/GARCH Models

A time series may display heteroscedastic behaviour or a non-constant variance structure. Additionally, it has been observed that a time series may experience alternative periods of small variations followed by larger variations; i.e. a time series may display ‘volatility clustering’ behaviour. Such a behaviour has crucial implications for the validity and efficiency of statistical tests used in the regression analysis. Moreover, the time series may be characterised by positive autocorrelations has been displayed by the autocorrelation function of squared returns. Therefore, although the returns may be hard to predict (assuming they follow a random walk), the volatility is time-dependent and a function of the past periods’ volatility.

Financial data have, in general, been characterized by periods of sporadic disturbances and high volatility. Further, such episodes are clustered and, therefore, errors would be serially correlated which necessitates the application of GARCH methodology to capture these effects. The seminal paper by Engle, (1982) extends the autoregressive (AR) framework for modelling the mean equation to the volatility equation such that the conditional variance is modelled with autoregression in the squares of the residuals and is called an autoregressive conditional heteroscedastic process of order q or ARCH(q). The conditional variance of a zero mean and serially uncorrelated process ε_t can be represented by an ARCH(q) process as.

Mean equation:

$$r_t = E(r_t) + \varepsilon_t \tag{5}$$

where r_t denotes the time series, E is the expectations operator, $E(r_t)$ can be specified as appropriate with lagged and exogenous regressors and ε_t are errors in the mean equation. Further, we can write $\varepsilon_t = v_t\sqrt{h_t}$, where h_t is the conditional variance of r_t and v_t is white noise or the standardized residuals.

Volatility equation:

$$h_t = Var(\varepsilon_t|\mathcal{F}_{t-1}) = E\big(\varepsilon_t^2|\mathcal{F}_{t-1}\big) = \gamma_0 + \gamma_1\varepsilon_{t-1}^2 + \cdots + \gamma_q\varepsilon_{t-q}^2 \tag{6}$$

where $\mathcal{F}_{t-1} = \{\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots\}$ is the set of past information on the error or $\varepsilon_t|\mathcal{F}_{t-1} \sim N(0, h_t)$.

It was later realized that many series required ARCH processes with large orders to capture the dynamics in the conditional variances adequately. Therefore, Bollerslev, (1986) suggests an extension analogous to autoregressive moving average (ARMA) models which improved parsimony. This model is called generalized autoregressive conditional heteroscedasticity with order p and q or GARCH (p,q), wherein the conditional variance contains an autoregression in the squared residuals of order q as well as a moving average component of order p and is specified as.

Mean equation:

$$r_t = E(r_t) + \varepsilon_t \tag{7}$$

where r_t, E, $E(r_t)$ and ε_t are as defined above and we have $\varepsilon_t = v_t\sqrt{h_t}$, with h_t and v_t as before.

Volatility equation:

$$h_t = \gamma_0 + \gamma_1\varepsilon_{t-1}^2 + \cdots + \gamma_p\varepsilon_{t-p}^2 + \varrho_1 h_{t-1} + \cdots + \varrho_q h_{t-q} \tag{8}$$

The condition for existence of unconditional variance in the above model is that $\gamma_1 + \cdots + \gamma_p + \varrho_1 + \cdots + \varrho_q < 1$. If the above condition is met then the unconditional variance of ε_t is $\sigma_\varepsilon^2 = \frac{\gamma_0}{1-\gamma_1-\cdots-\gamma_p-\varrho_1-\cdots-\varrho_q}$. Most empirical applications of univariate GARCH models resort to a GARCH(1,1) model.

3.3 Multivariate GARCH Models (MGARCH)

At a time, the economic variables (or financial markets) may be inter-linked and an increase in the volatility of one market may impact the volatility of the other markets. These scenarios warrant the use of multivariate GARCH models to study the co-movement and spillovers among these asset markets. Despite being intuitively straightforward, generalization of univariate GARCH models to multivariate specifications '*involves very large parameter spaces and thus will prove to be analytically and computationally quite demanding*' Herwatz, (2004, p. 212). Generalization requires estimation of large number of parameters (curse of dimensionality), estimation problem increasingly becomes complicated leading to convergence issues, needs to ensure that the conditional variances are positive and the implied correlation coefficients lie between -1 and $+1$. The univariate GARCH model was extended to a multivariate framework by Bollerslev et al., in 1988. This model came to be known as Vech-GARCH. It is the most generalized specification but was marred by too many parameters to be estimated.

3.3.1 Exponentially Weighted Moving Average Model (EWMA)

One possible method to model univariate conditional heteroscedasticity in a multivariate framework is to use exponential smoothing to assign higher weight to recent shocks and thereby generate a time-varying covariance matrix (Riskmetrics, 1996).

Volatility equation:

$$h_{ij,t} = (1 - \vartheta)\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \vartheta h_{ij,t-1} \tag{9}$$

The decay factor ϑ is estimated from the data. The model is easy to apply, work with and simple from the perspective of estimation although it imposes similar dynamics on all the series.

3.3.2 Constant Conditional Correlation (CCC) GARCH and Dynamic Conditional Correlation (DCC) GARCH Models

Nonlinear combinations of univariate GARCH models such as constant conditional correlation (CCC) and dynamic conditional correlation (DCC) specify the conditional variances of the series as well as the conditional correlation matrix. These models can be estimated easily, account for heteroscedasticity, do not suffer from the curse of dimensionality and can be, therefore, utilized to model high-dimensional data.

$$r_t|\mathcal{F}_{t-1} \sim N(0, \Sigma_{t|t-1}) \tag{10}$$

where r_t are the stock market returns, $\mathcal{F}_{t-1}$ is the past set of information, $\Sigma_{t|t-1}$ is the $N \times N$ conditional covariance matrix.

These models are estimated in two steps. In the first step, a univariate GARCH model is specified for the conditional variances. Subsequently, given the conditional variances obtained in the first step, the conditional correlation matrix is computed by imposing the assumption that it would be positive definite at all points of time.

In Bollerslev, (1990)s constant conditional correlation (CCC) formulation, the conditional correlation matrix is assumed to be constant and the conditional covariances are constructed by taking the product of the conditional correlations and the respective conditional standard deviations.

$$\Sigma_{t|t-1} = D_t R_t D_t = (\rho_{ij}\sqrt{\sigma_{ii,t}\sigma_{jj,t}}) \tag{11}$$

where $D_t = diag(\sigma_{1t|t-1}, \ldots, \sigma_{Nt|t-1})$ is the $N \times N$ diagonal matrix containing time-dependent standard deviations on the diagonal, $\sigma_{ii,t}$ are the conditional variances each of which is estimated as a univariate GARCH model, $R = \rho_{ij}$ is an $N \times N$ constant, symmetric and positive definite matrix of conditional correlations ρ_{ij} with $\rho_{ii} = 1, \forall i$.

However, in the case of financial time series, the assumption of constant conditional correlation seems implausible. The dynamic conditional correlation (DCC) model proposed by Engle, (2002) and Tse and Tsui, (2002) allows the matrix R to be time-dependent. The DCC model (Engle, 2002) is defined as follows

$$\Sigma_{t|t-1} = D_t R_t D_t \tag{12}$$

with D_t defined as above and R_t is now a time-varying matrix defined as

$$R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1} \tag{13}$$

R_t is the $N \times N$ conditional correlation matrix with the diagonal terms as one and the off-diagonal terms less than one in absolute value, and $Q_t = (q_{ij,t})$ is the $N \times N$ symmetric positive definite matrix of v_t such that

$$Q_t = (1 - \alpha - \beta)S + \alpha\left(v_{t-1}v_{t-1}^{'}\right) + \beta Q_{t-1} \tag{14}$$

where $S = E(v_t v_t^{'})$ is the $N \times N$ unconditional correlation matrix of the standardized residuals v_t (v_t is the standardized innovation vector with elements $v_{it} = \varepsilon_{it}/\sigma_{it}$), the scalar parameters α and β are such that $0 \leq \alpha, \beta \leq 1 and \alpha + \beta \leq 1$. These restrictions guarantee that the estimated matrix R_t is positive definite. Therefore, the $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}}$ with $i, j = 1, 2, \ldots, 7$ and $i \neq j$ is the correlation estimator which is positive definite.

The DCC model can be estimated consistently using a two-step procedure to maximize the log-likelihood function. Let θ_1 denote the parameters in D_t and θ_2 be the parameters in R_t then the log-likelihood function LL_t can be written as-

$$
\begin{aligned}
LL_t(\theta_1, \theta_2) = & \left[-\frac{1}{2} \sum_{t=1}^{T} (Nlog(2\pi) + log|D_t|^2 + v_t^{'} D_t^{-2} v_t) \right] \\
& + \left[-\frac{1}{2} \sum_{t=1}^{T} (\log|R_t| + v_t^{'} R_t^{-1} v_t - v_t^{'} v_t) \right]
\end{aligned}
\tag{15}
$$

So, the log-likelihood function can be written as a sum of the mean and volatility component, and the correlation component (Engle, 2002). In the first part of the above equation, volatility is calculated by adding up the individual GARCH likelihoods and is maximized in the first stage of estimation over the parameters θ_1 in D_t. Once the parameters in the first stage are obtained, in the second stage maximization of the correlation part of the likelihood function is undertaken to get the estimated correlation coefficients.

4 Empirical Estimation Strategy and Data

This section provides details of the estimation strategy adopted and data utilized to examine the inter-linkages between U.S. and Asian stock markets, namely China, Hong Kong, India, Japan and Singapore. The objective of this study is to unearth the inter-linkages between stock markets in Asia with those of the U.S. Our approach to investigate the linkages is to focus on the correlations among the respective stock markets. However, as per the suggestion of Forbes and Rigobon, (2002), we focus on the conditional correlations. In order to estimate the time-varying conditional correlation coefficients, we resort to three alternative multivariate GARCH models, viz. CCC, DCC and EWMA, which have been detailed in the previous section.

4.1 Estimation Strategy

Following our earlier work (Dua and Tuteja, 2016a), we define contagion as '*a significant increase in cross-market linkages after a shock to an individual country (or groups of countries) as measured by the degree to which asset prices or financial flows move together across markets relative to this co-movement in tranquil times*' (see, Dornbusch et al., 2000; p. 177). Therefore, testing for the impact of recent crises on the inter-linkages across stock markets entails identification of turbulent/crisis (and tranquil/non-crisis) time periods, measurement of the degree of co-movement among asset markets, and testing for a significant increase in the co-movement during turmoil times.

Our empirical modelling strategy consists of the following steps. In the first step, we test for stationarity of the financial market returns. We undertake three unit root tests, namely Dickey–Fuller generalized least squares (DF-GLS proposed by Elliott et al., 1996), KPSS (given by Kwiatkowski et al., 1992) and Lee and Strazicich, (2003).[2] In the second step, we utilize the crisis periods selected by the Markov-switching model formulation[3] for the stock and currency markets of US and Eurozone, respectively. The analysis yields the following crisis episodes.

Pre-crisis Phase I GFC dummy (2008): $DGFC_1 = \begin{cases} 1 \text{ if } t \in \left\{\begin{matrix} 07.27.2007 - 08.17.2007; \\ 01.04.2008 - 02.01.2008; \\ 03.07.2008 \end{matrix}\right\} \\ 0 \quad \text{otherwise} \end{cases}$

Phase II GFC dummy (2008): $DGFC_2 = \begin{cases} 1 \text{ if } t \in \{09.19.2008 - 10.10.2008\} \\ 0 \quad \text{otherwise} \end{cases}$

Phase III GFC dummy (2008–09): $DGFC_3 = \begin{cases} 1 \text{ if } t \in \left\{\begin{matrix} 10.17.2008 - 01.30.2009; \\ 02.20.2009 - 05.15.2009; \\ 06.19.2009; \\ 07.10.2009 - 07.17.2009 \end{matrix}\right\} \\ 0 \quad \text{otherwise} \end{cases}$

Phase I EZDC dummy (2010): $DEZDC_1 = \begin{cases} 1 \text{ if } t \in \{05.07.2010\} \\ 0 \quad \text{otherwise} \end{cases}$

Phase II EZDC dummy (2011): $DEZDC_2 = \begin{cases} 1 \text{ if } t \in \left\{\begin{matrix} 07.15.2011; \\ 08.05.2011 - 08.12.2011; \\ 09.09.2011; 11.25.2011; \\ 12.16.2011 \end{matrix}\right\} \\ 0 \quad \text{otherwise} \end{cases}$

The selected crisis episodes are depicted in Fig. 1 (Lower Panels A and B). Thereafter, we specify alternative multivariate GARCH models which yields time-varying conditional correlation coefficients for the equity market returns. Finally, we test for the existence of contagion/flight-to-quality/interdependence effects in international equity markets.

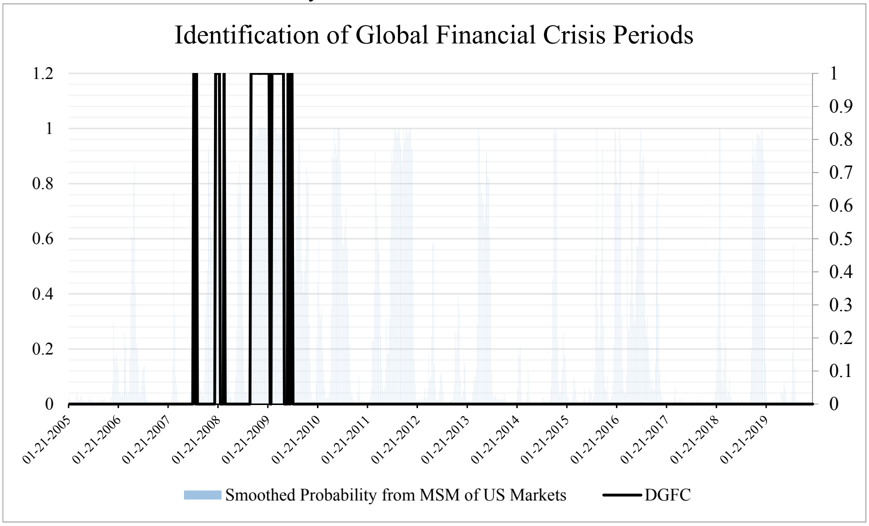
4.2 Testing for Changes in Conditional Correlation During the Crises

Several recent studies such as Chiang et al., (2007), Syllignakis and Kouretas, (2011), Min and Hwang, (2012), Ahmad et al., (2013), Kenourgios et al., (2016) and Dua and

[2] A distinct advantage of the Lee & Strazicich, (2003) test for a unit root is that it allows for structural breaks in the null hypothesis of the presence of a unit root or non-stationarity.

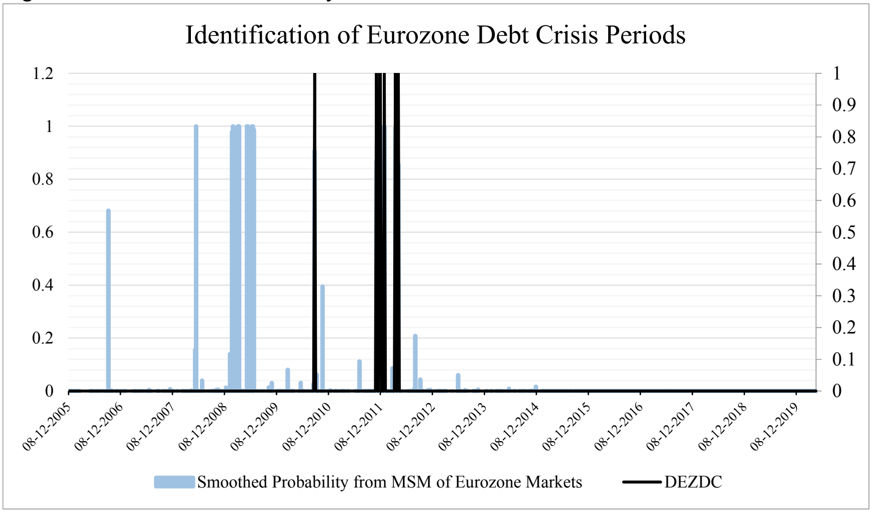
[3] Detailed results are available with the authors on request.

Panel A: U.S. Stock and Currency Markets



Note: The overall dummy variable DGFC is the aggregate of all the GFC episode dummies i.e. $DGFC = DGFC_1 + DGFC_2 + DGFC_3$.

Figure 1B: E.Z. Stock and Currency Markets



Note: The overall dummy variable DEZDC is the aggregate of all the EZDC episode dummies i.e. $DEZDC = DEZDC_1 + DEZDC_2$.

Fig. 1 Identification of crisis periods from multivariate Markov-switching models

Tuteja, (2016a) test for contagion on the basis of the conditional correlation coefficients obtained using the DCC-GARCH framework. Upon estimation of the time-varying conditional correlations (TVCCs), testing for contagion across the markets is accomplished using ordinary least squares (OLS) estimation. It is notable that Favero and Giavazzi, (2002) have questioned usage of the word 'contagion' to describe the transmission of shocks post-crisis in an economy or region. They point out that this precludes the prospect of flight-to-quality effects, i.e. the possibility of a lowering of correlations across asset returns in the post-crisis scenario.

Using the five dummy variables that we constructed using the crisis timelines given by the Markov-switching VAR models for the different sub-samples, we examine the dynamic evolution of the correlation coefficients across the various crisis and non-crisis phases. This univariate regression is estimated for each of the 15 TVCC series obtained from the DCC-GARCH model. In order to test for the impact of the two crises on the markets, we utilize an OLS regression with robust standard errors and estimate the following specification for the TVCC estimates

$$\begin{aligned}\hat{\rho}_{ij,t} = \delta_0 + \delta_1 DGFC_1 + \delta_2 DGFC_2 + \delta_3 DGFC_3 \\ +\delta_4 DEZDC_1 + \delta_5 DEZDC_2 + \vartheta_t\end{aligned} \tag{16}$$

where $\widehat{\rho}_{ij,t}$ is the pair-wise correlation coefficient between market i and market j; i and j denote the stock markets of China, India, Hong Kong, Japan, Singapore and US, respectively, dummy variables $DGFC_1$, $DGFC_2$, $DGFC_3$, $DEZDC_1$ and $DEZDC_2$ are as defined in the previous subsection and δ_0 is the intercept term which signifies the correlation coefficients during the stable period. A positive and significant coefficient $\delta_i, i = 1, \ldots, 4$ indicates a significant rise in the conditional correlation during the crisis time period vis-à-vis the stable period and is termed 'contagion'. A negative and significant coefficient would imply a divergence (or fall) in the dynamic conditional correlation among the asset markets during the crises in comparison to the normal time periods and is dubbed 'flight-to-quality'. An insignificant coefficient during the crises coupled with a significant coefficient in tranquil times is indicative of 'interdependence' among the markets. The estimation framework, therefore, allows us to test for the existence of contagion (flight-to-quality) or interdependence across stock and currency markets where in a significant rise (fall) in correlation is taken to be signal of the heightened (diminished) co-movement across the markets during the period under study. Utilizing the dummy variables allows us to ascertain the sub-periods which exhibit statistically significant linkages among the financial markets.

4.3 Data

We utilize data at weekly frequency which has been collected from the Wall Street Journal database over the period January, 2000 to December, 2019. We consider the following stock market indices for the analysis, Shanghai SE Composite Index for

China, Hang Seng Index for Hong Kong, Bombay Sensitive Index for India, Nikkei 225 Index for Japan, Singapore Strait Times Index for Singapore and Dow Jones Industrial Index for U.S. As discussed earlier, the markets have been selected by keeping in mind the economic growth, market capitalization and global presence. We particularly focus on the impact of recent crises, namely global financial crisis and Eurozone crisis on the stock markets.

As has been standard in the literature, the time series for stock market prices and exchange rates are modelled as logarithmic first differences or in returns form.[4] The descriptive statistics and the unconditional correlation matrix for returns in the nine markets are presented in Table 2 (Panel A and B). The average weekly returns are highest for the Indian stock market index BSE SENSEX and lowest for the Singapore stock market index. Moreover, the Indian stock market, i.e. BSE SENSEX index, also has the most volatile returns. The least volatile returns series is that for the U.S. stock market index Dow Jones. Further, the unconditional correlation among the stock markets is generally positive. Table 3 Panels A–B provide the results of the unit root tests which indicate that the null hypothesis of the existence of a unit root is rejected for all the stock market returns.

5 Results

This section discusses the results of the alternative multivariate GARCH formulations and the test for existence of contagion across the equity markets during the recent crises.

5.1 Multivariate GARCH Estimates

We have presented estimates of three multivariate GARCH models which were formulated to capture dynamics of the stock market returns. These are: Model I-Multivariate GARCH(1,1) DCC, Model II-Multivariate GARCH (1,1) CCC and Model III-Multivariate GARCH (1,1) EWMA. It is important to note that the second and third models are restrictive and their results are meant to serve as a robustness check for the findings of Model I. We are investigating the results in the context of alternative assumptions on the multivariate GARCH structure. Results of GARCH-CCC, GARCH-EWMA and GARCH-DCC specifications are given in Tables 4, 5 and 6, respectively. In view of the non-normal nature of the stock market returns, we utilize the t-distribution in all the cases. We find that the t-distribution shape parameter is estimated and is significant in all the model specifications. The volatility plots

[4] $y_t = 100 \times \log(\frac{Y_t}{Y_{t-1}})$ where y_t denotes the returns form for Y_t which represents the stock index in levels.

Table 2 Descriptive statistics and unconditional correlations

	s_t^{US}	s_t^{IND}	s_t^{CHN}	s_t^{JPN}	s_t^{SNG}	s_t^{HK}
Panel A—Descriptive statistics						
Mean	0.000398	0.00086	0.000338	0.000119	0.000122	0.000227
Std. Dev	0.007959	0.045454	0.012677	0.011036	0.009246	0.011246
Skewness	−0.87347	0.162265	−0.46203	−0.69152	−0.23598	−0.34159
Kurtosis	9.478539	452.1165	6.654533	6.713108	9.084947	5.433311
Jarque–Bera	1951.008	8,740,582	615.7455	680.3325	1614.138	276.8026
Minimum	0.035176	1.003989	0.057196	0.046071	0.06593	0.051443
Maximum	−0.06326	−0.99676	−0.084	−0.07722	−0.05348	−0.05689
Panel B—Unconditional correlations						
s_t^{US}	1					
s_t^{IND}	0.12	1				
s_t^{CHN}	0.18	0.03	1			
s_t^{JPN}	0.60	0.10	0.23	1		
s_t^{SNG}	0.65	0.17	0.27	0.62	1	
s_t^{HK}	0.61	0.16	0.38	0.61	0.77	1

Note s_t^{US} denotes the stock market returns of U.S., s_t^{IND} denotes the stock market returns of India, s_t^{CHN} denotes the stock market returns of China, s_t^{JPN} denotes the stock market returns of Japan, s_t^{SNG} denotes the stock market returns of Singapore, and s_t^{HK} denotes the stock market returns of Hong Kong, respectively

Table 3 Unit root test results

Panel A: DF-GLS and KPSS test (constant and trend)

Variable	DF-GLS statistic	DF-GLS: inference	KPSS statistic	KPSS: inference
s_t^{US}	−6.30***	I (0)	0.029	I (0)
s_t^{IND}	−23.14***	I (0)	0.075	I (0)
s_t^{CHN}	−25.40***	I (0)	0.050	I (0)
s_t^{JPN}	−13.65***	I (0)	0.063	I (0)
s_t^{SNG}	−13.97***	I (0)	0.076	I (0)
s_t^{HK}	−6.53***	I (0)	0.051	I (0)
Critical values				
10%	−2.58		0.119	
5%	−2.89		0.146	
1%	−3.47		0.216	

Panel B: Lee-Strazicich unit root test with structural breaks

Variable	Trend break model	Crash model	Inference
s_t^{US}	−21.89***	−20.13***	I (0)
s_t^{IND}	−35.82***	−35.70***	I (0)
s_t^{CHN}	−20.78***	−20.11**	I (0)
s_t^{JPN}	−22.74***	−21.01***	I (0)
s_t^{SNG}	−22.41***	−21.00***	I (0)
s_t^{HK}	−22.97***	−17.67***	I (0)
Critical values			
Crash model	1%	5%	10%
LM_τ	−4.545	−3.842	−3.504
Trend break model	$\boldsymbol{\lambda}_2$		
λ_1	0.4	0.6	0.8
0.2	−6.16, −5.59, −5.27	−6.41, −5.74, −5.32	−6.33, −5.71, −5.33
0.4	–	−6.45, −5.67, −5.31	−6.42, −5.65, −5.32
0.6	–	–	−6.32, −5.73, −5.32

DF-GLS Test: H_0 is non-stationarity (or that there exists a unit root)
KPSS Level stationarity test: H_0 is stationarity (or absence of a unit root)
Lee-Strazicich Test: H_0 is non-stationarity

Note s_t^{US} denotes the stock market returns of U.S., s_t^{IND} denotes the stock market returns of India, s_t^{CHN} denotes the stock market returns of China, s_t^{JPN} denotes the stock market returns of Japan, s_t^{SNG} denotes the stock market returns of Singapore, and s_t^{HK} denotes the stock market returns of Hong Kong, respectively. *, ** and *** denote 10%, 5% and 1% levels of significance respectively. λ_j denotes the location of breaks. Optimal lags are selected on the basis of BIC from the GARCH-EWMA and GARCH-DCC models are given in Fig. 2 Panels A-F, and the conditional correlation plots are furnished in Fig. 3 A–O.

In Table 4, we provide the results for the GARCH-CCC model. The mean returns are positive for all the markets. We find significant ARCH and GARCH coefficients in all the cases except the Japanese stock market. The constant correlation coefficients are estimated and are positive and significant in all the cases. The correlation coefficients are more than 0.5 for the stock market pairs of Japan-U.S., Singapore-U.S., Hong Kong-U.S., India-Hong Kong, India-Singapore, Japan-Singapore, Hong Kong-Japan and Hong Kong-Singapore. The highest correlation is among the Hong Kong and Singapore stock markets. The correlation coefficients are plotted in Fig. 3 Panels A–O. Table 5 presents estimates of the simple GARCH-EWMA model. The average stock market returns are similar to the above case. The decay factor is estimated from the data as 0.049 and is significant. The volatility and time-varying correlation estimates derived from the model are given in Fig. 2 Panels A–F and Fig. 3 Panels A–O, respectively.

Table 6 presents the results of the multivariate GARCH-DCC model for the stock markets of China, India, Hong Kong, Japan, Singapore and USA The mean returns are positive for all the equity markets. The estimated GARCH-DCC (1,1) specification has significant parameters[5] α and β at 1% level which indicates that there is a great deal of time-varying co-movement in the asset markets. Moreover, the equity market returns exhibit high volatility persistence (given by the sum of the constants for ARCH and GARCH) with all the markets depicting persistence greater than 0.80 during the period under study. The lowest volatility persistence is displayed by the BSE SENSEX index returns and the highest by the Nikkei index returns. Moreover, the coefficients for lagged volatility and lagged error terms in the variance equations for all the markets are significant at 10% level.

The volatility plots estimated from multivariate GARCH-DCC and GARCH-EWMA models have been shown in Fig. 2A–F. It may be noted that volatility in all the stock markets surged during the U.S. financial crisis of 2008–09. It is noteworthy that the volatility in the equity markets was much higher post the housing bubble burst in late 2007 and much before the announcement of Lehman Brothers' bankruptcy in September, 2008. In Panel A which shows the volatility estimates for the Chinese stock market, we notice that the volatility peaks during the dot-com bubble burst of 2000–01, the global financial crisis and during April, 2015 when the Chinese stock market developed a bubble. Panel B presents the volatility estimates for Hang Seng which are higher during the dot-com bubble burst, housing bubble burst, global financial crisis, Eurozone crisis and the Chinese stock market bubble. Panel C depicts the volatility estimates for Bombay Stock exchange which increased the most during the dot-com bubble burst and global financial crisis. In Panel D which gives the volatility estimates for Nikkei, we observe a significant rise during the global financial crisis. Volatility estimates for the Singapore Strait Times index (Panel E) increase during the same periods as the Hang Seng index. Finally, the volatility estimates for

[5] The estimates of the mean-reverting process are $\alpha = 0.018$ and $\beta = 0.981$. It is noteworthy that $0 < \alpha < \beta < 1$ and $\alpha + \beta < 1$.

Table 4 Results of CCC-GARCH model

	s^{US}	s^{IND}	s^{CHN}	s^{JPN}	s^{SNG}	s^{HK}
Mean	0.0010***	0.0019***	0.0004	0.0009***	0.0008***	0.0010***
Variance equations						
Constant	0.000003***	0.000031***	0.000003**	0.000003	0.000003***	0.000006***
A	0.096854***	0.183505***	0.089268***	0.029321	0.071693***	0.049026***
B	0.842627***	0.559024***	0.893851***	0.940795***	0.874885***	0.896407***
Correlation matrix and distribution						
	s^{US}	s^{IND}	s^{CHN}	s^{JPN}	s^{SNG}	s^{HK}
s^{US}	1					
s^{IND}	0.46***	1				
s^{CHN}	0.20***	0.19***	1			
s^{JPN}	0.60***	0.48***	0.19***	1		
s^{SNG}	0.62***	0.57***	0.27***	0.59***	1	
s^{HK}	0.57***	0.58***	0.38***	0.55***	0.72***	1
t-distribution	7.536***					

Note s_t^{US} denotes the stock market returns of U.S., s_t^{IND} denotes the stock market returns of India, s_t^{CHN} denotes the stock market returns of China, s_t^{JPN} denotes the stock market returns of Japan, s_t^{SNG} denotes the stock market returns of Singapore, and s_t^{HK} denotes the stock market returns of Hong Kong, respectively. *, ** and *** denote 10%, 5% and 1% levels of significance respectively

Table 5 Results of EWMA-GARCH model

	s^{US}	s^{IND}	s^{CHN}	s^{JPN}	s^{SNG}	s^{HK}
Mean	0.0009***	0.0012***	0.0001	0.0005*	0.0006**	0.0008**
Variance–covariance equation						
Estimated Coefficient (ϑ)				0.0497***		
t-distribution				8.7591***		

Note s_t^{US} denotes the stock market returns of U.S., s_t^{IND} denotes the stock market returns of India, s_t^{CHN} denotes the stock market returns of China, s_t^{JPN} denotes the stock market returns of Japan, s_t^{SNG} denotes the stock market returns of Singapore, and s_t^{HK} denotes the stock market returns of Hong Kong, respectively. *, ** and *** denote 10%, 5% and 1% levels of significance, respectively

Dow Jones index are heightened during the dot-com bubble burst, global financial crisis, Eurozone crisis and Federal Government Shutdown of 2015–16.

The conditional correlation plots for the markets estimated from Models I, II and III are presented in Fig. 3A–O. We find the plots generated by the multivariate GARCH-EWMA specification are much more accentuated than those generated by the multivariate GARCH-DCC specification. Further, estimates derived from the GARCH-CCC model are plotted in the same figure as well. The GARCH-EWMA and GARCH-DCC models allow for time-varying correlation and from the plots we observe significant variation in the conditional correlation coefficients over time. It is pertinent to note that the existence of time-varying correlation between the stocks has a crucial bearing on the allocation of assets in a portfolio and risk management, especially from the perspective of portfolio diversification.

The conditional correlation across the Chinese and Indian stock markets seems to have been negative or less than 0.2 till end of 2007. It remained much higher and positive from the Global Financial Crisis of 2008–09 onwards till end of 2014 when it dipped again (Fig. 3A). A similar pattern emerges in Fig. 3B which plots the conditional correlation between U.S. and Indian stock markets where the GARCH-CCC model estimates a coefficient of 0.46 over the entire period but the correlation is much higher during the financial crisis of 2008–09, Eurozone crisis and recently during 2015–16. The figures in Panels C–O are similar to the cases discussed above with the correlation coefficients peaking post the global financial crisis of 2008–09 except in the case of China.

5.2 *Test for Contagion*

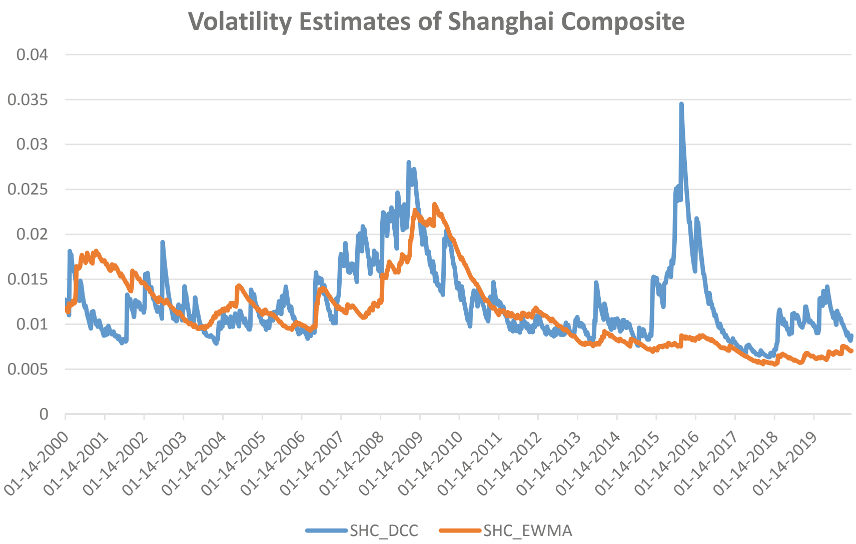
We now discuss the findings for the impact of the episodes of GFC and EZDC on the time-varying conditional correlation across Asian and U.S. stock markets given in Table 7. The first five columns of the table indicate the change in the time-varying conditional correlation coefficient among the equity markets during the sub-phase highlighted in the column heading. The fifth column of the table provides the

Table 6 Results of DCC-GARCH model

	s^{US}	s^{IND}	s^{CHN}	s^{JPN}	s^{SNG}	s^{HK}
Mean	0.0009***	0.0017***	0.0002	0.0007***	0.0007***	0.0009***
Variance equations						
Constant	0.000002***	0.000024***	0.000003**	0.000002	0.000002**	0.000004***
A	0.092061***	0.189452***	0.096153***	0.031755*	0.071579***	0.049250***
B	0.873451***	0.616521***	0.888811***	0.953307***	0.899250***	0.923213***
Persistence	0.965512***	0.805973***	0.984964***	0.985062***	0.970829***	0.972463***
Multivariate DCC equation						
α	0.018***					
β	0.981***					
t-distribution	7.800***					

Note s_t^{US} denotes the stock market returns of U.S., s_t^{IND} denotes the stock market returns of India, s_t^{CHN} denotes the stock market returns of China, s_t^{JPN} denotes the stock market returns of Japan, s_t^{SNG} denotes the stock market returns of Singapore, and s_t^{HK} denotes the stock market returns of Hong Kong, respectively. *, ** and *** denote 10%, 5% and 1% levels of significance respectively

Panel A: China



Panel B: Hong Kong

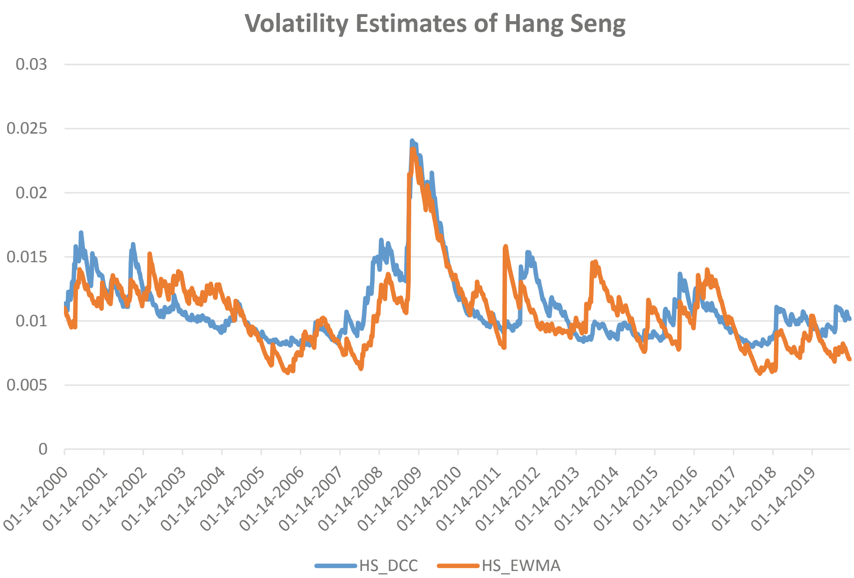
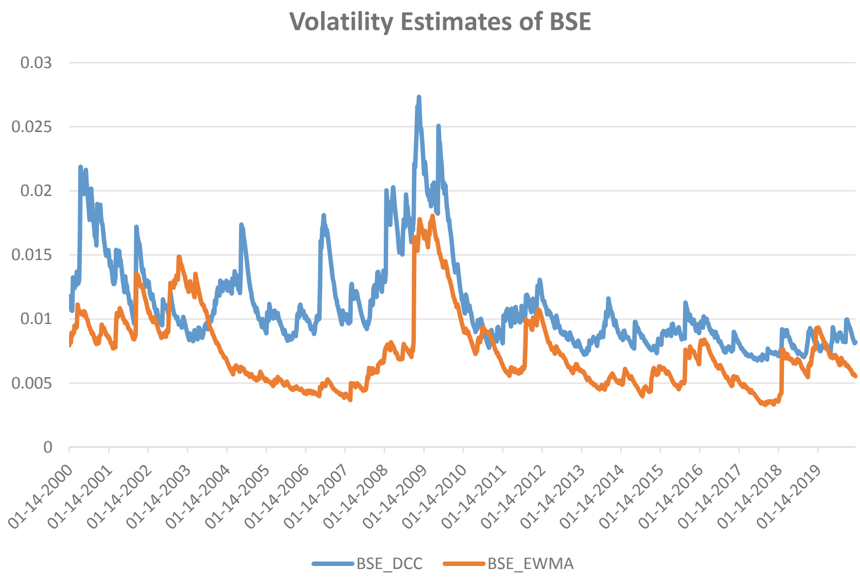


Fig. 2 Volatility estimates from DCC-GARCH and EWMA-GARCH models.

Panel C: India



Panel D: Japan

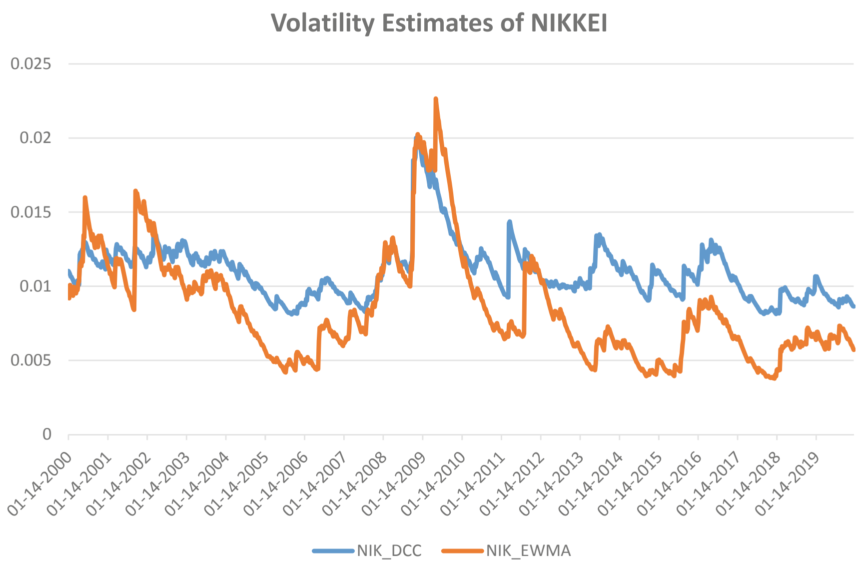
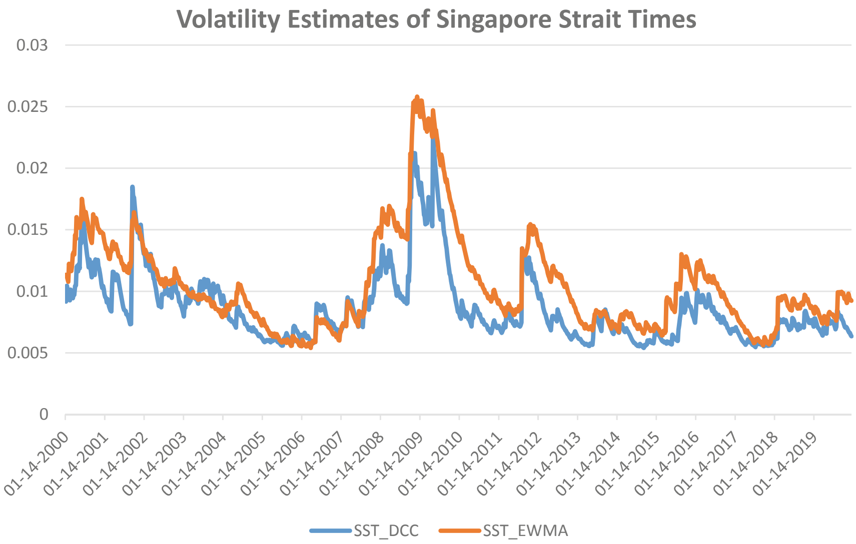


Fig. 2 (continued)

Panel E: Singapore



Panel F: U.S.

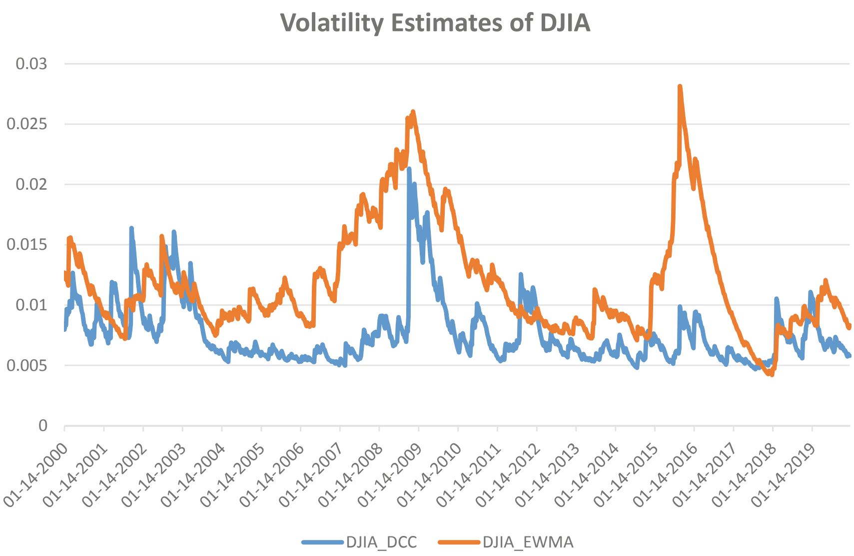
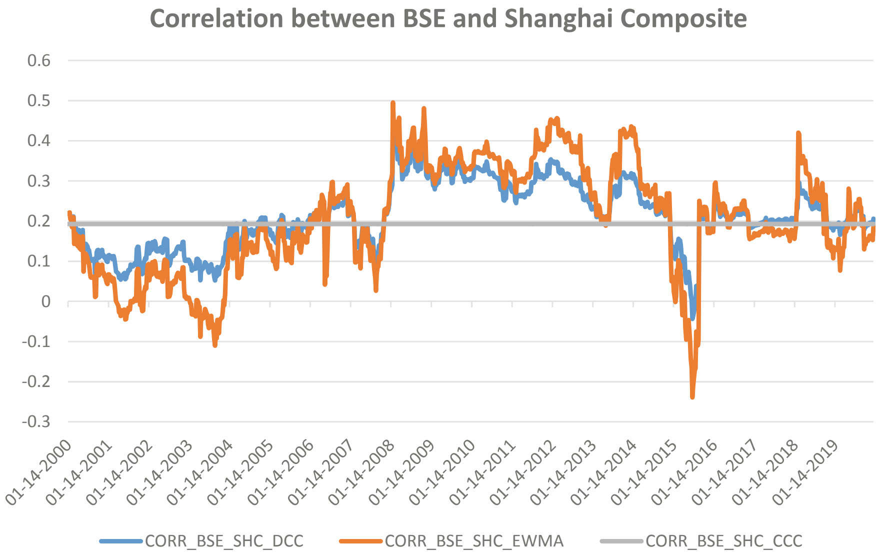


Fig. 2 (continued)

Panel A: BSE and Shanghai Composite Indices



Panel B: BSE and DJIA Indices

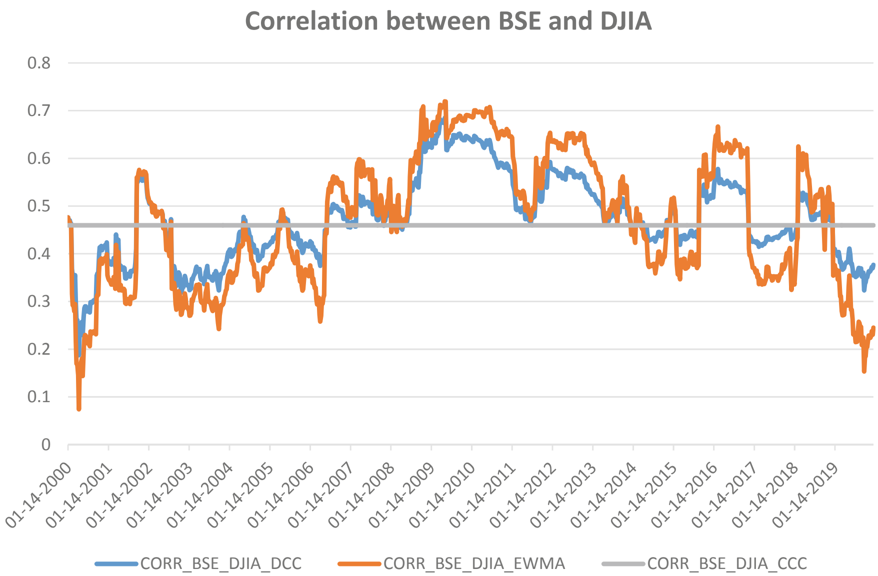
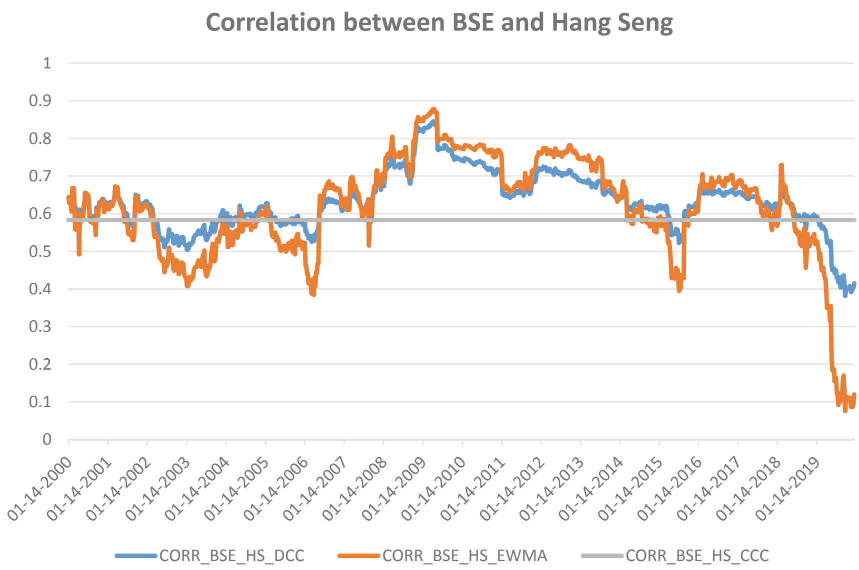


Fig. 3 Correlation coefficients for market pairs.

Panel C: BSE and Hang Seng



Panel D: BSE and NIKKEI Indices

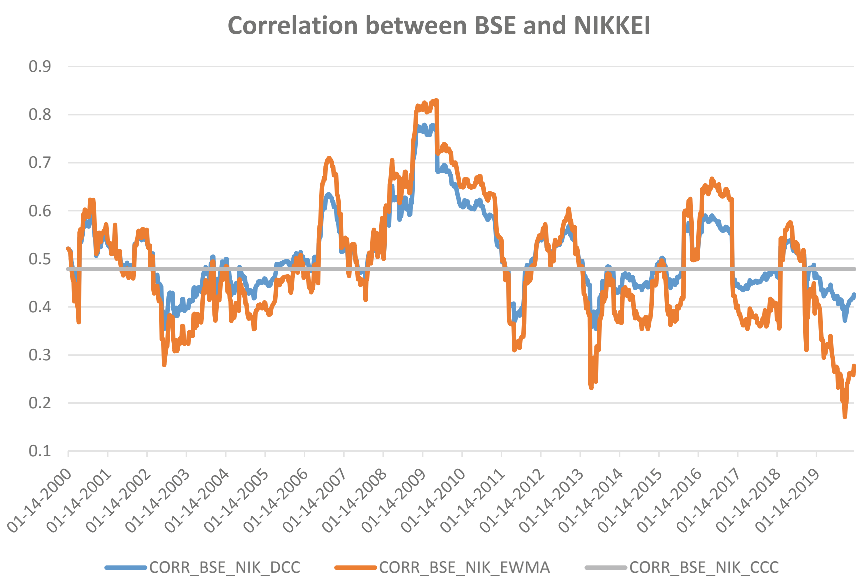
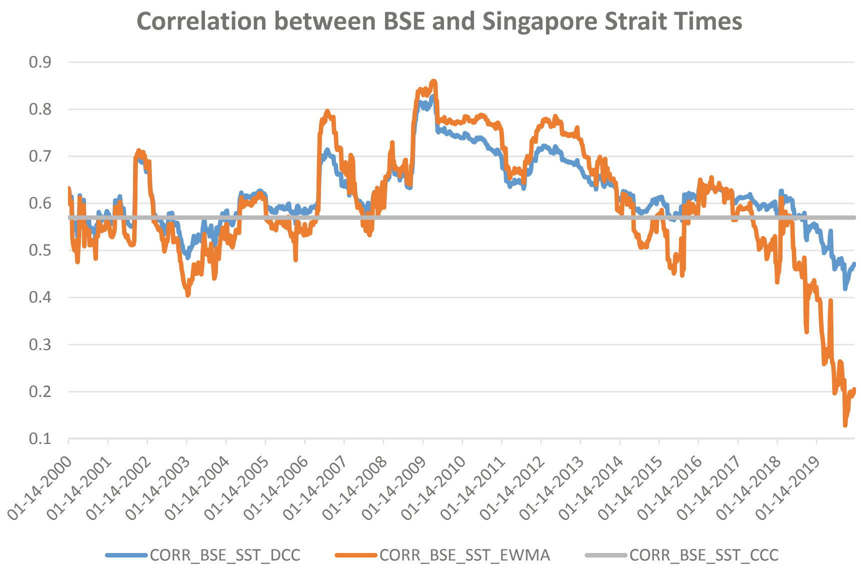


Fig. 3 (continued)

Panel E: BSE and Singapore Strait Times



Panel F: Shanghai Composite and DJIA Indices

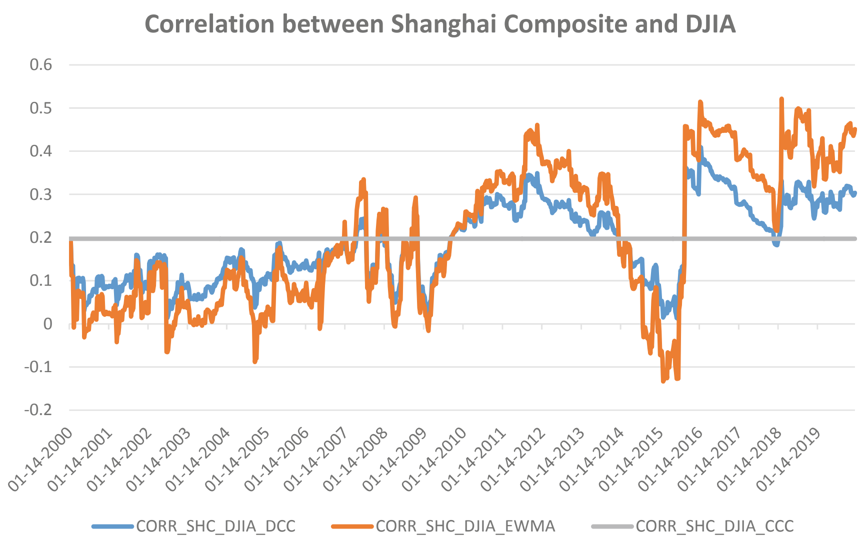
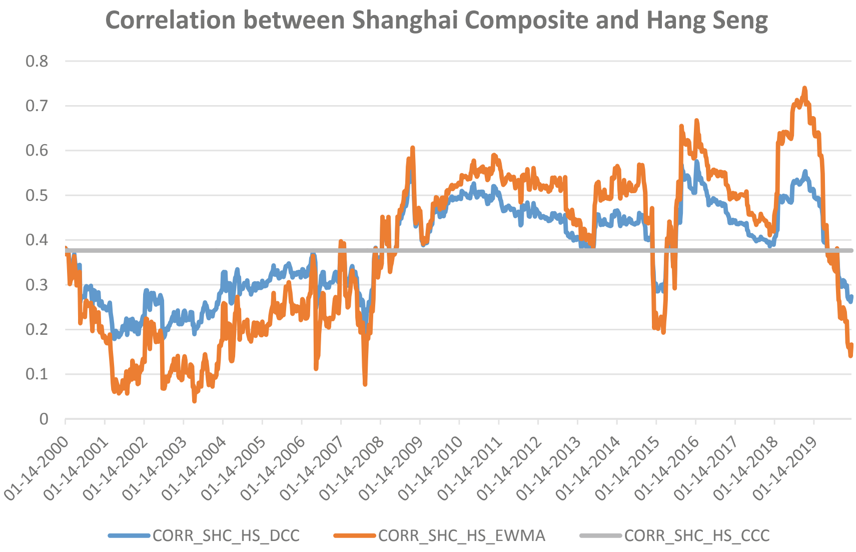


Fig. 3 (continued)

Panel G: Shanghai Composite and Hang Seng Indices



Panel H: Shanghai Composite and NIKKEI Indices

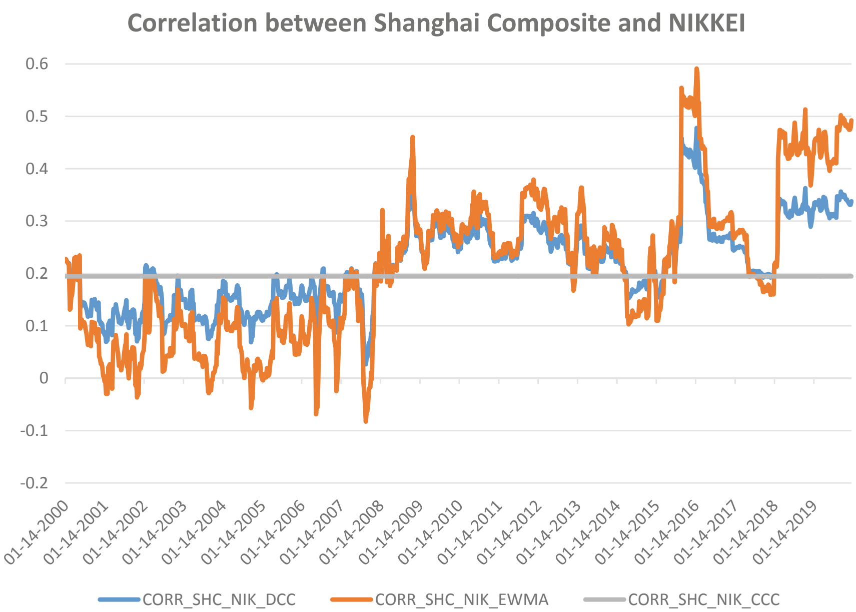
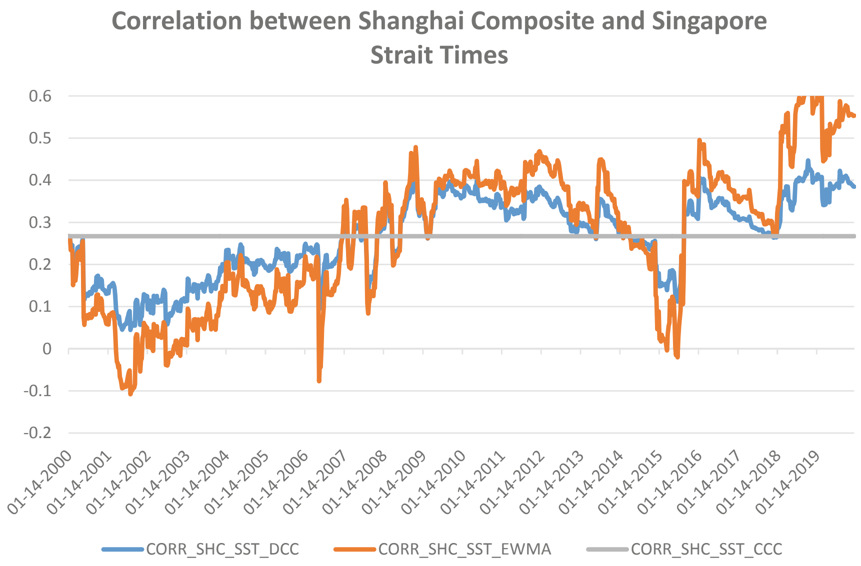


Fig. 3 (continued)

Panel I: Shanghai Composite and Singapore Strait Times Indices



Panel J: DJIA and Hang Seng Indices

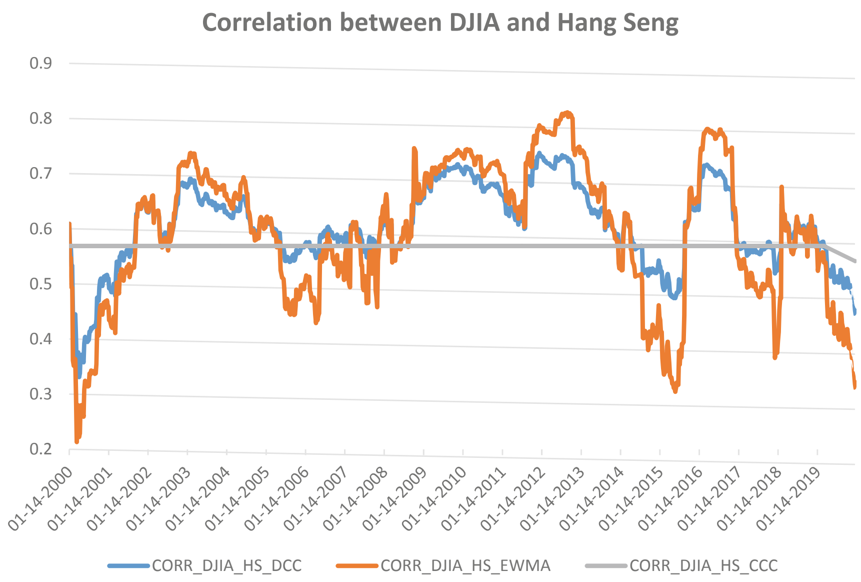
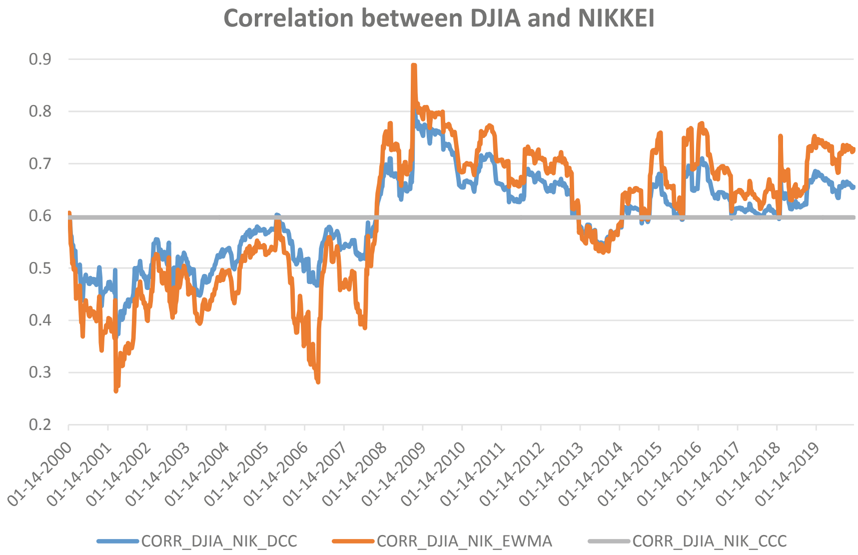


Fig. 3 (continued)

Panel K: DJIA and NIKKEI Indices



Panel L: DJIA and Singapore Strait Times Indices

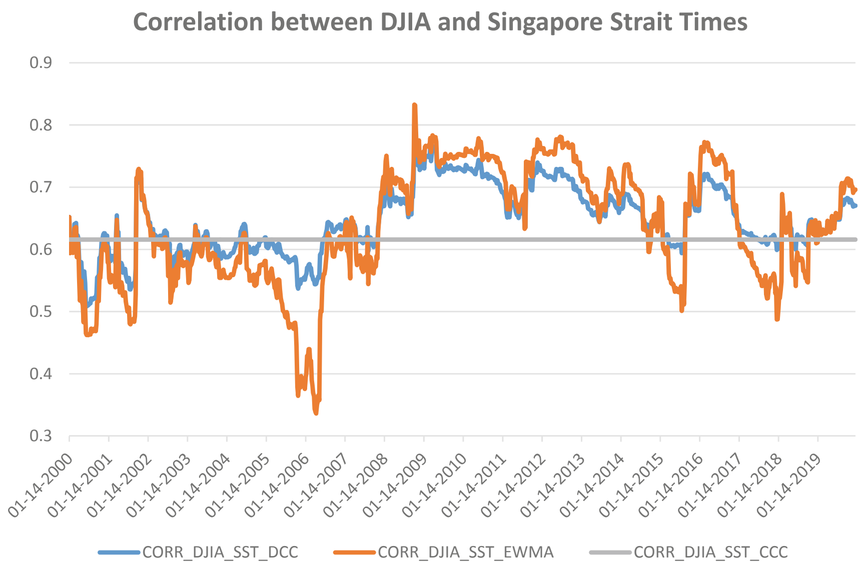
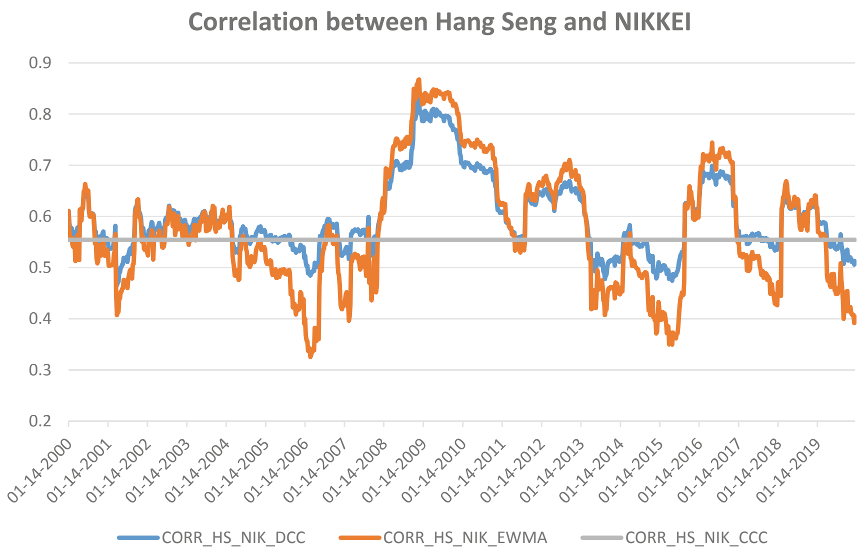


Fig. 3 (continued)

Panel M: Hang Seng and NIKKEI Indices



Panel N: Hang Seng and Singapore Strait Times Indices

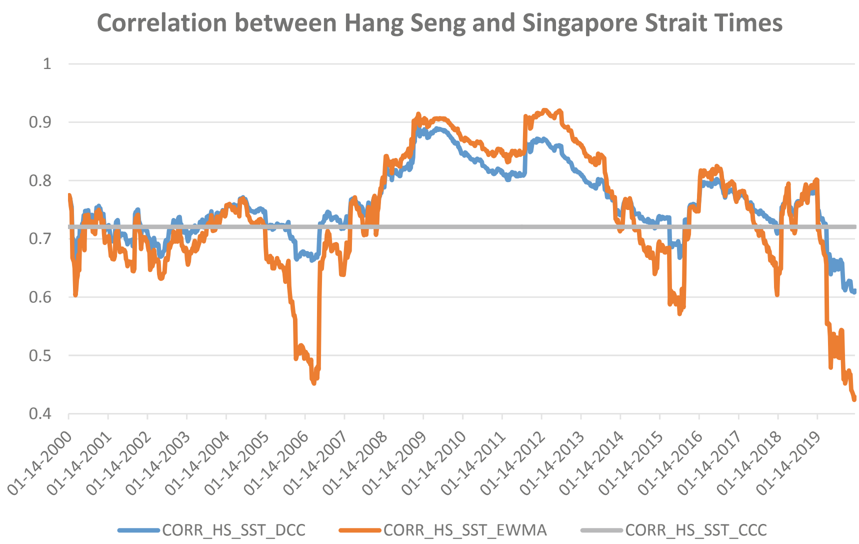


Fig. 3 (continued)

Panel O: NIKKEI and Singapore Strait Times Indices

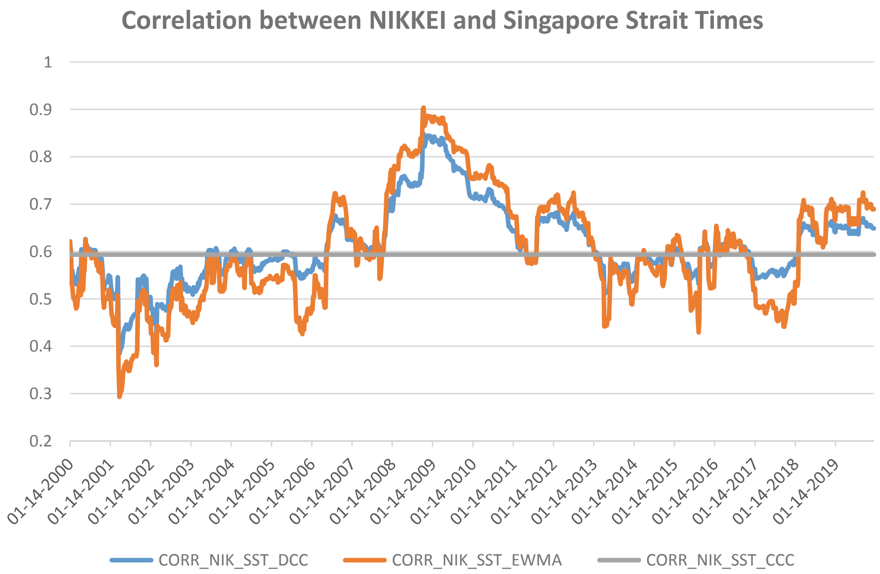


Fig. 3 (continued)

conditional correlation coefficient during the stable period. The last column gives the summary inference for each of the equity market pairs across the crisis episodes in the order of phases I, II and III of GFC followed by phases I and II of EZDC.

In our analysis, we compare the crisis period results for the market pairs with the results for the stable period in order to infer the direction of the impact. We find that the correlation coefficients across the stock markets are positive and significant at 1% level during the stable period. This means that all the stock markets are significantly correlated during the stable period with the lowest correlation coefficient of 0.189 among the Chinese and U.S. stock markets and the highest correlation coefficients of 0.757 between the Hang Seng and the Singapore Strait Times indices. We observe the stock market pairs, across the board, show significantly higher correlation during the episode III of global financial crisis (except China-U.S. markets during phase III). Similarly, we witness a significant increase in the correlation coefficients among the equity markets during the two phases of the Eurozone debt crisis barring the Indian-Japanese stock markets during phase II.

On comparison across the three phases of the GFC, we conclude that the impact was maximum during phases II and III of the crisis which led to significant contagion effects among the equity markets. To begin with, we examine the correlation coefficients between U.S. and Asian markets. First, we consider U.S. and Indian stock markets where the correlation coefficients progressively increase during the episodes of GFC and reduce in phase II of EZDC. The overall magnitude of contagion effects is higher in GFC. In case of U.S.-China, however, the correlation coefficients decrease

Table 7 Impact on dynamic conditional correlations (based on GARCH-DCC) among stock markets during the phases of global financial crisis and Eurozone debt crisis (using OLS with robust standard errors)

	$DGFC_1$	$DGFC_2$	$DGFC_3$	$DEZDC_1$	$DEZDC_2$	Stable period	Inference
s^{US} and s^{IND}	0.017**	0.103***	0.181***	0.156***	0.053***	0.466***	C, C, C, C, C
s^{US} and s^{CHN}	−0.007	−0.009	−0.077***	0.039***	0.109***	0.189***	I, I, F, C, C
s^{US} and s^{JPN}	0.041*	0.080**	0.180***	0.056***	0.066***	0.590***	C, C, C, C, C
s^{US} and s^{SNG}	0.016	0.040***	0.104***	0.077***	0.040***	0.643***	I, C, C, C, C
s^{US} and s^{HK}	−0.008	0.011	0.078***	0.080***	0.056***	0.603***	I, I, C, C, C
s^{IND} and s^{CHN}	0.055*	0.134***	0.124***	0.118***	0.102***	0.207***	C, C, C, C, C
s^{IND} and s^{JPN}	0.019	0.117***	0.254***	0.102***	−0.043***	0.501***	C, C, C, C, F
s^{IND} and s^{SNG}	0.003	0.047**	0.184***	0.115***	0.049***	0.615***	I, C, C, C, C
s^{IND} and s^{HK}	0.044***	0.074***	0.191***	0.103***	0.045***	0.627***	C, C, C, C, C
s^{CHN} and s^{JPN}	−0.028	0.095***	0.069***	0.055***	0.056***	0.216***	I, C, C, C, C
s^{CHN} and s^{SNG}	0.027	0.127***	0.077***	0.105***	0.077***	0.262***	I, C, C, C, C
s^{CHN} and s^{HK}	-0.043*	0.148***	0.074***	0.129***	0.074***	0.377***	F, C, C, C, C
s^{JPN} and s^{SNG}	0.070***	0.156***	0.225***	0.102***	0.025	0.604***	C, C, C, C, I
s^{JPN} and s^{HK}	0.021*	0.138***	0.210***	0.099***	0.008	0.591***	C, C, C, C, I
s^{SNG} and s^{HK}	0.027***	0.076***	0.125***	0.074***	0.080***	0.757***	C, C, C, C, C

Note s_t^{US} denotes the stock market returns of U.S., s_t^{IND} denotes the stock market returns of India, s_t^{CHN} denotes the stock market returns of China, s_t^{JPN} denotes the stock market returns of Japan, s_t^{SNG} denotes the stock market returns of Singapore, and s_t^{HK} denotes the stock market returns of Hong Kong respectively. The alphabets C, F and I denote contagion, flight-to-quality and interdependence respectively. $DGFC_1$, $DGFC_2$, $DGFC_3$, $DEZDC_1$, and $DEZDC_2$ denote the dummy variables for phases I, II and II of GFC and phases I and II of EZDC respectively. *, ** and *** indicate significance at 10%, 5% and 1% respectively during GFC. On the other hand, during EZDC the market pair depicts significantly higher correlation. The case for U.S.-Japan, U.S.-Singapore and U.S.-Hong Kong is similar to the findings for the U.S.-India stock markets. Next, we study the co-movement among the Asian stock markets. Most Asian markets were unaffected during phase I of the global financial crisis except the market pairs for India-China, India-Hong Kong, Japan-Singapore, Japan-Hong Kong and Singapore-Hong Kong. In this case, most of the market pairs depict sequentially higher correlation during GFC but significantly much lower correlation during EZDC. On the other hand, market pairs with China depict highest contagion during phase II of GFC but a much lower contagion during phase II of EZDC vis-à-vis phase I of EZDC. Finally, the Singapore-Hong Kong market pair shows progressively higher correlation during both the crises. Since, 2nd phase, marked by adverse news announcements was the most chaotic phase of GFC, it is shows the highest spike in correlations. On the other hand, the magnitude of contagion effects is lower in most cases during the EZDC phases. It is noteworthy that the Asian markets are more correlated with each other than with the U.S. stock market and are also more impacted by contagion effects during the crises.

Table 8 gives the results for the time-varying correlation coefficient estimates derived from the GARCH-EWMA model. These are utilized to test the robustness of our findings obtained from the GARCH-DCC estimates above. We infer that the findings above the robust to change in the multivariate GARCH model specification. The only exception is the relationship between the stock markets during the first phase of GFC However, the magnitude remains fairly low even in this case.

It is notable that most stock market pairs are affected by contagion during the GFC and EZDC. We find evidence of significant contagion across Asian and U.S. stock markets which is in line with the results obtained by Syllignakis and Kouretas, (2011), Min and Hwang, (2012), Ahmad et al., (2013), and Dua and Tuteja, (2016a, 2016b).

6 Conclusion

This chapter examines the existence of contagion effects among Asian and U.S. stock markets during the global financial crisis and Eurozone debt crisis. In order to do that, we employ three alternative specifications of the multivariate GARCH model, viz. CCC, DCC and EWMA. We utilize the MS-VAR technique similar to Dua and Tuteja (2016a) to construct the dummy variables for the phases of the crises. We employ a slightly different specification using the TED spread and Dow Jones stock index for the identification of GFC episodes. Finally, we test for the existence of contagion/interdependence/flight-to-quality effects among the stock markets during the various phases of the two crises.

The volatility estimates and the conditional correlation coefficients among the markets depict a distinct pattern during the crisis phases. Our findings suggest indicate that there was significant contagion both within Asian stock markets and across Asian

Table 8 Impact on time-varying conditional correlations (based on GARCH-EWMA) among stock markets during the phases of global financial crisis and Eurozone debt crisis (using OLS with robust standard errors)

	$DGFC_1$	$DGFC_2$	$DGFC_3$	$DEZDC_1$	$DEZDC_2$	Stable period	Inference
s^{US} and s^{IND}	0.045***	0.166***	0.214***	0.225***	0.093***	0.461***	C, C, C, C, C
s^{US} and s^{CHN}	−0.004	−0.021	−0.108***	0.038***	0.179***	0.204***	I, I, F, C, C
s^{US} and s^{JPN}	0.045	0.127***	0.217***	0.088***	0.102***	0.589***	I, C, C, C, C
s^{US} and s^{SNG}	0.031	0.072***	0.132***	0.118***	0.068***	0.633***	I, C, C, C, C
s^{US} and s^{HK}	−0.009	0.037***	0.102***	0.126***	0.096***	0.590***	I, C, C, C, C
s^{IND} and s^{CHN}	0.077*	0.169***	0.153***	0.170***	0.181***	0.198***	C, C, C, C, C
s^{IND} and s^{JPN}	0.036	0.185***	0.318***	0.168***	−0.058*	0.482***	I, C, C, C, F
s^{IND} and s^{SNG}	0.017	0.085***	0.236***	0.181***	0.100***	0.591***	I, C, C, C, C
s^{IND} and s^{HK}	0.073***	0.112***	0.238***	0.161***	0.088***	0.608***	C, C, C, C, C
s^{CHN} and s^{JPN}	−0.044	0.129***	0.082***	0.079***	0.093***	0.213***	I, C, C, C, C
s^{CHN} and s^{SNG}	0.036	0.158***	0.083***	0.139***	0.131***	0.267***	I, C, C, C, C
s^{CHN} and s^{HK}	−0.067*	0.180***	0.086***	0.175***	0.136***	0.377***	F, C, C, C, C
s^{JPN} and s^{SNG}	0.110***	0.238***	0.280***	0.160***	0.045**	0.594***	C, C, C, C, C
s^{JPN} and s^{HK}	0.031	0.217***	0.271***	0.167***	0.029	0.567***	I, C, C, C, I
s^{SNG} and s^{HK}	0.046***	0.121***	0.163***	0.121***	0.141***	0.738***	C, C, C, C, C

Note s_t^{US} denotes the stock market returns of U.S., s_t^{IND} denotes the stock market returns of India, s_t^{CHN} denotes the stock market returns of China, s_t^{JPN} denotes the stock market returns of Japan, s_t^{SNG} denotes the stock market returns of Singapore, and s_t^{HK} denotes the stock market returns of Hong Kong, respectively. The alphabets C, F and I denote contagion, flight-to-quality and interdependence respectively. $DGFC_1$, $DGFC_2$, $DGFC_3$, $DEZDC_1$ and $DEZDC_2$ denote the dummy variables for phases I, II and II of GFC and phases I and II of EZDC, respectively. *, ** and *** indicate significance at 10%, 5% and 1% respectively and U.S. equity markets. The impact of the crises is most severe during phases II and III of GFC and phase I of EZDC. We also obtain evidence of flight-to-quality in some of the cases such as the Chinese-U.S. stock markets during phase III of GFC. It is noteworthy that the Asian markets are more correlated with each other than with the U.S. stock market and are also more impacted by contagion effects during the crises.

Our findings have significant implications for portfolio managers and hedgers, governments and central banks. In view of the heightened co-movement of stock markets during the crises, international portfolio diversification benefits may not exist. The possible impact of a simultaneous downfall in world stock markets and the transmission of shocks to investment in an economy via Tobin's q (which may lead to domino effects in the real economy), international policy coordination may be required to insulate the real sectors of the economy from external shocks.

Questions To Think About

1. What could be the advantages of using GARCH-BEKK and GARCH-DCC vis-a-vis GARCH-Vech in the study?
   Hint: The first-generation multivariate GARCH models such as GARCH-Vech suffer from the curse of dimensionality issue as the number of endogenous variables increases. In contrast to GARCH-Vech, the GARCH-BEKK and GARCH-DCC specifications ensure positive definiteness of the covariance matrix by construction and can accommodate a larger set of time series.
2. What could be the impact of crises such as the global financial crisis and Eurozone crisis on inter-linkages across assets?
   Hint: We have to control for the periods of the crises in the analysis. See Dua and Tuteja, (2016a) for an application.
3. Can we apply the methods discussed in the chapter to more assets?
   Hint: We need to analyse the problem in the context of cross-asset linkages. See Dua and Tuteja, (2016b) for details.

References

Ahmad, W. S., Sehgal & Bhanumurthy, N. R. (2013). Eurozone crisis and BRIICKS stock markets: Contagion or market interdependence? *Economic Modelling, 33*, 209-225

Bae, K. H., Karolyi, G. A., & Stulz, R. M. (2003). A new approach to measuring financial contagion. *Review of Financial Studies, 16*, 717–763.

Bahng, J. S., & Shin, S.-M. (2003). Do stock price indices respond asymmetrically? *Evidence from China, Japan, and South Korea, Journal of Asian Economics, 14*, 541–563.

Baur, D. G., & Fry, R. A. (2009). Multivariate contagion and interdependence. *Journal of Asian Economics, 20*, 353–366.

Bekaert, G., Harvey, C. R., & Ng, A. (2005). Market integration and contagion. *The Journal of Business, 78*, 39–69.

Billio, M., & Caporin, M. (2010). Market linkages, variance spillovers, and correlation stability: empirical evidence of financial contagion. *Computational Statistics & Data Analysis, 54*, 2443–2458.

Bodart, V., & Candelon, B. (2009). Evidence of interdependence and contagion using a frequency domain framework. *Emerging Markets Review, 10*, 140–150.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics, 31*, 307–327.

Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A capital asset pricing model with time-varying covariances. *Journal of Political Economy, 96*, 116–131.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model. *Review of Economics and Statistics, 72*, 498–505.

Calvo, S., & Reinhart, C. M. (1996). Capital flows to Latin America: is there evidence of contagion effects. In G.A. Calvo, M. Goldstein & E. Hochreitter (Eds.), *Private capital flows to emerging markets*, Institute for International Economics, Washington DC.

Chiang, T. C., Jeon, B. N., & Li, H. (2007). Dynamic correlation analysis of financial contagion: Evidence from Asian markets. *Journal of International Money and Finance, 26*, 1206–1228.

Dornbusch, R., Park, Y. C., & Claessens, S. (2000). Contagion: Understanding how it spreads. *The World Bank Research Observer, 15*, 177–197.

Dua, P., & Tuteja, D. (2016a). Financial crises and dynamic linkages across international stock and currency markets. *Economic Modelling, 59*, 249–261.

Dua, P., & Tuteja, D. (2016b). Linkages between Indian and US financial markets: Impact of global financial crisis and Eurozone debt crisis. *Macroeconomics and Finance in Emerging Market Economies, 9*(3), 217–240.

Dungey, M., Fry, R., González-Hermosillo, B., & Martin, V. L. (2005). Empirical modelling of contagion: A review of methodologies. *Quantitative Finance, 5*, 9–24.

Dungey, M., Milunovich, G., & Thorp, S. (2010). Unobservable shocks as carriers of contagion. *Journal of Banking & Finance, 34*, 1008–1021.

Elliott, G., Rothenberg, T. J., & Stock, J. H. (1996). Efficient tests for an autoregressive unit root. *Econometrica, 64*, 813–836.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*, 987–1007.

Engle, R. F. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroscedasticity models. *Journal of Business and Statistics, 20*, 339–350.

Favero, C. A., & Giavazzi, F. (2002). Is the international propagation of financial shocks non-linear? Evidence from the ERM. *Journal of International Economics, 51*, 231–246.

Forbes, K., & Rigobon, R. (2002). No contagion, only interdependence: Measuring stock market co-movements. *Journal of Finance, 57*, 2223–2261.

Herwatz, H. (2004). Conditional Heteroscedasticity. In H. Lütkepohl & M. Krätzig (Eds.), *Applied Time Series Econometrics* (pp. 197–221). Cambridge University Press.

Jin, X. (2016). The impact of 2008 financial crisis on the efficiency and contagion of Asian stock markets: A Hurst exponent approach. *Finance Research Letters, 17*(2016), 167–175.

Kaminsky, G. L., & Reinhart, C. M. (2000). On crises, contagion, and confusion. *Journal of International Economics, 51*, 145–168.

Kenourgios, D., Naifar, N., & Dimitriou, D. (2016). Islamic financial markets and global crises: contagion or decoupling? *Economic Modelling, 57*, 36–46.

Kenourgios, D., Samitas, A., & Paltalidis, N. (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *Journal of International Financial Markets, Institutions and Money, 21*, 92–106.

Kim, J. S., & Ryu, D. (2015). Effect of the subprime mortgage crisis on a leading emerging market. *Investment Analysts Journal, 44*, 20–42.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root. *Journal of Econometrics, 54*, 159–178.

Le, T. P. T. D., & Tran, H. L. M. (2021). The contagion effect from US stock market to the Vietnamese and the Philippine stock markets: The evidence of DCC-GARCH model. *The Journal of Asian Finance, Economics, and Business, 8*(2), 759–770.

Lee, J., & Strazicich, M. C. (2003). Minimum lagrange multiplier unit root test with structural breaks. *The Review of Economics and Statistics, 85*, 1082–1089.

Min, H.-G., & Hwang, Y.-S. (2012). Dynamic correlation analysis of us financial crisis and contagion: Evidence from four OECD countries. *Applied Financial Economics, 22*, 2063–2074.

Morales, L., & B. Andreosso-O'Callaghan,. (2012). The Current global financial crisis: Do Asian stock markets show contagion or interdependence effects? *Journal of Asian Economics, 23*, 616–626.

Pesaran, M. H., & Pick, A. (2007). Econometric issues in the analysis of contagion. *Journal of Economic Dynamics and Control, 31*, 1245–1277.

Riskmetrics (1996). *Riskmetrics Technical Document* (4th ed.). J.P. Morgan: New York.

Samarakoon, L. P. (2011). Stock market interdependence, contagion, and the US financial crisis: The case of emerging and frontier markets. *Journal of International Financial Markets, Institutions and Money, 21*, 724–742.

Syllignakis, M. N., & Kouretas, G. P. (2011). Dynamic correlation analysis of financial contagion: Evidence from the central and eastern European markets. *International Review of Economics & Finance, 20*, 717–732.

Tran, T. B., & Ngoc. (2018). Contagion risks in emerging stock markets: New evidence from Asia and Latin America. *Journal of Risk and Financial Management, 11*(4), 89.

Tse, Y. K., & Tsui, A. K. C. (2002). A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. *Journal of Business and Economic Statistics, 20*, 351–362.

Yiu, M. S., Ho, W.-Y.A., & Choi, D. F. (2010). Dynamic correlation analysis of financial contagion in Asian markets in global financial turmoil. *Applied Financial Economics, 20*, 345–354.

Chapter 13
The Increasing Synchronization of International Recessions

Anirvan Banerji and Pami Dua

Abstract This paper examines various measures of synchronization of recessions, including clustering of the onset of and exit from recession across economies, the proportion of economies in expansion, and the diffusion index of international coincident indexes. It shows that the recent COVID recession and recovery were the most concerted in the post-world war period. Factors that contributed to the synchronization and severity of the recession, such as common shocks, trade and supply chain dynamics, and financial linkages, are analyzed.

Keywords Global recession · COVID pandemic · Synchronization measures

JEL Classification E32 · E37

1 Introduction

With the U.S. economy experiencing its deepest recession in 75 years, beginning in February 2020, the global economy also experienced the most synchronized recession on record, surpassing the recession that accompanied the Global Financial Crisis (GFC). The breadth and depth of that earlier concerted global recession had been a reflection of increased globalization and strong global interdependence among economies, in terms of both their financial interconnections and trade linkages. Those factors greatly amplified the transmission of the recession to the export-oriented economies due to declines in consumer demand the world over, but especially in major developed economies, such as the US and Japan. Consequently, the economies of virtually all major developed countries shrunk rapidly, along with those of many export-dependent developing economies (Banerji and Dua, 2010).

A. Banerji
Economic Cycle Research Institute, New York, NY, USA
e-mail: anirvan@businesscycle.com

P. Dua (✉)
Department of Economics, Delhi School of Economics, University of Delhi, Delhi, India
e-mail: dua@econdse.org

P. Dua (ed.), *Macroeconometric Methods*,
https://doi.org/10.1007/978-981-19-7592-9_13

In that prior global recession, which accompanied the GFC, China experienced its worst slowdown in nearly two decades, with over 20 million migrant workers reportedly having lost jobs by late 2008. India too experienced a sharp slowdown, meaning a downshift in the pace of positive growth in economic activity. A recession, in contrast, would have been more severe, involving a vicious cycle of pronounced, pervasive, and persistent cascading declines in output, income, employment, and sales. In 2020, both economies experienced short but sharp recessions.

The even greater international synchronization of recessions this time was driven by the simultaneous shocks from the global pandemic, which resulted in a lockdown in China in February 2020, and in much of the rest of the world starting in March 2020. Of course, the transmission of the resulting demand and supply shocks through trade channels exacerbated the global recession, as did the brief but sudden swoon in international stock prices.

But the recession start dates were not perfectly synchronized around the world. While the U.S. recession officially began in February 2020, as did those in India and Brazil, in hindsight we find that most major developed and emerging economies entered their recessions in 2019, as countries where economic activity had begun to decline a bit were tipped abruptly into sharp contractions by the COVID crisis.

This paper is organized as follows. Section 2 discusses various ways to measure the synchronization of recessions and applies these to the latest global recession. Section 3 examines the states of key economies in the lead-up to the COVID crisis, which had a bearing on their recession start dates. Section 4 focuses on the roles of common shocks, including mandated shutdowns, along with supply chains and financial integration, in this global recession. Section 5 summarizes the main conclusions and concludes the paper.

2 Synchronization of Recessions: Measures

The severity of a recession[1] is measured in terms of its diffusion, depth, and duration. In the context of international recessions, diffusion is the extent to which the recession has spread to different economies. Diffusion of a recession thus refers to how concerted the global recession is. We therefore analyze the diffusion, or synchroniza-

[1] A *recession* is a vicious cycle of pronounced, pervasive, and persistent cascading declines in output, income, employment, and sales, eventually giving way to an *expansion*, which is an analogous virtuous cycle of rising economic activity. Sometimes, an economy exhibits not a recession but a milder counterpart called a *slowdown*, meaning a downshift in the pace of positive growth in economic activity. The transitions between the vicious and virtuous cycles are the *peaks* and *troughs* in the cycle, also known as cyclical *turning points*.

tion, of a global recession. The synchronization of a global recession can be gauged by the following:

- Clustering of recession start and end dates
- Proportion of economies in expansion
- Diffusion Index of the coincident indexes[2] of different countries

2.1 Clustering of Start and End Dates of Recessions

The Economic Cycle Research Institute (ECRI) has tracked 22 countries over a long period of time. These include the following: the US, Canada, Mexico, Brazil, Germany, France, the UK, Italy, Spain, Switzerland, Sweden, Austria, Poland, Russia, Japan, China, India, Korea, Australia, Taiwan, New Zealand, and South Africa.

ECRI has long established the recession start and end dates for all the economies it tracks.[3] Table 1 on Business Cycle Chronologies provides recession dates for those countries, using the same approach used by the National Bureau of Economic Research to determine the official U.S. recession dates.[4] This dating reveals a highly synchronized recession, but also many economies that slipped into recession before the start of the COVID crisis.

To represent the closeness of the start of recession dates in a graphical manner, we examine ECRI's 21-Country Composite Coincident Index, shown in Fig. 1. Although

[2] *Coincident indicators* are those that move reliably in step with the economy, so their peaks and troughs roughly coincide with those of the economy itself. A *coincident index* for a particular economy comprises various coincident indicators that collectively represent the current state of the economy. It indicates whether the economy is currently expanding or is in a recession. It is a summary measure designed to track fluctuations in aggregate economic activity that make up the business cycle. Thus, a coincident index can be used to decide the phase of the business cycle the economy is in at a given point in time. The index can therefore be used to help determine the timing of recessions and expansions, as well as speedups and slowdowns in the economy. *Classical business cycles* measure the ups and downs of the economy, with the absolute levels of coincident indicators constituting the coincident index.

[3] The timing of recessions and expansions of business cycles is determined on the basis of a careful consideration of the consensus of cyclical co-movements in the coincident indicators that comprise the coincident index. (Details are described in Dua and Banerji, 1999, 2004, 2007). A specific cycle, that is, a set of turning points for each series, is obtained. A *reference cycle chronology* is then determined based on the central tendency of the individual turning points in a set of coincident economic indicators. A reference cycle based on the levels of the coincident indicators thus gives the consensus of turning points of the coincident indicators.

[4] The GFC, or Global Financial Crisis, was global by definition, but it was not in the nature of an *economic* cycle, though it strongly influenced economic cycles around that time. While some might consider the GFC to have begun with the Lehman Brothers collapse in mid-September 2008, there is no objective way to determine its precise end date. In other words, unlike recessions, the GFC did not have specific start and end dates that can be determined in an analogous fashion. Also, the term "Great Recession" is not synonymous with the GFC since it is specific to the US, and during that period in 2007–09, some economies like China, India, Australia, and Poland did not experience any recessions.

Table 1 Business Cycle Chronologies: Americas and Europe

Period	Peak / Trough	Americas: United States	Americas: Canada	Americas: Mexico	Americas: Brazil	Europe: Germany	Europe: France	Europe: United Kingdom	Europe: Italy	Europe: Spain	Europe: Switzerland	Europe: Sweden	Europe: Austria	Europe: Russia	Europe: Poland
1948-	P	11/48													
1950	T	10/49													
1951-	P														
1952	T							8/52							
1953-	P	7/53	5/53												
1955	T	5/54	6/54												
1956-	P	8/57	10/56				11/57								
1959	T	4/58	2/58				4/59								
1960-	P	4/60													
1961	T	2/61													
1962-	P					3/66			1/64						
1966	T								3/65						
1967-	P														
1968	T					5/67									
1969-	P	12/69							10/70			10/70			
1973	T	11/70							8/71			11/71			
1973-	P	11/73				8/73	7/74	9/74	4/74		4/74	7/75	8/74		
1975	T	3/75				7/75	6/75	8/75	4/75				6/75		
1976-	P														
1978	T										3/76	11/77			
1979-	P	1/80				1/80	8/79	6/79	5/80	3/80		2/80	2/80		
1980	T	7/80					6/80								
1981-	P	7/81	4/81	3/82			4/82				9/81				
1983	T	11/82	11/82	7/83	12/83	10/82		5/81	5/83		11/82	6/83	1/83		
1984-	P			10/85											
1986	T			11/86			12/84			5/84					

(continued)

Table 1 (continued)

Period	*Peak / Trough*	***Americas*** *United States*	*Canada*	*Mexico*	*Brazil*	***Europe*** *Germany*	*France*	*United Kingdom*	*Italy*	*Spain*	*Switzerland*	*Sweden*	*Austria*	*Russia*	*Poland*
1987-1988	P				2/87										
	T				7/87										
1989-1991	P	7/90	3/90		8/89	1/91		5/90		11/91	3/90	6/90			
	T	3/91													
1992-1994	P			10/92			2/92		2/92				4/92		
	T		3/92	10/93	3/92	4/94	8/93	3/92	10/93	12/93	9/93	7/93	6/93		
1994-1996	P			11/94	3/95						12/94		5/95		
	T			7/95	9/95						9/96		3/96	11/96	
1997-1999	P				10/97									12/97	
	T				4/99									1/99	
2000-2001	P	3/01		8/00	2/01	1/01					3/01		1/01		
	T	11/01			12/01								12/01		
2002-2003	P				10/02		8/02								
	T			8/03	6/03	8/03	5/03				3/03				
2004-2010	P	12/07	1/08	4/08	8/08	4/08	2/08	5/08	8/07	2/08	5/08	4/08	2/08	5/08	
	T	6/09	7/09	5/09	1/09	1/09	2/09	1/10	3/09		5/09	3/09	6/09	5/09	
2010-2011	P						4/11		4/11						
	T														
2012-2018	P				1/14									12/14	
	T				10/16		11/12		10/14	7/13				5/16	
2019-2020	P	2/20	12/19	2/19	2/20	5/19	11/19	10/19	7/19	11/19	11/19	4/19	2/20	4/19	2/20
	T	4/20	4/20	5/20	6/20	4/20	4/20	4/20	4/20	4/20	4/20	6/20	4/20	5/20	4/20

ECRI 21-COUNTRY COINCIDENT INDEX

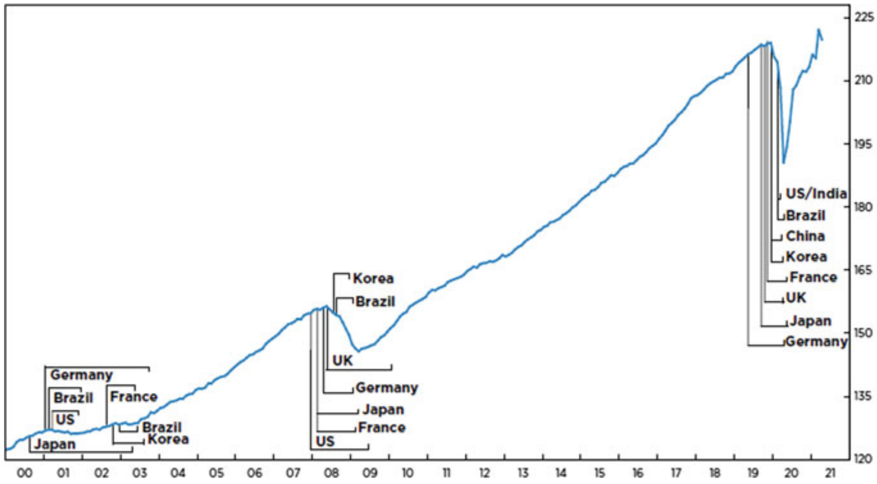


Fig. 1 ECRI 21-country coincident index. *Source* Economic Cycle Research Institute

only the main economies are shown in the figure (for the sake of clarity), it clearly reflects how closely the recessions have been clustered in the three global downturns in the twenty-first century.

It is evident that the recession start dates in the COVID crisis are bunched just as closely together as those in the GFC, which, in turn, are clustered more closely together than those in the global recession that began in the early 2000s. Specifically, the COVID crisis recessions all began between February 2019 and February 2020, and those in the GFC started between August 2007 and August 2008—both one-year time spans—whereas the early-2000s recessions started between August 2000 and December 2002, which is a 28-month span.

But during the COVID crisis, all the recessions ended in a very tight three-month time frame, between March and June 2020; after the GFC, the recessions ended between December 2008 and January 2010, which is a 14-month span; and those in the early 2000s ended within a two-year time frame between September 2001 and September 2003. Said another way, all the COVID recessions occurred within a 16-month period between February 2019 and June 2020, the GFC recessions transpired during a 29-month time span between August 2007 and January 2010, and the early-2000s recessions were spread out over a 37-month time span between August 2000 and September 2003.

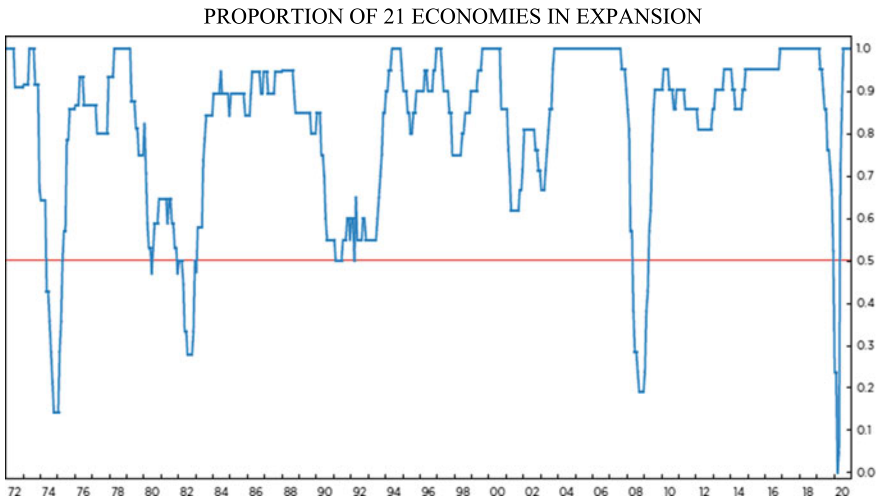


Fig. 2 Proportion of 21 economies in expansion. *Source* Economic Cycle Research Institute

2.2 *Proportion of Economies in Expansion*

The number of economies in expansion as a proportion of the total number of economies tracked is another measure of the diffusion of a global recession. In a widespread global recession, the size of the decline in the proportion of economies in business cycle expansions measures this extent of diffusion.

Using this measure, Fig. 2 shows that the proportion of economies (tracked by ECRI) in expansion fell in 2001 to its lowest reading since 1993, plunged in 2008 to a 33-year low, and nosedived in 2020 to zero, which is a record low. This therefore demonstrates that twenty-first-century recessions have been increasingly widespread.

2.3 *Diffusion Index of the Coincident Indexes of Various Countries*

The Diffusion Index of ECRI's coincident indexes for different economies measures the proportion of the coincident indexes that are higher than they were three months earlier.

The top portion of Fig. 3 shows the proportion of the coincident indexes for the Group of Seven (G7) economies (US, Japan, Germany, France, UK, Italy, Canada) that were higher at each point in time than they were three months earlier. The G7 diffusion index dropped in mid-2001 to its lowest reading since the end of 1992, and touched zero in late summer, 2008, and again in 2020, meaning that every one of the seven economies was contracting. Thus, the recessions in the major developed

DIFFUSION INDEX OF INTERNATIONAL COINCIDENT INDEXES

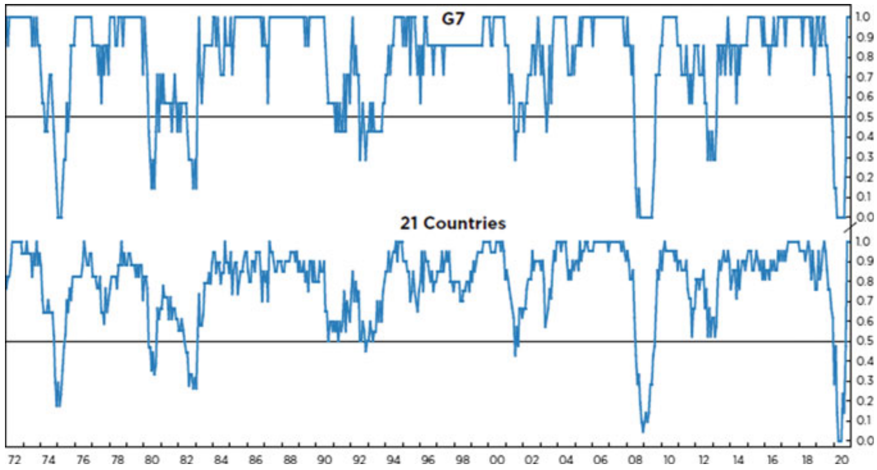


Fig. 3 Diffusion index of international coincident indexes. *Source* Economic Cycle Research Institute

countries were somewhat concerted in the early 2000s, but completely concerted during the GFC and COVID crisis.

The bottom line in Fig. 3 shows the 21-country coincident index diffusion index, which is the proportion of the coincident indexes for 21 economies monitored by ECRI that were higher at each point in time than they were three months earlier. This index paints a different picture, showing that it fell to an 18-year low in 2001, tumbled to a record low in 2008, and plummeted to a new record low of zero during the COVID crisis, as every economy monitored by ECRI—including China and India—fell into recession for the first time.

Thus, the three measures of diffusion of a global recession show that global recessions in the twenty-first century have been getting progressively more concerted, increasingly widespread, and yet shorter, having become more and more closely bunched together in terms of timing. The question is why this has been happening.

3 The COVID Crisis and Its Recessionary Antecedents

ECRI's dating of international recessions reveals an instructive sequence of events, especially during the latest recession. We therefore turn to the 2019–20 global recession to understand the reasons underlying recession timing in this recession.

Among the major economies, it was really Germany that was in the vanguard of this global recession, tipping into an economic contraction in May 2019. A key driver of that downturn was global industrial production, whose growth rate had been slowing since the end of 2017, before global industrial production began to actually decline from its May 2019 peak. In fact, industrial production in Germany—whose manufacturing sector is highly sensitive to global industrial growth—peaked in late 2017 and kept declining for over two years.

In turn, German GDP peaked in Q1 2019 and dipped by 0.5% in Q2 2019 before staging a partial revival, ticking up by 0.3% in Q3 2019. It then declined for three straight quarters, starting with a marginal 0.02% slippage in Q4 2019, and followed by a COVID-driven plunge in the first two quarters of 2020. Aggregate sales also turned down in May 2019, though employment and income dived only after the COVID crisis hit in early 2020. On balance, the key coincident indicators peaked around the spring of 2019, which is therefore when the German recession began (Fig. 1, Tables 1 and 2).

Meanwhile, Japan—unbeknownst to policymakers—was already in a recessionary window of vulnerability in 2019, based on reliable leading indexes of its economy. Under such circumstances, it was predictable that "any negative shock, such as the planned October sales tax hike, would be sufficient to tip the economy into recession" (Economic Cycle Research Institute, 2019). Sure enough—to the government's surprise—Japanese economic activity peaked in September 2019 before that poorly timed sales tax increase triggered a full-blown recession that was extended by the COVID crisis, which arrived a few months later.

In essence, many of the dominoes began to topple before the advent of the pandemic. Because some of their coincident economic indicators had already begun to decline ahead of—and independent of—the pandemic, Mexico tipped into recession as far back as February 2019, followed by Sweden and Russia in April; Italy and South Africa in July; the UK in October; and France, Spain, and Switzerland in November 2019. Economic activity peaked in China in December 2019 before starting to weaken in January 2020, and Canada, Australia, Korea, and Taiwan—being heavily dependent on exports to China—also entered recession in December 2019 (Tables 1 and 2).

This is not to suggest that all of these economies—unlike Japan, for instance—would have inevitably tipped into recession absent the COVID crisis. However, those economies were all in sufficiently wobbly states months before the pandemic—in terms of at least minor declines in key coincident indicators that would not by themselves have amounted to a recession—that the COVID shock was sufficient to pitch them into recessions. Their recession start dates consequently predate the early-2020 COVID shock.

In contrast, economic activity in the US, India, and Austria peaked in February 2020, before lockdowns starting in March caused economic activity to plummet. But in Brazil, as well, economic activity peaked in February 2020 and began to fall as the pandemic spread, even though the first local lockdown did not begin until May (Tables 1 and 2).

The dates for the onset of the latest recession in various economies imply that the majority entered recession in 2019 before pandemic-related plunges in economic activity triggered a global recession, just as the vast majority of economies went into recession before the Global Financial Crisis began in September 2008 (Banerji and

Table 2 Business Cycle Chronologies: Asia-Pacific and Africa

Period	*Peak/ Trough*	*Asia-Pacific*							*Africa*
		Japan	*China*	*India*	*South Korea*	*Australia*	*Taiwan*	*New Zealand*	*South Africa*
1948-1950	P								
	T								
1951-1952	P					6/51			
	T					9/52			
1953-1955	P	1/53				12/55			
	T	12/54							
1956-1959	P								
	T					8/56			
1960-1961	P					12/60			
	T					9/61			
1962-1966	P			11/64					
	T			11/65					
1967-1968	P			4/66				6/66	
	T			4/67				3/68	
1969-1973	P			6/72					
	T			4/73					
1973-1975	P	11/73		11/73		6/74	12/73	4/74	
	T	2/75		6/75		1/75	1/75	3/75	
1976-1978	P							3/77	6/76
	T							3/78	11/77
1979-1980	P			3/79	3/79				
	T			12/79	10/80				
1981-1983	P					6/82		4/82	11/81
	T					5/83		5/83	1/83
1984-1986	P							11/84	6/84
	T							3/86	2/86
1987-1988	P		8/88					9/86	9/88
	T		12/89						

(continued)

Table 2 (continued)

Period	*Peak/ Trough*	*Asia-Pacific*							*Africa*
		Japan	***China***	***India***	***South Korea***	***Australia***	***Taiwan***	***New Zealand***	***South Africa***
1989-1991	P			3/91		6/90			
	T			9/91		12/91		6/91	
1992-1994	P	4/92							
	T	2/94							8/92
1994-1996	P			5/96					
	T			11/96					
1997-1999	P	3/97			8/97			10/97	4/97
	T	7/99			7/98			5/98	11/98
2000-2001	P	8/00			12/02		8/00		
	T	4/03			9/03		9/01		
2002-2003	P	2/08			7/08		2/08	11/07	4/08
	T	3/09			12/08		1/09	5/09	4/09
2004-2010	P	8/10						5/10	
	T	4/11						10/10	
2010-2011	P	1/12							
	T	1/13							
2012-2018	P	3/14							
	T	8/14							
2019-2020	P	9/19	12/19	2/20	12/19	12/19	12/19	12/19	7/19
	T	5/20	3/20	4/20	4/20	4/20	5/20	6/20	4/20

Dua, 2010). In essence, this global contraction was even more highly concerted than the previous one.

4 Common Shocks, Supply Chain Dynamics, and Global Recessions

It is worth recalling that most economies entered recessions associated with the GFC well before a full-blown financial crisis was triggered by the collapse of Lehman Brothers in September 2008. A case in point is the US, where the recession started in December 2007.

In fact, most of these economies had already entered windows of vulnerability, within which any significant shock would tip them into economic contraction. As a result, the knock-on effects of slowing consumer spending in major economies like the US were sufficient to trigger those recessions.

Basically, between the early 1990s and the GFC, the world's economies became increasingly interdependent, with greater openness in the flows of services, capital, and trade—especially in merchandise—from one country to another. As a result, exports as a percentage of GDP increased sharply in almost every country, consistent with the intensification of globalization. These enhanced trade linkages served as a more efficient mechanism for the transmission of business cycles across the globe and had become the primary method of international transmission of business cycles (Banerji and Dua, 2010). Indeed, though globalization has retreated somewhat since the GFC, this mechanism remains a key reason for the international synchronization of recessions.

In fact, because slowing demand growth at the consumer level results in unexpected inventory build-ups escalating up the supply chain, it is amplified into bigger and bigger swings in demand as orders move up the supply chain away from the consumer (Mack, 1956). This magnification of shifts in consumer demand growth up the supply chain is called the Bullwhip Effect, in analogy to the way a little flick of the wrist produces a big arc at the end of a bullwhip. Such supply chain dynamics played key roles in triggering—and roughly synchronizing—the recessions that began around the world before the actual financial crisis, which amplified them much further.

But when the rate of decline in consumer demand eases, the supply chain is once again caught by surprise and has to readjust. In other words, slower decline in consumer demand typically translates to progressively amplified increases in demand up the supply chain. This flip side of the Bullwhip Effect helps to account for the synchronized recoveries from the GFC. In other words, the aftermath of the common shock of the Lehman Brothers collapse and the resulting global financial reverberations did help to synchronize the timing of emergence from recessions in various economies, but—as Tables 1 and 2 and Fig. 1 show—those recessions mostly began well before that common shock materialized.

During the GFC, international financial linkages also played an important role in transmitting the recession around the world. Indeed, the U.S. financial crisis, triggered by the plunge in the value of securitized subprime mortgages and exacerbated by the onset of recession in late 2007, reverberated around the world because these financial instruments were owned by investors globally. Notably, in the fourth quarter of 2008, foreign entities owned almost nine times the amount of U.S. credit market instruments as they did in 1990. Thus, international financial institutions were among the hardest hit, and in the US and Europe, a number of banks needed capital infusions to stay afloat. As “toxic assets” mushroomed on banks’ balance sheets, they eviscerated their capital bases, along with their ability to lend. With suspicions about the solvency of most major banks mounting rapidly, interbank lending ground to a halt and letters of credit, which are used in the vast majority of transactions involving developing countries, became virtually impossible to obtain. In this fashion, while the collapse of demand in developed economies spread in an amplified fashion through international supply chains, engulfing developing countries, even south-south trade involving just developing countries ground to a virtual halt due to the dearth of letters of credit.

The ensuing global credit crunch also crimped lending to emerging economies and increased the cost of trade finance and had a major impact on emerging economies. This is why there was such a concerted and sudden plunge in global economic activity. Separately, international stock prices also swooned in unison, with the high correlation between U.S. stock prices against not only European stock prices, but also those of Asia, rendering international diversification useless in protecting investors from losses in international recessions (Banerji and Dua, 2010).

5 Conclusion

The main conclusions of this paper are as follows:

- The COVID crisis was accompanied by the most synchronized global recession in the post-war period, surpassing the GFC and also tipping China and India into short but sharp recessions.
- In the twenty-first century, international recessions have become increasingly deep and synchronized, but also bunched more and more tightly together over shorter time spans.
- While common shocks like mandated lockdowns—along with international supply chain dynamics—have helped to synchronize international recessions and recoveries, the majority of recessions around the world began months before those lockdowns, just as most recessions associated with the GFC had started months before the collapse of Lehman Brothers.

Questions To Think About

1. What is the difference between a recession and a slowdown? Describe some measures to analyze synchronization of a global recession.
2. Why was the COVID crisis accompanied by the most synchronized global recession in the post-war period, surpassing the recession associated with the GFC?

   Hint: Refer: Banerji and Dua (2010).
3. Explain the Bullwhip effect.

References

Banerji, A., & Dua, P. (2010). The synchronization of recessions in major developed and emerging economies. *Margin: The Journal of Applied Economic Research,* 4(2), 197–223.

Dua, P., & Banerji, A. (1999). An index of coincident economic indicators for the Indian economy. *Journal of Quantitative Economics, 15*, 177–201.

Dua, P., & Banerji, A. (2004). Monitoring and predicting business and growth rate cycles in the Indian economy. In Dua, P (Ed.), *Business cycles and economic growth: An analysis using leading indicators*. Oxford University Press.

Dua, P., & Banerji, A. (2007). Business cycles in India. In Basu, K (Ed.), *Oxford companion to economics in India*, Oxford University Press.

Economic Cycle Research Institute. (2019). *International Cyclical Outlook Essentials*, XXIV (6), 1–4

Mack, R. (1956). *Consumption and business fluctuations: A case study of the shoe, leather, hide sequence*, National Bureau of Economic Research.