India Studies in Business and Economics

Suresh Chand Aggarwal
Deb Kusum Das
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Accelerators of India's Growth—Industry, Trade and Employment

Festschrift in Honor of Bishwanath Goldar

Springer

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About Professor Bishwanath Goldar

Professor Bishwanath Goldar studied at Delhi School of Economics (DSE) for his Masters and Ph.D. He taught Economics at the Shri Ram College of Commerce from 1971 to 1979 and then joined the Institute of Economic Growth. He was with the Institute of Economic Growth since 1979 and was Professor from 1996 till his retirement in 2014. He has worked as a Senior Fellow at the National Institute of Public Finance and Policy (NIPFP) during 1988–90 and as a Professor at the Indian Council for Research on International Economic Relations (ICRIER) during 2003–04. He also served as Professor at Jawahar Lal Nehru University (JNU) during 2012–13. He was a National Fellow of the Indian Council of Social Science Research (ICSSR), affiliated with IEG, for two years in 2015 and 2016. He has also been a Visiting Fellow at the Institute of Economic Research, Hitotsubashi University, Tokyo and the Institute of Developing Economies, Tokyo.

Professor Goldar specializes in industrial economics, environmental Economics, and international trade and foreign investment. He has supervised a vast number of research scholars for their Ph.D. on different aspects of industry, trade, and FDI. Most of his research has been on productivity and employment in Indian industries, price-cost margin and competitiveness of Indian manufacturing industry, export performance of Industrial firms, effective protection of Indian industries, impact of trade reforms on the performance of industrial firms, and foreign direct investment in India. He has also undertaken studies on pollution of river water in India and on the environmental aspects of Indian industries including studies on energy efficiency in Indian industrial firms and the impact of environmental performance of industrial firms on their stock prices. He has published a number of books and more than 100 research papers and reports in reputed International and National Journals and has also disseminated his research through newspapers and by participating in numerous national and international conferences and seminars.

Professor Goldar has also been associated from the very beginning with the India KLEMS project funded by RBI to create a productivity data base for the Indian Economy, where he has been guiding research on Productivity in the Indian Economy. The entire team has immensely benefitted from his strong grip on the data on Indian Economy. The research output of the KLEMS project has been presented by him (and other team members) in many International Conferences.

He has been associated with a number of important official committees, and is currently the Chairman of the Standing Committee of Industrial Statistics (NSO). He has been a member of the National Statistical Commission. He has also been on the editorial advisory board of many reputed Journals. For his outstanding career and contribution to the discipline, he was conferred the Distinguished Alumnae Award by DSE in Feb 2018. This book is a humble tribute to his academic excellence and to his leadership in research on industry, trade and employment.

Foreword

This volume of essays contributed by several eminent scholars with long professional association with Prof. Bishwanath Goldar is a fitting tribute to him. Professor Goldar by the dint of his academic commitment and research contributions in various fields of economic research has been a great source of inspiration to younger scholars all over India and even abroad. The title of this volume aptly reflects the broad areas in which Prof. Goldar distinguished himself.

I have known Prof. Bishwanath Goldar for about five decades. He was one of my brightest and most diligent students in the M.A. Economics programme at the Delhi School of Economics during 1969–71. He worked with me and late Prof. Mrinal Datta Chaudhuri for his Ph.D. on Productivity Growth in Indian Industry in the 1970s at the DSE. It gives me immense pleasure to pay my compliments to him on the occasion of his friends and students bringing out a festschrift volume in his honour.

However, I must admit that in the task of attempting to depict his academic profile, I cannot do justice to the richness and range of his academic achievements in this very short account. His academic output is stupendous spanning diverse areas and using various methodologies. His areas of specialization have included industrial economics, empirics of international trade, environmental economics, productivity measurement and analysis, Indian Official Statistical System, and applied econometrics. He has authored more than one hundred research papers, coedited several books, and supervised dozens of Ph.D. and M.Phil. theses.

Professor Goldar has been either the chairperson or a member of many high-powered committees appointed by the Government of India. His advice has been in great demand.

I would like to focus on Prof. Goldar's important role in and the valuable contributions to the India KLEMS research project headed by me first at ICRIER and later at the Centre for Development Economics (CDE) at DSE during the past one decade, with financial support from the RBI and technical advice from CSO. With his intimate knowledge of the Indian Official Statistical System, he has guided the research team in the construction of data sets on outputs and five KLEMS inputs at the disaggregate industry level from the year 1980–81 onwards. After the construction of the data sets year after year, Prof. Goldar and other members of the team have authored analytical papers and presented them at internal workshops and international conferences.

I personally owe a great deal to Prof. Goldar for his advice and help.

I wish to conclude by thanking the organizers of this volume for their noble initiative.

K. L. Krishna
Former Director
Delhi School of Economics
New Delhi, India

Preface

This volume was conceived to honour our long-standing friend, co-author, guide and mentor Bishwanath Goldar, who has mentored and inspired not only the three of us but a whole lot of researchers in India and aboard through his outstanding contribution to the literature in economics and to productivity in particular.

It was a very pleasant experience to identify and get contributions from the authors to this volume, as all of them were quite enthusiastic and committed to contribute. The contributions to this volume have come from his students, and many colleagues with whom he has worked and interacted over the years. The themes selected for this volume—industry, trade, and employment—cover widely the areas of research which Prof. Goldar has over the years engaged.

Indian economy has faced many challenges since the global meltdown of 2008, but these challenges have become more serious since 2011–2012 when the average growth rate has fallen and there is a negligible growth in employment. The "jobless" growth is accompanied by farm distress in agriculture and a stagnant manufacturing sector (especially the unorganized manufacturing sector). The pressure on fiscal deficit and falling growth in exports has further added to the challenges of growth. The changes in technology are also putting pressure on employment and income. The questions are being raised about the growth in GDP, in employment, in investment, and in exports and FDI. In such a scenario, there is a need to understand these challenges and identify the accelerators of growth and the policies and strategies which need to be followed to face them. The collection of the research papers in this volume have attempted to analyse and answer some of the issues facing the Indian economy today.

We owe our gratitude to all the contributors of this volume who not only readily agreed to be part of this volume but contributed the original research papers, which has enriched this publication. We would also like to thank Nupoor Singh and Ravivarman Selvaraj from Springer and their entire team for supporting this volume and making it possible to bring it out at the earliest.

New Delhi, India — Suresh Chand Aggarwal
New Delhi, India — Deb Kusum Das
Geneva, Switzerland — Rashmi Banga

Introduction

India has faced many challenges in the past two decades but has been able to sustain its growth even when the global economy was turbulent. Many policies, strategies, and initiatives have supported India's growth in the past. Industrial growth along with growth in services supported the overall growth of the economy. However, growth in the last two years and especially the Q4 of 2018–2019 has slowed down considerably and the unemployment rate, as revealed by the latest PLFS is at an all-time high. Since 2011–2012, the growth in GDP has not been accompanied by subsequent growth in the employment. Some of the reasons for the slowdown could be external shocks, like BREXIT, competitive protectionism, slowdown in world trade but domestic factors like farm distress, fiscal deficit stress, slowdown in the growth of personal consumption and slow investment and export growth may also have contributed to it. The economic challenges before the nation today are to recover from the slowdown and generate employment, as the medium and the long-term prospects for India are bright. Efforts are on by the policy makers in India to usher in policies aimed at faster and inclusive growth. Efforts are on to design policies which could address the problem of low agriculture productivity, boost export growth, attract more FDI, generate employment, improve the skills of labour, and have more equitable growth.

This volume is a collection of distinguished papers which have attempted to identify the growth accelerators of India and have suggested policies and strategies to make India's growth sustainable and inclusive. The broad themes covered in the volume are related to India's Industrial Growth: Opportunities and Challenges, Role of Trade and FDI as India's Growth Accelerators: Opportunities and Challenges, and Growth accompanied with Employment Generation: Challenges and Way Forward. A brief overview of the chapters follows.

Part: India's Industrial Growth: Opportunities and Challenges

The pace and level of India's industrial development has been a challenge for policy makers for several decades. The share of manufacturing value added in GDP has remained consistently low, and manufacturing products remain less integrated with the world markets due to issues of international competitiveness. In terms of employment generation, the large presence of informal firms in manufacturing leads to very small share of job creation by formal manufacturing. In addition, several other factors constrain manufacturing growth—the inability of labour-intensive firms to lead India's export growth, low penetration into global value chains, and contractualization of employment. The government has introduced several policy directives to enhance the pace of industrialization especially with schemes like "Make in India" as well as "Skill India". The objective behind such programmes is to increase both sectoral shares and job creation by manufacturing firms. However, key drivers for improving both domestic and international competitiveness of the industrial sector in India continue to pose several challenges to increasing the productivity of the sector. Some of these, which need immediate attention, are infrastructure, digitalization including ICT, macroeconomic stability, and availability of skill workforce.

The essays presented in this part aim to address some of these issues. Issues such as technology, productivity, value chains, environment, and expenditure for the industrial sector are some of the pertinent challenges that remain to be addressed if India is to emerge as a manufacturing hub in its industrialization programme. The first chapter by N. S. Siddharthan considers the Paradigm Changes in Technology and Employment. The chapter starts with the Schumpeterian concept of creative destruction resulting in turmoil consequent to paradigm shifts in technology. Unlike trajectory changes in technology, paradigm changes are not incremental changes and they could destroy and replace the existing technologies and products—the rapid increase in the introduction of robots in manufacturing in the Asian countries led by China. The author argues that the ongoing digital and genomics revolutions are knowledge-based and knowledge-intensive wherein human capital plays a crucial role. Technology and knowledge transfers through foreign direct investments will work only in the presence of highly skilled workforce. In the case of India, the states that enjoyed better human capital in terms of education and health enjoyed higher growth rates of employment and productivity. The chapter concludes by outlining the opportunities for India and discusses likely advantages India would have when the quantum computers are introduced in future, opening opportunities for participation in hardware and software. Opportunities that could emerge in solar energy in particular when products like quantum dots and paper-thin solar cells are introduced in future.

The second chapter by Pilu Chandra Das and Deb Kusum Das provides an overview of the manufacturing sector with respect to productivity and employment. Using neoclassical growth accounting technique and the India KLEMS data set, the authors examine the manufacturing performance at the aggregate level as well as 13 disaggregated industries and present an industry-level perspective on the manufacturing performance. Labour productivity growth, total productivity growth, and the sources of growth are documented for the period 2000–2016 and the two sub-periods, thereby allowing a comparison between two distinct phases of Indian economy—before global financial crisis (2000–2007) and financial crisis period (2008–2016). The chapter shows wide variation across industries and over time with respect to both labour and total factor productivity. While the high rates of growth of labour productivity are observed across different industries, the TFP growth remains low for the entire period as well as for both sub-periods.

The chapter by Atsushi Kato and Atsushi Fukumi addresses the question of the state's role for industrialization especially the political economy of state government expenditures allocated to industrialization. An investigation has been done of why some governments do not institute public policy conducive to industrialization from the viewpoint of the balance of political power between the agricultural and industrial sectors. The political influence of the agricultural sector can limit the allocation of expenditures conducive to industrialization, resulting in the stagnation of regional state economies. More specifically, the degree of the political power of rural elites tends to reduce the allocation of development expenditures favourable to the industrial sector at the state level in India. The chapter concludes albeit weaker that as the political influence of urban elites increases, expenditures for the industrial sector tend to increase. There is some sort of battle over the allocation of government expenditures between rural and urban elites, and rural elites may exert an influence that limits the allocation of government expenditures conducive to industrialization. In that sense, the political influence of rural elites can be harmful to economic development in a broad sense.

The role of international trade in driving productivity and growth has been widely analysed in the context of India, particularly in the formal manufacturing sector. However, with the rapid increase in the global production fragmentation, the rise of global value chains and its implication for manufacturing sectors in India remains unexplored due to low levels of penetration of manufactured products in the world markets. Abdul A. Erumban in his chapter documents the involvement of India in the global value chain by 27 individual sectors—both manufacturing and non-manufacturing—consisting of the entire economy—both formal (organized) and informal. The study shows some interesting observations: (1) the foreign content in domestic production is highest in the manufacturing sector, and this has increased over the years. Even though market services stay second, the foreign share in domestic production in this sector has not been growing in recent years. (2) Regarding the presence of Indian content in foreign production, we observe that the global textile sector has the highest relative proportion of Indian input, although its relative contribution to India's GDP is not the highest, and is further declining. Overall, the chapter provides estimates of foreign content in domestic production in Indian industries, Indian content in the production of global industries, and the reliance of income generated in Indian industries on foreign demand.

The last chapter in this part addresses the issues of the environment and its implication for development in particular. The study by Purnamita Dasgupta and Chetana Chaudhuri looks at the usage of electricity and the economic opportunity that it creates for the population by improving social infrastructure and increases productivity. In this study, they examine the relationship between economic growth and electricity consumption and make projections in electricity demand based on evidence from international experience. Drawing upon insights from international experience, the study estimates this relationship for India. Several observations are noted from the paper—ensuring energy access for all, energy security and energy efficiency have been India's policy focus along with the target of achieving sustainable development goals. Demand forecast for electricity sector is a necessary requirement for efficient management of the energy system and preparedness of the system to ensure economic growth and sustainable development. In the light of the above findings, it becomes clear that it is important for India to continuously augment its electricity generation in order to resolve access issues at all levels. The authors in conclusion highlight some of the recent developments in the policy arena, which can help in taking forward the Indian electricity sector, such that the transition towards an upper middle-income country is smooth.

Overall, the different chapters which comprise this part provide an array of issues which continue to be important for India's industrialization attempts even after more than two decades of policy reforms. Paradigm shifts in technology (genomics and digital technologies including artificial intelligence, robotics, and cloud computing), fragmentation of production and consequences for India's integration into global value chains, inability of manufacturing firms to improve their productivity, lack of convergence between rural and urban sectors, and changes in environment all continue to challenge India's industrialization programme especially with respect to manufacturing sector's inability to drive the engine of economic growth in India and thereby generating jobs and improving standard of living.

Part: Role of Trade and FDI as India's Growth Accelerators: Opportunities and Challenges

Trade and foreign direct investments have always been considered as important accelerators of growth in developing countries, and India has relied heavily on these accelerators. The reforms undertaken in early 1990s aimed at boosting India's exports, imports, and inward foreign direct investments with the expectation that these accelerators will boost the productivity of Indian firms and lead to higher growth, employment, and incomes. Since then India has implemented targeted policies aimed at maintaining a healthy balance of trade along with increasing both inward and outward FDI. It is important to examine whether India has succeeded in boosting foreign trade and FDI in the post-reform period and whether these accelerators have been able to increase productivity and growth in India. The advent of the fourth digital industrial revolution has also brought in new challenges for trade and investments in India. To what extent will India be able to sustain its competitive advantage in foreign trade and FDI and what policies need to be put in place is also an issue which needs to be deliberated. With these objectives, this part of the volume focuses on India's performance, potential, and challenges in the areas of foreign trade.

Chapter "India's Merchandise Exports in a Comparative Asian Perspective" contributed by Veeramani and Aerath examines the policy interventions needed with respect to international trade in order to concretize the role of international trade as an accelerator for India's growth. The chapter highlights that India's merchandise exports recorded a very strong growth rate of 20% per annum in the period 1991–2000, but from 2000–2012, the growth rate logged a negative growth rate of 7.95 per annum. Consequently, in the period 2001–2015, India's merchandise imports grew faster than its exports leading to a rising current account deficit. The reason why India has not been able to sustain its commendable export performance of the period 1991–2000, according to the authors, lies in the composition of India's exports. Despite being a labour-abundant and capital-scarce country, the fast-growing exports from India are either skilled labour intensive or capital intensive. This has locked out India from vertically integrated global supply chains in many manufacturing industries and increased its exports to relatively poorer regions (such as Africa) giving India a comparative advantage in these countries. However, this has come with a cost of losing market shares in the richer countries.

Using a much-disaggregated data, i.e. HS 8-digit on bilateral exports from Directorate General of Commercial Intelligence and Statistics (DGCI&S), Government of India for the period 2000–2015, the authors undertake analysis of India's exports to 155 partner countries. Based on the method proposed by Hummels and Klenow (2005), the authors estimate export penetration of India in its partner countries, where export penetration can be expressed as the product of extensive margin (new trading relationships) and intensive margins (increase in trade of existing relationships). The results show that India's export penetration rate has declined significantly in high-income countries in the period 2000–2015. This can be attributed mainly to the negative growth rate (-3.5%) of intensive margin, implying that the lack of specialization and intensification, rather than a lack of product diversification is primarily responsible for a significant decline in India's export penetration rate in high-income countries. Thus, specialization out of the traditional labour-intensive products led to a general loss of India's export potential in advanced country markets. The analysis suggests that India can reap rich dividends by adopting policies aimed at accelerating export growth at the intensive margin and expand its export relationships with the traditional developed country partners. However, this would necessitate India's greater participation in the vertically integrated global supply chains and a realignment of its specialization in labour-intensive processes and product lines. To this end, the authors suggest that it is important to make the labour markets more flexible, promote investment in physical infrastructure, remove market distortions, and reduce the administrative costs on business.

Chapter "Digitalization and India's Losing Export Competitiveness" of this volume, contributed by Banga and Banga, examines the impact of growing digitalization on India's exports. Corroborating the export trends highlighted by Veeramani and Aerath, the authors highlight that the average annual growth rate of India's merchandise exports had been impressive at 21% in the period 2003–2010, but it declined to 5.5% in the period 2011–2017. While it can be argued that the global slowdown may have led to this slide in the average annual growth rate of exports, the average annual growth of India's share in global exports also experienced a drastic fall from 8.4% in the period 2003–2010 to 3.1% in the period 2011–2017. India's share in global exports declined in some of its traditional exports like textile fibres (1.1%), plastic materials (0.4%), leather manufacturers (0.6%), non-metallic minerals n.e.s (2.3%), and crude chemicals (2.7%). To investigate this further, the authors estimate the Revealed Comparative Advantage of India's exports in different sectors and products and find that out of 15 broad sectors, India lost its comparative advantage in nine sectors and most of these sectors are India's top traditional exports like textiles and clothing, footwear, food products, and chemicals. Most of India's traditional export products are also found to be losing their comparative advantage including precious stones, spices, jewellery, cotton, tea, fabrics, clothing articles, and leather.

The chapter examines to what extent the advent of Industry 4.0 is responsible for India's declining export competitiveness. An analysis is undertaken both at the sector level and at the firm level. Rise in digital content in manufacturing exports is identified as one of the factors which increase the export competitiveness in Industry 4.0. At the sectoral level, two estimates are used, i.e. consumption of digital services (computer programing and information services and telecommunication services) in the production of manufactured products, and value added by digital services in exports of manufactured products in India as compared to other identified developed and developing countries in the period 2000–2014.

Using the National Input–Output Tables, a comparison of digital services used as an input in manufacturing output show that it has increased in developed countries like USA and the UK, while it has declined in most of the developing countries. However, India has experienced a rise in this ratio. Further, using Leontief's decomposition and input–output data from the World Input–Output Dataset, the authors find that in 2014, the share of manufacturing exports in total value added by digital services in India's exports was only 9%. The corresponding figure for other countries is much higher at 78% in Turkey, 60% in China, 57% in Indonesia, and 54% in Brazil. The authors argue that value added by digital services is an important estimate of digital content in the country's manufacturing exports and also an indicator of digital competitiveness of manufacturing exports. A closer look at the share of sectors in value added by digital services to India's exports reveals that digital services not only contributed very little value added to India's manufacturing exports; the share of most manufacturing sectors was found to be less than 1%. Most of the value added by digital services was contributed to exports of computer programing and telecommunication services, which together accounted for 88% of total value added contributed to total exports. This lopsided value addition by digital services to manufacturing exports in India has had serious implication on its export competitiveness in the digital era.

At the firm level, the chapter empirically estimates the impact of increasing digital assets on export intensity of Indian manufacturing firms in the period 2000–2015, using panel data methodologies of System GMM and Random Effects Tobit. Firm-level empirical results confirm the important role of digitalization as a driver of export competitiveness in Indian manufacturing firms. System GMM and Tobit results reveal that as the share of digital assets in overall plant and machinery increases in a firm, its export intensity rises, other things constant. The authors emphasize that there is an urgent need for targeted policies and strategies for increasing digitalization of India's exportable sectors, particularly of traditional exports like textiles and clothing and leather and leather products, as these sectors generate large-scale employment for low-skilled workers.

Chapter "Firm-Level Productivity and Exports: *The Case of Manufacturing Sector in India*", contributed by Narayanan and Sahu, also undertakes the analysis for the period 2003–2015, focusing on the total factor productivity (TFP) differentials between exporting and non-exporting firms and investigates if exports have contributed to the TFP differentials. The methodology adopted in the chapter compares the entire distribution of productivity as against the marginal movements in the TFP, which fills an important gap in the literature on TFP in India. TFP is estimated using Levinsohn and Petrin (2003) approach of estimating production function using intermediate inputs. Two hypotheses are put forward: firstly, the productivity distribution of exporting firms, entering exporters and continuing exporters, dominates the productivity distribution of non-exporting firms; the productivity growth between exporting and non-exporting firms is statistically different and increases for those firms that are already in the export market after a new export firm enters the market.

The chapter draws the data from the Centre for Monitoring Indian Economy Prowess IQ database. The analysis is undertaken for an unbalanced panel of 54,139 firm-year observations. Using the nonparametric approach, the chapter ranks the distributions using stochastic dominance and their differences using Kolmogorov–Smirnov tests.

The results of the chapter show that exporting firms in India have a higher level of TFP as compared to the domestic firms, and however, the firms with higher TFP self-select to the export market. Further, the authors find that firms that are not able to have a higher level of productivity are forced to exit the export market, so the continuing exporters have higher TFP. Two important variables to consider when comparing export performances are the firm size and the age of the firm. The results show that the size of the firm plays an important and a greater role than the age of the firm. Thus, the firms that enter into exports market have higher TFP and are bigger in size.

Chapter "FDI and Export Spillovers: A Case Study of India", contributed by Mondal and Pant, focuses on an earlier period of 1994–2010 and estimates the contribution of FDI to exports of India. FDI can impact on export performance of domestic firms through the diffusion of information, knowledge and technology brought by the foreign firms. These spillover effects of FDI on the export performance of domestic firms can therefore take different forms of horizontal spillovers like information spillovers, competition spillovers, imitation spillovers, and skill spillovers and together can lead to the improved export performance of the domestic firms.

Using a panel data set on Indian manufacturing firms from 1994–2010 from PROWESS database provided by Centre for Monitoring Indian Economy (CMIE), the chapter estimates the FDI spillover effects on the export performance of the domestic firms. The impact of FDI on export spillover is estimated by examining two aspects of export performance of the domestic firm: (i) non-exporter firm's decision to export and (ii) export propensity of the exporting firms. To avoid the problem of self-selection and to capture these two activities of the domestic firms, the Heckman two-stage selection model (Heckman 1979) is used. This model treats the selection problem as the omitted variable problem. As the model takes into account firms' decision to enter the export market or not, it removes the problem associated with the selectivity bias that occurs when only the exporting firms are considered.

The export performance of domestic firms is captured through two activities, i.e. first, whether the decision of the non-exporter firms changes and second, how the export propensity of the self-selected exporting firms gets influenced by foreign activities. The results do not find any significant positive impact on foreign firms' domestic activities or export activities on export performance. Competition spillovers and skill spillovers from foreign firms are found to have a significant negative impact on the export propensity of domestic firms.

To examine whether these results are mainly driven by the initial periods of liberalization since the fact is that the domestic firms take few years to adjust to the new environment before they take advantages from foreign activities, the chapter undertakes separate analysis for two sub-periods: 1994–2001 and 2002–2010. The results show that the decision to export is not influenced by any of the activities of foreign firms in India during the period 1994–2001. FDI spillover, in fact, has a negative impact on the export performances of the domestic firms during 2002–2010. A plausible reason for this, according to the authors, seems to be that the exporting foreign firms were reluctant to share their knowledge about international markets with their domestic competitors. The positive impact of competition spillover in the period 2002–2010 reaffirms the competitive pressure from FDI on export performance of domestic firms. The authors conclude that the foreign firms were attracted to India as they could use the country as the export platform for the southern region of the globe, which obstructed the export decision of the domestic firms. They recommend that it is important to understand the motive of the foreign investment, while incentivizing foreign investments into the economy.

Chapter "Foreign Involvement and Firm Productivity: An Analysis for Indian Manufacturing, Service, Construction and Mining Sectors", contributed by Chawla, focuses on outward foreign direct investment (OFDI) from India and compares the total factor productivity (TFP) of firms that engage in OFDI and exports, to those which engage in exports, and domestic operations only. The analysis is undertaken not just for the manufacturing firms, but also includes firms that operate in services, construction, and mining sectors. For manufacturing firms, sunk costs/physical transport costs may result in only more productive firms investing abroad, while for service firms the decision to export versus undertaking outward investment is likely to be shaped by additional factors, including the need for direct communication with customers, difficulties in contracting foreign affiliates for non-routine activities, and the presence of near-zero transaction costs.

To examine the nature of productivity differentials across firm categories based on foreign involvement, the chapter uses firm-level data from the *Prowess* data set in the period 1995–2010 and deploys the nonparametric approach of first-order stochastic dominance (Kolmogorov–Smirnov test). An important methodological contribution of the study is the comparison of productivity measurement using the Levisohn and Petrin (2003) methodology and its modification proposed by Wooldridge (2009). In addition, the study applies modifications in the construction of real output, value added and input series used for estimating TFP, and uses different threshold categories for classifying foreign investors to check the validity of productivity rankings by firm categories.

For *manufacturing* and *construction* sectors, the cross-sectional differences in TFP between outward investors that also export, pure exporters, and domestic firms are found to follow the Helpman, Melitz and Yeaple (2004) hypothesis of self-selection into foreign markets, i.e. firms with the highest productivity are more likely to invest abroad. The value-added specification, however, suggests an upward bias in the productivity advantage of internationally engaged firms, highlighting the importance of controlling the "value-added bias". Productivity differentials are also at times found to considerably vary by 2-digit industry/industry groups. In *services*, TFP comparisons show that pure export firms dominate the purely domestic firms, and overseas investors that also export dominate purely domestic firms, while in *mining*, only the dominance of pure export firms over purely domestic firms could be established for the latter half of the sample period.

It is further noted that productivity and other firm characteristics in OFDI firms that initially start small is similar to larger OFDI firms, suggesting that if financing is a constraint, the government could support a more liberal financial system that specifically aims at firms with initially small OFDI.

Part: Growth Accompanied with Employment Generation: Challenges and Way Forward

One of the most important concerns before the policy makers today is the issue of employment generation. Though India has been growing rapidly since 2004–2005, but employment growth has not followed the same pace. Many have even described the Indian growth during this period as the period of "jobless" growth. The latest data released by NSO of the Periodic labour Force Survey (PLFS) also shows unprecedented high unemployment rates in the economy during the period 2017–2018 and a fall in labour force participation rate, especially of rural women. Among the many reasons cited by experts for the situation are the failures of the Indian manufacturing sector to generate sufficient number of jobs despite the focus of the New Manufacturing Policy, and the impact of new technology on jobs, as capital intensity of production has been increasing. Certain other trends in employment have been noticed—the absolute fall in employment in agriculture and the shift of these workers mainly to the construction sector. The workers are thus shifting mainly from one low productivity sector to another low productivity sector. The growth in the regular workers has been very slow, and it is only the casual labour and the self-employed which have grown substantially over the period. Simultaneously, even in the small organized sector a growing trend of informalization of workers is taking place. Sub-contracting and outsourcing of jobs has become the new norm. As a result, there has been a substantial increase in the number of contractual workers without much social security and legal contracts. With the growth in digital economy and E-commerce, the scope for generating employment is shrinking in many industries, especially manufacturing. Also, there is a need and demand for new skill sets for the twenty-first-century jobs, which the new technology demands, but India is lacking. It is in this context that attention is to be paid to some of these issues facing labour today.

The chapter by Anant is a tribute to the contribution of Prof. Goldar to the measurement of "Labour Input" (LI) and value added by different types of workers in the informal sector in the national income estimation in India, especially since 2011–2012. He describes the different methodologies used in its estimation over the period and how an improvement in its measurement for the informal sector was suggested by Goldar in the revision of National Income Estimates with a base 2011–2012. Before the 2011–2012 base revision, the value added in the informal sector was based on estimates of value added per worker and the total LI, which were all considered as homogeneous as hired workers. However, for the 2011–2012 base revision LI was distinguished into different types of workers and their separate productivity (value added) was estimated, which is crucial in calculating their value added. The chapter is an important contribution towards a better understanding of the measurement of labour input from the perspective of national accounts estimation.

The potential of the organized manufacturing sector in creating "good jobs" in India is assessed by Singh and Mitra in their contribution "Who Creates Large

Number of Good Jobs in India's Organized Manufacturing? Small Versus Large and Start-Ups Versus Old", and a scorecard of the manufacturing firms is prepared by the authors on the basis of the size and age of the firm to gauge the potential of manufacturing firms for creating ample quality and sustainable jobs. Using the unit level data of ASI for the period 2011–2012 and 2012–2013, the authors observe that (i) it is the young firms which employ a large proportion of the workers in the total organized manufacturing in India, and as firms grow old, their employment share declines; (ii) it is the medium and large plants which create most of the new employment in the organized manufacturing sector in India; (iii) relatively more contract workers are hired in medium and ultra-large factories and lowest by start-ups, and however, wages paid by young firms are relatively better. Further, the wages decline as plants grow young and they are lowest in the older plants. However, beyond 10 years of age, wage increases as the factory gets older; and (iv) the employment is most diversified in medium-sized plants followed by small and large plants. Further, the highest concentration of employment is observed in the start-ups. In view of these observations, the authors have suggested that the policy for promoting employment in organized manufacturing in India should focus on the most dynamic group, i.e. middle-sized young factories, to generate largest number of new and sustainable jobs.

Through the latest available data and information, Sarkar and Sahu have tried to find the phenomenon and the reasons for increasing dualism in the Indian labour market. They observe that the labour market in India has been multifaceted and has been influenced by regional diversity, differences in rural/urban locations, status of workers, education and skill level, caste and religion, industry and institutional basis of labour regulation, etc. They find that though the share of self-employed workers is still the maximum, the share of regular job holders (often considered as better jobs) has increased after 1999–2000. However, the increments in regular jobs are mostly of contractual or informal types, which share several common characteristics with casual workers. The difference between regular jobs and casual jobs may be narrowing due to the faster growth of casual wage compared to regular wage (Mazumdar, Sarkar and Mehta 2017; Sarkar 2015). According to the authors, "these pattern and trends of nature and quality of employment in the country may suggest two simultaneous and contradictory processes: informalization or casualization of formal/regular employment as well as improvements in the wage level of low paid workers". The patterns of globalization and changes in technology seem to have impacted on the status of labour. The results of their analysis show that as a whole, across broad groups, wage differentials did not increase over time except for increasing gap within tertiary-educated regular wage workers. However, they find that the distribution of earnings of casual workers had also spread out over the years and the earnings of an increasing proportion of the casuals had come nearer the regulars and almost coincided with the latter in the year 2011–2012. They also find that the earnings structure of the informal sector worker and formal sector informal worker is becoming increasingly similar. In terms of wage rate, they find a clear trend of development of dual wage labour market with workers with social security benefits (regular formal sector formal workers) and workers without it (constituting casual wage, regular informal sector and regular formal sector informal) workers. They conclude that the reason for the increasing dualism in the Indian labour market is the substantial increase in the youth labour force and feels that ineffective labour market institution in the formal sector and the absence of labour market institution in the informal sector have created a situation where unemployed youths with various level of education or skill are having similar reservation wage.

While it is believed that the new technology, which is easily accessible, is job replacing and converting more and more jobs in to informal jobs even in the formal sector, its impact on the earning distribution of the workforce is not much investigated. Kapoor in "Technology, Jobs and Inequality: Evidence from India's Manufacturing Sector" attempts to find out the impact of technology on income and wage inequality in India's organized manufacturing sector. Using enterprise-level data from the Annual Survey of Industries, she finds that the role of labour vis-à-vis capital has declined due to increased capital intensity of production which has benefitted those industries which rely more on skilled workers and capital as opposed to unskilled/low-skilled workers. The results show that during the period 2000–2001 and 2011–2012, the share of total emoluments paid to labour and the share of wages to workers in GVA has declined and even within the working class, inequalities have increased. The author finds that while the share of skilled labour (supervisory and managerial staff) in the total wage pie rose, that of unskilled labour (production workers) fell. However, she finds that the share of managerial and supervisory staff in total employment seems to have remained stagnant, while the share of contract workers in production workers has increased sharply over the last decade. Kapoor attributes the rising share of contract workers as also the reason for rising inequality. Her results also indicate the existence of capital-skill complementarity as firms with higher capital intensity employed a higher share of skilled workers and the wage differential between skilled and unskilled workers was higher in these firms. The author also observes a serious supply-side constraint in a large increase in the supply of educated workers, as a very small proportion of the total workers engaged in manufacturing have any technical education. Attempts are made to fill the gap through "Skill India" programme, but she cautions that an assembly line method of skill development will not be able to meet the skill requirements of future technological changes in the economy. According to her, the phenomenon of contractualization also poses a serious threat to the skilling challenge because workers are discouraged from acquiring skills as they feel that even though skilling-up may result in improved productivity, it may not translate into higher wages as firms will prefer to hire them as cheap contract labour.

In the chapter titled "Skills, Productivity and Employment: An Empirical Analysis of Selected Countries", Aggarwal has attempted to find the link between the supply of skilled labour, labour productivity, and employment for the aggregate economy and in the disaggregate industries for nine selected countries. He extends the same analysis to the organized and unorganized sector of the Indian economy to examine differences in the skill composition and the growth of productivity and employment between these sectors. Because of data limitations, his analysis is restricted to the period of 1995 to 2009 for international comparison and from

1999–2000 to 2011–2012 for the Indian economy. He notices that in a rapidly changing world with increased globalization, fast technical change, demographic transitions, migration and immigration have put pressure on the structure of skill requirements in most countries in recent decades. He examines the supply of three different types of skills—high skills, medium skills, and low skills and observes that generally, the share of high-skill employed persons has increased over the period of the study. It is also evident from his study that in the selected nine countries, the change in the share of high-skill workers is associated with a positive change in labour productivity and total employment with some exceptions. The share of high capital-intensive industries in the value added and employment has also witnessed an increase in the majority of the countries. The author also finds that the growth in employment of high-skill workers within high capital-intensive industries is positive in all the selected countries. The econometric analysis undertaken in the study also lends support to the positive association between the share of high-skill persons engaged and labour productivity. From the Indian organized and unorganized sector, the author finds evidence that the share of high-skill employed persons and the level of labour productivity are higher in the organized sector than the unorganized sector and a catching up of labour productivity by the unorganized sector is found. The study observed that while the share of high capital-intensive industries in value added has increased over the period of 1999 to 2011, its share in employment has declined, which could be possible due to the labour displacing nature of capital-intensive industries, a result similar to Kapoor in her study. One distinct feature observed within high capital-intensive industries is that while employment of all the three skill levels increased in the organized sector; it is only the low-skill employment which grew in the unorganized sector. Based on the evidence, the author argues that since there is a close association between skills of the person employed and the labour productivity, therefore the countries have to make serious efforts to improve the share of the (hours worked by) high-skill workers to both improve their labour productivity and thus economic growth; as well as to quickly adapt to the "fourth industrial revolution". The author recommends that in India government, intervention is required to promote the organized sector in the economy and also to improve the productivity of the unorganized sector. Efforts by individuals, firms and governments are required to minimize the mismatch in the demand and supply of skills by continuously updating the skills through education and training.

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India's Industrial Growth: Opportunities and Challenges

Paradigm Changes in Technology and Employment

N. S. Siddharthan

1 Introduction

Whenever paradigm changes took place in technology, issues relating to employment or the fear of technological unemployment assumed importance. As Schumpeter (1942) emphasized, unlike trajectory changes in technology that are incremental, paradigm changes resulted in new goods and processes that didn't compete with the existing goods at the margin but resulted in the destruction of the existing goods and processes. He termed them the processes of 'creative destruction'. The neo-Schumpeterians have been terming the trajectory changes as 'creative accumulation' (Archibugi et al. 2013). To illustrate the concepts, Schumpeter gave examples of the introduction of railways resulting in the destruction of stagecoaches, and the introduction of steam power and its use resulting in the sharp decline of artisans. However, in these cases despite the destruction of some industries and sectors the overall employment didn't decline. The technological revolution contributed to a sharp decline in the prices of the goods, in particular, textiles, clothing and consumer durables that were earlier produced by artisans. The sharp decline in prices made these goods to come within the reach of the middle and lower middle-income groups. Earlier the markets for these goods were provided mainly by the rich. The rapid expansion of the markets and the huge entry of new consumers more than compensated for the loss of jobs in the affected sectors. Employment in the economy as a whole increased.

In more recent times, when banking, travel and insurance were computerized, there were protests from trade unions against computerization. The unions feared that it would result in the loss of jobs. In the banks the number of workers per account

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did decline but the overall employment did not decline, in fact it increased. The banking services before computerization were not comparable to the services in the post computerization era. The demand for the new banking services increased rapidly resulting in more employment. Similar is the case with travel and insurance sectors. It is important to keep these in mind while discussing the current technological revolution and its impact on employment.

2 Gainers and Victims

Examples of paradigm changes include Genomics and Digital technologies including artificial intelligence, robotics and cloud computing. They are likely to affect all sectors—health, medicine, agriculture, manufacturing, trade and financial intermediation. They will affect all nations. This is one of the reasons for not terming the current revolution as industrial revolution as it was the case earlier. With regard to employment, paradigm changes will benefit some and harm others. The objective of this section is to identify to the extent possible the gainers and victims. All technological revolutions bring with it beneficiaries and victims. The victims of the first industrial revolution, namely, the steam revolution were the artisans, weavers, garment manufactures and stagecoach operators. Due to the expansion of the markets and increased demand for the new products, the overall employment in the economy did not decline. Autor (2015) partly attributes this to not considering output elasticity of demand along with income elasticity of demand. However, he also admits to some sections of population becoming victims and unemployed. Nevertheless, there will also be gainers. He argues that computers cannot perform abstract tasks and professionals and persons performing personal services will not be adversely affected. Furthermore, currently collaborative efforts are assuming importance and they need human interactions and cannot be handled by machines. His evidence suggests that technology has boosted the output of the professionals and the demand for their services have increased. He cites the examples of health care, law, finance, engineering, research and design. Likewise, the demand for manual task intensive occupations will also increase resulting in societal income. However, there will be turmoil in the middle-level jobs and that would require policy intervention.

The results of the study on 'Average change per decade in US occupational employment shares for 1980–2010' show decline in occupational employment shares in the following sectors: agriculture (this sector experienced much higher decline in the earlier decades starting from 1940), operative labour (this sector also has been experiencing decline for a long time), skilled blue-collared workers and clerical staff in sales. Among these only sales staff has been experiencing steady increase in employment share in decades before 1980 and could be attributed to the current technology and in particular to web-based commerce. On the other hand, there has been a phenomenal increase in the growth of employment among services and managerial staff. Growth among professional and technical persons has also been high. So the clear gainers are technical personnel, services and managerial staff.

Likewise, their chart showing change in employment by major occupational categories for the period 1979–2012, only labour employed in operations, production and sales experience declined. Sectors like personal care, food and professionals showed growth of employment. Data supports the conclusion that mechanization and artificial intelligence cannot replace professionals and personal care.

His results dealing with changes in occupational employment shares in low, middle and high-wage occupations in 16 European Union countries for the period 1993–2010 reveal a positive growth rates for low- and high-wage jobs. However, the growth rate is negative for middle-income jobs. For most European countries the decline was more than 10%. This led to his conclusion that many of the middle-skill jobs are susceptible for automation. Even here some of the middle-skill jobs like medical support occupations—radiology, technicians, nurse technicians and others showed rapid growth. In other words, there would be a shift in occupational structure in the middle category.

Certain other studies also predict loss of low- and medium low-skilled jobs. For example, Frey and Osborne (2017) based on an in-depth study of probability of computerisation of 702 detailed occupations drawing upon recent advances of 'Machine Learning' and 'Mobile Robotics' forecast that about 47% of US employment is in the high-risk category of job losses. Unlike earlier studies that predicted computerization in mainly routine tasks, this study argues that non-routine tasks like legal writing and track driving would also be automated soon. The study draws on recent developments in skills like machine learning, including data mining, machine vision, computational statistics and artificial intelligence. They suggest that as technology forges ahead workers should relocate from low-skilled jobs to tasks that are not susceptible to computerization like jobs that require creative and social intelligence. This would require skill upgradation and massive retraining.

3 Robots

The UNCTAD Policy Brief (2016) mentions the increasing use of Robots in the manufacturing sector and its implications for employment. The introduction of robots is not necessarily led by capital-rich and labour scarce developed countries. Labour-rich countries like China are in the lead. The Policy Brief presents their estimates of year-end operational stock of industrial robots for select countries and regions for the period 2013–2018. In their estimate, China leads with more than 600,000 units of industrial robots, followed by Republic of Korea and Japan—both less than 300,000 robots each. The whole of Europe and North America (United States and Canada put together) will have only about 300,000 robots. Other Asian countries, that is, excluding China, Korea and Japan will also have about 200,000 robots. South America and Africa will have negligible quantity of Robots. Thus the Asian countries will be dominating in the production and the use of Robots. China, in particular, has started using Robots in textiles and garments sectors. India should take note of this and plan accordingly.

With regard to the industrial distribution of Robots, automobiles dominate and accounts for a large share followed by electrical and electronics sectors. Metals and chemicals also use robots but much less than automobiles and electronics and electrical goods (UNCTAD 2016). However, the entry of robots in employment-intensive sectors like textiles and garments could change the current industrial distribution of robots. On the other hand, scholars like Arntz et al. (2017) and Mani (2017) are of the view that fears of unemployment due to the increasing use of robots are exaggerated. They argue that the studies that have been estimating the use of robots in some sectors like automobiles and electronics and consequent unemployment fears are based on 'occupation' based approach in classifying robot intensive sectors. Instead, they advocate 'task based' approach for analysing the impact of robots.

In their view, in sectors like automobiles, etc. the whole occupations are not automated and only certain job tasks are prone to automation. For example in the automobile sector (a sector that dominates the use of robots) robots are used only in specific tasks like welding and arc welding. They have not spread to other areas of automobile manufacturing in the past four decades. Tasks related to welding, in their view, are harsh and repetitive for human beings to perform. Thus occupation-based approach exaggerates the impact of automation on unemployment. Findings of Mani (2017), show that the Indian experience is not different from the international experience. In India also robots are mainly used in automobiles, plastics and rubber in tasks that are inhospitable for human labour and that require precision. Mani (2017) also argues that India might not suffer much by the automation of the textile sector and in particular garments. The software used in garments is very expensive and cannot compete with Indian labour. These are also used only in sewing which is already automated.

UNCTAD Policy Brief (2016) in the concluding part clearly states that the digital revolution cannot be stopped and hence it is important for the developing countries to take appropriate steps so that they benefit. To achieve this, the developing countries should embrace the digital revolution and redesign their educational system. Heavy investments in education and human resource development are important. Countries that neglect skill formation could become victims. Huge public investments in logistics and telecommunications and infrastructure are needed to take part in the revolution. Once human and ICT infrastructure is created, developing countries would develop an advantage in combining robots and three-dimensional printing. China is already doing this on a big scale.

4 Human Capital and Development

The ongoing digital and genomics revolutions are knowledge based and knowledge intensive wherein human capital plays a crucial role. In some respects, it is a continuation of the knowledge and information technology revolutions that blossomed in the last quarter of the twentieth century. Hence, one could draw lessons from research studies conducted in the past decade or two on the role of human capital in promoting growth and employment. Furthermore, several studies show that foreign direct investments (FDI) would promote growth and employment only in countries that enjoyed high quality of human capital. To represent human capital most studies use indicators like enrolments in high schools and universities to consider the role of education in influencing the growth of employment. In addition, indicators like life expectancy and mortality rates are used as indicators of the health of the population. Human development index would include both education and health indicators.

There are several cross-country studies using panel data techniques that link human capital and in particular knowledge and skill base of the workforce to growth of income and employment. They also show that in the absence of educated and knowledge-intensive workforce FDI inflows and technology transfers will not result in growth and reduce poverty. For example, Borensztein et al. (1998) using Panel data for two decades (1970–79 and 1980–89) for 69 developing countries found the role of human capital and in particular enrolments in education crucial in explaining growth rate of incomes. Moreover, FDI by itself did not contribute to growth but when FDI and human capital were used in a multiplicative form it turned out to be significant. This was so even during the early stages of knowledge revolution. Wang (2009) using data from 12 Asian economies over the period of 1987–1997 found that FDI in manufacturing alone contributed to the growth of per capita income in the presence of human capital. FDI in service and nonmanufacturing sectors did not contribute to growth. In other words, mainly countries that concentrated in education and health achieved higher growth. Similar results are also found for cross-border mergers and acquisitions (Wang and Wong 2009).

Studies for India based on interstate differences in the growth of employment also found enrolment levels in higher secondary schools important in explaining growth of employment.

Bhat and Siddharthan (2012) analysed determinants of interstate differences in the growth of labour productivity and employment for the period 2003–2007. The human capital variable was represented by the proportion of students in the age group of 14–18 years in the schools. This variable was the most important variable determining interstate differences in the growth of employment in the manufacturing sector. This variable was also significant in explaining growth of labour productivity. Thus, the Indian states that ensured attendance in schools of students in the age group of 14–18 enjoyed higher employment growth rates. In the Indian case, growth of labour productivity and growth of employment went together as both were driven by the skill and knowledge base of the population. The major four states of India that have a heavyweight in the Indian Parliament, namely, Uttar Pradesh, Bihar, Madhya Pradesh and Rajasthan, are lagging behind in human development index and in particular education facilities. These states receive less investment both domestic and foreign and they also lag behind in the growth of employment. They are the victims of the knowledge revolution and to avoid further decline and the consequent adverse consequences they should go in for a crash programme aimed at human resource development. A more recent study by Bhat (2018) reinforces this conclusion. Her study finds interstate differences in education levels the main determinant of the growth of employment, wage and salaries.

In addition to emphasizing the importance of education and skill levels at the entry point of employments, studies also point to the importance of in house training. In an era of fast technological changes continuous upgradation of skills of the workers already employed is essential. The study by Shampa Paul and Kaushalesh Lal (2018) based on 2011–16 Indian data shows that expenditure by the firms on welfare and training of workforce has positive and significant influenced on employment generated by the firm. Thus firms that have been employing more persons have been spending on skill upgradation.

Product Creation, Process Innovation and Employment

The role of human resources is very important in the creation of new products and processes. Human resources play a crucial role in R&D, manufacturing and commercialization of the products. Some scholars like Calvino and Virgillito (2018) argue that R&D resulting in the creation of new products fits into the Schumpeterian concept of 'creative destruction' as new products could replace the earlier products. However, process development is more like 'creative accumulation'. Calvino and Virgillito (2018) based on their survey literature in this area conclude that at the firm and industry level new product creations contribute to employment at the firm and industry level. This is particularly so for high-tech industries. In these cases, product innovation and employment growth are positively correlated. Studies further show that despite the creation of new products resulting in the destruction of the older products employment even at the micro-level does not suffer.

However, the results for the process innovations and employment are mixed. Studies show that either they are not related or they harm employment growth. Several of these studies tend to show (Calvino and Virgillito 2018) a negative covariation between process innovation and employment. This could be because process innovation and productivity are highly related. Studies also show that the relationship between process innovation and employment is more complex and several issues need to be sorted out before deriving conclusions. In this paper, we are mainly concerned with product innovation and employment and they are positively related.

5 Outward Foreign Direct Investment, Outsourcing and Employment

Information Technology and digitalization facilitates networking and promotes global manufacturing. As discussed by Chen (2010), in the globalized world different segments in the production chain could be split and undertaken in different countries based on efficiency of production. Chen gives the example of integrated circuits, where the designing could be in the US, chips production in another country and the final consumer of chips could be large electronic corporations belonging to a third country. This could be achieved either through licensing or FDI depending on the transaction costs involved in technology transfers and production transfers. This practice has now become a political and electoral issue in the developed countries.

Outward FDI is accused of creating employment in other countries and declining employment in the home country.

There were widespread fears in Europe regarding transferring of low-tech manufacturing jobs to cheap labour countries. It was argued that outward FDI would result in deindustrialization and unemployment in Europe. In this context, the study by Navaretti et al. (2010) shows that for France and Italy there were no adverse impacts. In fact, productivity and employment increased in the medium run. The paper examines the impact of outward FDI on employment, gross output, and value added, total factor productivity of what the authors call the economic activities maintained at home by the investing firms. They estimated a multinominal logit model and computed propensity scores for three possible scenes, namely, 1. not investing abroad, 2. investing in developing countries and 3. investing in developed countries. For[1] both France and Italy they find no negative effect on investing abroad on firm performance. For Italy, they find a significant increase in total factor productivity of the Italian (home country) firms 3 years after investing in a less developed country. Employment dropped slightly (not statistically significant) immediately after investment but recovered fast and after 3 years was higher by 8 percent compared to the controlled group.

European investments abroad could be to expand business and penetrate distant markets. The firms could retain their core areas of competence at home and shift only non-core areas to foreign locations. This will not reduce employment at home. Federico and Minerva (2008) analysed the impact of outward FDI on local employment for Italy. The analysis was carried out for the period 1996–2001 covering 103 Italian administrative provinces and 12 manufacturing industries. They found that employment in provinces that specialized in a single industry did not grow. On the other hand, employment in provinces with diversified industries (they took the inverse of H index) grew faster. With regard to OFDI, outward investment to the world and to developed countries contributed positively to employment growth. The coefficient of investment to less developed countries was not statistically significant in explaining employment growth.

A more recent study by Valacchi and Doytch (2018) and Doytch and Valacchi (2018) show that firms that have been investing abroad and patenting are also the ones that have been creating jobs. In other words, job creation, patenting and OFDI go together.

By and large, empirical studies do not support the concern of some policymakers of developed countries about the adverse impact of outward FDI to other countries and in particular to low-wage countries. In a globalized atmosphere, it is not advisable to produce all products and components in a single country. Locating some of the non-core activities in other countries mainly improved the competitiveness of the local firms and enhanced the employment opportunities.

[1] It is reused from http://esocialsciences.org/eBook/eBook_Siddharthan.pdf with permission from eSocialSciences.

6 Shape of Things to Come

This section is based on the vision of the scientists as expressed by Anthes (2017) in the science journal *Nature*. She includes artificial intelligence, robotics and cloud computing under digital technologies and is of the view that it would transform almost all sectors from agriculture, medicine to manufacturing to sales, finance and transportation. This was also true of the information technology and computer revolution. It also affected all sectors and countries. As discussed in the introduction all major technological revolutions would affect jobs and several jobs would be destroyed. At the same time several new jobs would be created. As rightly observed by Schumpeter, development is turmoil. The role of policy during the period of creative destruction is to identify the areas of creation and prepare the workforce to participate and benefit. This would also involve retraining of persons to suit the needs of technological change.

By and large, scientists are more positive about the ongoing digital revolution and argue that unemployment fears are exaggerated. Their main argument is that current research and international business involve collaborations across countries and face-to-face interaction in the work units. Machines will fail in both the cases. We saw in Sect. 5 that thanks to the digital revolution transaction costs have radically come down and the production process has drastically changed. Different stages of the development of the product are done in different countries either by the same enterprise or by different enterprises depending on transaction costs involved. Participation in the global production network would involve frequent interactions and collaborations by different teams. Machines are not good in carrying out processes where collaborations and interactions are important. However, workforce needs to be retrained. In the future world, people need to collaborate and need to know each other better. Standalone solo workers would disappear.

In areas like health and medicine also as observed by Anthes (2017), if automated systems start making routine medical diagnoses, it could free doctors to spend more time interacting with patients and working on complex cases. They will become better doctors. It will not replace doctors. The same is true of paramedical staff. However, doctors will also have to undergo retraining in handling medical equipment and increase their knowledge of genomics. The gene revolution can also help in identifying rare genetic diseases and help in their treatment through genetic modifications. Web-based technology would also help the doctors to locate and identify other patients suffering from similar disorders in other parts of the world and examine the effectiveness of their gene treatments.

A Report of the World Economic Forum (Partington 2018), states that rapid technological advances over the next decade would create 133 million new jobs globally and would only displace 75 million jobs. Thus it will create double the number of jobs than it would destroy. It cites the similarities with the earlier steam and electricity revolutions where it created more jobs than it destroyed. However, it would require greater investment in training and education and creation of safety net for the victims.

7 Opportunities for India

As emphasized by scientists the technological revolution cannot be stopped. The only option available to India is to look for opportunities that are available and plan appropriate strategies to benefit from technology. In its absence, India could become a victim. Fortunately, there are several aspects that India could exploit to its advantage provided India realizes the importance of skill intensity and train its workforce in the skills required.

Quantum Computers

Quantum computers are likely to emerge in a decade or two. They will revolutionize the Information Technology sector and India has a good opportunity to participate and benefit by contributing to the production of both hardware and software. The current computer technology is based on 2-digit bit configuration while the quantum computer is based on 3-digit configuration. In effect, there will be a movement from BIT to QUBIT. This will facilitate 'n' parallel processing and simultaneous presence in more than one place. When the quantum computers come most of the existing hardware and software developed for the current computers cannot be used. This gives enormous opportunities for Indian software experts. This is much more than what Y2K offered. That was once for all correction. The quantum of software for the quantum computers will be several times more and will also be a continuous process. India could also enter the hardware market. Currently, the Indian share in the hardware market is not significant. However, India could leapfrog to the future technological world. It is important to train the technologists in quantum physics and its computer applications.

Solar Energy

Technological change in solar energy has also been rapid. Bulky and unwieldy inefficient solar panels are now being replaced by thin-film panels. These are also more efficient in converting solar energy to power. Quantum dots are also likely to emerge. Sooner or later printed solar cells that are paper thin, lightweight and extremely inexpensive to produce are likely to emerge (Pardos 2017). They are labour intensive in their operations and India can again leapfrog.

Three-Dimensional Printing

Three-dimensional printing is another area where India could benefit. At present, it is mainly used in biomedical devices such as surgical planning, prosthetics and applications (Rengier 2010), and bone tissue engineering (2013). It is likely to spread to other sectors soon. The process is labour intensive and Indian workers could be trained in this area.

It is important to identify areas where India could have potential advantage and prepare for effective participation.

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India's Manufacturing Story: Productivity and Employment

Pilu Chandra Das and Deb Kusum Das

1 Introduction

Services have been the driver of India's overall growth since the onset of economic reforms in India and particularly beginning the 2000s. However, India's manufacturing sector continues to draw attention despite several decades of reforms covering industrial policies and trade liberalization. The government through its several initiatives—National Manufacturing Policy as well as 'Make in India' program continues to drive the sector's role in the overall growth and development. The sector is targeted to contribute around 25% of GDP by 2025 as against its current 16% share. In the recent past, Indian manufacturing has attained a sharp rise in growth and this augurs well for a sector that has seen stagnancy in its share of GDP in the last several decades. The lack of jobs in organized manufacturing has remained an under fulfilled agenda of India's industrial achievement and add to that the large number of people employed in informal manufacturing activities remained a development dilemma. The productivity performance of manufacturing industries has been well documented and shows that it continues to exhibit low productivity growth. A recent study by Das et al. (2016) however finds labour-intensive manufacturing outperforming non-labour-intensive goods during the period 2000–15 and this is important when we have evidence of declining labour intensity even in labour-intensive manufacturing (Sen and Das 2015). Several challenges remain if productivity is to be improved. Most critics would point to the labour market rigidities for the inefficiency in the manufacturing sector, but there remain several issues beyond simple labour market

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reforms that need to be addressed—particularly those related to skill formation and its impact on labour quality.

The government has launched an ambitious 'Make in India' policy initiative aimed at making India a manufacturing hub. This along with the previous, 'National Manufacturing Policy' (Government of India 2011), are important for India's future growth and employment generation. Several challenges, complex and simple are to be overcome if India is to resume the high growth path of the period 2003–08. Some researchers have scrutinized and commented on different aspects of the Make in India initiative and identified major issues relates to different sectors. On the basis of detailed empirical analysis, Veeramani and Dhir (2017) find that the two groups of industries hold the greater potential for export growth and employment generation are (i) Traditional unskilled labour-intensive products—textiles, clothing, footwear and toys, and (ii) Final assembly of a range of products, particularly electronics and electrical machinery, where the manufacturing process is internationally fragmented. Suresh (2017) highlights the importance of high-technology industries in Indian Manufacturing. He mentions three industries—aerospace industries, pharmaceutical industry and automotive industry, where India achieved success and telecommunication equipment as an unsuccessful case. Chakraborty (2017) argues that Make in India focuses on 'industrial corridors' and 'manufacturing clusters'. The initiative pays attention to transportation costs but not to the external or agglomeration economies, the implication is that the initiative has the potential to succeed in some key sectors relying on internal-scale economies and reduced transportation costs. Finally, Chanda (2017) argues that any holistic policy framework for boosting the manufacturing sector in India must take into account the interdependence between manufacturing and services. A competitive and vibrant service sector should be seen as an enabler for the manufacturing sector and not as a competitor to manufacturing.

A few other important literature on growth and productivity has also analysed the Indian manufacturing industries. Maiti (2014) is a comprehensive study of productivity growth in Indian manufacturing in the reform era. The study relates to productivity growth to trade liberalization. However, it also takes into account market distortions in computing productivity growth estimates and shows that TFPG estimates are much lower than those which ignore market distortions. Maiti considers the global financial crisis (GFC) of 2007–09 and the resultant labour market adjustment in Indian Manufacturing. He draws attention to the formalization of labour due to the rigidity of the labour market. There are other studies dealing with productivity growth in manufacturing in India—Goldar and Sengupta (2016) present new estimates of TFPG for the 31-year period 1980–81 to 2010–11 for the manufacturing sector divided into organized and unorganized segments at the disaggregated level of two-digit industry groups and for 19 major states. Their empirical results show a gradual rise in output (GVA) growth over the decades—from almost 6.0% per annum in the 1980s to 8% in the 2000s—but not so in employment which remains around 2.0% per annum over the decades. TFPG steadily improved over the three decades from 0.6% per annum in the 1980s to 2.4% per annum in the 2000s.

The present study covers the manufacturing industries for the period 2000–2016 in an attempt to understand the productivity dynamics in the manufacturing sector and its relation to employment. Using a neoclassical growth accounting technique and the India KLEMS dataset, we examine the manufacturing performance at the disaggregated level and present an industry level perspective on manufacturing performance. The study uses the rich India KLEMS dataset, which allows disaggregated measurement of total factor (TFP) as well as labour productivity (LP) at the industry level to examine the contributions of TFP as well as factor input in understanding growth and its sources. The period of study also takes into account the several phases of the Indian economy including pre-global slowdown, slowdown and recovery phase. The time period of the study that pertains to the period of post 2000 is divided into two distinct sub-periods—(1) 2000–01 to 2007–08, the period prior to global financial crisis and (2) 2008–09 to 2016–17 labelled as the post-GFC period.

The paper is structured as follows—the methodology for measuring productivity at the industry level is discussed in Sect. 2. The India KLEMS dataset is outlined in Sect. 3. Employment and productivity growth are explained in Sect. 4. The final section provides the summary and key findings of the study.

2 Methodology

This section describes the procedures and methodologies used in estimating the total factor productivity and labour productivity at disaggregate 13 manufacturing industries level. For computing the total factor productivity, the methodology developed and presented in Jorgenson et al. (2005) is adopted. This methodology has been followed recently in Timmer et al. (2010) for the European Union and the US. Our measurement of TFP growth for different industries of the Indian economy is based on a gross output production function for each industry i:

$$Y_i = f_i(K_i, L_i, E_i, M_i, S_i, A_i) \tag{1}$$

Y is industry gross output, L is labour input, K is capital input and E, M and S are energy, material and services inputs and A is an indicator of technology. An important feature of the gross output approach is the explicit role of intermediate inputs. In our study, we have considered three intermediate inputs—energy, material and services and this is important as we may find that intermediate inputs are the primary component of some industries outputs. Under the assumptions of constant returns to scale and competitive markets, the growth of output can be decomposed into contributions from capital, labour, energy, material, services and total factor productivity growth (v^A) as

$$\Delta\, lnY_i = \overline{v}_i^K\, \Delta\, lnK_i + \overline{v}_i^L\, \Delta\, lnL_i + \overline{v}_i^E\, \Delta\, lnE_i + \overline{v}_i^M\, \Delta\, lnM_i + \overline{v}_i^S\, \Delta\, lnS_i + v_i^A \tag{2}$$

where $\overline{v}_i^K$, $\overline{v}_i^L$, $\overline{v}_i^E$, $\overline{v}_i^M$ and $\overline{v}_i^S$ are the two-period average shares of capital, labour, material, energy and services input in the nominal value of gross output.

Labour productivity has been computed by the difference in growth rate of value of gross output and growth rate of persons employed by UPSS. The gross output approach is useful at the industry level as it accurately reflects the contribution of intermediate inputs also to the growth of labour productivity. We defined labour productivity as gross output per person employed (N). So $LP_i = \frac{Y_i}{N_i}$ and let be $k_i = \frac{K_i}{N_i}$ capital intensity or capital input per person, similarly $e_i = \frac{E_i}{N_i}$, $m_i = \frac{M_i}{N_i}$, $s_i = \frac{S_i}{N_i}$ and if we decompose labour input growth into employment growth and labour composition growth:

$$\Delta\, lnL_i = \Delta\, lnN_i + \Delta\, lnLC_i$$

where LC is labour composition of labour quality. Similar to output growth, we can also decompose labour productivity growth as

$$\Delta\, lnLP_i = (\overline{v}_i^K\, \Delta\, lnk_i + \overline{v}_i^L\, \Delta\, lnLC_i + \overline{v}_i^E\, \Delta\, lne_i + \overline{v}_i^M\, \Delta\, lnm_i + \overline{v}_i^S\, \Delta\, lns_i + v_i^A) \tag{3}$$

The contribution to labour productivity growth thus comes from four sources, namely capital deepening where more or better capital makes labour more productive; labour quality or labour compositional changes; contribution of intermediate input deepening which reflects the impact of more intermediate-intensive production on labour productivity; and finally, from TFP growth which contributes to labour productivity point for point.

3 Dataset

The data used in the empirical analysis of this study is the India KLEMS dataset version 2018.[1] India KLEMS dataset version 2018 provides time-series data from 1980–81 up to 2016–17 for 27 industries across all sectors of the economy. This study, however, covers the 13 manufacturing industries for the period 2000–2016.

Here we again discuss[2] both the raw data sources and the adjustments that have been made to generate the comprehensive time series on variables consistent with the official National Accounts. The main sources of data are the National Accounts Statistics (NAS), Input–Output (IO) tables, Annual Survey of Industries (ASI), and the follow-up surveys of unorganized manufacturing conducted by NSSO, Office of the Economic Advisor and Ministry of Commerce and Industry. This paper obtained industry wise data on Gross Value of Output, Value Added and Intermediate Input (Energy, Material and Services) at current prices and at 2011–12 prices and also

[1] The data is available at the RBI website.

[2] The details are also available in the Data Manual at the RBI website.

Capital Service Input, Number of Employees, Labour Composition Index and Labour Income Share.

Gross Value added: Gross value added of a sector is defined as the value of output less the value of its intermediate inputs. NAS provides estimates of Gross Domestic Product (GDP or gross value added) by industries at both current and constant prices since 1950. We use the data for the period 2000–01 to 2016–17 from the most recent National Accounts series (NAS 2018, NAS 2014 and Back series 2011). Using concordance between NAS classification and the 13 manufacturing industries, the GVA series for 2000–01 to 2015–16 has been constructed. 2011–12 onwards, GVA series for 13 manufacturing industries have been obtained from NAS 2018. Prior to 2011–12, GVA series have been extended applying growth rate obtained from NAS 2014 and Back series 2011. Out of the 13 industries, for 6 industries, gross value-added series both in current and constant prices (at 2004–05 prices) is directly available from NAS. For 7 manufacturing industries, direct estimates of GVA were not available from NAS; estimates have been constructed by splitting the data for 6 NAS industries using additional information from ASI and NSSO unorganized manufacturing data. The major NSSO rounds for unorganized manufacturing used are 40th (1984–85), 45th (1989–90), 51st (1994–95), 56th (2000–01), 62nd (2005–06), 67th round (2011–12) and 73rd round (2015–16). GDP estimates are adjusted for Financial Intermediation Services Indirectly Measured (FISIM). The value of such services forms a part of the income originating in the banking and insurance sector and, as such, is deducted from the GVA.

Gross output series: Similar to GVA series, NAS has been providing estimates of gross output (GVO) at a disaggregate industry level at current and constant prices since 1950–51. 2011–12 onwards, estimates of GVO at both current and constant (2011–12) prices for all industries are directly obtained from NAS 2018. GVO series at current and constant (2011–12) prices were extended backward up to 1980–81 using annual growth rate. Prior to 2011–12, GVO data was directly available for Agriculture, Mining and Quarrying, Construction and Manufacturing sectors (Registered and Unregistered Manufacturing). NAS provides GVO for a few manufacturing industry groups are at a more aggregate level. In such cases, we split the aggregate estimates using additional information from ASI and NSSO rounds to obtain estimates at KLEMS industry level. As motioned earlier, before 2011–12 NAS did not provide any estimates of GVO for service sectors and hence we use GVA/GVO ratio estimated from Input–Output transaction Tables (1978–79, 1983–84, 1989–90, 1993–94, 1998–99, 2003–04, 2007–08 and SUT 2012–13) to get estimates of value of output.

Employment and labour composition: Labour input is measured by combining data on labour persons and data on labour composition based on educational levels. In the KLEMS framework, it is desirable to estimate changes in labour composition by industries on the basis of age, gender and education. The source of human capital could be through investment in education, experience, training, etc. The contribution to output by each person also comes from this embodied capital and the reward (wages and earnings) to each person also includes the reward for investment in human capital. Therefore, it is essential to separate out these differences in labour to clearly understand the underlying differences in labour characteristics. The major rounds of Employment and Unemployment Surveys (EUS) by National Sample Survey Office (NSSO) and the estimated population series based on the decennial population census are the main data sources for estimating the workforce by industry groups, as per the National Industrial Classification (NIC). The other data sources on employment are Economic Survey (for public enterprises), Annual Survey of Industries (ASI for organized manufacturing Industries) and Labour Bureau Surveys (available since 2009–10). The interpolated population is used for intervening years. The work participation estimates obtained from EUS are adjusted for population, using various population censuses. In the EUS, the persons employed are classified on the basis of their activity status into usual principal status (UPS), usual principal and subsidiary status (UPSS), current weekly *status* (CWS) and current daily status (CDS). UPSS is the most liberal and widely used of these concepts. Despite that, the UPSS has some limitations[3]; this seems to be the best measure to use given the data and hence we estimate the number of employed persons using UPSS definition.

We use the number of workers estimated using UPSS assumption as our measure of employment, and our measure of labour input in any industry j (L_j) is computed as a Tornqvist volume index of persons worked by individual labour types 'l' as follows:

$$\Delta \ln L_j = \sum_{1}^{n} \overline{v}_{l,j}^{L} \Delta \ln L_{l,j} \tag{4}$$

We use three education categories ($n = 3$ in the above equation), namely up to primary, between primary and higher secondary, and above higher secondary. The weights $\overline{v}_{l,j}^{L}$ in the above equation are obtained as the compensation share of employee category l in total wage bill of industry j, averaged through the current and previous year, i.e.

$$\overline{v}_{l,j}^{L} = \frac{P_{l,j}^{L} L_{l,j}}{\sum_{l}^{n} P_{l,j}^{L} L_{l,j}}$$

Capital services: As in the case of labour input, where workers differ in terms of skill and experience, capital also consists of different vintages and asset types. And these assets are not directly used in the production process, rather the service delivered by these assets are the inputs to the production. For the measurement of capital services, we need capital stock estimates for detailed asset types and the shares of each of these assets in total capital remuneration. As in the case of labour input (4), we measure capital input K_j as a Tornqvist volume index of individual capital assets as follows:

[3]Problems in using UPSS includes (1) the UPSS seeks to place as many persons as possible under the category of employed by assigning priority to work; (2) no single long-term activity status for many as they move between statuses over a long period of 1 year; and (3) usual status requires a recall over a whole year of what the person did, which is not easy for those who take whatever work opportunities they can find over the year or have prolonged spells out of the labour force.

$$\Delta \ln K_j = \sum_k^n \overline{v}_{k,j}^K \Delta \ln K_{k,j} \tag{5}$$

where $\Delta \ln K_j$ is the growth rate of aggregate capital services in any given industry j, $\Delta \ln K_{k,j}$ is the growth rate of capital stock in asset k (we distinguish between three types of capital assets: construction, machinery and transport equipment,) and the weights $\overline{v}_{k,j}^K$ are given by the period average shares of each type of asset in the total value of capital compensation, such that the sum of shares over all capital types add to unity.

$$\overline{v}_{k,j}^K = \frac{P_{k,j}^K K_{k,j}}{\sum_k P_{k,j}^K K_{k,j}}$$

where individual capital stocks K_k are estimated using standard Perpetual Inventory Method (PIM) with geometric depreciation rates:

$$K_{k,t} = K_{k,t-1}(1 - \delta_k) + I_{k,t}$$

And the rental prices of capital $p_{k,j}^K$ are computed as

$$P_{k,t}^K = P_{k,t-1}^I i_t^* + \delta_k P_{k,t}^I$$

where p_k^I is the investment price of asset k, i^* is real external rate of return[4] and δ_k is the assumed geometric depreciation rate of asset k. We measure the real external rate of return, i^* by a long-run average of real bond rate and market interest rate, obtained from Reserve Bank of India.

Intermediate inputs: The methodology for measuring intermediate inputs was developed by Jorgenson et al. (1987) and extended by Jorgenson (1990). Following a similar approach as explained in Jorgenson et al. (2005, Chap. 4) and Timmer et al. (2010, Chap. 3), the time series on intermediate inputs for the Indian economy has been constructed. The cornerstone of this approach is the use of Input–Output (IO) tables which give the flows of all commodities in the economy, as well as payments to primary factors. As the starting point, a concordance table between the industrial classifications used in our study and the IOTT has been prepared. For the Benchmark IOTT years of 1998, 2003, 2007 and supply use table (SUT) 2013 proportions of Material Inputs, Energy Inputs, and Service Inputs in Total Intermediate Inputs are calculated. Proportions for intervening years are obtained by linear interpolation of the benchmark proportions. This involves an implicit assumption for each IO sector that technological change or efficiency improvement in input use between two benchmark IOTT years indicated by the corresponding two IO tables occurred

[4]In the India KLEMS Database version 2018, we use an external rate of return. However, one can also use an internal rate of return, which will ensure complete consistency with NAS (see Jorgenson and Vu 2005). This will be attempted in the future. See Erumban (2008) for a discussion on alternative approaches to the measurement of rental prices.

progressively between the benchmark years, by an equal amount in each intervening year to be more specific. Next, to ensure consistency with National Accounts series, the projected input vector has been proportionately adjusted to match the gap between gross output and value added of NAS such that when we aggregate all the inputs at the current price, it should exactly match the intermediate input of NAS. To transform the nominal intermediate input series to volumes weighted, WPI deflators are used. The weights are based on the column of the relevant industry in the Input–Output tables. Different weights have been used for different time periods. Two IOTTs have been used for deriving weights—1998 and 2007. The price series based on 1998 table has been used from 2000 to 2003 and the 2007 table has been used for the price series from 2003 to 2016. Once the two series have been formed, these have been spliced. The deflators for Material, Energy and Service Inputs for each industry have been used to deflate the Current price Intermediate Input series to Constant price.

Labour Income Share: Share of total compensation paid to all workers in any industry in gross nominal value added in that industry is labour income share. *National Accounts Statistics* (NAS) of the CSO publishes the NDP series comprising of compensation of employees (CE), operating surplus (OS) and mixed income (MI) for the NAS industries. The income of the self-employed persons, i.e. mixed income (MI) is not separated into the labour component and capital component of the income. Therefore, to compute the labour income share out of value added, one has to take the sum of the compensation of employees and that part of the mixed income which are wages for labour. The computation of labour income share for the 13 manufacturing industries involves two steps. First, estimates of CE, OS and MI have to be obtained for each of the 13 study industries from the NAS data which are available only for the NAS sectors. The estimates available in NAS have to be distributed across the study industries. In certain cases, the estimates of CE, OS and MI for a particular NAS sector have been distributed across constituent study industries proportionately in accordance with the gross value added in those industries. Second, the estimate of mixed income has to be split into labour income and capital income for each industry for each year.

Employment and Productivity Growth in Pre- and Post-global Financial Crisis Period:

In this section using the India KLEMS dataset 2018, we document and analyse the performance of the Indian economy in the twenty-first century. The period 2000–01 to 2016–17, the latest year for which the KLEMS dataset has been compiled has been split into two periods—(1) 2000–01 to 2007–08 and (2) 2008–09 to 2016–17. This has been done to understand the sources of growth, especially both labour as well as multifactor productivity during the period of high growth that India achieved (2003–08) subsequent to the widespread economic reforms encompassing both overhauling of trade regime alongside industrial deregulation and financial sector reforms.

We start with the value-added shares and employment shares of different sectors to understand how the different sectors have behaved over the last decade. We find that during the last two decades, the Service sector has contributed nearly half of the Indian gross value added followed by Agriculture and Manufacturing. Manufacture occupies more than 18% share of aggregate economy value added in 2000–01. However, value-added share of the manufacturing has declined by 2 percentage point between 2008–09 and 2016–17. In case of employment, more than 40% of the employed population depends on agriculture activities whereas close to 30% are engaged in services activities.[5] For the Indian economy, the manufacturing sector absorbs only around 11–12% workers, which justifies the popular hypothesis of Manufacturing's inability to generate jobs.[6]

At disaggregate manufacturing industry level, we observe from Table 1 that the three industry groups 'Chemical Product', 'Textiles' and 'Transport Equipment' occupy more than 40% share of manufacturing value added. Value-added share of

Table 1 Gross value added and employment share for selected years

KLEMS industry description	GVA share			Employment share		
	2000–01	2008–09	2016–17	2000–01	2008–09	2016–17
Food, Beverages and Tobacco	2.1	2.0	1.5	2.5	2.4	2.4
Textiles	3.0	2.1	2.3	2.9	3.1	2.5
Wood	0.6	0.3	0.2	1.1	1.0	0.6
Pulp and Paper	0.6	0.5	0.4	0.3	0.3	0.3
Petroleum	0.9	1.8	1.7	0.0	0.0	0.0
Chemical Products	2.4	2.5	2.7	0.5	0.4	0.4
Rubber and Plastic	0.7	0.6	0.6	0.2	0.2	0.3
Non-Metallic Mineral	1.2	1.4	0.9	0.9	1.0	1.1
Metal Products	2.6	3.1	1.8	0.9	0.9	1.1
Machinery, n.e.c.	1.3	1.6	1.1	0.3	0.4	0.5
Electrical and Optical Equipment	0.9	1.3	1.0	0.3	0.4	0.9
Transport Equipment	1.4	1.3	1.9	0.1	0.2	0.2
Manufacturing, n.e.c.	0.5	0.5	0.5	0.8	1.2	1.5
Manufacturing	**18.4**	**18.9**	**16.8**	**10.8**	**11.5**	**11.8**
Agriculture	**23.4**	**18.2**	**17.9**	**59.4**	**52.0**	**40.5**
Services	**45.2**	**47.5**	**52.8**	**24.3**	**27.9**	**31.4**

Source Authors calculation based on India KLEMS Database 2018

[5]More than 94% of total employed persons were engaged in the three sectors (agriculture, manufacturing and services) in 2000–01, where the combined employment share of these sectors drop to nearly 84% in 2016–17. Employment share of construction sector significantly rises during this period by merely 10%.

[6]Goldar et al. (2017) has analyzed in considerable detail the growth, productivity and employment generation in India Manufacturing during the 35-year period of 1980–81 to 2014–15, with a focus on organized sector of manufacturing which dominates in Indian manufacturing in terms of capital stock, output and value added. They observe that trend growth rate in employment was less than 1% during 1980–2002, and it was more than 4.5% per annum during 2003–14.

the Chemical Products and Transport Equipment in aggregate value added has been increasing steadily over the period and on the contrary, the share of Textiles has been decreasing. Wood and Wood products depict lowest value-added share—less than 0.3%—followed by Pulp and Paper, Manufacturing n.e.c., Rubber and Plastic—each occupies less than 1% share. In case of employment share, Textiles and Food, Beverages and Tobacco absorbs much more workers than the others, and they contribute more than 40% of manufacturing employment. Petroleum is the worst performer in terms of employment share followed by Transport Equipment, Rubber and Plastic, Pulp and Paper and Chemical Products. Individually they comprise less than 0.5% of manufacturing employment.

The growth rate of gross output varied across sectors, ranging from 2.7 to 12.7% during the whole study period. Wood and Wood products is the only sector which depicts output growth less than 3% where rest of the industries grew at a much higher rate of around 7% or more (Table 2). Manufacturing n.e.c. have been the fastest

Table 2 Gross output and employment growth

KLEMS industry description	Output growth			Employment growth		
	2000–01 to 2007–08	2008–09 to 2016–17	2000–01 to 2016–17	2000–01 to 2007–08	2008–09 to 2016–17	2000–01 to 2016–17
Food, Beverages and Tobacco	8.5	5.3	6.7	0.5	1.0	0.8
Textiles	7.8	7.3	7.5	2.9	-2.0	0.1
Wood	2.1	3.3	2.7	0.0	-4.9	-2.8
Pulp and Paper	10.8	4.9	7.5	2.8	-1.3	0.5
Petroleum	9.6	7.5	8.4	6.4	-0.5	2.5
Chemical Products	7.3	9.6	8.6	1.2	0.3	0.7
Rubber and Plastic	7.8	9.2	8.6	3.4	4.9	4.2
Non-Metallic Mineral	6.9	5.9	6.3	3.8	1.3	2.4
Metal Products	10.2	6.4	8.1	2.0	2.6	2.3
Machinery, n.e.c.	10.4	6.3	8.1	3.1	4.3	3.8
Electrical and Optical Equipment	12.0	7.5	9.5	5.5	11.1	8.7
Transport Equipment	7.5	10.8	9.4	2.1	5.1	3.8
Manufacturing, n.e.c.	18.8	8.0	12.7	6.0	3.3	4.5

Source Authors calculation based on India KLEMS Database 2018

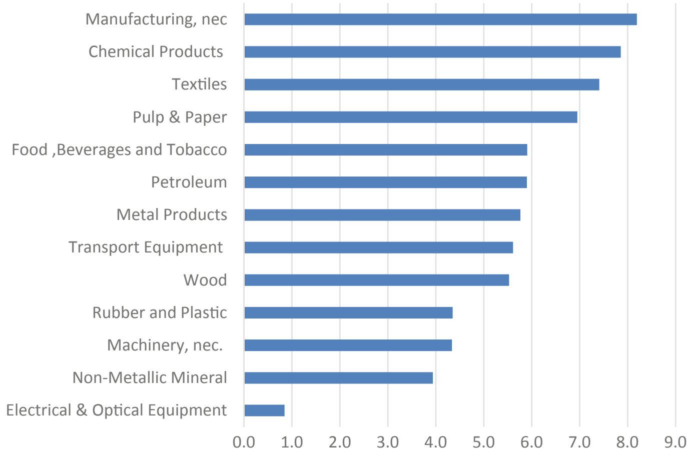

Fig. 1 Labour productivity growth for 2000–01 to 2016–17. *Source* Authors calculation based on India KLEMS Database 2018

growing sector in the entire period, growing at above 12% per annum, followed by Electrical and Optical Equipment and Transport Equipment. Out of 13 manufacturing industries, the output growth rate of nine industries has been affected by the financial crisis during 2007–08. Manufacturing n.e.c. observes highest decline in output growth by around 10 percentage points, followed by Pulp and Paper and Electrical and Optical Equipment. Transport Equipment, Chemical Products and Rubber and Plastic are the industries which were not affected by the global financial crisis. The employment growth rate for all manufacturing sector except Electrical and Optical Equipment was less than 5% per annum, where Wood and Wood products depicts negative employment growth rate while in the post-financial crisis period as much as four industries observe negative employment growth, and these are Textile, Wood, Pulp and Paper and Petroleum.

In Fig. 1 and Table 3, we present the labour productivity growth estimates for 13 industry groups between 2000 and 2016, for the whole period as well as the two sub-periods. The individual sectors show sharp fluctuations in LP for the period 2000–16 as well as for the two sub-periods. Manufacturing n.e.c., Chemical products and Textiles are the only three industries which observe more than 7% labour productivity growth while Electrical and Optical Equipment shows the lowest labour productivity growth around 0.8%, followed by Non-Metallic Mineral, Machinery, n.e.c.

Given that the world over has seen a decline in labour productivity in the aftermath of the global recession, it is important to examine the Indian scenario with respect to labour productivity in the two periods under consideration in the paper. In the first period, we find that apart from Manufacturing n.e.c., many manufacturing industries exhibit higher growths in LP—Metal Products, Pulp and Paper and Food, Beverages and Tobacco. Textiles, Chemical Products and Wood and Wood products are the industries which have higher LP growth post 2008. Six out of 13 industries

Table 3 Labour productivity growth

KLEMS industry description	Labour productivity growth		
	2000–01 to 2007–08	2008–09 to 2016–17	2000–01 to 2016–17
Food, Beverages and Tobacco	8.0	4.3	5.9
Textiles	5.0	9.3	7.4
Wood	2.1	8.2	5.5
Pulp and Paper	8.0	6.2	7.0
Petroleum	3.1	8.1	5.9
Chemical Products	6.0	9.3	7.9
Rubber and Plastic	4.4	4.3	4.4
Non-Metallic Mineral	3.1	4.6	3.9
Metal Products	8.2	3.9	5.8
Machinery, n.e.c.	7.3	2.0	4.3
Electrical and Optical Equipment	6.5	-3.6	0.8
Transport Equipment	5.4	5.7	5.6
Manufacturing, n.e.c.	12.8	4.6	8.2

Source Authors calculation based on India KLEMS Database 2018

record improvements in LP in the period 2008–16. Electrical and Optical Equipment registers a decline of more than 9.5 percentage points between the two sub-periods.

Figure 2 on the sources of labour productivity growth for the period 2000–16 indicates a small but positive contribution from TFP growth. Intermediate inputs, namely energy, material and services together by far make the largest contribution to overall growth in labour productivity. We find that across all sectors, the contribution from labour composition remains negligible and is less than 2%. Non-Metallic Mineral showed the highest contribution of capital service per person employed to LP growth followed by Machinery, n.e.c., and Wood and Wood products.

We now attempt to investigate the measured changes in total factor productivity at the disaggregate level of individual industries. This will enable to evaluate the importance of growth in real factor inputs as well as multifactor productivity as sources of economic growth. This is significant to understand the progress of Indian economy through periods of high growth achieved domestically and later on the impact of global economic slowdown on India and how this is reflected across different industries which make up India's GDP.

In Fig. 3, we present the TFP growth estimates for 13 manufacturing industries between 2000 and 2016. TFP growth rate for these classified manufacturing sectors shows wide variations. The variations of TFP growth rate ranges from a low of −1.0% per annum to a high of 1.6% per annum for the entire period of analysis. Eleven industries recorded positive TFP growth, whose combined value-added share is more than 85% of aggregate manufacturing. Only two industries recorded negative

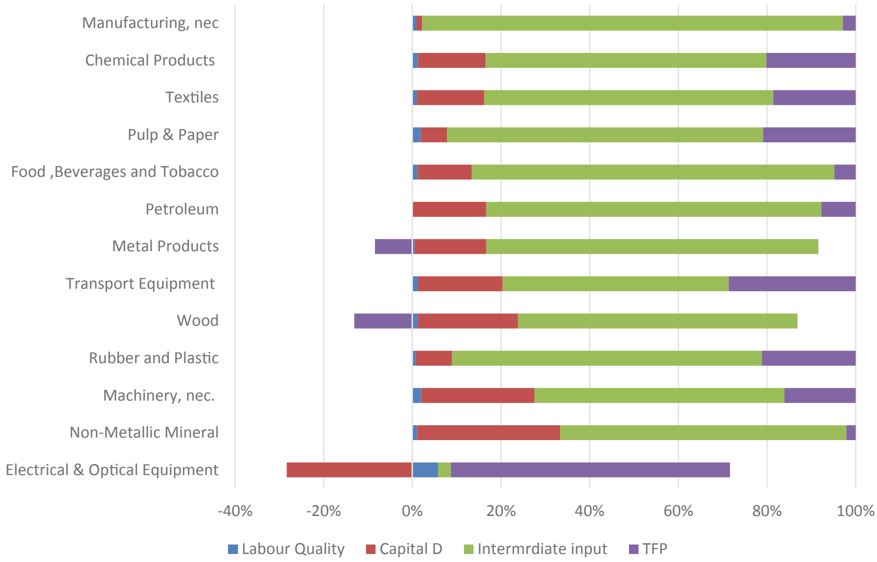

Fig. 2 Sources of labour productivity growth for 2000–01 to 2016–17. *Source* Authors calculation based on India KLEMS Database 2018

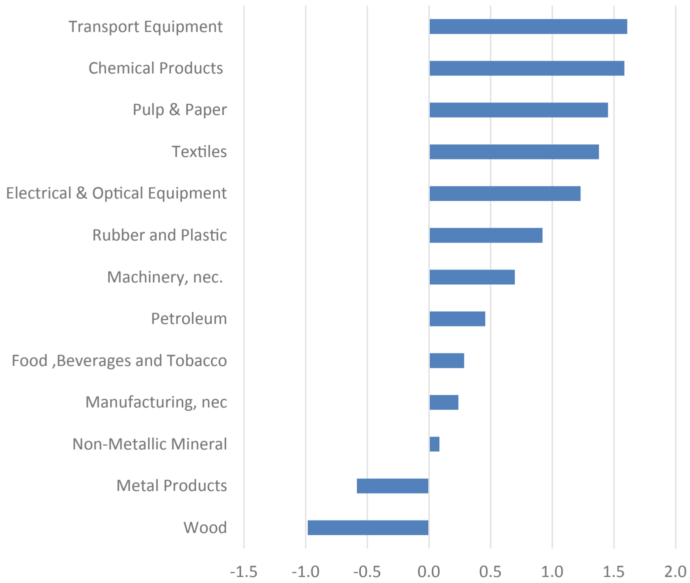

Fig. 3 Total factor productivity growth for 2000–01 to 2016–17. *Source* Authors calculation based on India KLEMS Database 2018

TFP growth. Wood and Wood products is the worst performer in terms of average annual TFP growth rate followed by Metal Products. On the other hand, only two industries recorded TFP growth rate in excess of 1.5% per annum. These industries are Transport Equipment and Chemical Products.

Comparing across the two phases of twenty-first century India, we find that six manufacturing industries—Food, Beverages and Tobacco, Textiles, Wood, Rubber and Plastic, Non-Metallic Mineral, Metal Products and Manufacturing, n.e.c. have in fact recorded better TFP growth in the second period when an economic slowdown encompassed the world economy. The remaining manufacturing industries experienced a productivity decline during the global financial crisis period. The scatter plot of TFP growth rate across the two phases of the period 2000–16 shows only a few industries which experienced a larger growth in TFP—Transport Equipment, Chemical Products and Pulp and Paper. Metal Products is the only industry which recorded negative TFP growth in both phases. Wood and Wood products depicted highest increase in TFP growth between the first and second period and on the contrary TFP growth rate of Coke and Petroleum Products has declined from around 2.5% in 2000–07 to more than −1.1% in 2008–16 (Fig. 4).

In accounting for the observed growth during the period 2000–16, we find that the industries with real output growth below 7% per annum are Wood and Wood products, Non-Metallic Mineral and Food, Beverages and Tobacco; the rest of the industries have recorded on an average growth of more than 7% per annum. Figure 5 below accounts for the output growth for the period 2000–16 across various input categories. At disaggregate level, we note that all industries' TFP growth contribution lies in the range of 0–20% except Wood and Wood products and Metal Products and they are the only two industries that show negative TFP contribution. Pulp and Paper and Chemical Products recorded highest TFP contribution to output growth around 19%, followed by Textiles and Transport Equipment. We also find that more than

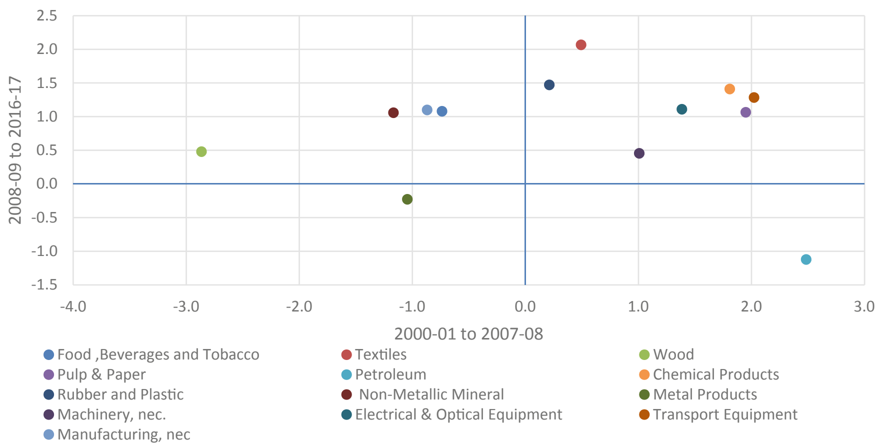

Fig. 4 Pre- and post-global financial crisis total factor productivity growth. *Source* Authors calculation based on India KLEMS Database 2018

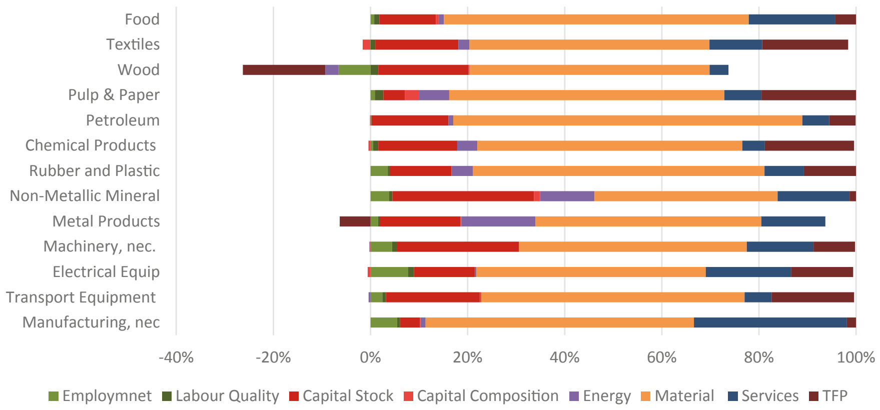

Fig. 5 Sources of output growth for 2000–01 to 2016–17. *Source* Authors calculation based on India KLEMS Database 2018

half of the output growth is contributed by material expansion, followed by capital input and services input while energy and labour input have a minor contribution to output growth barring a few industries. This implies that for most of the industries, the output growth has been still driven by intensive use of inputs.

4 Summary and Conclusion

The study uses the latest India KELMS dataset 2018 to analyse the growth and productivity performances of the Indian manufacturing industries. Labour productivity growth, total productivity growth and the sources of growth are documented for the period 2000–16 and the two sub-periods, thereby allowing a comparison between two distinct phases of Indian economy—before global financial crisis (2000–07) and post-global financial crisis period (2008–16). Using a growth accounting framework of productivity measurement incorporating a KLEMS production function, detailed industry-level estimates are analysed to assess both input contributions—primary inputs (labour and capital) and intermediate inputs (materials, energy and services) and productivity growth in accounting for sources of growth.

Our estimates of LP and TFP growth show wide heterogeneity across industries and over time. While we observe high rates of growth of labour productivity across different industries, the TFP growth remains low for the entire period as well as for both sub-periods. The growth rate of LP varied across industries ranging from 4 to 8% per annum except Electrical and Optical Equipment. Examining the sources of LP growth, we find a striking observation of negligible contribution from labour composition. In most sectors, we find intermediate input emerging as the largest contributor to LP growth. The contributions of TFP growth and capital input are also small. As indicated before, TFP growth remained by and large low at less than 1.6%

per annum. The output growth came mainly via intermediate input expansion and in particular, the material input growth.

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An Analysis of Global Value Chain Incomes in Indian Industries

Abdul A. Erumban

1 Introduction

International trade has been argued to be an important driver of economic growth (Frankel and Romer 1999; Alcalá and Ciccone 2004). Therefore, what determines a country's involvement and excellence in international trade is widely discussed in the literature. The theoretical literature in this area is as old as the profession of economics. For instance, in the Wealth of Nations, Adam Smith (1776) proposed that countries focus on the production of goods where they have 'absolute advantage'—the ability of a country to produce more or better than other countries—which helps them participate in international trade. This was later contested by David Ricardo's comparative advantage theory, which argued that it is the comparative advantage—a country's ability to produce at a lower opportunity cost—which exists due to differences in technology or natural resources, rather than the absolute advantage that makes countries engage in trade. Differences in factor endowments were not featured in either theory, which was the core of the later developments in the literature. The Heckscher–Ohlin theory argued that differences in factor endowments between countries determine international trade.[1] The hypothesis here is that countries will export goods and services that use factors abundant locally and import goods and services that require factor inputs that are scarce in the country. However, empirically, this was contested by Leontief (1953). In his application of the theory into the US data, he observed that, despite being a capital abundant economy, US exports were less capital intensive than its imports—often called the Leontief paradox. Later

[1]The theory was initially developed by Heckscher (1919), which was further expanded by Ohlin (1933) and Samuelson (1949, 1953).

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theoretical literature delved more into incorporating increasing returns to scale[2] and network effects into trade theory, and empirical literature relied substantially on gravity models, which attempted to explain trade in relation to distance between countries on several dimensions (Feenstra et al. 2001).

Most of this literature looked into the gross trade or the total volume of exports from or imports to a country. Since the early 2000s, there have been substantial changes in the nature and pattern of global trade, which makes it difficult to understand the trade dynamics using conventional trade theories. With the onset of information and communication technologies (ICT), the cost of communication and coordination fell substantially, facilitating the outsourcing of several labor-intensive activities from advanced economies to emerging market economies. This also coincided with the opening of several large economies such as India's liberalization policies in the 1990s and China joining the WTO in 2001. Fragmentation of production accelerated globally, and as a consequence, the composition of trade has shifted from trade in final goods to trade in intermediate goods. This enabled countries to participate in specific segments of an industry's value chain, depending upon their comparative advantage. This process is often called the second unbundling of globalization (the first is the separation of production from consumption, facilitated by advances in steam engine, electricity and transportation, see Baldwin 2016; Lundh and Erumban 2018). Considerable attention has been given to the issue of offshoring and production fragmentation from the perspective of individual countries such as the United States and also from a more global perspective (Feenstra 2010; Timmer et al. 2014). An essential feature of this stream of research is the important realization of the deficiency of conventional trade statistics in understanding the interdependencies of countries through the global value chain (GVC). This is because, the gross trade, or the trade in final goods and services, is likely to overestimate the actual value added by individual countries. For instance, Dedrick et al. (2010) show that only a tiny portion of the US market value of an Apple iPod 'made in China' and exported to the United States consists of Chinese value and is far lower than the reported gross export value from China. The accelerated phase of outsourcing (or offshoring) has increased the importance of analyzing global value chains and trade in value added for most economies participating in global trade and value chain. From a macro perspective, a widely used measure of offshoring is based on the share of imported intermediate inputs in an industry (Feenstra and Hanson 1996), while a more pertinent approach is to use measures of global value chain (Egger and Egger 2006; Schwörer 2013; Timmer et al. 2014). Several studies have relied on input–output data to understand the dynamics of the global value chain in the past, which is followed in this paper as well (see, for instance, Trefler and Zhu 2010; Johnson and Noguera 2012; Koopman et al. 2014; Timmer et al. 2015).

This paper is an attempt to document the participation of India in the global value chain. More specifically, we provide estimates of domestic and foreign content in

[2] This stream of literature, often called as the 'new trade theory', emphasizes that trade between countries could occur even when they have identical economic endowments if increasing returns to scale exists (See Krugman 1980).

domestic production in Indian industries—a backward linkage with global production—and the reliance of income generated in Indian industries on foreign demand—both direct and indirect (a forward linkage). Following Timmer et al. (2014), we apply a Leontief input–output framework to global input–output tables to examine how Indian industries participate in the global value chain. The paper makes use of the WIOD (World Input–Output Database) international input–output tables, for the period 2000–2014.

The paper is presented in six sections. Following the introduction, in Sect. 2, we discusses the methodology used to calculate the global value chain incomes in Indian industries. The results on foreign content in India's production of goods and services are presented in Sect. 3, and the Indian content in global production is discussed in Sec. 4. Section 5 analyzes the dependency of India's GDP on other countries, through the direct and indirect consumption of Indian goods and services by other countries. In the last section, we conclude.

2 Methodology and Data

What impact does it make when countries participate in the global value chain? When a sector, say *S* in country *N*, expands its production, it demands more intermediate inputs from upstream sectors from various countries that produce output used in the production of sector *S* in country *N*. This process can continue infinitely, as most sectors need intermediate inputs in the production of their output. Therefore, a direct and indirect chain of intermediate demand takes place, further triggering the expansion of production in the upstream sectors. This type of interconnectedness of sectors and countries is often termed as a backward linkage between sectors and countries. The increased output in sector *S* also imply that more output is now available to sectors/countries that use the output of sector *S* as intermediate input. Once these sectors expand production, other sectors that use their output as intermediate input also benefit, and so on. The chain of intermediate supply by upstream sectors available to the downstream sector expands, which is often termed as forward linkage.

The backward and forward linkages of the global value chain have important implications for the income and productivity of countries and industries participating in the global value chain. The backward linkages in the global value chain, which imply the use of foreign inputs in the production of domestic industries, helps firms raise productivity by improving the quality of inputs, lowering the costs of intermediate goods and services, and by facilitating specialization in areas where countries have a comparative advantage. In the case of forward linkage, when a country/industry participates in the global value chain and relies on foreign demand to generate national income, it often necessitates to produce it more efficiently, to ensure its competitive edge in the international market. Therefore, as evident from the Melitz model (Melitz 2003) in the case of exports, once firms participate in the global value chain, it is likely that the industry experience substantial structural transformation, with which inefficient firms are ousted from the market. As a consequence, the overall productivity of the sector is likely to improve.

This paper tries to break down the domestic and foreign content of final production taken place in India—the backward linkages of Indian industries with other countries. In addition, we also examine the reliance of India's income on foreign demand, not in terms of gross exports, but in terms of participation in the global value chain—the forward linkage. In other words, how much of India's GDP is due to consumption or investment of goods and services produced in India, that are directly or indirectly (i.e. embodied in the output of other countries) exported to foreign countries. For both the analyses, we rely on the World Input–Output Database (WIOD) [3] 2016 version, which provides input–output data for 43 countries including India and a rest of the world category, for 56 sectors classified according to the ISIC revision 4, for the period 2000–2014. To differentiate between the domestic and foreign content in domestic production, we apply a decomposition method based on the input–output framework introduced by Leontief (1949). Following Timmer et al. (2014) and Timmer et al. (2015), we define

- Y vector of output produced in each industry s ($s = 1, \ldots, S$) in each country n ($n = 1, \ldots, N$)
- C vector of consumption levels (i.e. the final demand, absorbed as consumption or investment). The treatment of the C variable varies between the two decompositions—the foreign content in Indian production, and the reliance of Indian industries on foreign demand to generate income. This will be explained later.
- B matrix with intermediate input coefficients, or technology coefficients (i.e. the amount of intermediate input required to produce one unit of output in a given industry)

Then, following the standard Leontief approach, we can express output as

$$Y = (I - B)^{-1}C \tag{1}$$

where I is an identity matrix, and $(I - B)^{-1}$ is the famous Leontief inverse, representing the gross values of output generated in various stages of production of one unit of consumption. Then the vector of value-added created in each sector that is involved in the value chain is derived as

$$V = v \cdot (I - B)^{-1}C \tag{2}$$

where v is a diagonal matrix[4] of value-added/output ratio. In Eq. (2) the final demand vector C is the total *global* demand for a given individual product aggregated across all countries. In the above decomposition, C is taken as a diagonal matrix, so that

[3] See Timmer et al. (2015) for an extensive discussion on the WIOD data and its uses.

[4] A similar approach is also used in Krishna et al (2019) to measure foreign content in Indian manufacturing industries.

only the consumption of S $\times$ N combination of the country–industry is taken on the diagonal. This helps us decompose the global value chain of a final good as a set of all value adding activities needed in its production. Such a decomposition will provide us value added from any given country–industry (participating in the value chain), delivered as the final product in the global value chain by a given country–industry where the final stage of production took place. The sum across the country–industry (where the products are identified as final product) will be the value added of a given country–industry. And the sum across value added from country–industry participating in the GVC will be the total final output value. This way, we can identify how much of the output in any given industry finalized in a country consists of value added from industries from various countries, including the country where the final output is produced. Excluding the own country value-added content, we get the foreign content in production. This can be done for all the countries in the database, and if we aggregate the Indian content embodied in the production in all other countries excluding India, that also provides us the magnitude of India's value-added embodied in the production of final goods and services in foreign countries.

For decomposing the dependency of Indian industries on external demand, or how much value added in a given industry in India is due to final consumption of its goods and services in a foreign country, a similar decomposition is used. The difference from the previous calculation is in the treatment of final demand vector, C. In this calculation, instead of taking C as global final demand on the diagonal, we take C as a consumption vector for each individual country. In this decomposition, we get the value added in each Indian industry decomposed into final demand (consumption or investment) in various countries.

All the calculations in this paper are based on the WIOD data, which provides global input–output tables that trace inter-industry transactions across countries. The WIOD data has been used by several studies in the past to analyze the global value chain (Timmer et al. 2013; and Los et al. 2015), domestic content of exports (Wang et al. 2013; Koopman et al. 2014; Johnson 2014) and the labor market effects of outsourcing (Schwörer 2013). For most of the analysis, we rely on the WIOD 2016 version, which provides data for 43 countries and a rest of the world category, which represents all the missing countries. The 2016 version covers the period 2000–2014 and contains data for 56 industrial sectors according to the ISIC revision 4. An earlier version—version 2013—of the WIOD provides data for the 1995–2011 periods, but for a smaller group of countries and industries. It consists of 40 countries and 35 sectors, which reduces the comparability between the two versions. Even more problematic is the difference between the two versions in terms of the industry classifications; while the 2016 version adheres to SNA 2008, the 2013 version is consistent with SNA 1993, which makes a strict comparison between the two difficult. However, in our aggregate comparisons, say for the entire economy, manufacturing or services sector, where both SNA classifications are largely comparable, we use both databases, while we confine our detailed sectoral analysis only to the 2016 version, hence, the 2000–2014 period only. For a detailed description of the WIOD database, please see Timmer et al. (2015).

3 Foreign Content in India's Production of Goods and Services

First, we examine the foreign content of domestic production in Indian industries. In Fig. 1, we provide the trend in foreign content in India's domestic production, for broad industries. As one would expect, manufacturing has the highest foreign value-added content in the Indian economy, with this sector being one of the most reliant on intermediate goods and services. There has been a consistent improvement from 1995 till 2000, and after a short stagnation period, it did pick up again since 2003. The increasing trend continued until 2008 but then decline in 2009. However, India's manufacturing sector production fragmentation picked up again and moved up albeit slowly until 2012. Since then the trend has been declining.

The second more dominant sector is market services, which includes professional, and ICT services. There has been a continuous uptick until 2006, and since then it has started stagnating or even declining in the recent period. Agriculture and non-market services remain largely insulated from the international input reliance and are relatively flat over the years.

In Fig. 2, we further look at the foreign content in domestic production by detailed two-digit industries, for two-time points, 2000 and 2014. The bars are organized in ascending order for each industry group—agriculture; mining, construction and utilities, manufacturing, market services, and non-market services. The agricultural sector has the lowest foreign content, at 2.5%, which increased to 3% by 2014. Among the non-manufacturing industries, utilities had the highest foreign content, at about 18%, which has increased from 13% in 2000, and construction, which went up from 14% in 2000 to 17% in 2014. Mining had relatively low foreign content at 5%, but it went up to less than 7% over nearly one and a half decades.

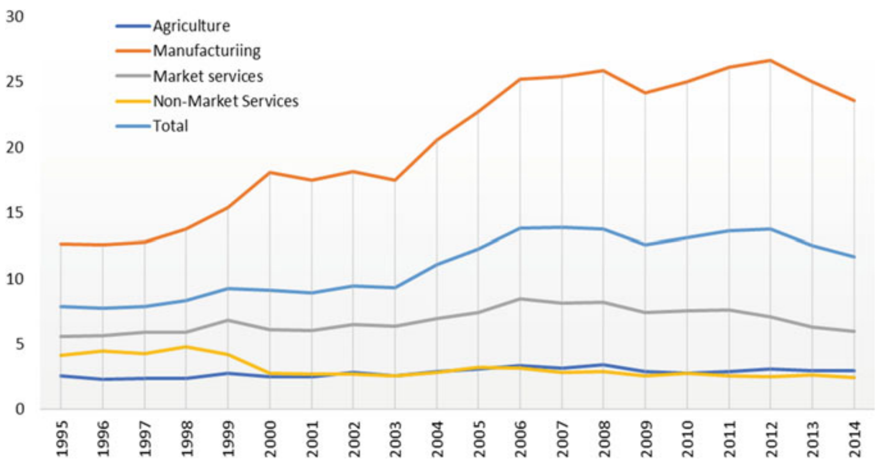

Fig. 1 Foreign value-added content in domestic production broad industries (percent of domestic production), 1995–2014. *Source* Authors' calculation using data from the WIOD

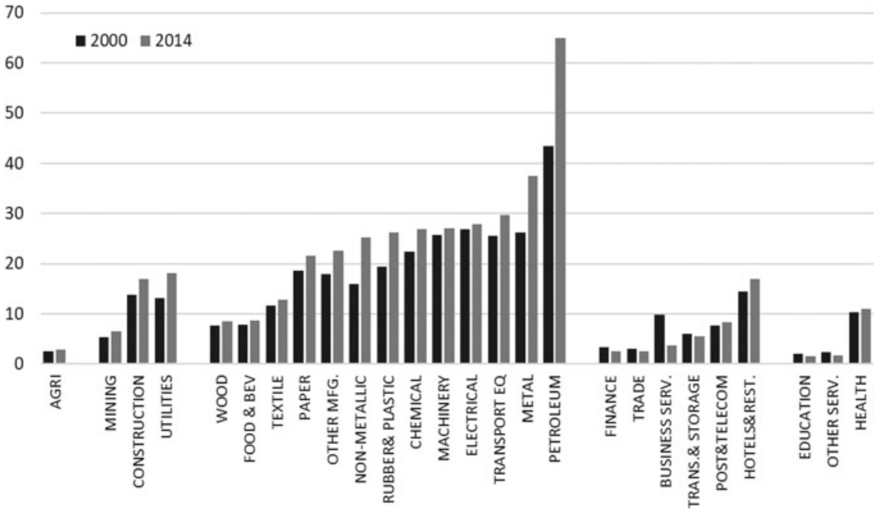

Fig. 2 Foreign value-added content in domestic production 2-digit industries (percent of domestic production), 1995–2014. *Source* Authors' calculation using data from the WIOD

In general, most manufacturing sectors had relatively high foreign content. Exceptions are wood and wood products, food and beverages, and textiles—in all these sectors, the foreign content was less than 15% but has moved up. In all other industries, the foreign content was above one-fifth of total domestic production, and it did increase everywhere, with the largest increase being in petroleum, metal and non-metallic minerals sectors. Notable increase in rubber and plastics, chemicals, and transport equipment have been observed. In fact, petroleum had a very high level of foreign content, at 65% of domestic production, which is perhaps a manifestation of external reliance for crude oil. Two other sectors with high foreign content of one-third or above are basic metals and transport equipment sectors. Non-metallic minerals, rubber and plastics, chemicals, machinery and electrical equipment sectors all had more than one-fourth of their domestic production consisting of foreign value added. Clearly, the use of foreign intermediate inputs directly or indirectly has been rising and has been relatively high in the manufacturing sector.

Among the market services sectors, hotels and restaurants had the highest foreign share in 2014, at 17% after a nearly 2.5% increase from 2000. Post and telecom, transport services and business services also had relatively high foreign content, while trade and financial services had the lowest level across market services sectors. Interestingly in all the market services sectors except in post and telecom and hotels and restaurants, the foreign content has declined. Apparently, the reliance on foreign inputs in these sectors has not increased, perhaps due to the increasing ability of Indian industries to produce upstream products domestically.[5] Except for health sector, where the import of machinery and several medical equipment, and materials

[5]See Kee and Tang (2016) for a similar argument in the case of China.

seem to have caused a relatively higher foreign content, other non-market services are showing less foreign content, and a further decline over years.

Overall, there has been a general increase in the foreign content in domestic production in all sectors in 2014 over 2000, except for the services sector. The biggest increase has been in petroleum, which is likely due to increased import of crude oil from abroad. The second largest increase is in basic metals and metal products.

4 Indian Content in the Production of Foreign Countries

As explained in the methodology section, summing across the Indian content in the production of various industries in countries other than India, we can obtain the total value-added generated in India, embodied in the foreign production of goods and services. The results are provided in Table 1. Note that these are the total value-added generated in India, regardless of the industry of origin, used in the production of a given sector globally, expressed as a percentage of overall GDP in India. In Figs. 1 and 2, the value-added generated in foreign countries, regardless of industry, embodied in the production of a given industry in India was expressed as a percentage of that industry's output. However, given that the Indian content used in the production of foreign output in any given industry can be originating from any industry in India, we do not express it relative to the output of a single sector, rather we choose to present it as a percent of overall GDP. For instance, in Table 1, the Indian value-added embodied in agricultural production in countries other than India consists of 0.23% of India's GDP in 2014. The same constitutes 0.25% of total agricultural production globally, excluding the production in India. Overall, we observe that the use of India's upstream sectors' output by downstream sectors abroad constitute about 8% of India's GDP, which went up by 1% from 7% in 2000.

Looking across the 27 KLEMS industries, we observe that the Indian value content used in the production of other countries, as a share of India's GDP was the highest in the construction sector, followed by food and beverages and textiles sectors (First two columns of Table 1). The demand for Indian inputs in the global construction sector also increased over the years. Other sectors with an improvement of Indian value are business services, transport services, and the health sector, whereas global textile sector's demand for Indian value added through global value chain has declined. In other words, the share of India's GDP emanated from output supplied, directly or indirectly, to the global textiles sector has declined the last 14 years from 2000.

However, from a foreign perspective—i.e. the share of Indian value added in respective global industry output—Indian presence was highest in textiles production of foreign countries, and it did increase as well (Last two columns of Table 1). This would imply that the reliance on global production of textiles on Indian inputs have gone up, even though its share in India's domestic GDP has not. Other sectors where Indian's content remains high are rubber and plastics, chemical, basic metals, and transport equipment. These sectors also had improvement. Business services, which

Table 1 Indian value-added content embodied in the production of other countries, by industry

	% of India's GDP		% of output in respective foreign industry	
	2000	2014	2000	2014
Agriculture	0.20	0.23	0.12	0.25
Mining	0.02	0.03	0.09	0.17
Food, beverages and tobacco	0.56	0.64	0.14	0.32
Textile, leather	0.66	0.46	0.47	0.78
Wood and wood products	0.02	0.01	0.17	0.33
Paper, printing and publishing	0.08	0.06	0.06	0.13
Petroleum	0.12	0.15	0.17	0.30
Chemical	0.19	0.21	0.16	0.38
Rubber and plastics	0.06	0.06	0.24	0.56
Non-metallic mineral	0.03	0.02	0.15	0.28
Basic metal and metal prod.	0.09	0.10	0.14	0.35
Machinery, nec.	0.32	0.29	0.12	0.28
Electrical and optical eqp.	0.21	0.24	0.12	0.27
Transport eqp.	0.44	0.59	0.14	0.34
Other manufacturing	0.18	0.12	0.15	0.28
Utilities	0.17	0.18	0.12	0.22
Construction	1.01	1.45	0.12	0.29
Trade	0.46	0.46	0.05	0.11
Hotels and restaurants	0.26	0.39	0.11	0.31
Transport and storage	0.08	0.10	0.06	0.15
Post and telecom	0.25	0.27	0.08	0.17
Financial services	0.16	0.14	0.05	0.10
Business services	0.20	0.39	0.06	0.20
Public administration	0.47	0.50	0.05	0.11
Education	0.15	0.19	0.04	0.09
Health and social work	0.34	0.45	0.05	0.12
Other services	0.32	0.32	0.03	0.06
Total	7.05	8.05	0.09	0.19

Source Authors' calculation using data from the WIOD

include IT-related services, where India has been excelling since the late 1990s, also had seen a notable improvement over the years.

Looking at individual countries/regions, we observe that Indian value-added embodied in the production of foreign countries as a share of GDP in India was the highest in the European Union (EU28), followed by the United States, China, and Japan (Table 2). While Indian value added used embodied in China's production

Table 2 Indian value-added content embodied in the production of other countries, by country

	% of India's GDP		% of output in respective foreign industry	
	2000	2014	2000	2014
EU 28	1.12	1.10	0.07	0.14
of which:				
Germany	0.24	0.20	0.07	0.13
France	0.14	0.16	0.05	0.13
United Kingdom	0.19	0.16	0.06	0.13
United States	0.93	0.80	0.04	0.10
China	0.29	0.17	0.03	0.08
Japan	0.20	0.60	0.08	0.12
South Korea	0.12	0.14	0.11	0.22
Total	7.05	8.05	0.09	0.19

Source Authors' calculation using data from the WIOD

has seen the most significant increase from 2000 to 2014, it declined in the EU 28, the US and Japan. Within the EU, two large economies Germany and the UK saw declines as well. However, in terms of their own domestic production, Indian content has increased in all countries, and it remains highest in South Korea, followed by the EU 28 and China.

5 Dependency of India's GDP on Foreign Final Demand

In the previous section, we examined the foreign content in India's domestic production of various industries, and also the trend in Indian content in foreign production. Such backward linkages with global industries provide us insights about how much India's production and exports are integrated with the global value chain. What is also important is to understand how participation in the global value chain impacts income generation in India. There has hardly been any study that attempts to document India's forward linkages in global value chain. In this section, we examine the impact of India participating in global value chain, on its GDP. In other words, how much Indian GDP has been accrued due to final demand for Indian products and services in the foreign market.

External dependence of India's overall GDP has increased from 11% in 2000 to 17% in 2006 (Fig. 3). However, it started declining since 2007, with a notable drop during the global financial crisis. Since 2010, even though it rebounded a bit, remained somewhat stagnant at about 14% of GDP, before dropping to 13% in the last year of our data. In terms of value, however, it continued to expand reaching 190 billion US dollars in 2008 from 50 billion dollars in 2000, with no decline in a

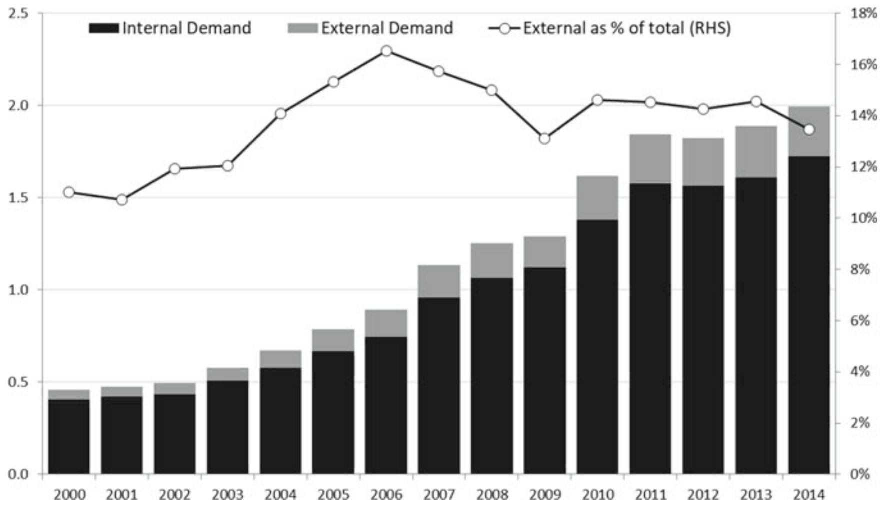

Fig. 3 Composition of GDP in IND (in US$ trillion, current price). *Source* Authors' calculation using data from the WIOD

single year. After dropping to less than 170 billion dollars in 2009, it rebounded and continued to increase, reaching nearly 270 billion dollars in 2014.

A comparison of foreign dependence on domestic income across selected countries is provided in Table 3. Among the mature economies, Korea and Germany have the highest share of foreign reliance at above one-third of their overall GDP. Moreover, in both countries, it did go up, from a quarter in 2000. In France, the foreign reliance remained somewhat constant at one-fifth of the GDP and in Japan, it went up from 10 to 14% of Japanese GDP. In the United States, the reliance of domestic

Table 3 Foreign dependence of GDP: select countries

	2000	2006	2014
Mature economies			
South Korea	25%	25%	32%
Germany	24%	30%	32%
France	20%	19%	20%
Japan	10%	13%	14%
United States	7%	7%	9%
Emerging markets			
Turkey	21%	21%	23%
Indonesia	32%	25%	20%
China	18%	28%	19%
India	11%	17%	13%

Source Authors' calculation using data from the WIOD income on foreign consumption is 9% in 2014, a 2% increase from 2000—thus it is the least reliant among the large mature economies.

Among the emerging markets, Indonesia and Turkey have one-fifth or above of their national GDP coming from foreign demand. While it went up marginally over the years in Turkey, it did decline from one-third to one-fifth in Indonesia. China indeed had a substantial increase in its foreign dependence from 2000 to 2006 but has dropped massively reaching back to its 2000 level in 2014. Partially, the dynamics in China may be attributed to the rapid changes in its domestic economy—the accelerated move from a manufacturing, export, investment-driven economy to services, domestic and consumer-driven one. Earlier studies also find evidence for the rising substitution of domestic for imported materials by individual processing exporters in China (Kee and Tang 2016). Obviously compared to India, large mature and emerging market economies have exposed more intensely to the rest of the world to raise their incomes. The United States is a possible exception. This also suggests India has a substantial potential to further integrate with the rest of the world, for creating jobs and incomes. In the subsequent section, we examine which industries are more reliant on foreign demand.

In Fig. 4, the same line shown in Fig. 3 is replicated but now split into consumer demand and investor demand. A major portion of the final demand abroad that contributed to India's GDP has been by foreign consumers—varying from 9% out of 11% total foreign share (i.e. 80% of overall foreign reliance) in 2000 to 9% out of the total 14% (or 70% of overall foreign reliance) in 2014. In 2000 one-fifth of total foreign reliance of India's GDP was due to demand for investment goods and services. This has consistently increased until 2008, reaching one-third, and after a

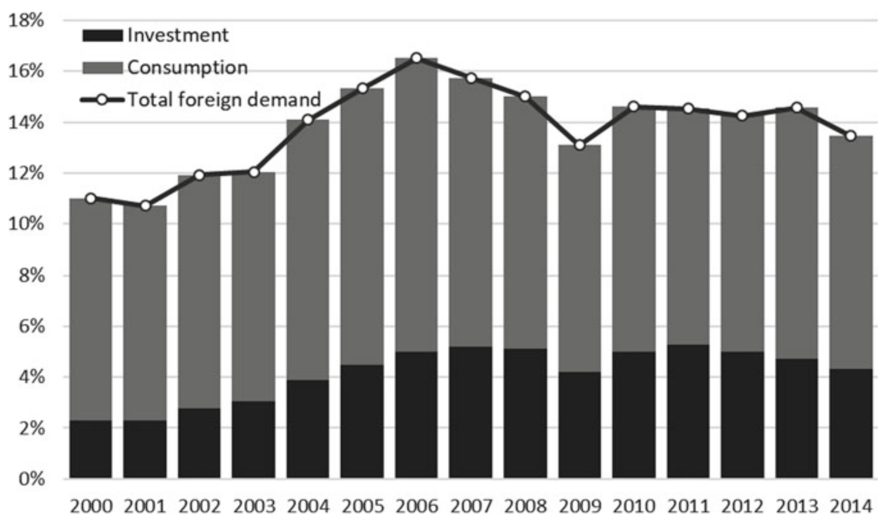

Fig. 4 Composition of foreign demand for final goods and services from India. *Source* Authors' calculation using data from the WIOD

Table 4 Composition of foreign demand for final output from India

	2000	2006	2011	2014
Total foreign share	11.0	16.5	14.5	13.5
of which:				
Advanced economies	6.1	7.7	4.8	4.4
United States	2.3	2.6	1.6	1.6
Japan	0.6	0.6	0.3	0.3
EU 28	2.6	3.7	2.2	2.0
Germany	0.5	0.5	0.4	0.3
France	0.3	0.4	0.3	0.3
Emerging markets	0.9	2.0	2.0	1.7
China	0.3	1.2	1.2	0.9
Rest of the world	4.0	6.8	7.7	7.4

Note The share of income generated in Indian economy due to final consumption of goods and services, generated in India, by all countries
Source Authors' calculation using data from the WIOD

small drop in 2009, it further continued to attain 36% in 2011. Since then there has been a continuous decline dropping down to 32% by 2014.

The country origins of India's foreing GDP component are presented in Table 4. Overall, India's income had the highest reliance on advanced economies in 2000, with more than half of the total income generated in India due to foreign consumption came from advanced economies. However, that has changed over the years, with emerging markets (including the rest of the world category in the WIOD dataset) increasing their role over the years. More importantly, the rest of the world category has increased substantially taking 7.4% of the total 13.5% foreign share in 2014. Note that this group includes several middle east economies where India exports hefty, as the WIOD data does not include these economies. India's reliance on China has gone much faster than any other region/country, from just below 0.3% (3% of total foreign income) to 0.9% (nearly 7% of the total) in 15 years. United States, Japan and EU 28 all declined, with both Germany and France also seeing deteriorations. A more comprehensive analysis including many countries that are currently not part of the database is warranted.

Now looking at the regional origins at the sectoral level, the overall foreign reliance of India's agricultural income remains low but has increased, primarily because of the increased presence of Chinese consumption, which went up from 0.1% of agricultural output in 2000 to 0.6% in 2014 (Table 5). Even though the relative importance of advanced economies in driving India's agricultural foreign income has declined over years, by and large, it still remains the largest, at 3% of agricultural income (or 36% of total 8.1% foreign share in the sector). The United States is one of the largest contributors as a single country, and EU 28 and the entire emerging region contributes about 1.3% of agricultural income.

Table 5 Composition of foreign demand for final output from India's agricultural sector (foreign demand as a share of domestic value added in agriculture)

	2000	2006	2011	2014
Total foreign share	6.7	8.2	7.4	8.1
of which:				
Advanced economies	4.3	4.3	2.7	3.0
United States	1.6	1.6	0.9	1.0
Japan	0.5	0.3	0.2	0.2
EU 28	1.8	1.9	1.2	1.3
Germany	0.3	0.3	0.2	0.2
France	0.2	0.2	0.1	0.2
Emerging markets	0.6	1.1	1.4	1.3
China	0.1	0.6	0.7	0.6
Rest of the world	1.9	2.9	3.3	3.9

Source Authors' calculation using data from the WIOD

The reliance of India's manufacturing income on foreign consumption is by far the highest and has consistently increased, from about one-fifth of manufacturing GDP in 2000 to nearly one-fourth in 2014 (Table 6). The role of advanced economies has shrunk here too, from 13.8% (or 67% of the total) to 10% (i.e. 41% of the total), with Japan seeing the highest decline followed by the United States, Germany and France. The US contribution to India's manufacturing value added has dropped from near to 6% in 2000 to less than 4% in 2014. To offset the drop in the mature markets, emerging markets (excluding the rest of the world group) have increased

Table 6 Composition of foreign demand for final output from India's manufacturing sector (foreign demand as a share of domestic value added in manufacturing)

	2000	2006	2011	2014
Total foreign demand share	20.6	23.5	20.1	24.1
of which:				
Advanced economies	13.8	13.6	8.8	10.0
United States	5.9	5.3	3.0	3.8
Japan	1.1	0.8	0.5	0.6
EU 28	5.5	5.9	4.1	4.2
Germany	1.1	1.0	0.8	0.8
France	0.7	0.7	0.5	0.6
Emerging markets	1.7	2.6	3.0	3.4
China	0.4	1.1	1.2	1.4
Rest of the world	5.1	7.3	8.3	10.7

Source Authors' calculation using data from the WIOD

Table 7 Composition of foreign demand for India's market services (foreign demand as a share of domestic value added in market services)

	2000	2006	2011	2014
Total foreign share	16.3	23.5	23.3	18.4
of which:				
Advanced economies	7.2	8.9	6.5	4.9
United States	2.8	3.4	2.4	1.8
Japan	0.7	0.7	0.4	0.3
EU 28	3.0	3.9	2.9	2.2
Germany	0.7	0.7	0.5	0.4
France	0.4	0.4	0.5	0.3
Emerging markets	1.2	1.6	1.8	1.5
China	0.3	0.8	0.9	0.8
Rest of the world	7.9	12.9	15.0	11.9

Source Authors' calculation using data from the WIOD

1.7% of manufacturing value added to 3.4%, with China seeing a substantial threefold increase. The share of the rest of the world group also improved markedly from 5.1 to 10.7%.

Finally, in Table 7, we have India's fast-growing market services sector, where the foreign reliance was about 16% of total sectoral GDP in 2000, which increased to nearly a quarter in 2011, before falling down to 18% in 2014. Clearly, there has been a shift from mature markets to the emerging world, which drove the uptick until 2011. While the mature markets' role has declined from 7.2% in 2000% to less than 5% in 2014%, emerging has increased from 1.2 to 1.5%, and when included the rest of the world group, it even further went up from 9 to 13.5% of overall market services GDP.

The impact of GVC participation on productivity and growth is widely discussed in the literature. Participation in GVCs helps countries specialize in activities where they have productivity advantage, which will have a positive impact on overall productivity growth. Moreover, the rising share of foreign content in domestic production—or the use of foreign intermediate inputs—is argued to stimulate domestic technology diffusion and help export and output growth. This is particularly true if the foreign inputs embody high-tech components. Empirically, the past literature that examined the impact of GVC participation on productivity observes a positive relationship between the two (Baldwin and Yan 2014; Constantinescu et al. 2017;

Damijan et al. 2013).[6] Existing evidence on India's manufacturing sector also confirms such positive impact of participating in the global supply chain on productivity and performance (Srivastava and Sen 2015; Athukorala 2016). In this paper, we only document the empirical regularities in terms of the trend and composition of India's value chain participation and do not attempt any sophisticated analysis of the impact of GVC participation on productivity or growth. However, given the substantial literature that stresses the role of exports in general, and participation in the global value chain in particular, in driving productivity, we examine the simple correlation between the two. In. Figure 5, we plot the relative levels of labor productivity in specific industries against their foreign demand intensity.

An interesting dynamic here is that the relationship between the two has been quite weak and flat in 2000, but has become strong and positive over the years. A detailed look at the dynamics in individual sectors further points to an even stronger

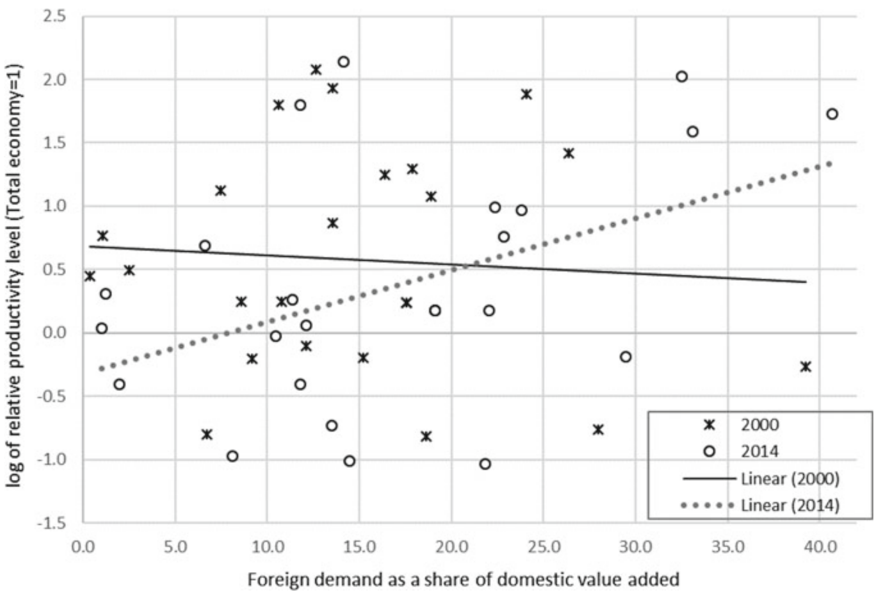

Fig. 5 Correlation between relative labor productivity levels and foreign demand share in Indian industries. *Note* Petroleum sector is excluded from this chart as it remains an outlier in terms of productivity level. *Source* Authors' calculation using data from the WIOD and India KLEMS

[6]Also there are several studies that examine the impact of offshoring and participation in GVC on productivity and jobs, especially on the home markets from where the production of specific activities are shifted to the offshoring economy (see Milberg and Winkler 2013; Taglioni and Winkler 2014; Schwörer 2013). Often it is argued that the offshoring causes loss of jobs in the home countries. The opposing view is that if the positive productivity effects are large enough, it can enhance job creation and/or wages in the home markets, especially in the long-term (Grossman and Rossi-Hansberg 2008). We do not delve into this literature. See Farole et al. (2018) for an in-depth discussion on the labor market implications of the global value chain.

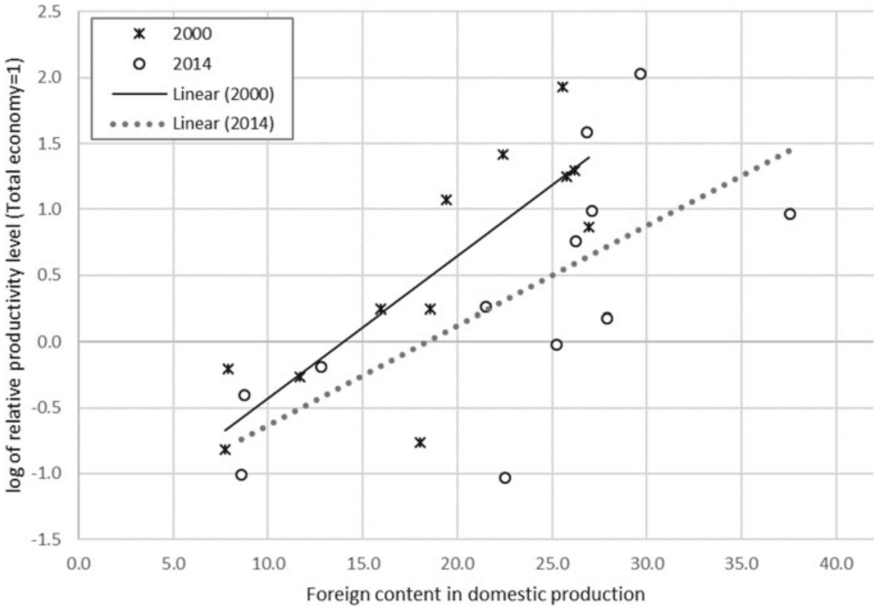

Fig. 6 Correlation between relative labor productivity levels and foreign content in Indian manufacturing industries. *Note* Petroleum sector is excluded from this chart as it remains an outlier in terms of productivity level. *Source* Authors' calculation using data from the WIOD and India KLEMS

relationship in the manufacturing sector compared to other sectors of the economy.[7] This implies that the sectors that got more exposed to the foreign market and supplied to foreign demand have become more productive. Even though we establish no causal relationship here, the seminal Melitz model (Melitz 2003) suggests that exposure to trade leads to reallocation of resources within the industry, pushing least efficient firms out of markets, thus raising the industry productivity. It is quite likely that firms in industries that are engaged in the global value chain are relatively more technology and capital intensive than those which are not. We do not delve into this question further, but future research may take this aspect into account by examining the factor intensity of production in sectors with high global value chain impact. Also, it may be noted that an earlier study by Goldar (2013) attributes the substantial increase in the use of imported intermediate inputs in Indian manufacturing industries in the post-reform period to growing export orientation of the sector. Our observation that the foreign demand intensity has increased in the manufacturing, and the positive relationship between foreign demand share and labor productivity is relatively stronger in this sector seems to agree with this finding.

In Fig. 6, we further plot the correlation between foreign value-added content in domestic production and the relative labor productivity levels in individual industries,

[7]A simple OLS regression of labor productivity on foreign demand share shows 0.03 points larger coefficient for manufacturing sector compared to the entire economy.

but only in the manufacturing sector. Since the foreign content is mostly a reflection of the use of foreign intermediate inputs, the manufacturing sector is more likely to show the impact of the foreign value content in domestic production on productivity. However, the inputs that are used in the sector can come from any sector of foreign economies. Interestingly, the relationship is quite positive but has weakened in 2014 over 2011. Within India's manufacturing sector, sectors that use foreign intermediate inputs seem to have achieved relatively higher productivity levels. As mentioned earlier, our results are to be taken as indicative only, as we do not establish a causal relationship between the two variables. However, they seem to support recent evidence on the positive relationship between TFP growth and foreign input use in the manufacturing sector (Krishna et al. 2019) and the higher total factor productivity growth in India's organized manufacturing sector when accounted for the role of imported intermediate inputs (Goldar 2015).

6 Conclusion

The role of international trade in driving productivity and growth has been widely analyzed in the context of India, particularly in the organized (formal) manufacturing sector. However, with the rapid increase in the global production fragmentation, the conventional trade measures—gross exports and imports—are often considered to be less insightful in giving an adequate picture of the volume of a country's participation in global trade. As a consequence, literature has shifted to using measures of trade in value added, and global value chain participation. This paper documents the involvement of India in the global value chain by 27 individual sectors—both manufacturing and non-manufacturing-, consisting of the entire economy—both formal (organized) and informal (unorganized). These sectors are consistent with the India KLEMS database, which provides detailed data on sectoral employment, capital, and productivity—both labor productivity and total factor productivity. We provide estimates of Indian industries' backward (or foreign content in domestic production) and forward (the dependence of Indian industries on foreign demand) linkages with global production and demand.

We find that in India, the foreign content in domestic production is highest in the manufacturing sector, and this has increased over the years. Even though market services stay second, the foreign share in domestic production in this sector has not been growing in recent years. Within the manufacturing sector, the backward production linkage with the rest of the world was weak only in wood and wood products, food and beverages, and textiles and leather industries. These are sectors where the upstream sectors are likely strong in the domestic economy. Overall, it appears that the expansion of India's manufacturing, and to some extent, market services create demand for output from upstream sectors in other countries that produce intermediate inputs used in the downstream sectors in India.

Looking at the presence of Indian content in foreign production, we observe that the global textile sector has the highest relative proportion of Indian input, although its relative contribution to India's GDP is not the highest, and is further declining. Obviously, while the prominence of participation in the textiles value chain as a contributor to national GDP is on the decline, the reliance of foreign countries on this sector in India is not. India's business services, on the other hand, see an upward trend in its contribution to foreign production. From a domestic perspective, the largest contribution to India's GDP comes from Indian value-added embodied in foreign production in the global construction industry.

The share of India's overall GDP that relies on foreign final demand is sizable, yet relative to several other economies—both mature and emerging—it is on the lower side. However, nearly a quarter of India's manufacturing income accounts for foreign final demand suggesting substantial benefit accruing from foreign consumers and investors. Obviously compared to India, large mature and emerging market economies have exposed more intensely to the rest of the world to raise their incomes. This also suggests India has a substantial potential to further integrate with the rest of the world, for creating jobs and incomes. Moreover, as is evident from our simple descriptive analysis there is a strong relationship between productivity in Indian industries and their exposure to the foreign market, through GVC participation, which signifies the importance of increased participation in the global value chain.

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The Political Economy of the Allocation of State Government Expenditures for the Industrial Sector

Atsushi Kato and Atsushi Fukumi

1 Introduction

Economic development is a critical requirement for improving peoples' standard of living. There is a voluminous body of development economics literature on normative economic growth strategies and industrialization policy (see, for example, Rodrik 2005, 2007). It seems reasonable to suppose that economic development would increase the likelihood of the survival of incumbent political leaders, including their chances of being reelected in democratic countries. However, not all governments implement public policy that promotes economic development. Given that industrialization is supposed to promote economic development (e.g., Robinson 2009), we investigate why some governments do not institute public policy conducive to industrialization by focusing on the balance of political power between the agricultural and industrial sectors. More specifically, we examine whether a higher rural Gini coefficient—a proxy for the degree of political influence of rural elites—tends to reduce the allocation of development expenditures favorable to the industrial sector at the state level in India.

Positive political economy analyses of industrialization policy, which focus on the political processes by which industrialization policy is adopted and implemented, are surprisingly scarce. Robinson (2009) calls the attention of economists and international organizations to this research gap by stating, "To really promote industrialization in a society we need a positive theory of the political equilibrium of that society which leads to particular policy choices." In this study, we attempt to show

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that the political influence of rural elites can limit the allocation of state government expenditures for the industrial sector.

The theory of political survival (e.g., Mesquita et al. 2003), which is an influential theory in the context of public policy choices, states that incumbent political leaders maximize their probability of remaining in office, regardless of the type of political regime. According to this theory, an incumbent government would choose public policies conducive to industrialization when the industrial sector is within the political leader's winning coalition. This proposition can be interpreted as indicating that, when the industrial sector is politically more influential than other conflicting socioeconomic groups, an incumbent government would institute pro-industrial public policy.

However, measuring the extent of political influence is fraught with challenges. Dahl (1991) noted that political leaders' decisions on public policy could be influenced by a variety of political resources, including money, votes, the threat of force, information, friendship, and social standing. In this study, we indirectly examine the negative effects of the rural Gini coefficient and rural population share on the allocation of state government expenditures to the industrial sector. The rural Gini coefficient is considered to be related to money, votes, leadership, and connection with powerful public officials among various political resources.

Focusing on India, we conduct a state-level analysis for the period from 1980 to 2010. We examine the effect of Gini coefficients and population shares, of both rural and urban areas, on the ratio of development (capital) expenditures for industry, energy, transportation, and communications. Although these expenditure items are beneficial to other sectors, including households, they contribute to the industrial sector to a larger extent. Thus, we regard these items as being favorable to the industrial sector. In terms of budget allocations, other socioeconomic groups have demands that are independent from and conflicting with those of the industrial sector. Especially, the agricultural sector encompasses a large share of the population, and agricultural elites, or landlords, have been dominant in the political realm since India gained independence (Bardhan 1984). Furthermore, some previous studies assert that agricultural elites overtly oppose industrialization because they perceive it as reducing their bargaining power vis-à-vis agricultural workers and peasants, because it provides job opportunities for them. Taken together, our estimation results show that the rural Gini coefficient robustly has a significant negative coefficient, and rural population share, though less robustly, has a significant negative coefficient. These results imply that the agricultural sector can limit budget allocations conducive to industrialization, resulting in stagnation of the economy.

The rest of the article is organized as follows. Section 2 briefly surveys the related literature and Sect. 3 provides relevant contextual information on India. Section 4 delineates our empirical strategy and the variables used for our estimation. Next, Sect. 5 presents our estimation results and, finally, Sect. 6 offers conclusions.

2 Literature Review

Development economics has produced a voluminous literature on normative industrialization policy, which has shown which kinds of policy interventions are desirable under what conditions and how to implement them in order to industrialize a country (see, for example, Rodrik 2005, 2007). These industrialization policies can be effective only if they are appropriately chosen and implemented. However, there still remains much to understand about why some governments effectively choose and implement industrialization policies, but others do not.

Political scientists have long examined political processes that affect public policy choices. Among the many strands of political thought, elite theory, for instance, argues that a small in-group consisting of economic, political, and military leaders holds overwhelming control over policy decisions (e.g., Mills 1956). In contrast to this view, pluralism posits that politics is instead guided by competition and coordination among numerous interest groups, leading to policy outcomes (e.g., Dahl 1961). The statist approach, by contrast, asserts that the government more or less autonomously determines public policy, independent of pressure from interest groups (e.g., Evans et al. 1985).

One influential theory that has emerged from this debate is the theory of political survival (e.g., Mesquita et al. 2003), which states that incumbent political leaders maximize the probability of remaining in office, regardless of the type of political regime. On the basis of this theory, we presume in this study that incumbent political leaders choose policies that most effectively increase the probability of their political survival.

In the literature analyzing policy choices by governments, the clout of special interest groups has been highlighted (e.g., Grossman and Helpman 2001). Special interest groups demand benefits from government, via policies, in exchange for political support in the form of votes and political donations. According to the theory of political survival, as long as a special interest group is perceived by politicians to be an important part of their support base, the demands of the interest group may receive special consideration and thus are likely to be reflected in government policy.[1]

A well-known instance of a socioeconomic group's influence on public policy is that of landlords' opposition to land reform policy (see, for example, Kohli 2009a, b). Political economy scholars examining land reform have long argued that the leverage traditionally held by landlords in many countries impedes land reforms. As Banerjee (2001) argues, if land reforms make tenants the owners of land, they would invest more in land and both physical and human capitals, leading to an increase in the

[1]However, some scholars argue that politicians may also pay attention to the general interests of broad socioeconomic groups (Persson and Tabellini 2000). For instance, empirical research on the determinants of non-tariff trade barriers has shown that not only industries that are politically organized, but also industries that are uncompetitive, exposed to the threat of imports, or in decline, as well as those that have a high unemployment rate are also likely to be protected by such trade barriers (e.g., Finger et al. 1982; Trefler 1993; Lee and Swagel 1997). These studies indicate that incumbent political leaders may implement policies that are favorable to general interests if they believe that doing so will enhance the probability of their political survival.

productivity of agriculture and personal incomes.[2] Higher incomes lead tenants to save and invest more, which enables them to raise incomes further. However, land reforms are, in many cases, opposed by landlords, because they are concerned about losing wealth and political power.

A well-known example of the impact of industrialists on policy is the Anti-Corn Law League. Dating back to the nineteenth century, the Anti-Corn Law movement was led by Richard Cobden and John Bright and was supported by the newly emerging class of industrialists in Manchester who advocated free trade and succeeded in repealing the Corn Laws in 1846. This case illustrates how an increase in the political influence of industry and industrialists can change public policy in their favor. Similarly, the literature on the political economy of trade theory has long investigated the determinants of trade policy, especially regarding the choice between open- and close-trade regimes, and has provided evidence that politically organized industries are more likely to be protected by non-tariff barriers (e.g., Goldberg and Maggi 1999; Gawande and Bandyopadhyay 2000). Some scholars in this strand of research have shown that interest groups formed along industry sector lines have exerted significant political influence on trade policy (e.g., Irwin 1996; Irwin and Kroszner 1999; Magee 1980; Busch and Reinhardt 2000).[3]

Robinson (2009) states that "industry policy has been successful when those with political power who have implemented the policy have either themselves directly wished for industrialization to succeed, or been forced to act in this way by the incentives generated by political institutions." He refers to the Glorious Revolution in England in 1688, and argues, on the basis of Pincus (2009), that the success of the Revolution was a result of the Whig coalition, which included many politicians who had their own industrial enterprises and who aimed to stimulate manufacturing. According to Robinson (2009), the Whig coalition "started the Bank of England, facilitated the development of the transportation sector via canals and turnpike roads, reorganized the tax system and changed commercial policy." Thus, as the political power of industrialists, vis-à-vis other socioeconomic groups, especially the agricultural sector, expands, public policy favorable to industry is more likely to be adopted and implemented.

As such, previous studies examining policy choice have highlighted the importance of the political influence of certain socioeconomic groups. Indeed, despite the claim of statist scholars, we could posit that public policy choices are substantively influenced by the interests of particular groups. Nonetheless, there have been relatively few studies with political economy explanations for the adoption and implementation of industrialization policy. According to the theory of political survival, we can predict that an incumbent government would choose public policy desirable for industrialization when the industrial sector is within the political leader's winning

[2]Banerjee et al. (2002) show that, in a successful case of land reforms in West Bengal in India, "the tenancy reform program called Operation Barga explains around 28% of the subsequent growth of agricultural productivity there."

[3]Other scholars, however, have argued that coalitions formed along social class lines are more important (e.g., Rogowski 1989; Mayda and Rodrik 2005).

coalition. This indicates that, when the industrial sector is politically more influential than other conflicting socioeconomic groups, an incumbent government would opt for public policy interventions which are favorable to the industrial sector.

One difficulty in investigating the political influence of a socioeconomic group lies in obtaining an objective measure of its political influence, because this may depend on many ambiguous factors such as the mobilization of people within the group at election time, political donations provided both legally and illegally, and the prospect of future support by the group to incumbent political leaders. It is unimaginable that any precise measure of a socioeconomic group's political influence could integrate all the various types of political resources noted in Sect. 1. Furthermore, Dahl (1991) claims that actual political influence depends on the willingness to use political resources as well as the techniques for utilizing them effectively. Thus, we must rely on a rather indirect measure of political influence of socioeconomic groups in any empirical research.

Ansell and Samuels (2014), in their intriguing study on democratization, took landholding and income Gini coefficients as proxies for the political power of landlords and industrialists, respectively, and showed that democratization is more likely when the political power of industrialists increases. Following their work, we use the rural Gini coefficient as a proxy for the political power of landlords and the urban Gini coefficient as a proxy for that of industrialists. This approach appears justified because as wealth becomes more concentrated in a smaller number of elites, they would find it easier to coordinate their actions for influencing politicians. Previous studies on collective action assert that as the number of actors increases, it becomes more difficult for them to coordinate their actions for collective objectives such as lobbying for achieving desirable public policy (e.g., Olson 1965). Moreover, as the Gini coefficient rises, a smaller number of rich people, who obtain levels of income far beyond what is necessary to meet their needs, could utilize money to mobilize a large number of poor people, or to influence public officials through political donations or bribery.

In this study, we presume that public policies are determined through inter-elite competition, especially that between agricultural and industrial elites. If their interests are not at odds, they do not confront each other. However, their interests often conflict, so it is important to explore allocation of government expenditures from the perspective of the balance of political power between these two groups of economic elites.

We conduct our empirical research using state-level data for India. Differences in electoral systems, the formal distribution of authority inside governments, and political cultures may also affect the political processes that determine the choice and implementation of public policy (see, for example, Persson et al. 2003; Almond and Verba 1963). These factors must be properly controlled for in cross-national analyses, but doing so is difficult. By making comparisons between regional states within a single country, which follow more or less uniform formal rules, we can control for the variations in political institutions and legal frameworks in which public policy is determined. Therefore, we can more precisely estimate the effect of the political influence of agricultural and industrial sectors. Moreover, Indian states vary significantly in terms of the extent of industrialization, the industrial policies adopted by state governments, and their political and social structures.[4] As Kohli (1987) argued, India is a "laboratory for comparative political analysis."

For our estimation, we apply ordinary least squares (OLS) regression with panel-corrected standard errors (see Beck and Katz 1995), panel data analysis, and maximum likelihood estimation to data for 27 states for the period 1980–2010. The number of states and sample periods vary across the estimation due to differences in the availability of data for each variable included in the estimation.

3 The Indian Context

Following independence, the Government of India adopted a highly restrictive industrialization policy that required businesses to obtain approval for every aspect of corporate activity from the government. The burdensome licensing system was termed the "License Raj."[5] This policy stance was relaxed in the middle of the 1980s under Rajiv Gandhi's administration and liberalized further in the early 1990s. In the period following this economic liberalization by the Central Government, political leaders of Indian regional state governments gained more freedom to adopt industrialization policy at the state level.

However, not all state governments made serious efforts to promote industrialization in response to this opportunity. Bajpai and Sachs (1999) evaluated policy reforms undertaken by Indian state governments in the 1990s in areas such as industrial policy, the power sector, infrastructure development, and the tax system, and then classified 15 major states as either reform-oriented, intermediate, or lagging reformers.[6] They also loosely demonstrated that reform-oriented states performed

[4]Jenkins (2004) stated, "India's federal system has created 29 'mini-democracies' with almost identical institutional infrastructures, at least in terms of the formal systems of representation. India's States, moreover, operate under a set of common conditions, including New Delhi's foreign and economic policy framework and the legal protections enshrined in the Indian Constitution. These control variables represent a major boon to students of comparative politics who seek to understand and explain the divergent patterns and outcomes that the practice of democracy can produce."

[5]The Industries (Development and Regulation) Act of 1951 required both private and public entities to obtain a license to establish a new firm, expand a factory's capacity, start selling a new product, change its location, and so forth. The licensing process often took a long time and imposed a tremendous burden on firms. Due to the discretion of bureaucrats, the approval of a license was uncertain, which also induced corruption. A portion of the licensing system was abolished in the middle of the 1980s and most of the remainder was deregulated in 1991. The time period from 1951 to 1991 is known as the "License Raj Era" in India.

[6]According to Bajpai and Sachs (1999), the reform-oriented states are Andhra Pradesh, Gujarat, Karnataka, Maharashtra, and Tamil Nadu; the intermediate states are Haryana, Orissa, and West Bengal; and the lagging reformers are Assam, Bihar, Kerala, Madhya Pradesh, Punjab, Rajasthan, and Uttar Pradesh.

better in terms of growth rates of per capita gross state domestic product in the 1990s compared with other states.

Many scholars have confirmed that gross state domestic product (GSDP) and per capita GSDP have diverged across Indian states since the 1990s.[7] For instance, Gaur (2010) identified increases in a variety of dispersion indices among Indian states. Comparing the GSDP growth rates of 14 major states, Ahluwalia (2000) showed that the degree of growth rate dispersion was higher in the 1990s than the 1980s. The World Bank (2006) reported that the increasing gap in average growth rates of per capita GSDP between middle-income states and poorer states in the 1990s was mainly due to the accelerated growth in middle-income states, rather than slower growth in poorer states. It appears that Ahluwalia (2000) ascribes a large portion of the divergence in growth rates across states in the 1990s to differences in state government policies, stating that "[s]ince the 'payoff' from superior management has increased because of liberalization it is very likely that variations in the quality of economic management will lead to greater inter-state variation in management performance than was the case earlier."[8,9]

The Government of India classifies government expenditures into development and nondevelopment expenditures. It is considered that "[d]evelopment expenditure has a beneficial impact and leads to economic and social development" (Reserve Bank of India 2010). In this study, we examine the effects of Gini coefficients and population shares, both rural and urban, on development (capital) expenditures for industry, energy, transportation, and communications, which we refer to as expenditures for the industrial sector.[10]

There is a dearth of literature focusing on industrialization policy pursuits by Indian state governments from the perspective of political economy. One of the notable exceptions is Sinha's (2005) comparison between Gujarat, West Bengal, and Tamil Nadu. She draws the conclusion that the Gujarat government was able to adopt

[7]Interestingly, according to Mukherjee and Chakraborty (2010), the dispersion in indicators of human development in such areas as health and education has declined among Indian states.

[8]Ahluwalia (2000) emphasizes the importance of private investment, and says that "[p]rivate corporate investment is potentially highly mobile across states and is therefore likely to flow to states which have a skilled labor force with a good 'work culture', good infrastructure especially power, transport and communications, and good governance generally. The mobility of private corporate investment has increased in the post-liberalization period since decontrol has eliminated the central government's ability to direct investment to particular areas, while competition has greatly increased the incentive for private corporate investment to locate where costs are minimized."

[9]Yet at the same time other scholars (e.g., Nagaraj et al. 2000; Aiyar 2001; Trivedi 2002; World Bank 2006; Nayyar 2008) have found evidence of conditional convergence. However, since the conditions with respect to human capital, infrastructure, public policy, and so forth vary significantly across states, conditional convergence has not reduced disparities among states in the last two decades. In the words of Nayyar (2008), Indian states are "converging to very different steady states."

[10]For instance, Iarossi (2009), on the basis of Investment Climate Survey data, constructed an Investment Climate Index using principal component analysis. He considered three broad business categories, namely, infrastructure, inputs, and institutions, and claimed that infrastructure and institutions are more critical bottlenecks for the business climate of Indian states. Furthermore, power outages and transportation are the most serious business constraints within infrastructure, while those within institutions are corruption and tax regulation.

effective industrialization policy because the electorate was more supportive of (or at least, less opposed to) industrialization policy because of certain unique characteristics such as more industrialized rural areas and weak support from political parties for the labor movement. Kennedy et al. (2013) compared Andhra Pradesh, Haryana, Kerala, and Orissa in terms of state-level responses to economic liberalization policy reforms by the central government. They argue that the policy choices of state governments are "an outcome of a political process based in part on the capability of local groups to promote their interests." Baru (2000) documents that the Telugu Desam Party in Andhra Pradesh opted for pro-industry policies in response to a new class of emerging industrialists such as those represented by Kammas, an influential caste in Andhra Pradesh, whose demands are not met by incumbent political parties that are more aligned with nationwide business groups. Although these studies are illuminating, their approaches are mostly descriptive. Thus, our study adds to the literature by providing statistical evidence to complement their arguments.

4 Empirical Strategy

4.1 Empirical Formulation

Our basic estimation model is as follows:

$$Y_{it} = \alpha + \delta Y_{i,t-1} + \beta Gini_{it} + \gamma Pop_{it} + \rho Control_{it} + \theta_i + \theta_t + \varepsilon_{it},$$

where Y_{it} is the dependent variable, and Y_{it-1} is the dependent variable lagged by one period. Since the lagged dependent variable is included as an independent variable, the estimated coefficients of the other independent variables measure the effect of each variable on the variance of the dependent variable that is unexplained by the lagged dependent variable. In other words, the coefficients capture the effects of variables on contemporaneous changes in the dependent variable relative to the level of the dependent variable in the previous period. We employ four types of ratios as dependent variables, where each ratio is calculated by two components of state government expenditures, as explained shortly. $Gini_{it}$ represents Gini coefficients for either urban or rural areas, and Pop_{it} is the population share of either urban or rural areas. Subscripts denote the state (i) and time (t). Since these variables, especially population ratios of urban and rural areas, are highly correlated, the equation above is estimated separately for urban and rural areas. $Control_{it}$ is a set of control variables that are considered to affect the allocation of state government expenditures. θ_i and θ_t are state and year dummies, respectively, and ε_{it} is the error term.

Moreover, we will also examine the following formulation.

$$Y_{it} = \alpha + \delta Y_{i,t-1} + \varphi Gini_{it} * Pop_{it} + \rho Control_{it} + \theta_i + \theta_t + \varepsilon_{it},$$

where the interaction of a Gini coefficient and population ratio, $Gini_{it} * Pop_{it}$, is included as an independent variable, instead of two separate variables. This is because their combination in this way is expected to capture political power to a greater extent than would be captured by proportionate changes in each variable in isolation.

We use three different estimation methods. First, we conduct an OLS regression with panel-corrected standard errors. Beck and Katz (1995) argue that this estimation method is superior to other methods, such as feasible generalized least squares, when the data are small in cross-sectional terms but cover a long time frame (this is typical in comparative politics). Indeed, previous studies in this field have also adopted this method (e.g., Saez and Sinha 2009; Nooruddin and Chhibber 2008). Second, we conduct a panel data analysis that enables us to control for time-invariant attributes associated with each state. Third, we apply maximum likelihood estimation, which has desirable attributes such as asymptotic unbiasedness, consistency, asymptotic efficiency, and asymptotic normal distribution.[11]

As noted above, according to the classification of Indian government expenditures, we consider four items of development expenditures (industry, energy, transportation, and communications) to be most relevant for the industrial sector. Of course, these items are also desirable for the agricultural sector, as well as other sectors, including households. However, previous studies exploring India's business environment report that insufficient and low-quality infrastructure is among the most serious obstacles to doing business in India (see, for example, the Enterprise Survey conducted by the World Bank in 2006 for India, available at http://www.enterprisesurveys.org/Data). More specifically, we focus on the sum of development expenditures and the sum of development capital expenditures for industry, energy, transportation, and communications. We calculate ratios of these two expenditure items with respect to total state government expenditures and total development expenditures, which include revenue expenditures, as well as capital expenditures. Therefore, our dependent variables are as follows: the ratio of development expenditures for the industrial sector to aggregate state government expenditures; the ratio of development capital expenditures for the industrial sector to aggregate state government expenditures; the ratio of development expenditures for the industrial sector to aggregate development expenditures; and the ratio of development capital expenditures for the industrial sector to aggregate development expenditures.[12]

[11]We also conducted an estimation based on the generalized method of moments (GMM). However, the data utilized herein did not pass the overidentification tests associated with that method and as such we refrain from reporting those results.

[12]Previous studies have shown that the composition of government expenditure may have effects on economic performance; see, for example, Marjit et al. (2013).

4.2 Data Sources and Construction of Variables

Data for state government expenditures are obtained from the EPW Research Foundation database. The principal explanatory variables are rural and urban Gini coefficients, which are available from the Planning Commission website, based on data collected through National Sample Surveys. We also examine the effects of urban and rural population shares using census data because it is reasonable to expect that, in a democratic political system, these shares represent an important factor affecting policy-making.

With respect to public policy choices by governmental entities, we construct a variety of political, social, and economic variables as control variables.

First, to capture the extent of political competition, we include a fractionalization index of political parties' seat shares in the State Legislative Assemblies (see Appendix B for details of the calculation). Data on seats won by political parties in every state legislative assembly (Vidhan Sabha) election in the past can be obtained from the website of the Election Commission of India.

Other political factors have been identified as affecting public policy choices, such as political party identities (Alesina 1987; Alesina and Roubini 1999; Boix 1997), political cycles (Nordhaus 1975; Franzese 2002), and voter turnout (Besley and Burgess 2002; Chhibber and Nooruddin 2004).[13] Herein, we include a voter turnout variable to control for such political factors. An increase in voter turnout reflects increased political activism, by which incumbent political leaders who perform well are more likely to win votes (Besley and Burgess 2002). Moreover, in India, a rise in voter turnout in the 1980s and 1990s was caused by increased participation in elections by poorer segments of society, such as scheduled castes and scheduled tribes. Thus, in this case, the income of the median voter declined, which may have influenced the political strategy of incumbent political parties (see, for example, Chhibber and Nooruddin 2004).

From a sociological viewpoint, social cleavages induced by factors such as ethnic divisions, caste conflicts, and social class confrontation may restrict governments in allocating public goods to different groups (Alesina Baqir, and Easterly 1999; Chandra 2004; Frankel and Rao 1987). For instance, Chandra (2004) argues, based on a detailed analysis of the elites and voters of the Bahujan Samaj Party, that in a patronage-democracy such as India, ethnic demographics play a crucial role in whether an ethnic party succeeds in elections; in particular, the size of a party's target ethnic category should be large enough to allow the party to win. In the book edited by Frankel and Rao (1987), several important chapters show how interactions between castes, religion, and ethnicity have changed Indian society, which is characterized by the dominance of upper castes, in relation to state power.[14] To examine

[13]Note that these studies pay attention to the effects on other dependent variables such as social welfare and infrastructure, not industrialization policy.

[14]Rudolph and Rudolph (1987) also state that "[o]f the many cleavages that animate Indian politics, class usually matters less than other social formations, such as caste, religious and language communities, and regional nationalisms. Other cleavages rival or surpass class on political saliency

the effects of social cleavages, we include variables capturing religious diversity and the heterogeneity of language distribution. Kitchelt and Wilkinson (2007) indicate that social cleavages may serve to sustain clientelistic politics longer. We also control for the population share of scheduled castes and tribes. It would also be desirable to control for the population distribution of each caste, but such data have not been collected since the 1931 census. Moreover, to control for conflicts between social classes, poverty rate is included as a variable. As another sociological variable, literacy rate is also included.[15]

Data on religion are available from censuses. We use data on the relative number of followers of six major religions (Hindu, Muslim, Christian, Sikh, Buddhism, and Jain) and calculate the fractionalization index for each state using the same equation as per the fractionalization index of political parties discussed above and made available in Appendix B.

Similarly, we use census data for the linguistic fractionalization index. In the 1971 Census, 1,652 languages were identified as being spoken in India. However, many of these languages are only spoken by a relatively small number of individuals. In our calculations, we use only the 22 scheduled languages and the 100 nonscheduled languages highlighted in the 2001 Census, which are available from the Census website of the Government of India. The list of languages derived from the 1981 and 1991 Censuses is very similar to the list of languages we are using from the 2001 Census, with differences in terms of only a few languages which are not widely spoken.

Previous studies regarding the effect of scheduled castes and scheduled tribes and religious distribution on policy choice have presented mixed results. For instance, Betancourt and Gleason (2000) find that rural areas with high concentrations of Muslims or scheduled castes have fewer doctors, nurses, and teachers. Banerjee and Somanathan (2007) show that areas with a higher proportion of scheduled castes gained better access to high schools, health centers, and piped water between 1971 and 1991, while those areas where the population was dominated by scheduled tribes and Muslims continued to be at a disadvantage.

Table 1 presents descriptive statistics for the dependent and independent variables; these variables exhibit large variances across states and year. Next, Table 2 presents a bivariate correlation matrix which suggests that no pair of explanatory variables is correlated to the extent that multicollinearity is a serious concern here.

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because the consciousness and commitment focused on them are usually more transparent and accessible than those focused on class."

[15]The data for all of these sociological variables were acquired either from censuses (conducted every ten years in India) or from National Sample Surveys, which are undertaken roughly every 5 years. Linear interpolation was used to generate data for non-census and non-survey years. Therefore, the estimated coefficients associated with these variables should be interpreted with caution and as such we do not emphasize them in our discussion of results.

Table 1 Descriptive statistics

Variable	Obs	Mean	Std. dev.	Min	Max
Ratio of development expenditure for industrial sector to aggregate government expenditure	786	0.10	0.068	0.00629	0.435
Ratio of development capital expenditure for industrial sector to aggregate government expenditure	786	0.04	0.038	0.00004	0.215
Ratio of development expenditure for industrial sector to aggregate development expenditure	786	0.20	0.092	0.02910	0.560
Ratio of development capital expenditure for industrial sector to aggregate development expenditure	786	0.08	0.056	0.00007	0.324
Fractionalization index of Vidhan Sabha party seats	795	0.59	0.165	0.000	0.955
Voter turnout ratio	795	68.55	11.398	23.820	91.530
Urban Gini coefficient	634	0.32	0.048	0.174	0.498
Rural Gini coefficient	634	0.26	0.042	0.156	0.417
Urban population share	802	24.96	10.609	6.258	60.933
Rural population share	802	75.00	10.669	39.067	93.742
Linguistic fractionalization index	802	0.41	0.231	0.063	0.926
Religious fractionalization index	750	0.34	0.170	0.073	0.733
Scheduled caste ratio	791	11.73	8.049	0.000	28.850
Scheduled tribe ratio	791	21.85	27.322	0.000	94.750
Poverty ratio	802	29.78	12.780	3.420	67.680
Literacy rate	865	59.52	14.766	24.124	93.605

5 Estimation Results

Estimation results are presented in Tables 3 through 6, each corresponding to a different dependent variable. In each table, columns (1)–(3) are estimation results based on OLS with panel-corrected standard errors, columns (4)–(6) are results from panel data analysis, and columns (7)–(9) are results from maximum likelihood estimation. Columns (1), (4), and (7) pertain to models where the rural Gini coefficient and rural population ratio are included as independent variables. Columns (2), (5), and (8) pertain to models where the urban Gini coefficient and urban population ratio are included as independent variables. This separation reflects the fact that these variables are highly correlated. For columns (3), (6), and (9), the interaction terms of the rural Gini coefficient and rural population share and of the urban Gini coefficient and urban population ratio are included as independent variables. These interaction terms are not highly correlated. As a precursor to panel data analysis, we conducted a Hausman test to determine whether a random-effects model was

Table 2 Correlation coefficients

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1. Ratio of development expenditure for industrial sector to aggregate government expenditure	1.000															
2. Ratio of development capital expenditure for industrial sector to aggregate government expenditure	0.656	1.000														
3. Ratio of development expenditure for industrial sector to aggregate development expenditure	0.419	0.229	1.000													
4. Ratio of development capital expenditure for industrial sector to aggregate development expenditure	0.083	0.538	0.586	1.000												

(continued)

Table 2 (continued)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
5. Fractionalization index of Vidhan Sabha party seats	−0.220	−0.287	−0.071	−0.150	1.000											
6. Voter turnout ratio	−0.094	−0.015	0.196	0.193	0.114	1.000										
7. Urban Gini coefficient	−0.269	−0.229	−0.129	−0.164	0.158	−0.056	1.000									
8. Rural Gini coefficient	−0.063	−0.086	−0.150	−0.154	−0.088	−0.263	0.546	1.000								
9. Urban population share	−0.047	−0.284	0.238	−0.107	0.084	0.052	0.192	0.183	1.000							
10. Rural population share	0.048	0.284	−0.235	0.108	−0.087	−0.051	−0.194	−0.184	−1.000	1.000						
11. Linguistic fractionalization index	0.038	0.160	0.338	0.421	0.003	0.330	−0.460	−0.513	−0.068	0.069	1.000					
12. Religious fractionalization index	−0.031	−0.040	0.224	0.163	0.317	0.253	−0.163	−0.111	0.182	−0.182	0.305	1.000				
13. Scheduled caste ratio	0.079	−0.010	−0.235	−0.293	−0.134	−0.244	0.342	0.283	−0.210	0.210	−0.593	−0.385	1.000			
14. Scheduled tribe ratio	−0.065	0.084	0.228	0.359	−0.112	0.304	−0.497	−0.428	0.012	−0.011	0.577	0.062	−0.618	1.000		
15. Poverty ratio	−0.129	0.033	−0.538	−0.203	−0.067	−0.322	0.065	0.126	−0.352	0.350	−0.081	−0.310	0.105	−0.084	1.000	
16. Literacy rate	−0.318	−0.303	0.306	0.208	0.221	0.467	0.269	−0.015	0.451	−0.452	0.011	0.296	−0.326	0.189	−0.518	1.000

Table 3 Estimation results for development expenditures for the industrial sector relative to aggregate government expenditures

Dependent variable: ratio of development expenditure for industrial sector to aggregate government expenditure

	OLS with panel-corrected standard errors			Panel data analysis			Maximum likelihood estimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged dependent variable	0.152* (0.0814)	0.146* (0.0805)	0.147* (0.0815)						
Fractionalization index of Vidhan Sabha party seats	−0.0227* (0.0122)	−0.0219* (0.0125)	−0.0202 (0.0123)	−0.0302** (0.0119)	−0.0282** (0.0120)	−0.0281** (0.0119)	−0.0289** (0.0116)	−0.0272** (0.0117)	−0.0268** (0.0116)
Voter turnout ratio	0.000147 (0.000348)	5.50e-05 (0.000355)	0.000153 (0.000342)	0.000244 (0.000210)	0.000143 (0.000218)	0.000206 (0.000208)	0.000178 (0.000205)	9.07e-05 (0.000214)	0.000143 (0.000203)
Linguistic fractionalization index	−0.0300 (0.0320)	−0.0204 (0.0317)	−0.0329 (0.0320)	−0.0320 (0.0265)	−0.0291 (0.0270)	−0.0365 (0.0267)	−0.0420 (0.0268)	−0.0365 (0.0271)	−0.0465* (0.0268)
Religious fractionalization index	0.206*** (0.0453)	0.199*** (0.0465)	0.207*** (0.0455)	0.123*** (0.0340)	0.137*** (0.0350)	0.128*** (0.0347)	0.142*** (0.0408)	0.150*** (0.0407)	0.142*** (0.0403)
Scheduled caste ratio	0.00304**	0.00379***	0.00291**	0.00180*	0.00200*	0.00211**	0.00202*	0.00222*	0.00223*
	(0.00126)	(0.00129)	(0.00127)	(0.00106)	(0.00109)	(0.00107)	(0.00115)	(0.00119)	(0.00114)
Scheduled tribe ratio	0.000716	0.00114	0.000441	8.79e-05	0.000522	0.000222	8.59e-05	0.000512	0.000194
	(0.000703)	(0.000699)	(0.000684)	(0.000335)	(0.000349)	(0.000345)	(0.000373)	(0.000380)	(0.000372)
Poverty ratio	0.000990**	0.000794**	0.000981**	0.000424	0.000248	0.000473	0.000653*	0.000449	0.000656*
	(0.000388)	(0.000391)	(0.000383)	(0.000314)	(0.000326)	(0.000312)	(0.000345)	(0.000350)	(0.000338)
Literacy rate	−0.00161***	−0.00160***	−0.00127**	−0.000869**	−0.000858**	−0.000739*	−0.000858*	−0.000812*	−0.000669
	(0.000552)	(0.000580)	(0.000570)	(0.000424)	(0.000436)	(0.000431)	(0.000447)	(0.000452)	(0.000445)
Rural population share	0.000146			−0.00100**			−0.00102*		
	(0.000594)			(0.000491)			(0.000520)		

(continued)

Table 3 (continued)

Dependent variable: ratio of development expenditure for industrial sector to aggregate government expenditure									
	OLS with panel-corrected standard errors			Panel data analysis			Maximum likelihood estimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rural Gini coefficient	−0.168***			−0.209***			−0.216***		
	(0.0496)			(0.0563)			(0.0554)		
Urban population share		−0.000603			0.000537			0.000560	
		(0.000602)			(0.000514)			(0.000536)	
Urban Gini coefficient		0.113			0.139**			0.122*	
		(0.0742)			(0.0653)			(0.0641)	
Rural Gini coefficient*rural population share			−0.00230***			−0.00275***			−0.00290***
			(0.000670)			(0.000737)			(0.000725)
Urban Gini coefficient*urban population share			0.000478			0.00166			0.00163
			(0.00110)			(0.00108)			(0.00109)
R−squared: overall	0.646	0.636	0.645	0.2202	0.1949	0.202			
R−squared: within				0.4264	0.4199	0.4302			
R−squared: between				0.1146	0.078	0.1026			

(continued)

Table 3 (continued)

Dependent variable: ratio of development expenditure for industrial sector to aggregate government expenditure									
	OLS with panel-corrected standard errors			Panel data analysis			Maximum likelihood estimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Wald Chi2 (p-value)	1835.68(0)	7918.57(0)	8519.6(0)	465.14(0)	451.76(0)	472.61(0)			
LR Chi2 (p-value)							371.47(0)	359.9(0)	375.04(0)
Year dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
State dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	706	706	706	707	707	707	712	712	712
Number of st_id	27	27	27	27	27	27	27	27	27

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

preferable to a fixed-effects model. The results favor a random-effects except for column (6) in Table 6, where a Hausman test could not be executed. Because all the other columns show the estimation results of a random-effects model, the results of a random-effects model are also shown in column (6) of Table 6. Results from all models reported in Table 3 through Table 6 have reasonable values of R-squared, Wald chi-squared in columns (1)–(6), and likelihood ratios in columns (7)–(9).

First, we examine the estimation results in Table 3, where the dependent variable is the ratio of development expenditures for the industrial sector to aggregate state government expenditures. Therein, the rural Gini coefficient has significantly negative coefficients across all three estimation methods, and rural population share has a negative coefficient in columns (4) and (7). The negative coefficients of these variables, which reflect the political power of the agricultural sector, indicate that in a state-year where rural political power is strong, the ratio of industrial development expenditures to total expenditures is lower. In contrast, in columns (5) and (8) the urban Gini coefficient has significantly positive coefficients, though the degree of significance is lower than that for the rural Gini coefficients. This result can be interpreted in terms of the political power of the industrial sector, realized through the concentration of wealth, inducing an increase in the ratio of industrial development expenditures to total expenditures. As explained above, the combination of higher concentration of wealth and a larger population share may yield disproportionate political power. We examine the effects of the interaction terms of the Gini coefficient and population share, both rural and urban, in columns (3), (6), and (9). The interaction term has a highly significant negative estimated coefficient for rural areas, but not for urban areas. This suggests that the negative effect of the strengthening rural political power is stronger than the positive effect of the strengthening urban political power, with respect to the ratio of industrial development expenditures to total expenditures. This implies that the agricultural sector could be a political obstacle to industrialization, namely, that it tends to limit the allocation of government expenditures favorable to the industrial sector.

Moving onto Table 4, here the dependent variable is the ratio of development expenditures for the industrial sector to aggregate development expenditures. Thus, nondevelopmental expenditures are excluded from the denominator. In other words, we are examining the effects of the balance of political power in terms of budget allocations within development expenditures. Table 4 shows that rural population share has a significant negative coefficient in column (4) but other variables related to rural political power do not have significant coefficients. Further, the urban Gini coefficient has a significant positive coefficient in columns (2), (5), and (8). Urban population share also has a significant positive coefficient in column (5). In columns (3), (6), and (9), we also observe that the coefficients of the interaction term of the urban Gini coefficient and urban population share are significantly positive. These results indicate that in the allocation of development expenditures to either the industrial sector or other sectors, the political power of urban elites is a determining factor, rather than that of rural elites.

Table 4 Estimation results for development expenditures for the industrial sector relative to total development expenditures

Dependent variable: ratio of development expenditure for industrial sector to aggregate development expenditure									
	OLS with panel-corrected standard errors			Panel data analysis			Maximum likelihood estimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged dependent variable	0.209***	0.208***	0.196***						
	(0.0414)	(0.0410)	(0.0415)						
Fractionalization index of Vidhan Sabha party seats	−0.0310**	−0.0296*	−0.0278*	−0.0476***	−0.0458***	−0.0451***	−0.0454***	−0.0437***	−0.0425***
	(0.0156)	(0.0157)	(0.0157)	(0.0161)	(0.0161)	(0.0161)	(0.0156)	(0.0156)	(0.0155)
Voter turnout ratio	−4.07e-05	−0.000168	−0.000116	8.68e-05	−2.99e-05	−1.77e-06	5.75e-05	−7.15e-05	−3.21e-05
	(0.000355)	(0.000360)	(0.000352)	(0.000283)	(0.000293)	(0.000281)	(0.000272)	(0.000283)	(0.000270)
Linguistic fractionalization index	−0.0559	−0.0547	−0.0611	−0.103***	−0.104***	−0.110***	−0.0945**	−0.0940**	−0.102***
	(0.0398)	(0.0396)	(0.0402)	(0.0367)	(0.0367)	(0.0366)	(0.0373)	(0.0372)	(0.0372)
Religious fractionalization index	0.245***	0.239***	0.242***	0.203***	0.210***	0.202***	0.236***	0.239***	0.232***
	(0.0567)	(0.0569)	(0.0568)	(0.0483)	(0.0485)	(0.0484)	(0.0546)	(0.0542)	(0.0542)
Scheduled caste ratio	−0.000221	−3.59e-05	−0.000885	0.00127	0.00130	0.00138	0.000983	0.00109	0.000999
	(0.00180)	(0.00179)	(0.00183)	(0.00151)	(0.00152)	(0.00150)	(0.00166)	(0.00166)	(0.00166)
Scheduled tribe ratio	−0.000720	−0.000555	−0.00126	−3.86e-05	0.000277	0.000143	−8.65e-05	0.000247	4.03e-05
	(0.00112)	(0.00109)	(0.00112)	(0.000486)	(0.000488)	(0.000489)	(0.000577)	(0.000574)	(0.000578)
Poverty ratio	0.00168***	0.00150***	0.00160***	0.00108**	0.000913**	0.00105**	0.00149***	0.00129***	0.00144***
	(0.000459)	(0.000471)	(0.000458)	(0.000434)	(0.000443)	(0.000427)	(0.000465)	(0.000470)	(0.000457)
Literacy rate	0.000234	0.000366	0.000894	0.000754	0.000817	0.00104*	0.000692	0.000782	0.00108*
	(0.000704)	(0.000706)	(0.000738)	(0.000592)	(0.000597)	(0.000596)	(0.000620)	(0.000623)	(0.000633)

(continued)

Table 4 (continued)

Dependent variable: ratio of development expenditure for industrial sector to aggregate development expenditure									
	OLS with panel-corrected standard errors			Panel data analysis			Maximum likelihood estimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rural population share	−0.000779			−0.00160**			−0.00149**		
	(0.000916)			(0.000694)			(0.000753)		
Rural Gini coefficient	−0.0715			−0.114			−0.110		
	(0.0687)			(0.0765)			(0.0745)		
Urban population share		0.000621			0.00131*			0.00119	
		(0.000912)			(0.000709)			(0.000763)	
Urban Gini coefficient		0.145*			0.148*			0.154*	
		(0.0852)			(0.0880)			(0.0858)	
Rural Gini coefficient*rural population share			−0.00107			−0.00150			−0.00150
			(0.000943)			(0.000999)			(0.000975)
Urban Gini coefficient*urban population share			0.00425***			0.00424***			0.00437***
			(0.00162)			(0.00149)			(0.00155)
R-squared: overall	0.723	0.723	0.722	0.1814	0.1689	0.1672			
R-squared: within				0.2916	0.2936	0.2988			
R-squared: between				0.3782	0.3624	0.3747			
Wald Chi2 (p-value)	2920.41 (0)	19407.46 (0)	18880.58 (0)	276.32 (0)	277.51 (0)	284.29 (0)			
LR Chi2 (p-value)							247.39 (0)	248.65 (0)	253.86 (0)

(continued)

Table 4 (continued)

Dependent variable: ratio of development expenditure for industrial sector to aggregate development expenditure									
	OLS with panel-corrected standard errors			Panel data analysis			Maximum likelihood estimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
State dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	706	706	706	707	707	707	707	707	707
Number of st_id	27	27	27	27	27	27	27	27	27

Standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

We now turn to Table 5, where the dependent variable is the ratio of development capital expenditures for the industrial sector to aggregate state government expenditures. The results in Table 5 are very similar to those in Table 3. The rural Gini coefficient has highly significant negative coefficients in all columns, and the rural population ratio also has significant negative coefficients in columns (4) and (7). The urban Gini coefficient has significant positive coefficients in columns (5) and (8). The interaction terms of the rural Gini coefficient and rural population share have highly significant negative coefficients in all columns. Moreover, in Table 5, the interaction terms for urban areas have positive coefficients in column (3). Thus, the implication drawn from Table 3 seems to also hold here: greater rural political power tends to reduce allocation of development expenditures for the industrial sector, while greater urban political power tends to increase it, though the effect of rural political power is stronger, overwhelming the effect of urban political power.

Lastly, we examine the estimation results in Table 6, where the dependent variable is the ratio of development capital expenditures for the industrial sector to aggregate development expenditures. In columns (4) and (7), the rural Gini coefficient has significant negative coefficients, and the interaction term of the rural Gini coefficient and rural population share has a significant negative coefficient. We find that the ratio of industrial development capital expenditures to aggregate development expenditures is affected more strongly by rural political power, compared to urban political power, though the opposite is the case in Table 4. This issue represents a potential topic for future research. Still, it is noteworthy to observe that the negative effect of rural political power on the allocation of state government expenditures for the industrial sector also holds in Table 6.

In sum, throughout Tables 3, 4, 5 and 6, we find that variables considered to be related to the political power of rural elites exert negative effects on the ratio of government expenditures for the industrial sector. Also, we find that, although the effects are relatively weak, the variables considered to be related to the political power of urban elites exert positive effects on the ratio of development expenditures for the industrial sector.

Regarding the estimation results for control variables, first, the fractionalization index of Vidhan Sabha seats has robustly and significantly negative coefficients from Tables 3, 4, 5 and 6. This is consistent with Kitschelt and Wilkinson (2007), who suggest that as political competition intensifies, politicians tend to rely more on individualistic clientelistic exchanges, so the allocation of expenditures for the industrial sector tends to shrink. The religious fractionalization index appears to be working in the other direction, albeit less robustly. This result is contrary to our expectations. However, one explanation here could be that as religious groups become more concentrated, politicians find it cheaper to rely on clientelistic exchanges, so expenditures for the industrial sector would decline. Conversely, as religious groups become more fragmented, it becomes costlier for politicians to sustain clientelistic relationships. As a result, budgetary allocations for clientelistic goods decrease and expenditures directed to the industrial sector increase in relative terms. However, this does not explain the relatively consistent results of negative coefficients for the fractionalization index of linguistic groups. We leave this issue for future research.

Table 5 Estimation results for development capital expenditures for the industrial sector relative to total expenditures

Dependent variable: ratio of development capital expenditure for industrial sector to aggregate government expenditure

	OLS with panel-corrected standard errors			Panel data analysis			Maximum likelihood estimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged dependent variable	0.140*	0.158**	0.128						
	(0.0813)	(0.0804)	(0.0812)						
Fractionalization index of Vidhan Sabha party seats	−0.0269***	−0.0260***	−0.0254***	−0.0352***	−0.0339***	−0.0338***	−0.0351***	−0.0339***	−0.0337***
	(0.00769)	(0.00775)	(0.00771)	(0.00671)	(0.00680)	(0.00669)	(0.00649)	(0.00657)	(0.00647)
Voter turnout ratio	0.000271	0.000214	0.000253	0.000338***	0.000298**	0.000320***	0.000339***	0.000298**	0.000320***
	(0.000184)	(0.000187)	(0.000181)	(0.000118)	(0.000124)	(0.000117)	(0.000114)	(0.000119)	(0.000113)
Linguistic fractionalization index	−0.0328*	−0.0228	−0.0348*	−0.0269*	−0.0237	−0.0302**	−0.0277*	−0.0238	−0.0313**
	(0.0193)	(0.0188)	(0.0193)	(0.0149)	(0.0150)	(0.0149)	(0.0148)	(0.0146)	(0.0148)
Religious fractionalization index	0.0330*	0.0286	0.0335*	0.0290	0.0338*	0.0295	0.0301	0.0344*	0.0308
	(0.0198)	(0.0197)	(0.0199)	(0.0193)	(0.0192)	(0.0193)	(0.0193)	(0.0190)	(0.0195)
Scheduled caste ratio	0.00188**	0.00245***	0.00181**	0.000888	0.000933	0.00107*	0.000955	0.000979	0.00115*
	(0.000735)	(0.000755)	(0.000749)	(0.000600)	(0.000599)	(0.000597)	(0.000621)	(0.000633)	(0.000618)
Scheduled tribe ratio	0.000288	0.000565	0.000209	4.06e-05	0.000288	0.000118	4.93e-05	0.000297	0.000129
	(0.000418)	(0.000406)	(0.000396)	(0.000190)	(0.000189)	(0.000192)	(0.000192)	(0.000191)	(0.000196)
Poverty ratio	0.000381*	0.000253	0.000354	0.000139	2.95e-06	0.000155	0.000159	1.29e-05	0.000175
	(0.000227)	(0.000222)	(0.000224)	(0.000177)	(0.000182)	(0.000174)	(0.000180)	(0.000184)	(0.000175)
Literacy rate	−0.00115***	−0.00115***	−0.000908**	−0.000837***	−0.000816***	−0.000748***	−0.000862***	−0.000828***	−0.000764***
	(0.000344)	(0.000360)	(0.000361)	(0.000240)	(0.000242)	(0.000240)	(0.000244)	(0.000243)	(0.000240)
Rural population share	−0.000511			−0.000594**			−0.000619**		
	(0.000353)			(0.000278)			(0.000282)		

(continued)

Table 5 (continued)

Dependent variable: ratio of development capital expenditure for industrial sector to aggregate government expenditure									
	OLS with panel-corrected standard errors			Panel data analysis			Maximum likelihood estimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rural Gini coefficient	−0.132***			−0.149***			−0.150***		
	(0.0354)			(0.0317)			(0.0308)		
Urban population share		0.000204			0.000312			0.000324	
		(0.000350)			(0.000283)			(0.000283)	
Urban Gini coefficient		0.0582			0.0676*			0.0673*	
		(0.0456)			(0.0368)			(0.0357)	
Rural Gini coefficient*rural population share			−0.00184***			−0.00196***			−0.00199***
			(0.000495)			(0.000414)			(0.000405)
Urban Gini coefficient*urban population share			0.00108*			0.000931			0.000989
			(0.000644)			(0.000604)			(0.000605)
R-squared: overall	0.555	0.547	0.552	0.1419	0.1507	0.1225			
R-squared: within				0.3265	0.304	0.3323			
R-squared: between				0.0747	0.0875	0.0449			
Wald Chi2 (p-value)	3344.75 (0)	3379.36 (0)	3194.64 (0)	302.85 (0)	275.35 (0)	309.17 (0)			
LR Chi2 (p-value)							265.43 (0)	245.40 (0)	269.98 (0)

(continued)

Table 5 (continued)

Dependent variable: ratio of development capital expenditure for industrial sector to aggregate government expenditure

	OLS with panel-corrected standard errors			Panel data analysis			Maximum likelihood estimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
State dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	706	706	706	707	707	707	707	707	707
Number of st_id	27	27	27	27	27	27	27	27	27

Standard errors in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 6 Estimation results for development capital expenditures for the industrial sector relative to total development expenditures

Dependent variable: ratio of development capital expenditure for industrial sector to aggregate development expenditure									
	OLS with panel-corrected standard errors			Panel data analysis			Maximum likelihood estimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lagged dependent variable	0.382*** (0.0354)	0.387*** (0.0352)	0.385*** (0.0353)						
Fractionalization index of Vidhan Sabha party seats	−0.0330***	−0.0322***	−0.0312***	−0.0530***	−0.0522***	−0.0522***	−0.0533***	−0.0526***	−0.0522***
	(0.0101)	(0.0101)	(0.0101)	(0.0104)	(0.0104)	(0.0104)	(0.00999)	(0.0100)	(0.0100)
Voter turnout ratio	1.09e-06	−6.54e-05	−1.98e-05	0.000137	0.000112	0.000159	0.000132	0.000108	0.000160
	(0.000154)	(0.000161)	(0.000153)	(0.000182)	(0.000189)	(0.000181)	(0.000176)	(0.000182)	(0.000175)
Linguistic fractionalization index	−0.0332	−0.0300	−0.0344	−0.0609***	−0.0595***	−0.0642***	−0.0609***	−0.0602***	−0.0642***
	(0.0251)	(0.0247)	(0.0249)	(0.0228)	(0.0230)	(0.0225)	(0.0215)	(0.0216)	(0.0218)
Religious fractionalization index	0.0450	0.0409	0.0427	0.0603**	0.0640**	0.0601**	0.0587**	0.0617**	0.0602**
	(0.0323)	(0.0322)	(0.0322)	(0.0291)	(0.0293)	(0.0283)	(0.0271)	(0.0269)	(0.0276)
Scheduled caste ratio	0.000300	0.000522	8.00e-05	0.000690	0.000748	0.000890	0.000650	0.000671	0.000894
	(0.00106)	(0.00103)	(0.00106)	(0.000905)	(0.000913)	(0.000874)	(0.000841)	(0.000838)	(0.000851)
Scheduled tribe ratio	−0.00121	−0.00107	−0.00144*	0.000150	0.000319	0.000176	0.000156	0.000314	0.000176
	(0.000826)	(0.000808)	(0.000812)	(0.000284)	(0.000287)	(0.000277)	(0.000260)	(0.000259)	(0.000268)
Poverty ratio	−4.15e-05	−0.000149	−7.62e-05	−0.000244	−0.000328	−0.000184	−0.000255	−0.000338	−0.000183
	(0.000278)	(0.000280)	(0.000277)	(0.000271)	(0.000278)	(0.000263)	(0.000257)	(0.000261)	(0.000255)
Literacy rate	−0.000391	−0.000338	−0.000117	−0.000217	−0.000211	−0.000235	−0.000193	−0.000183	−0.000236
	(0.000448)	(0.000456)	(0.000481)	(0.000365)	(0.000369)	(0.000358)	(0.000346)	(0.000345)	(0.000347)

(continued)

Table 6 (continued)

Dependent variable: ratio of development capital expenditure for industrial sector to aggregate development expenditure									
	OLS with panel-corrected standard errors			Panel data analysis			Maximum likelihood estimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Rural population share	−0.000166			0.000268			0.000297		
	(0.000555)			(0.000421)			(0.000396)		
Rural Gini coefficient	−0.0650			−0.103**			−0.100**		
	(0.0515)			(0.0488)			(0.0471)		
Urban population share		1.97e-05			−0.000445			−0.000475	
		(0.000547)			(0.000432)			(0.000399)	
Urban Gini coefficient		0.0736			0.0450			0.0432	
		(0.0558)			(0.0562)			(0.0538)	
Rural Gini coefficient*rural population share			−0.000839			−0.00118*			−0.00118*
			(0.000713)			(0.000636)			(0.000622)
Urban Gini coefficient*urban population share			0.00131			−0.000506			−0.000498
			(0.000969)			(0.000906)			(0.000891)
R-squared: overall	0.661	0.662	0.664	0.3335	0.3474	0.3046			
R-squared: within				0.1665	0.1609	0.1658			

(continued)

Table 6 (continued)

Dependent variable: ratio of development capital expenditure for industrial sector to aggregate development expenditure									
	OLS with panel-corrected standard errors			Panel data analysis			Maximum likelihood estimation		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
R-squared: between				0.6062	0.6227	0.5881			
Wald Chi2 (p-value)	1434.89 (0)	1433.66 (0)	6971.27 (0)	160.14 (0)	155.04 (0)	160.92 (0)			
LR Chi2 (p-value)							148.71 (0)	144.85 (0)	146.77 (0)
Year dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
State dummy	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	706	706	706	707	707	707	707	707	707
Number of st_id	27	27	27	27	27	27	27	27	27

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

We also found that the ratio of the scheduled caste population and the poverty ratio have positive coefficients. These results are consistent with inter-elite competition theory. For a significant part of our sample period, scheduled caste people as well as poor people were politically inactive. As the ratio of these politically weak people rises, elites would be able to exert stronger leverage over the allocation of government expenditures. Thus, government expenditures to the industrial sector increase, rather than expenditures directed toward the social sector or clientelistic goods such as public sector jobs.

Lastly, the literacy rate coefficient is negative and highly significant in Tables 3, 4 and 5. This seems to indicate that as more people become educated, especially poor people who previously could not access education, they become aware of their possible influence on public policy and mobilize themselves politically. Then, they could advocate for the enactment of redistributive policies which would concomitantly reduce pro-industry expenditure allocations.

6 Conclusion

In this study, we examined how the political influence of the rural and urban sectors impacts the allocation of Indian state government expenditures for the industrial sector. Our estimation results indicate that as the political influence of rural elites increases, Indian state governments tend to reduce development expenditures, as well as development capital expenditures, to the industrial sector. We also find some evidence, albeit weaker, that as the political influence of urban elites increases, expenditures for the industrial sector tend to increase. Our results imply that there is some sort of battle over the allocation of government expenditures between rural and urban elites, and rural elites may exert an influence that limits the allocation of government expenditures conducive to industrialization. In that sense, the political influence of rural elites can be harmful to economic development in a broad sense.

Appendix: Data Sources and Construction of Variables

(Dependent Variables)

Ratios of development (capital) expenditures for the industrial sector: Data on state government expenditures were obtained from the EPW Research Foundation database.

(Independent Variables)

Gini coefficients: Gini coefficients for both rural and urban areas are available from the Planning Commission website and the original data were collected through National Sample Surveys.

Population shares of rural and urban areas: Data on population shares were obtained from different sources, including the Planning Commission website. All such data were collected in censuses.

Political competition variables: All data on Vidhan Sabha elections were obtained from the website of the Election Commission of India. We calculate the fractionalization index of Vidhan Sabha seats based on the following equation.

$$\text{Fractionalization index} = 1 - \sum_{i=1}^{n} (sh_i)^2,$$

where sh_i is the share of seats in a state assembly that party i won in the last election (see Alesina et al. 1999). The fragmentation index is one minus the Herfindahl index of political parties.

Voter turnout: Data on voter turnout rates are available from the website of the Election Commission of India.

Religious fractionalization: Data on religious distribution are available from censuses. Data on the relative number of followers of the six major religions (Hindu, Muslim, Christianity, Sikh, Buddhism, and Jain) are used to calculate the fractionalization index using the same equation as for the fractionalization index of political parties. We treat "other religions" and "religion not stated" as two separate religious groups so that the shares of all the religions add up to one. The shares of these two groups are negligible in that they do not substantively affect the calculated values of the indices. Linear interpolation was used to generate data in non-census years.

Linguistic fractionalization: We include the 22 scheduled languages and the 100 nonscheduled languages highlighted in the 2001 Census (see the Census website of the Government of India). For the 1981 and 1991 Censuses, the list of languages identified is almost the same as that in the 2001 Census. Linear interpolation was used to generate data in non-census years.

SC share and ST share: The population share of scheduled castes (SC) and scheduled tribes (ST) are available from the Planning Commission website, and the original data were collected through National Sample Surveys conducted by the National Sample Survey Organization approximately every 5 years. Linear interpolation was used to generate data in non-survey years.

Poverty rate: Data on poverty rates are available from the Planning Commission website, and the original data were collected through National Sample Surveys conducted by National Sample Survey Organization approximately every 5 years. Linear interpolation was used to generate data in non-survey years.

Literacy rate: Data on literacy rates were obtained from censuses. Linear interpolation was used to generate data in non-census years.

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Environment and Economic Development: An Analysis of Electricity Demand Projections for India

Purnamita Dasgupta and Chetana Chaudhuri

1 Introduction

Growth of electricity demand is closely related to the social and economic development of a country (Abdoli et al. 2015; Bayar 2014; Sengupta 2016). Increase in electricity use widens economic opportunity to the population, improves social infrastructure, and increases productivity. The per capita consumption of electricity is often considered to be a marker of development and well-being of the concerned population. The importance of access to electricity sits within the Sustainable Development Goal (SDG 7) which is to ensure access to affordable, reliable, sustainable, and modern energy for all (UN 2015). India, on one hand, has been hailed for its achievements in recent years for enhancing electrification and universal energy access through several government-driven programs, which seek to enhance energy efficiency (such as LED bulbs under the UJALA program) and access to clean fuels (such as LPG under the Ujjwala program), and expanded coverage through various initiatives in renewable energy (such as under the National Solar Mission).

However, as of 2016, it is estimated that over 205 million people in India do not have access to electricity, while many more have average consumption levels that are far below international thresholds for energy access for an acceptable quality of life. This can have far-reaching consequences for health and well-being. According to the WHO, one million deaths occur in India, due to the use of solid cooking fuels. The Government of India, through its Pradhan Mantri Ujjwala Yojana (PMUY), is seeking to improve access to LPG for low-income households, to enhance the use of cleaner cooking fuels and reduce the burden of disease associated with the indoor air

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pollution caused by use of solid cooking fuels. Electricity from clean sources may also be actively considered as an alternative option, at least for partial use.

It is, therefore, to be expected that over the coming years, as the economy grows, there will be an exponential growth in the demand for energy, of which electricity is a major component. This poses both a challenge and an opportunity for the country (Sengupta 2016; Dutta et al. 2015).

Meeting the electricity demand of a growing economy, with a rising population, raises concerns about a potential increase in the pollution level and environmental degradation, based on the fact that till date coal is the primary source of electricity generation in the country. 71% of India's total energy-related CO2 emission is generated from coal. Coal-based electricity generation contributes to both local pollution and global warming. Reducing dependence on coal is one of the major energy-related policy goals to curb pollution level for India. The threat of climate change is looming large on the world economy, and many countries are making efforts to reduce fossil fuel-based energy consumption to keep the rise in global temperature below 2 degree Celsius above pre-industrial level (IPCC 2018). India is also not an exception. Initiatives are taken to promote wind power, solar power, biogas, and other renewable energy sources. But electricity is one of the essential inputs in industrial production and access to electricity is one of the prerequisites to ensure a basic standard of living. With increase in population, associated rapid increase in demand for goods and services, and change in lifestyle, the demand for electricity is also increasing in an expeditious manner.

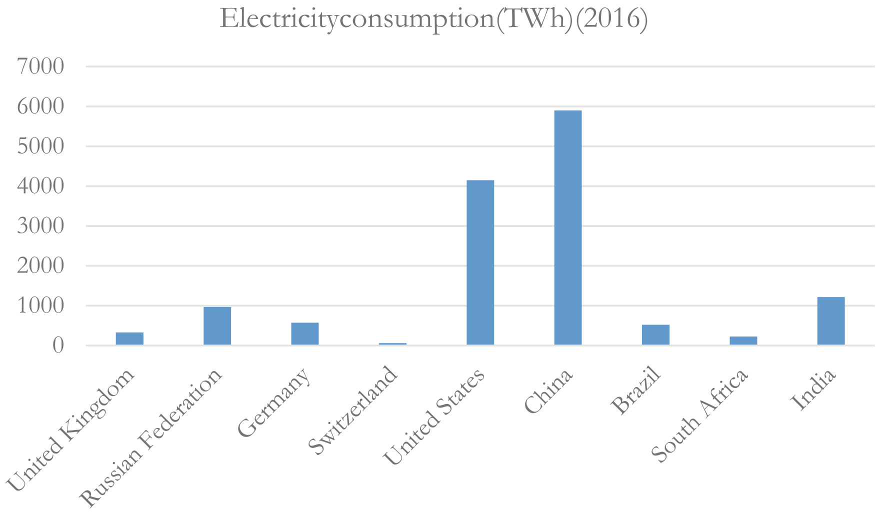
In this study, we examine the relationship between economic growth and electricity consumption, and make projections in electricity demand based on evidence from international experience. Section 2 elaborates on the context and rationale for the study, comparing global electricity consumption with India's consumption, in relation to its GDP. Section 3 analyzes the spatial and sectoral distribution of electricity consumption and generation within the economy. Section 4 draws upon insights from international experience on the relationship between economic growth and electricity consumption, and presents the methodology used in the paper for estimating this relationship for India. Section 5 presents the results, and Sect. 6 concludes with a discussion on the way forward in the light of recent policy initiatives in the energy sector.

2 Context and Rationale

Historically, there is very little evidence of strong decoupling of energy use and economic growth (Kan et al. 2019; Ward et al. 2016). India is a lower middle-income country (as defined by the World Bank in 2018), which has per capita GDP (at constant 2010 US$) of 1642.4 in 2014, while world average is 10,139.6 (World Bank 2019). Since India is thriving on achieving economic development, demand for electricity is also going to rise, since energy is essential for production process and for building up social infrastructure. Despite that, per capita electricity demand is very low in India, which was 805.6 Kwh in 2014, while the world average is 3127.5 Kwh, which is 3.9 times of the former. Average consumption of electricity also varies considerably across regions, depending on their stage of development; in Sub-Saharan Africa, per capita electricity consumption is 480.3 Kwh in 2014, while High-income countries on an average consumed 8834.3 Kwh per capita in the same year. So like other infrastructural parameters, electricity consumption is lagging behind in low-income countries as compared to high-income countries. Now, with the course of development, the low-income countries are expected to catch up the growth path of high-income countries. The study wants to explore the extent of growth of India in this context and how this is going to affect the nature of electricity consumption at different levels of development.

Total primary energy supply (TPES) of the world has increased from 6101.05 Mtoe to 13,761.45 Mtoe from 1973 to 2016 (IEA 2018). Majority of this can be attributed to huge increase in consumption of electricity, due to increase in access as well as diversified use of electricity. Electricity consumption per capita for the world as an average has increased from 1346.4 Kwh in 1973 to 3127.5 Kwh in 2014 (WDI 2019). But the increase in electricity consumption is not even, while the high-income countries moved toward very high consumption of electricity (8834.3 Kwh per capita in 2014), low- and middle-income countries are still limited to a low level of electricity consumption (1922.1 Kwh per capita in 2014). Comparison of total electricity consumption for some high-income and transition economies is shown in Table 1, which clearly shows that India's total electricity consumption is very low compared to China or Unites States, despite its large volume of population.

Table 1 Total electricity consumption (Twh) in 2016 across different countries



Source IEA Key World energy statistics (IEA 2018)

Table 2 Per capita electricity consumption (Kwh) and per capita GDP in constant 2010 US$ across countries for 2014

Country	Per capita electricity consumption (kwh)	Per capita GDP in constant 2010 US$
United Kingdom	5129.5	41,124.1
Russian Federation	6602.7	11,680.6
Germany	7035.5	45,132.3
Switzerland	7520.2	76,410.9
United States	12,994.0	51,015.1
China	3927.0	6108.2
Brazil	2601.4	11,866.4
South Africa	4198.4	7583.6
India	805.6	1642.4
World	3127.5	10,139.6

Source World development indicator (2019)

If we compare per capita electricity consumption of India with other countries of the world, it can easily be seen that India is lagging far behind from other developed countries like United States, Switzerland, Germany, Russian Federation, or United Kingdom (Table 2). Per capita electricity consumption of India is even lower than major economies in transition like Brazil and South Africa. Per capita GDP in India is also considerably lower than these countries.

3 The Indian Scenario

Total electricity consumption in India has increased from 237.6 Twh in 1990 to 1216.11 Twh in 2016 (IEA 2018). With increasing population and urbanization, the demand for electricity is rising rapidly. The demand is increasing not only in aggregate terms, but also in per capita terms also. Figure 1 shows the historical trend in electricity consumption and GDP over the years 1990–2014. As can be seen, with increase in GDP, electricity consumption has increased in the past.

Sector-wise distribution shows that though services sector has highest share in GDP, the share of industrial sector in electricity consumption is still very high, 40% of the total electricity consumption (Fig. 2). Residential sector has also very high share in electricity consumption (24%). Agriculture, which now contributes around 16% of Indian GDP, have a share of 18% of total electricity consumption.

From the supply side, electricity generation sources include thermal, hydro, nuclear, and renewable energy sources (RES). Still thermal power has the highest share (67%) in total installed electricity generation capacity for utilities in India (in 2017), whereas the share of renewable energy is 17%. Like other countries of the

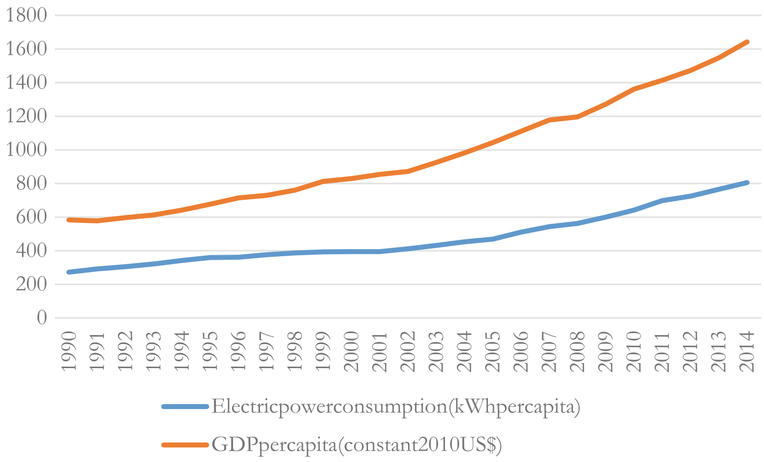


Fig. 1 Trend in electricity consumption (Kwh per capita) and GDP per capita (constant 2010 US$) over years in India *Source* World development indicator (2019)

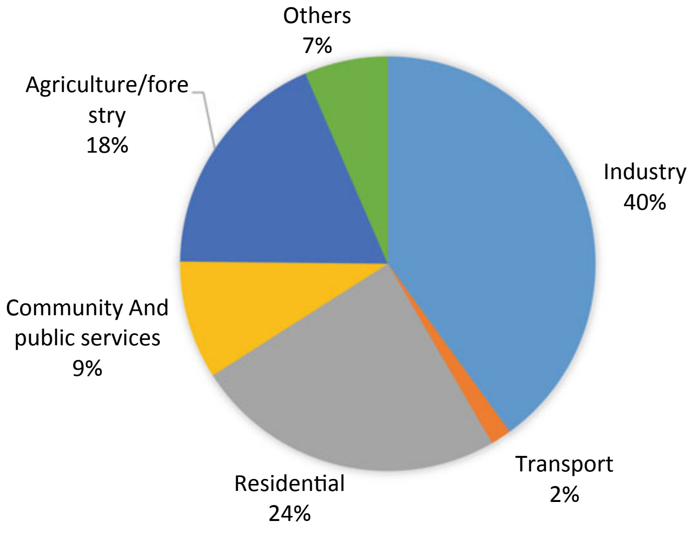


Fig. 2 Share of different sectors in electricity consumption in India (2016–17) *Source* Energy statistics (2018)

world, there has been major policy emphasis on promotion of renewable energy in recent years. Solar energy in India is increasing rapidly. According to Energy Statistics 2018, solar installed capacity has reached 12.28 GW in 2016–17. Major part of the installed electricity generation capacity is led by central government.

State-wise and central share in installed electricity generation capacity shows that major volume of electricity generation capacity is installed in centrally producing units. State-wise highest volume of electricity generation capacity is installed in Maharashtra, followed by Gujarat and Tamil Nadu (Table 3). It is also seen that major source of power generation is still thermal, 67% for All-India installed electricity generation capacity. In states like Maharashtra, Gujarat, Chhattisgarh, and Uttar Pradesh, thermal electricity generation capacity is quite high (23.74, 20.25, 14.23, and 12.57 GW, respectively). Tamil Nadu has the highest share in renewable energy generation capacity among states (19%), followed by Karnataka, Maharashtra, and Gujarat.

Share of different regions in installed electricity generation capacity shows that highest electricity generation capacity is for western region, with a subtotal of 112.38 GW, but majority of it is in thermal sector. In northeast region, hydropower generation capacity is highest compared to other regions. Southern region has highest electricity generation capacity from renewable energy installed (Fig. 3).

In the next section, we investigate the relationship between economic growth and electricity consumption, how it is interpreted in the literature, and how it be utilized to forecast India's future electricity demand.

4 Evolving a Method for Estimation of India's Electricity

4.1 Insights from International Experience

The relationship between electricity consumption and economic growth has been analyzed by several scholars using various methods. Most of the studies concentrated on the causal relationship between electricity consumption and GDP, and have come up with differing findings (Aslan 2014; Chang 2010; Shahbaz and Feridum 2012; Narayan and Smyth 2009; Squalli 2007; Yuan et al. 2007; Shiu and Lam 2004; Chen et al. 2007; Yoo 2005, 2006, Mozumder and Marathe 2007; Narayan and Singh 2007; Reynolds and Kolodziej 2008; Narayan and Prasad 2008; Wolde-Rufael 2004, 2006; Apergis and Payne 2009; Chandran et al. 2009; Bowden and Payne 2009; Soytas and Sari 2009). We discuss in detail some of the studies that are relevant for this paper.

We note that several studies have found unidirectional causality running from electricity consumption to economic growth (Altinay and Karagol 2005; Shiu and Lam 2004; Wolde-Rufael 2004; Narayan and Prasad 2008). On the other hand, (Hein 2019; Ouédraogo 2010; Ciarreta and Zarraga 2010; Ghosh 2002) have found that unidirectional causality runs from economic growth to electricity. Some studies have found that the two variables are jointly determined, which propagates a bidirectional causal relationship among the two (Jumbe 2004; Yoo 2005). Some studies have found that a causal relationship does not exist between electricity consumption and economic growth (Tang 2008). Yoo (2006) also did not find any such relationship between the two variables in Thailand and Indonesia.

Inter-country comparisons of two or more countries can sometimes help to bring out a clearer picture. Lin & Wang (2019) found inconsistency between economic

Table 3 State-wise share of installed electricity generation capacity of (utilities) for India (2017) (in GW)

States/UTs	Hydro	Thermal	Nuclear	RES	Total
Andhra Pradesh	1.75 (3.9%)	12.52 (5.7%)	0 (0%)	6.16 (10.8%)	20.43 (6.3%)
Bihar	0 (0%)	0.21 (0.1%)	0 (0%)	0.29 (0.5%)	0.5 (0.2%)
Chhattisgarh	0.12 (0.3%)	14.23 (6.5%)	0 (0%)	0.43 (0.8%)	14.78 (4.5%)
Gujarat	0.77 (1.7%)	20.25 (9.3%)	0 (0%)	6.67 (11.7%)	27.7 (8.5%)
Haryana	1.08 (2.4%)	5.03 (2.3%)	0 (0%)	0.25 (0.4%)	6.37 (1.9%)
Himachal Pradesh	2.37 (5.3%)	0 (0%)	0 (0%)	0.83 (1.5%)	3.2 (1%)
Jammu & Kashmir	1.23 (2.8%)	0.18 (0.1%)	0 (0%)	0.16 (0.3%)	1.56 (0.5%)
Jharkhand	0.13 (0.3%)	1.78 (0.8%)	0 (0%)	0.03 (0.1%)	1.93 (0.6%)
Karnataka	3.6 (8.1%)	7.23 (3.3%)	0 (0%)	7.46 (13%)	18.29 (5.6%)
Kerala	1.88 (4.2%)	0.33 (0.2%)	0 (0%)	0.34 (0.6%)	2.55 (0.8%)
Madhya Pradesh	1.7 (3.8%)	9.83 (4.5%)	0 (0%)	3.54 (6.2%)	15.07 (4.6%)
Maharashtra	3.33 (7.5%)	23.74 (10.9%)	0 (0%)	7.65 (13.4%)	34.72 (10.6%)
Odisha	2.06 (4.6%)	5.42 (2.5%)	0 (0%)	0.19 (0.3%)	7.68 (2.3%)
Punjab	2.57 (5.8%)	7.79 (3.6%)	0 (0%)	1.15 (2%)	11.52 (3.5%)
Rajasthan	1.09 (2.5%)	8.99 (4.1%)	0 (0%)	6.24 (10.9%)	16.32 (5%)
Tamil Nadu	2.2 (4.9%)	8.71 (4%)	0 (0%)	10.63 (18.6%)	21.54 (6.6%)
Telangana	2.31 (5.2%)	5.47 (2.5%)	0 (0%)	1.55(2.7%)	9.32 (2.9%)
Uttar Pradesh	0.72 (1.6%)	12.57 (5.8%)	0 (0%)	2.3 (4%)	15.59 (4.8%)
Uttarakhand	1.98 (4.5%)	0.55 (0.3%)	0 (0%)	0.52 (0.9%)	3.05 (0.9%)
West Bengal	0.99 (2.2%)	7.4 (3.4%)	0 (0%)	0.42 (0.7%)	8.81 (2.7%)
Other States total	1.08 (2.4%)	11.92 (5.5%)	0 (0%)	0.38 (0.7%)	13.41 (4.1%)

(continued)

Table 3 (continued)

States/UTs	Hydro	Thermal	Nuclear	RES	Total
Total central	11.51 (25.9%)	54.18 (24.8%)	6.78 (100%)	0 (0%)	72.47 (22.2%)
Total	44.47 (100%)	218.33 (100%)	6.78 (100%)	57.19 (100%)	326.81 (100%)

Source Energy statistics (2018)
Note Figures in parenthesis is the share of the state in total for that component

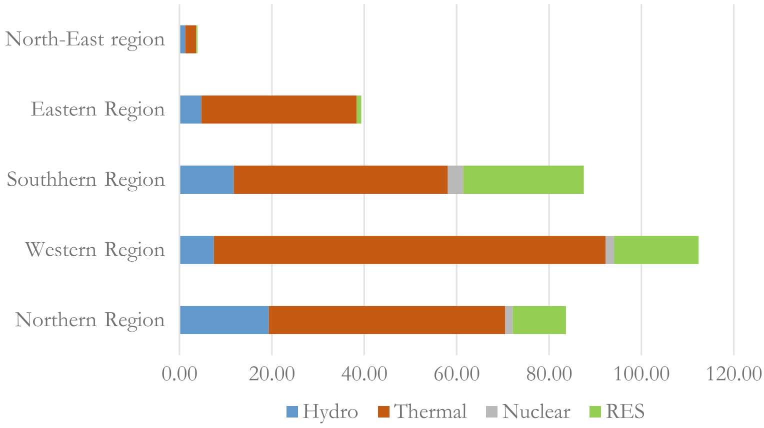


Fig. 3 Region-wise share of Installed electricity generation capacity of (utilities) for India (2017) (in GW) *Source* Energy statistics (2018)

growth and electricity consumption in China and explained that increases in inventory, fixed capital, and industrial electricity consumption are the reasons behind it. Wolde-Rufael (2006) tested the long-run and causal relationship between electricity consumption per capita and real gross domestic product (GDP) per capita for 17 African countries for the period 1971–2001. The paper found a positive unidirectional causality running from real GDP per capita to electricity consumption per capita for six countries, while opposite causality was found for three countries and bidirectional causality was found in the remaining three countries. Yoo and Kwak (2010) found that causality runs from electricity consumption to economic growth in Argentina, Brazil, Chile, Columbia, and Ecuador, while electricity consumption and economic growth Granger cause each other in Venezuela. Chen et al. (2007) estimated the relationship between GDP and electricity consumption for 10 newly industrializing and developing Asian countries using both single data sets and panel data procedures.

Abbas and Choudhury (2013) found a bidirectional causality between agricultural electricity consumption and the agricultural GDP in India, while for Pakistan, the causality was found to run in the opposite direction. Further studies examined the relationship introducing some other factors in the model as control variables along with electricity consumption and economic growth. Narayan and Smyth (2009) explored the causal relationship between electricity consumption, exports, and gross domestic product (GDP) for a panel of Middle Eastern countries and found both-way relationships between economic growth and electricity consumption. Odhiambo (2009) examined the relationship between electricity consumption, employment, and economic growth for Tanzania.

For India, Ghosh (2009) studied the relationship between electricity supply, employment, and real GDP using ARDL multivariate approach. Jamil and Ahmad (2010) analyzed the relationship among electricity consumption, its price, and real

GDP at the aggregate and sectoral level in Pakistan using annual data for the period 1960–2008, and found the presence of unidirectional causality from real economic activity to electricity consumption. Another study on Pakistan (Javid and Qayyum 2014) estimated electricity demand for Pakistan by applying the structural time series technique to annual data for the period from 1972 to 2012 and concluded that either energy-efficient equipment has not been introduced in these sectors or any energy efficiency improvement caused by technical progress is outweighed by other exogenous factors. Kantar and Keskin (2013) used hierarchical structure methods and a hierarchical tree to examine the relationship between energy consumption and economic growth in a sample of 30 Asian countries and found a strong relationship between energy consumption and economic growth for all income groups considered in this study. Karanfil and Li (2015) examined the long- and short-run dynamics between electricity consumption and economic activities, using a panel data of per capita electricity consumption and per capita GDP of 160 countries and showed that the electricity-growth nexus is highly sensitive to regional differences, countries' income levels, urbanization rates, and supply risks.

4.2 Data and Methodology

In most of the studies, the causal relationship between electricity consumption and economic growth is explored using time series data on one country or panel data for more than one country or region. But this relationship essentially depends on the characteristics of that particular country and the stage of growth in which it can be categorized. Historically, it is seen that for the most part, developing and least developed countries tend to follow a set path of development, which unfolds gradually as their economic and energy policies, institutional arrangements, infrastructure, public awareness to environmental issues, and energy supply mix evolves. This is a path that mirrors that followed by what is today considered to be the global north or the developed part of the world, albeit with varying time lags. As a consequence, cross-sectional data of different countries reflects different stages of development, which can be treated as representative of the growth path as a country transitions from a low-income stage to a high-income stage. In this paper, we explore the relationship between electricity consumption and economic growth, from the cross-sectional data of different countries, and use the development experience itself to estimate the future electricity demand for India.

In other words, we conduct a cross-sectional study to examine the dependence of per capita electricity consumption on economic growth across countries and based on these estimates, we project electricity consumption for India for future years. We assume a linear relationship between electricity consumption per capita and GDP per capita for simplicity. The objective here is to explore the directionality of the findings and establish the important linkages that need to be kept in mind for economic and environmental management using a simple approach.

To capture the change in the trends in electricity consumption that are considered to result from a change in the stage of development, we introduce a dummy variable as a proxy to capture the stage of economic development of the country. To represent the stage of economic development, we have used the categorization of countries by the World Bank (2018), viz., high-income countries, upper middle-income countries, and lower middle- and low-income countries. We have clubbed the first two as "high- and upper middle-income countries" and the last two as "Lower middle- and low-income countries" for defining the dummy variable. The relationship can be written as

$$\mathrm{Elec}_{\mathrm{pc}} = \alpha_0 + \alpha_1\, GDP_{\mathrm{pc}} + \alpha_2\, D + u$$

where $\mathrm{Elec}_{\mathrm{pc}}$ represents the electricity consumption per capita (kwh), $\mathrm{GDP}_{\mathrm{pc}}$ represents GDP per capita, and D represents the dummy variable for income category. Once this relationship is known to us, we can predict for future level of electricity consumption per capita developing alternative growth path scenarios for India. For example, if the value of dummy variable for "High- and upper middle-income countries" is assigned as "1" and the value of the dummy variable for "Lower middle- and low-income countries" is assigned as "0", then the intercept of the equation becomes "$\alpha_0 + \alpha_2$" for "High- and upper middle-income countries" and "α_0" for "Lower middle- and low-income countries." GDP is predicted across three scenarios: a pessimistic scenario (6% growth rate of GDP), a business-as-usual (BAU) scenario (6.7% growth rate of GDP), and an optimistic scenario (10% growth rate of GDP). Based on the predicted values of GDP in each of the scenarios, electricity demand per capita is predicted for India, depending on the year in which the economy is shifting its growth path from lower middle-income status to upper middle-income status.

It may also be noted that we estimated alternative formulations adding more variables such as urbanization, the structure of the economy in terms of value added from different sectors, electricity consumption, population, and urbanization. These could be expected to be major drivers of the economy in the future. However, we did not find a significant difference to the explanatory power of the equation, indicating that as far as estimating the relationship with GDP is concerned, the equation works well. The autoregressive distributed lag approach, or the ARDL approach, was also used to separately examine the short-run causalities between the variables and verify that there is indeed the existence of a long-run relationship among them. For this, time series data for a period of 40 years from 1970 to 2010 was used. Thereafter, having established the robustness of the relationship across models, we used the estimates to project electricity demand, using the simplest formulation.

Data on electricity consumption per capita and GDP are collected from the World Development Indicators published by The World Bank (2019). The GDP data is in constant 2010 US$ to make it comparable across countries and years. The country classification based on income follows the classification made by The World Bank 2018, which divides the economies among income groups according to their 2016 gross national income (GNI) per capita, which in turn is calculated using the World

Bank Atlas method. The definitions of groups are provided as low income, \$995 or less; lower middle income, \$996–3,895; upper middle income, \$3,896–12,055; and high income, \$12,056 or more (WDI 2019). GDP data is converted to GNI with suitable conversion factor to capture the year in which India is estimated to cross these aforementioned threshold levels. Since no population projection data is available published by Government of India based on Census 2011 or after, population projection data is collected from population forecasts done by UNFPA (2019).

5 Results

GDP and electricity consumption per capita data used in this study is for 136 countries for 2014, for which the latest electricity consumption per capita data are available. Among them, 15 countries are "low-income," 31 countries are "lower middle-income," 40 countries are "upper middle-income," and 50 countries are "high-income" countries. Figure 4 shows the scatter plot of electricity consumption per capita and GDP per capita for different countries in 2014. It is evident that the level of electricity consumption varies widely. Low-income countries are at the lowest consumption levels of electricity and with an increase in income, there is a significant jump in the electricity consumption.

The study estimates suggest that India would shift from being a lower middle-income country to an upper middle-income country in 2035 under the pessimistic

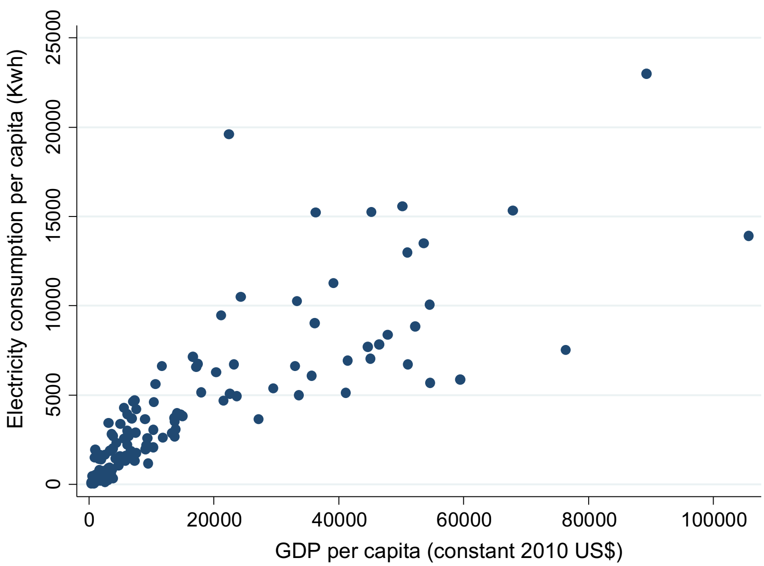


Fig. 4 Scatter plot of electricity consumption per capita and GDP per capita across countries (2014) *Source* WDI (2019)

scenario. Under a BAU scenario, India is expected to shift from being a lower middle-income country to an upper middle-income country in 2031, and further, to reach the high-income country level by 2050. Under an optimistic scenario with a very high growth rate, India may be expected to reach the upper middle-income level in 2025 and subsequently cross the threshold for a higher income level in 2038. A summary of the projected values of per capita GDP across scenarios is presented in Table 4.

The effect of economic growth on electricity consumption is shown in Table 5. Cross-sectional regression analysis of 136 countries shows that economic growth has a significant effect on electricity consumption.

The summary of predicted value of electricity consumption per capita is shown in Table 6. Results show that even under an optimistic scenario, India's per capita electricity consumption is lower than the current average electricity consumption of high-income countries (7980 Kwh) when it crosses its high-income level, i.e., in

Table 4 Predicted value of GDP

Scenarios		Year				
		2020	2030	2040	2045	2050
Pessimistic scenario	Projected values of GDP per capita in constant 2010 US$	2312.8	4022.0	7242.5	9830.1	13,374.4
	Status	Lower middle income	Lower middle income	Upper middle income	Upper middle income	Upper middle income
BAU	Projected values of GDP per capita in constant 2010 US$	2161.0	3356.2	5397.3	6922.9	8901.1
	Status	Lower middle income	Lower middle income	Upper middle income	Upper middle income	high income
Optimistic scenario	Projected values of GDP per capita in constant 2010 US$	2776.5	6547.8	15,989.2	25,271.8	40,039.8
	Status	Lower middle income	Upper middle income	high income	high income	high income

Source Authors' estimation

Table 5 Regression coefficients of per capita GDP on per capita electricity consumption

	Coefficients
Intercept	1950.722 (5.19)*
Per capita GDP	0.16 (13.17)*
Dummy variable for income category (Category2)	−1468.1 (−2.88)*
Adjusted R-squared	0.69
No. of observations	136

Note Figures in parenthesis are t-values. *means p-value is significant at 1% level
Source Authors' estimation

Table 6 Projected value of electricity consumption per capita (Kwh)

Electricity consumption per capita	Year				
	2020	2030	2040	2045	2050
Pessimistic scenario	826.5	1016.6	2809.5	3052.2	3367.0
BAU	850.6	1122.6	3103.1	3514.8	4078.8
Optimistic scenario	924.4	2992.6	4494.8	5971.8	8321.6

Source Authors' estimation

2038, for which year, India's value of per capita electricity consumption is expected to be 4077.3 Kwh under even an optimistic scenario.

6 Conclusion: Energy Policy and the Way Forward

Ensuring energy access for all, energy security and energy efficiency have been India's policy focus along with the target of achieving sustainable development goals. Demand forecast for electricity sector is a necessary requirement for efficient management of the energy system and preparedness of the system to ensure economic growth and sustainable development. In the light of the above findings, it becomes clear that it is important for India to continuously augment its electricity generation and to resolve access issues at all levels.

The high per capita electricity consumption in high-income countries seems to indicate that there is lack of evidence on the desired decoupling of electricity consumption and economic growth in these countries. Defining thresholds level of electricity consumption per capita for countries in different income strata is not an easy task. Most of the available evidence would point to the fact that electricity consumption for countries that are on a path of economic growth at present is likely to follow the same path as those who have already made the transition to the higher income bracket with some limited range of changes. However, what is interesting is that in the case of India, even with a high growth rate and a growing population, the findings suggest that electricity consumption per capita can be maintained at levels which are at nearly 50% or half of those seen in developed countries today, even under high growth scenarios.[1]

What this also seems to strongly indicate that current energy sector policies have been effective in moderating the relationship between economic growth and energy consumption per capita. Data clearly indicates that India has been very successful in promoting energy efficiency and energy savings through various policy measures.

It is evident that strides have been made in the very recent past to encourage generation in a manner that is consistent with India's aspirations and commitments toward meeting its SDGs. Therefore, in conclusion, we highlight some of the recent developments in the policy arena, which can help in taking forward the Indian electricity sector, such that the transition toward an upper middle-income country can be ensured in a manner consistent with meeting several SDGs, including those on reducing inequality, increasing income (and thereby the means to improve well-being and enhance capabilities), access to clean energy, and achieving climate action.

Several radical and minor policy reforms have initiated a significant shift in the overall operations of the electricity sector. The Indian economy has witnessed growth in national output, alongside expansion in the infrastructure sectors. Among these sectors, the expansion of the power sector has played a critical role, and this is likely to continue to be paramount for ensuring sustainability of economic growth and development. The power sector has been through transitions on both the demand and supply sides, especially in the last couple of decades.

The infrastructure related to power supply has been strengthened over time with substantial expansion in installed generation capacities, transmission, and distribution systems. Power exchanges and trading forums are developing to further facilitate innovative solutions toward reductions in the events of power shortages and meeting demand deficits in general (Saxena et al. 2017).

An important development within the sector has been the evolution of competition within the sector, post the Electricity Act, 2003. The resultant policy framework is perceived to have led to a greater involvement of private players within the sector and put a strong emphasis on the provision of green energy (PWC 2012). This also facilitates and emphasizes measures that help in the achievement of the country's commitments to reduce carbon emissions.

Apart from laying a wide network of infrastructure to increase the supply of conventional and renewable energy and ensuring accessibility of power (electricity) to the entire population, there has been a strong drive to infuse efficiency and in decarbonizing the sector, in keeping with long-term sustainability and environmental goals. Legal and institutional frameworks have evolved gradually to encourage investments

[1]It may be argued though that this macro level picture may not capture the sub-national inequities and inequities in access of specific communities such as the poor. It also does not address the question of how much per capita access should be the ideal amount for different parts of the country. This is an aspect that is beyond the scope of the present paper, and its exploration is in any case limited by data availability.

in energy efficiency by business enterprises. Noteworthy developments include the introduction of the Energy Conservation Act, 2001, Integrated Energy Policy (IEP), 2005 and the National Mission for Enhanced Energy Efficiency (NMEEE), 2008. Further, various demand-side management (DSM) and energy efficiency strategies have been introduced through recent policies. Plans have been developed to cater to the varying magnitudes and characteristics of demand from the end-use sectors such as industry, domestic, agriculture, and transportation.

DSM initiatives have been largely launched in the form of demand response and energy efficiency programs, as one way of bridging the observed demand–supply gap among the major power consumers in the country. In addition to the voluntary and autonomous energy efficiency improvements from the end users, the recent policy measures have been targeted toward achieving specific energy savings through programs such as Standards and Labelling, Perform, Achieve and Trade (PAT) scheme, Energy Efficiency Building Codes (ECBC), Unnat Jyoti by affordable LEDs for all (UJALA), Agricultural DSM, and Super Efficiency Equipment Program (SEEP), to name a few. These programs incorporate technological innovations and improvements in the energy utilization potential of the end-use equipment, such that these can provide the consumers with the requisite service without comprising the quality of the output. DSM can thus combine the virtues of cost-effectiveness with the potential to mitigate climate change (Shakti Sustainable Energy Foundation 2014).

An important aspect to note about the measures is that these are majorly or partially market-driven. It is reported that programs such as the Standards and Labelling Program, UJALA, and SEEP programs have led to market transformations where standards for product development as well as the creation of markets for such products have been laid down (BEE India 2018). In particular, the UJALA Yojana has been hailed as a market transformation measure. LED bulbs launched under the UJALA Yojana have had success stories in terms of penetration across states. Bulk procurements of these bulbs which led to cost reductions, facilitated by the EESL (Energy Efficiency Services Ltd), along with pan India initiatives to cover costs for residential consumers in easy monthly instalments through their electricity bills (Chunekar et al. 2017) have been cited as reasons for its success. Street lights in some states have also been replaced with efficient LED lights to reap energy savings at the level of municipalities. In a similar fashion, the PPP mode of investment has been credited with helping to drastically reduce the cost of replacing inefficient water pump sets in the agriculture and municipal sectors with the efficient ones. In addition to energy savings, the program has given additional benefits in terms of reducing the financial burden on DISCOMS and state governments that provide subsidized power to the agricultural sector (MP Ensystem and Shakti Sustainable Energy Foundation 2018).

Energy Conservation and Efficiency Acts have enabled the evolution of risk-sharing platforms for large investments in energy efficiency projects. The recipients of these investment facilitation measures can be government buildings, private buildings, multi-storey residential accommodations, municipalities, SMEs, and industries. Combinations of regulatory and market-based instruments such as the PAT scheme for the major power-consuming industries have also worked well in achieving desired objectives. The regulatory part of the program has encouraged reduction of specific power consumption, whereas the market-based part of the scheme has enabled the industries to reach these goals in a cost-effective way by enabling trade in energy savings (BEE 2016).

For moving forward with the initiatives that have already been taken, we would like to conclude by suggesting two key aspects. The first of these is the use of additional economic instruments in the economy to increase the push toward cleaner energy use. A prominent one being increasingly discussed today is carbon pricing.

These discussions on carbon pricing have emphasized the importance of design principles, and rightly so as it is strongly connected with the issue of reducing inequality and eradicating poverty by enhancing the energy access of the poor. Carbon is usually priced below the social cost of carbon (World Bank & Ecofys 2016; IPSP 2018) due to various reasons, one of these being the asymmetry between those who bear the costs (organized, fossil fuel industry) and those who are the beneficiaries of such action (future populations, dispersed in society). Maintaining revenue neutrality, or investing the resources generated through economic instruments such as environmental (Pigouvian) taxes in clean energy with targeted approach toward ensuring access for the poor, is among the suggestions for making economic instruments effective in meeting unmet energy needs alongside curbing emissions of local pollutants and GHGs. Thus, while a carbon price mechanism (presumably one which does much more than the existing coal cess) may theoretically be ideal and be deemed to be at par with a cap and trade scheme toward achieving clean energy outcomes, in practice both require careful thinking through on the implementational aspects.

The second point, specifically, in the context of the Indian economy, is that it is equally important to recognize that the effectiveness of such measures and supportive policy for enhancing the transition to clean energy sources will depend on the validity of the data used for the design of the policy. Typically economic agents, especially consumers, can take time to change their behavior in response to market-based instruments and/or policy incentives. For instance, a laudable achievement has been that over 60 million low-income households now have an LPG connection. Yet data suggests that many households continue to rely on solid biomass for a major part of their cooking. A recent study finds that making these households aware of the health benefits of moving to clean fuels creates a positive and significant impact on their utilization of LPG (Zahno et al. 2018).

Longitudinal datasets can be a valuable input into understanding how human society can best adapt to such changes. For the energy sector, there are dual imperatives of providing a minimum threshold level of clean energy for the poor alongside meeting the requirements of a growing economy. Data based on detailed sampling (classes) on consumption of the upper income groups can be as relevant as that on consumption of the poor. Both baseline surveys and ongoing monitoring are important. This would help to address cross-cutting influences in the strategy on increasing power consumption and enhancing energy efficiency and conservation. India, at its stage of development, needs to increase power production and consumption to ensure access to energy to all, to improve industrial productivity, to cope up with infrastructural challenges, for ease of doing business, and to reduce inequality in opportunities and capabilities. To make the growth path sustainable, policy interventions are required so that the energy transition, enabling the economic transition from a low middle-income country to a high middle-income one, can be achieved at a low environmental cost.

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Role of Trade and FDI as India's Growth Accelerators: Opportunities and Challenges

India's Merchandise Exports in a Comparative Asian Perspective

C. Veeramani and Lakshmi Aerath

1 Introduction

Since the early 1990s, India has undertaken important external sector reforms with a view to transforming its economic system from an inward-looking planned economy to one that is more outward-oriented. Trade and exchange rate policies have been liberalized and restructured in order to remove the anti-export bias endemic to import substitution policies. Focus of export policies shifted from product-specific incentives to more generalized incentives based on exchange rates. The pegged exchange rate system was terminated. The rupee experienced a two-step downward adjustment, by 9% and 11% in July 1991. It was expected that a market-determined exchange rate would make exporting activities inherently more attractive. The Liberalised Exchange Rate Management System, established in March 1992, involved an interim dual exchange rate arrangement, where exporters sold 60% of their foreign exchange earnings at the market rate and 40% to the government at a lower official rate. This system was later replaced by a unified market-determined regime in March 1993. In April 1993, a further move toward the deregulation of the external sector took place when the government adopted full convertibility on the trade account by unifying the official exchange rate with the market one. Finally, these steps led to the adoption of full current account convertibility in August 1994.

The quantitative restrictions (QRs) on importing capital goods and intermediate inputs were mostly dismantled in 1992, although the ban on importing consumer goods continued, with some exceptions, until the late 1990s. Alongside the removal of QRs, customs duties in several manufacturing industries were gradually reduced.

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Following the new tariff reductions introduced in the March 2007 budget, India has emerged as one of the world's low protection and open industrial economies (Pursell et al. 2007).

Did Indian exports respond positively to changes in the incentive structure engendered by the reforms? A previous study, focusing on merchandise exports, showed that the first decade of reforms (from 1993–94 to 2001–02) was characterized by a relatively low growth rate of dollar export earnings at 8% per year, while the second decade (2002–03 to 2010–11) stood apart for its strong growth rate of 21% a year (Veeramani 2012). Data for the more recent years, however, indicate that export growth has started to slow down. The value of exports plummeted from a peak of $323 billion in 2014 to $299 billion in 2017. Further, India's merchandise imports have been growing faster than exports throughout the post-reform period resulting in increasing merchandise trade deficit.

The long-term solution to the problem of current account deficit lies in ensuring that export growth keeps pace with the growth of imports. The crucial question is: what type of policy interventions would help achieve faster export growth? The answer, taking a cue from some recent studies, hinges on whether export performance is primarily driven by growth along the extensive margin (establishment of new trading relationships) or along the intensive margin (intensification of existing trade relationships). The intensive margin of a country's export growth is attributable to its persistent export relationships—that is, exports of already exported products (old products) to already existing market destinations for those products (old markets). Note that intensive margin growth can arise as a result of price growth, quantity growth, or both. The extensive margin refers to changes in the value of exports due to diversification of old products to new market destinations and/or due to the exports of new products.

Clearly, a proper understanding of trade growth along the different margins, as opposed to the usual focus on aggregate trade flows, would better inform policies. In order to decide whether export promotion policies be targeted at accelerating export growth at the intensive or at the extensive margin, we need to know the relative role that the two margins have played in determining India's past export growth. In this chapter, we decompose India's relative merchandise export performance across trading partners during 2000–2015 into extensive and intensive margins. Intensive margin is further decomposed into price and quantity margins.

The chapter is organized as follows. Section 2 provides a brief overall background by summarizing the performance of India's merchandise and services trade during the post-reform period.[1] Section 3 provides an analysis of commodity composition and geographical direction of merchandise exports. Section 4 discusses the methodology and data used to decompose India's bilateral exports into various margins. Section 5 discusses the decomposition results. Finally, Sect. 6 provides the concluding remarks.

[1]We consider 1993 as the benchmark for defining the post-trade reform period since full convertibility on trade account was introduced in that year.

2 An Overview of Merchandise and Services Trade Performance, 1993–2018

The reforms, by reducing the anti-export bias of protectionist policies, were expected to improve export competitiveness and growth. While India's merchandise exports in dollar terms grew moderately at about 8.1% per year during the first decade of economic reforms (1993–2001), the period from 2002 to 2011 witnessed higher a growth rate of 21.3% per annum (see Table 1). Data for the more recent years, however, indicate that merchandise exports declined from a peak of $323 billion in 2014 to $299 billion in 2017, before rebounding to $326 billion in 2018. Growth rate of exports turned negative at 1.9% per annum during the period 2012–2017.

Exports of commercial services grew relatively faster at the rate of 17.4% per year during 1993–2001 and at the rate of 24.2% a year during 2002–11. However, the growth rate declined significantly at 4.1% per annum during 2012–2017. While the share of services in India's total exports increased from 19% in 1993 to 38% in 2017, the merchandise group still accounts for the bulk of export earnings. In 2017, for example, India exported $184 billion worth of services while the value of merchandise exports stood at $299 billion. Merchandise exports as a percentage of GDP increased consistently from 7.8% in 1993 to 15.6% in 2008 and then declined briefly in the aftermath of the global financial crisis (Fig. 1). Merchandise exports, as a percentage of GDP, reached the peak of 16.7% in 2013 and then declined to 11.8% in 2017 (Fig. 1). As a percentage of GDP, merchandise exports remained consistently lower for India compared to the world average by a significant margin. India's services exports, as a percentage of GDP, stood at 1.8% in 1993, reached the peak of 8.4% in 2008, and then stabilized at the level comparable to that of world average. The main takeaway from Fig. 1 is that there exist a potential for India to significantly increase the share of merchandise exports in its GDP.

In general, the growth rate of Indian exports has been higher than world exports throughout the post-reform period (see Table 1). This is in contrast to the pre-reform period when Indian exports grew slower than world exports (Veeramani 2007). India's share in world merchandise exports increased from 0.6% in 1993 to 1.7% in 2018. For

Table 1 Growth rates of exports (US $)

	Merchandise		Commercial services	
	India	World	India	World
1993–2018	13.2	7.2	18.2	8.2
1993–2001	8.1	5.8	17.4	5.6
2002–2011	21.3	11.0	24.2	11.4
2012–2017	−1.9	−2.4	4.1	2.5
2012–2018	−0.1	−0.5	n.a	n.a

Note Growth rates are computed using semi-logarithmic regressions
Source Authors' calculation using data extracted from WTO Data Portal

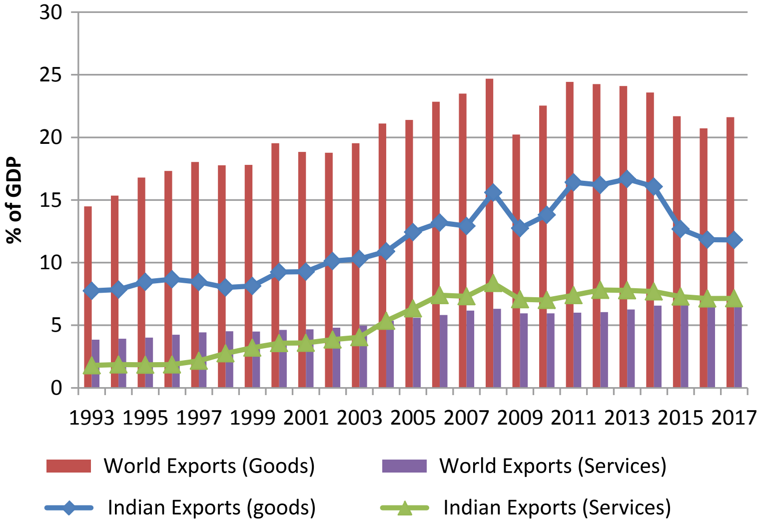

Fig. 1 Merchandise and services exports as a percentage of GDP, India and world. *Source* Plotted using data extracted from UNCATDstat

services, India's share in world exports increased from 0.5 in 1993 to 3.4% in 2017. Yet, India's world market share, particularly for merchandise, is paltry compared to China's (see Fig. 2). China records a higher market share than India in services

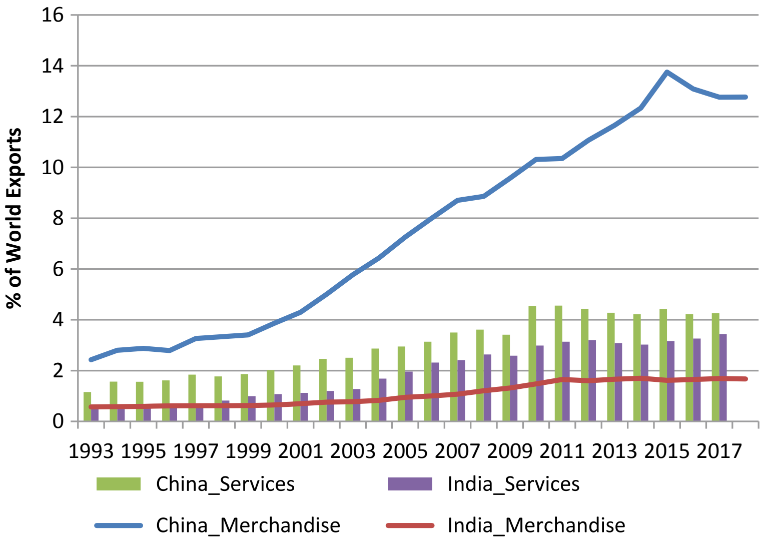

Fig. 2 World market shares, merchandise and services exports, India and China. *Source* Plotted using data extracted from UNCATDstat

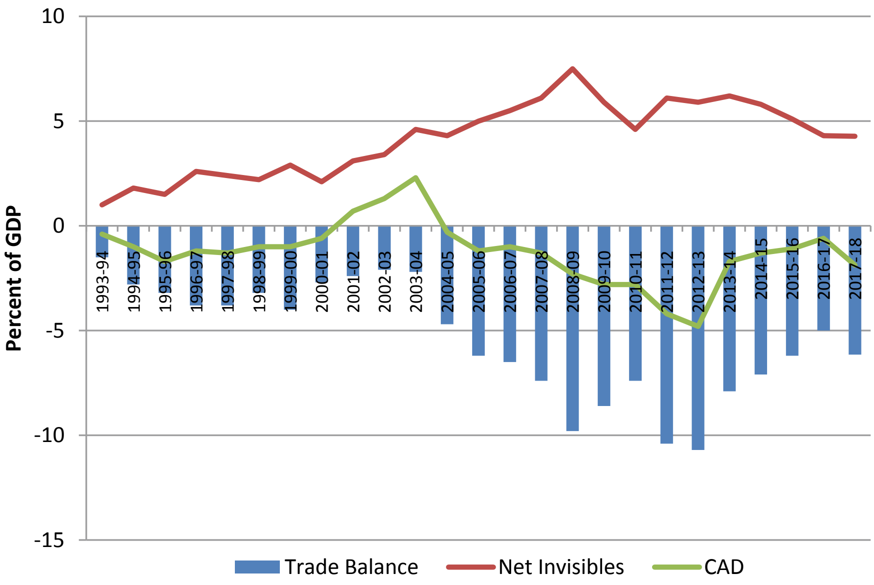

Fig. 3 Balance of payment indicators. *Source* Handbook of statistics on Indian economy, Reserve Bank of India

as well though the gap between the two countries is less pronounced for services compared to merchandise.

Throughout the post-reform period, India's merchandise imports have grown faster than merchandise exports resulting in increasing trade deficits (Fig. 3). During the period 1993–2018, while merchandise exports recorded a growth rate of 13.2% per annum, imports grew at the rate of 14.9% per annum. On the other hand, during this period, exports of services generally grew faster than imports, providing some cushion to current account deficit. In 2017–18, for instance, the merchandise trade account showed a deficit of $160 billion, of which about $111 billion was offset by invisible earnings, leaving a current account deficit of $49 billion, or 1.9% of GDP.

3 Commodity Composition and Geographical Direction of Exports

In order to examine changes in the commodity composition of exports, we compute the shares of different product categories in India's total merchandise exports. Figure 4 plots the share of aggregate manufacturing as well as the shares of individual commodity groups within manufacturing at the one-digit SITC level for the

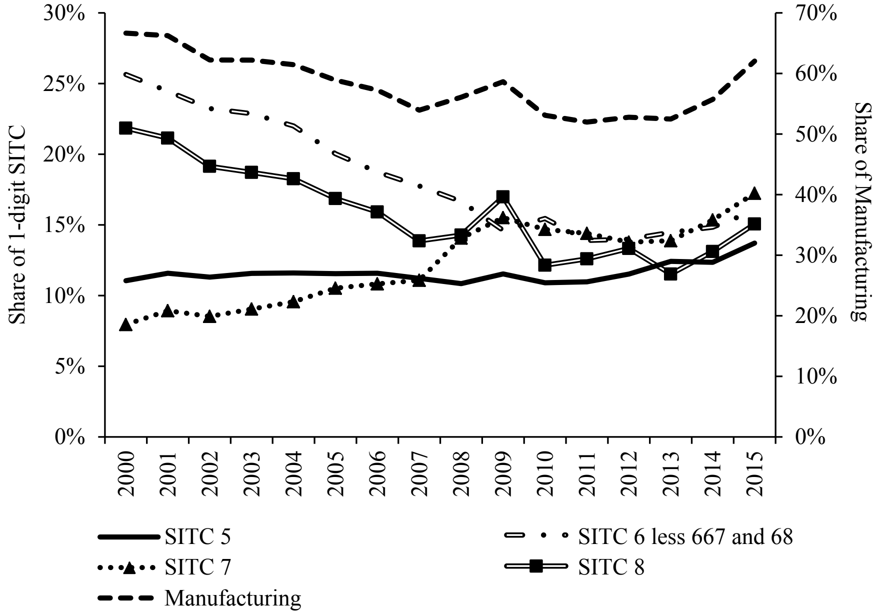

Fig. 4 Composition of India's exports (2000–2015). *Source* Authors' estimation using data from COMTRADE-WITS. *Notes* (i) Manufactured goods include chemicals (SITC 5), manufactured materials (SITC 6 less 667 and 68), machinery and transport equipment (SITC 7), and miscellaneous manufactured articles (SITC 8)

period 2000–2015.[2] The share of manufacturing in India's total exports declined from 66.7% in 2000 to 53.1% in 2010. Thereafter, during the more recent years, the share of manufactured exports has picked up slightly, increasing to 62.1% in 2015. In 2000, two categories within manufacturing—manufactured materials (SITC 6 less 667 and 68) and miscellaneous manufactured articles (SITC 8)—together accounted for about 47% of India's total exports. However, by 2015, their combined share in India's total exports fell noticeably to 31%. While the share of manufactured materials plunged from 25.6% in 2000 to 16% in 2015, that of SITC 8 declined from 21.8% to 15% during the same period. On the other hand, the shares of chemicals (SITC 5) and machinery and transport equipment (SITC 7) increased from 11% to 13.7% and from 8% to 17.2%, respectively, during 2000–2015.

It is evident that the fast growing commodity groups in the export basket (SITC 5 and SITC 7) are capital-intensive, while the traditional labor-intensive groups (SITC 6 and SITC 8) recorded lackluster performance. Thus, given that India's comparative advantage primarily lies in labor-intensive segments of manufacturing, the observed change in the composition of export basket is an anomaly and reflects a

[2]Manufactured goods include chemicals (SITC 5), manufactured materials (SITC 6 less 667 and 68), machinery and transport equipment (SITC 7), and miscellaneous manufactured articles (SITC 8).

distorted pattern of specialization. The observed trends are in contrast to the patterns of specialization postulated by Heckscher–Ohlin model of trade, according to which trade liberalization should lead to an expansion of labor-intensive industries in a labor-abundant country, such as India.

In order to analyze this idiosyncratic nature of specialization more clearly, we classify India's merchandise exports into five broad categories based on factor intensities in production of various goods—primary goods, natural resource-intensive goods, unskilled labor-intensive goods, technology-intensive goods, and human capital-intensive goods (Table 2). To this end, we use the factor-intensity classification of the International Trade Centre (ITC), adapted by Hinloopen and Marrewijk (2008).[3] It can be seen that while the share of capital-intensive goods (sum of technology-intensive, human capital-intensive, and refined petroleum products) in India's exports increased consistently, that of unskilled labor-intensive products recorded a steep decline. Between 2000 and 2015, the share of capital-intensive goods in the export basket increased from about 31 to 51.7%, while the share of unskilled labor-intensive products decreased from about 32 to 18.5%. The share of natural-intensive products and primary goods also declined, although not as rapidly as unskilled labor-intensive goods. Within the capital-intensive group, the share of technology-intensive goods increased more rapidly than that of human capital-intensive products.

There are reasons to believe that, despite trade liberalization, the general incentive structure is biased against labor-intensive industries and labor-intensive production processes in India. Many economists argue that India's rigid labor laws create severe exit barriers and discourage large firms from choosing labor-intensive activities and technologies (see Kochhar et al. 2006; Panagariya 2007; Krueger 2010). Another group of scholars, however, questions this argument (see Bhattacharjea 2006; Nagaraj 2011). Though there is no unanimity of opinion in this regard, a growing number of econometric studies suggest that the role of labor laws cannot be ignored (see Hasan et al. 2007; Aghion et al. 2008). Other constraints that stand in the way of labor-intensive manufacturing include inadequate supply of physical infrastructure (especially power, road, and ports) and a highly inefficient and cumbersome land acquisition procedure. Faced with power shortages, capital- and skill-intensive industries such as automobiles and pharmaceuticals might be in a position to rely on high-cost internal sources of power. But this option is unaffordable to firms in labor-intensive segments which typically operate with relatively low margin. Similarly, cumbersome land acquisition procedures create a bias against large-scale labor-intensive manufacturing industries.

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[3]As per the original classification of the ITC, the category "refined petroleum products" (SITC 334) is included as part of primary goods. However, since petroleum refining in India is based on imported crude oil and is a highly capital-intensive process, it is appropriate to include it in the capital-intensive, rather than primary category. Accordingly, we exclude SITC 334 from primary goods and include it under capital-intensive goods. Capital-intensive goods include human capital-intensive goods, technology-intensive goods, and SITC 334. The share of SITC 334 in India's export basket increased rapidly from just 0.2% in 2000 to as high as 19.1% in 2012 and then declined to 10.4% in 2015.

Table 2 Composition of India's exports based on factor-intensity classification (2000–2015)

Year	Primary goods	Natural resource-intensive goods	Unskilled labor-intensive goods	Capital-intensive goods			
				Capital-intensive goods	Technology-intensive goods	Human capital-intensive goods	Refined petroleum products (SITC 334)
2000	17.0	19.9	31.9	31.2	15.8	15.2	0.2
2001	18.4	19.0	30.0	32.7	17.5	15.2	0.0
2002	18.0	19.6	26.8	35.6	16.7	15.5	3.4
2003	15.8	19.1	24.4	40.6	17.9	17.1	5.6
2004	17.2	16.1	21.9	44.7	18.0	18.9	7.7
2005	16.6	16.7	20.2	46.4	18.3	18.0	10.1
2006	16.2	14.4	18.3	50.7	18.7	17.8	14.2
2007	17.0	14.5	16.3	51.8	18.6	16.5	16.8
2008	16.5	14.0	14.9	54.3	20.1	18.4	15.8
2009	16.1	13.5	17.5	52.9	21.0	18.1	13.7
2010	17.7	15.2	15.4	49.6	19.2	16.2	14.2
2011	16.4	14.9	14.9	52.0	19.3	15.7	17.0
2012	17.0	11.3	13.2	56.6	19.6	17.9	19.1
2013	16.4	13.1	13.9	55.2	20.7	15.7	18.8
2014	15.0	11.9	14.9	57.4	21.4	17.2	18.8
2015	14.3	13.5	18.5	51.7	23.6	17.7	10.4

Source Authors' estimation using data from comtrade-WITS database
Notes Values denote percentage shares in India's merchandise exports; see endnote 3 for further details pertaining to the classificaiton used here

In contrast to India, China's export composition shows a strong bias in favor of labor-intensive product groups. China's export promotion policies since the 1990s have relied heavily on a strategy of integrating its domestic industries with the global production networks (GPNs) (Athukorala 2014).[4] In particular, based on imported parts and components, China has emerged as a global hub for electrical and electronic goods assembly. Typically, China imports parts and components from other countries in East and Southeast Asia and exports finished goods to the US and Europe. A manifestation of China's participation in GPNs is the high share of machinery items in its export basket (Veeramani et al. 2018). While conventionally considered as capital-intensive, certain stages of production or tasks within the broad group of machinery, such as low-end assembly activities, are highly labor-intensive. Low-wage countries like China mainly specialize in labor-intensive stages of production within machinery. As noted by Amiti and Freund (2010, p. 36), "on the surface, it appears that China is dramatically changing its comparative advantage, yet a closer examination reveals that it is continuing to specialize in labor-intensive goods." They observe that once processing trade is accounted for, the labor intensity of China's exports remained unchanged during 1992–2005 and that its specialization patterns are in accordance with Heckscher–Ohlin trade model. Due to its idiosyncratic specialization in relatively capital- and skill-intensive product lines, India has been locked out of the GPNs in several manufacturing industries (Athukorala 2014; Krueger 2010; Veeramani and Dhir 2018).

Turning to the geographical direction of exports, we examine how export shares of different partner country groups, classified according to income level, have changed over the years (Fig. 5).[5] It can be seen that the share of high-income countries in India's merchandise exports has gone down considerably over the years, from 71% in 2000 to 58% in 2015. Separating high-income countries into OECD and non-OECD countries, we see that the decline is largely due to the fall in the share of high-income OECD countries. India's exports to high-income OECD countries declined from 56.3% in 2000 to 38.6% in 2015. On the other hand, the share of non-OECD high-income countries increased from 14.5% to 19.2% during the same period.[6] Further, India's exports to low-and middle-income countries increased steadily from 22.4% to 35.8% during 2000–2015.

To draw a comparison, we also plot the direction of China's merchandise exports to different country groups. It can be seen that the share of high-income countries in China's exports fell from 82.3% to 65.4% during 2000–2015 while the share of low-

[4]Global production networks refer to the links between a lead or a key firm and its suppliers in different countries (Weiss 2011). In certain industries, such as electronics and automobiles, technology makes it possible to subdivide the production process into discrete stages. In such industries, the fragmentation of production process into smaller and more specialized components allows firms to locate parts of production in countries where intensively used resources are available at lower costs.

[5]India's partner countries are classified into different income-based groups based on the World Bank Classification.

[6]This is mainly driven by India's exports to countries like UAE, Hong Kong, Singapore, and Saudi Arabia.

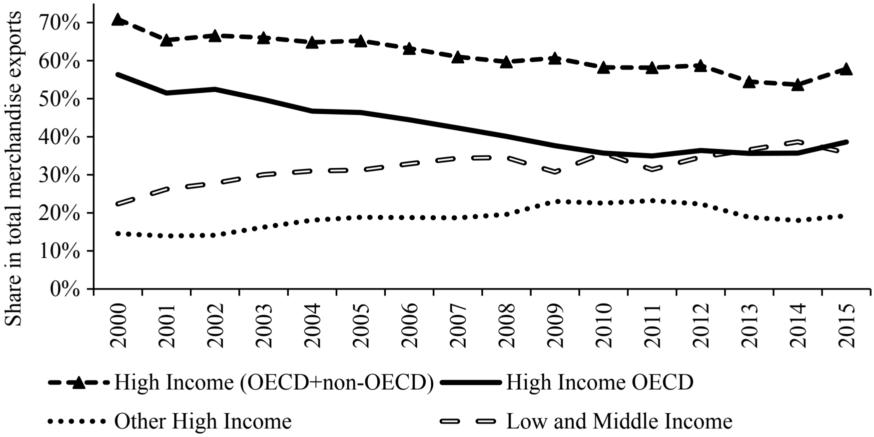

Fig. 5 Direction of India's merchandise exports (2000–2015). *Source* Authors' estimation using comtrade-WITS data

and middle-income countries increased (see Fig. 6). The observed changes in the direction of trade for India and China are consistent with the changes in the direction of overall world trade.[7] Yet, the direction of India's exports shows a disproportionate bias against high-income trading partners. About 65% of China's exports still go to high-income countries, significantly higher than India's 58%. When it comes to

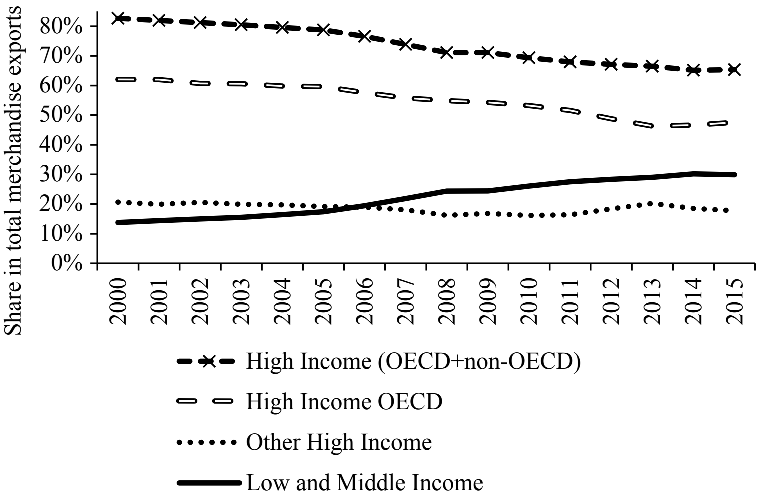

Fig. 6 Direction of China's merchandise exports (2000–2015). *Source* Authors' estimation using COMTRADE-WITS data

[7]Between 2000 and 2015, total world exports to high-income countries declined from 74.4 to 60.9% and that to high-income OECD countries declined from 70.4 to 56.2%.

high-income OECD countries, in particular, the difference between India and China is starker: in 2015, high-income OECD markets accounted for 47.6% of China's exports while the corresponding share for India was only 38.6%.

What explains India's relatively low market penetration in high-income OECD countries compared to China and world in general? It is plausible that the distorted pattern of India's commodity specialization, discussed above, has a bearing on the geographical direction of its exports. Arguably, as a result of relatively high specialization in capital- and skill-intensive industries, India would have gained a competitive advantage in relatively poorer markets but at the cost of losing market shares in richer countries. Capital-intensive products from India are unlikely to make inroads into the quality conscious richer country markets while India's labor-intensive products have significant potential to penetrate into these markets. Thus, specialization out of traditional labor-intensive products may imply a general loss of India's export potential in advanced country markets.[8]

We examine this argument further by comparing and contrasting the direction of India's exports, across partner country groups, in unskilled labor-intensive product groups versus capital-intensive product groups. From Figs. 7 to 8, it is clear that high-income partner countries accounts for the largest share of exports for both product groups. However, high-income partners' share is significantly larger for the unskilled labor-intensive product group than for the capital-intensive group. While high-income countries accounted for 71.6% of India's unskilled labor-intensive

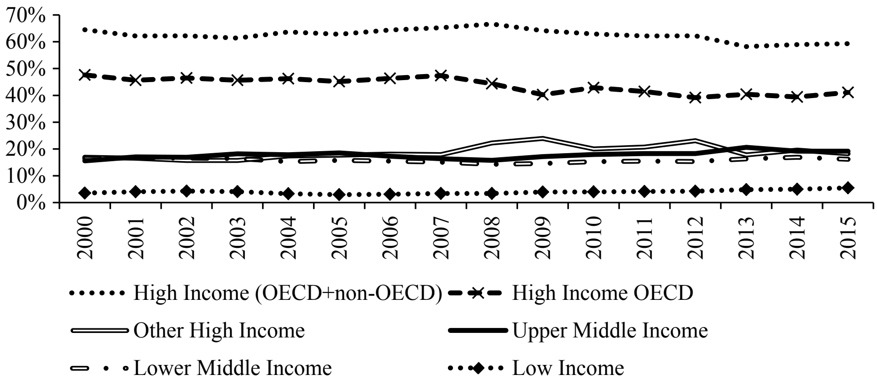

Fig. 7 Direction of India's capital-intensive exports (2000–2015). *Source* Authors' estimation using DGCI&S data

[8]An illustrative example will make this point clearer. India's exports of passenger motor vehicles (SITC 7810), a capital- and skill-intensive product, increased remarkably from $102 million in 2000 to $5392 million in 2015, registering an annual average growth rate of 34%. In 2015, high-income OECD countries accounted for only 22% of Indian exports of passenger motor vehicles while low- and middle-income countries accounted for 68%. On the other hand, India's exports of apparel (SITC 84), a traditional labor-intensive category, grew at a much lower rate of 9% per annum during 2000–2015. In 2015, while high-income OECD countries accounted for 64% of India's exports in this category, low- and middle-income countries accounted for just 12%.

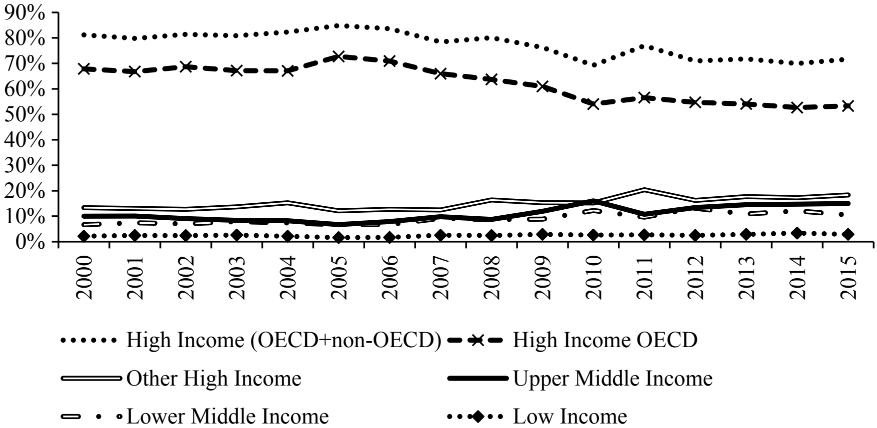

Fig. 8 Direction of India's unskilled labor-intensive exports (2000–2015). *Source* Authors' estimation using DGCI&S data

exports in 2015, its share in capital-intensive exports was only 59.3%. To highlight this difference more clearly, Fig. 9 shows the share of unskilled labor-intensive exports as a ratio of the share of capital-intensive exports across different partner country groups. It can be seen that, as expected, these ratios are the highest for high-income OECD group followed by other high-income countries. The ratios are the lowest for low- and middle-income countries.

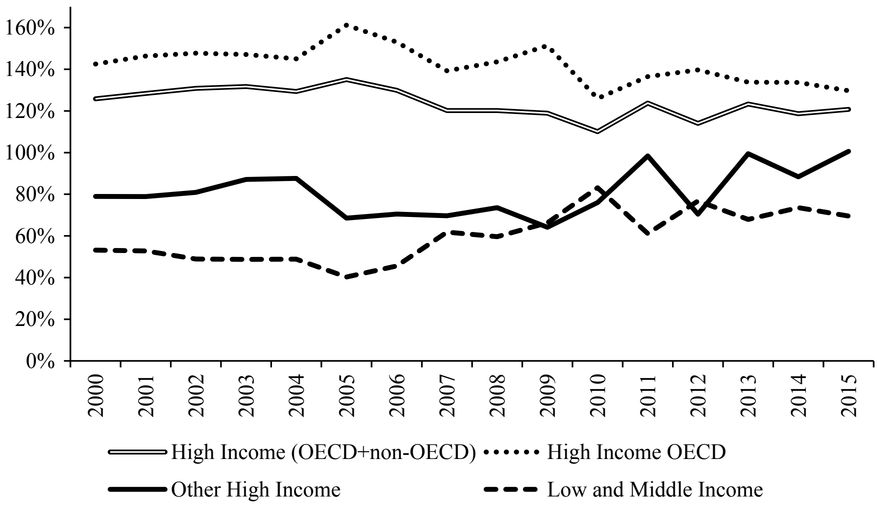

Fig. 9 Share of unskilled labor-intensive exports as a ratio of the share of capital-intensive exports across different partner country groups, 2000–2015. *Source* Authors' estimation using DGCI&S data

These findings are consistent with our conjecture that specialization out of unskilled labor-intensive products implies a loss of India's export potential in advanced country markets. High-income countries provide a larger market for India's unskilled labor-intensive products. However, the growing dominance of capital-intensive products in India's export basket has resulted in a disproportionate shift in India's direction of exports, from traditional rich country markets to other destinations. Indeed, one of the reasons for China's superior export performance compared to India is its high trade orientation in developed country markets, a result of China's high degree of specialization in labor-intensive products and processes.

4 Extensive and Intensive Margins of Exports: Concept, Decomposition Methodology, and Database

4.1 Concept of Trade Margins

Trade models differ in terms of the emphasis placed on different margins as channels of export growth.[9] Traditional trade theory based on the assumption of perfect competition considers industry as the unit of analysis, while firms within an industry are assumed to be identical and produce homogenous products. Since products are not differentiated, horizontally or vertically, there is no extensive margin and export growth comes from quantity expansion alone. Theoretical analyses of intra-industry trade usually rest on the assumption of horizontal (different varieties are of a similar quality and same price) or vertical (varieties are of different qualities and prices) product differentiation. Thus, in horizontal models, pioneered by Krugman (1979), exports grow along the extensive margin—that is, expansion of variety. In vertical models, as in Flam and Helpman (1987), exports can grow along the price and quantity margins as a result of improvement in quality.

The concept of extensive margin was formalized with the development of new-new trade models. In a seminal work, Melitz (2003) incorporates two dimensions of firm-level heterogeneity–productivity differences and fixed export costs – in Krugman's (1979) trade model. In this setup, involving heterogeneous firms and fixed costs of exporting, not only do firms change the volume of their exports (intensive margin) over the years, but the set of firms that engage in exports varies as well (extensive margin). In these models, exposure to trade will induce only the more productive firms to enter the export market, as entry into these markets is costly and can only be afforded by the more efficient firms. Exports along the extensive margin can grow with falling trade costs as new firms with horizontally differentiated variety enter the export market.

[9] See Hummels and Klenow (2005) for a detailed discussion on the importance of different export margins in different trade models.

As to the empirical literature, the relative role of extensive and intensive margin in the growth of trade has been debated. Using a cross-sectional data of 126 exporting countries in 1995 Hummels and Klenow (2005), found that extensive margin accounts for 62 percent of exports by larger economies. Similarly Evenett and Anthony (2002), found extensive margin to be quite important for growth in developing country exports. A number of more recent studies, however, conclude that intensive margin plays the dominant role (Helpman et al. 2008; Amiti and Freund 2010; Felbermayr and Kohler 2006; Eaton et al. 2008; Besedes and Prusa 2011; Veeramani et al. 2018). Besedes and Prusa (2011, pp 371) note that "a country's poor export performance is not because it struggles to start new relationships," (extensive margin) but mainly because it lags behind the better performing countries in terms of survival and deepening of existing export relationships (intensive margin).

Clearly, a proper understanding of export growth along the different margins, as opposed to the usual focus on aggregate trade flows, would better inform policies. In order to decide whether export promotion policies be targeted at accelerating export growth at the intensive or at the extensive margin, we need to know the relative role that the two margins have played in determining India's past export growth.

4.2 Decomposition Methodology

In line with the new strand of literature that emphasizes the need to distinguish between extensive and intensive margins of trade, we decompose India's bilateral export flows into the two margins. Since these margins signify two distinct channels of export growth, it is important to analyze how the pattern and direction of India's exports differ along the two margins. To this end, we decompose India's relative export performance across partner country groups during 2000–2015 into extensive and intensive margins. Intensive margin is further decomposed into price and quantity margins.

Based on the method proposed by Hummels and Klenow (2005), we analyze the structure of exports from India (i) to a partner country j ($j \in D$) in relation to all other partner countries ($r \in D, r \neq j$). To analyze the relative performance of India's exports in each partner j, we first define export penetration.

Export penetration of India in j relative to r is denoted as S_{ijt}:

$$S_{ijt} = \frac{X_{ijt}}{X_{irt}} = \frac{\sum_{h \in N_{ijt}^h} x_{ijt}^h}{\sum_{r \in D, r \neq j} \sum_{h \in N_{irt}^h} x_{irt}^h} \tag{1}$$

where

X_{ijt} value of aggregate exports from India to a partner country j in year t,
X_{irt} value of aggregate exports from India to a set of partner countries r in year t,
x_{ijt}^h value of exports from India to partner country j in product h (eight-digit HS) in year t,

x^h_{irt} value of exports from India to a set of partner countries r in product h in year t,
N^h_{ijt} the set of products that India exports to j in year t (i.e., the set where $x^h_{ijt} > 0$), and
N^h_{irt} the set of products that India exports to r in year t (i.e., the set where $x^h_{irt} > 0$).

Export penetration (S_{ijt}) can be expressed as the product of extensive and intensive margins. This decomposition is possible because S_{ijt} as defined above depends on (i) the number of products that India exports to a given partner j relative to all other partner countries (extensive margin) and (ii) the value of exports that India exports to a given partner j relative to all other partner countries within the common set of products (intensive margin). India's export penetration in a given partner market j could be low because India exports fewer number of products to j than r (that is, $N^h_{ijt} < N^h_{irt}$) and/or because the value of exports from India to j is lower than that to r within the common set of products.

India's intensive margin in j in year t can be expressed as

$$IM_{ijt} = \frac{X_{ijt}}{\sum_{r \in D, r \neq j} \sum_{h \in N^h_{ijt}} x^h_{irt}} \tag{2}$$

The denominator of IM_{ijt} measures total exports from India to r in those products that India exports to j in year t. Therefore, intensive margin is the ratio of India's exports to j to India's total exports to r within the common set of products. The value of IM_{ijt} is always positive and can be above or below unity.

For the case when N^h_{ijt} is a subset of N^h_{irt}, the extensive margin for India in j is defined as[10]

$$EM_{ijt} = \frac{\sum_{r \in D, r \neq j} \sum_{h \in N^h_{ijt}} x^h_{irt}}{X_{irt}} \tag{3}$$

The denominator of EM_{ijt} represents total exports from India to all partner countries r, other than j. The numerator is India's exports to all partner countries r, other than j, in those products that India exports to j. Thus, the extensive margin is a measure of the fraction of India's exports to r in those products that are exported to j. It can be considered as a weighted count of the number of products that are exported to j, where the weights are the export values to r. The measure lies between 0 and 1.

The numerator of extensive margin is equal to the denominator of intensive margin: thus, it can be seen that $S_{ijt} = EM_{ijt} \times IM_{ijt}$. For providing an illustration of the decomposition technique, we present a simple numerical example in Appendix.

Since intensive margin captures changes in the value of exports due to changes in quantity as well as price, it can be further decomposed into price margin and quantity margin.

[10]The assumption that N^h_{ijt} is a subset of N^h_{irt} means that the number of products that India exports to partner group j is lesser than that to all other partner countries r. This is indeed the case in our data.

$$IM_{ijt} = P_{ijt} \times Q_{ijt} \tag{4}$$

The price margin measures the aggregate weighted ratio of India's prices in j to that in r, where the weights are the logarithmic mean of share of product h in exports to j and r within the common set of products.

$$P_{ijt} = \prod_{h \in N_{ijt}^{h}} \left(\frac{uv_{ijt}^{h}}{uv_{irt}^{h}} \right)^{w_{ijt}^{h}} \tag{5}$$

where uv_{ijt}^{h} and uv_{irt}^{h} are unit values (proxy for prices) of product h exported by India to j and r, respectively, and w_{ijt}^{h} is the logarithmic mean of s_{ijt}^{h}(share of product h in India's exports to j) and s_{irt}^{h} (share of product h in India's exports to r).[11] Quantity margin is simply intensive margin divided by price margin.

4.3 Database

We use Harmonised System (HS) eight-digit level data on India's bilateral exports from Directorate General of Commercial Intelligence and Statistics (DGCI&S), Government of India for the period 2000–2015.[12] India's exports to r are measured as equal to the sum of India's exports to all partner countries (excluding j) in a given year. To reduce noise in the data, we exclude export flows to those partner countries whose average population during 2000–2015 is less than 1 million. Our sample contains a total of 155 partner countries. We group partner countries into four categories based on their income levels: high-income, upper middle-income, lower middle-income, and low-income countries. Out of the 155 partner countries in our sample, 45 are high-income countries, 39 are upper middle-income, 42 are lower middle-income, and 29 are low-income countries. The decomposition exercise has been carried out by pooling data for all countries within a given group of partner countries and for each year. The margins for each income group are calculated in such a way that the subscript j in Eqs. (1)–(5) comprises all partner countries belonging to the given group. The reference category (r) in Eqs. (1)–(5) denotes all other partner countries. For example, for the calculation of margins for high-income country group, j includes all 45 high-income countries and r includes the remaining 110 countries.

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[11] $s_{ijt}^{h} = \frac{x_{ijt}^{h}}{\sum_{h \in N_{ijt}^{h}} x_{ijt}^{h}}$ $s_{irt}^{h} = \frac{x_{irt}^{h}}{\sum_{r \in D, r \neq j} \sum_{h \in N_{ijt}^{h}} x_{irt}^{h}}$ and $w_{ijt}^{h} = \frac{\left(\frac{s_{ijt}^{h} - s_{irt}^{h}}{lns_{ijt}^{h} - lns_{irt}^{h}} \right)}{\sum_{h \in N_{ijt}^{h}} \left(\frac{s_{ijt}^{h} - s_{irt}^{h}}{lns_{ijt}^{h} - lns_{irt}^{h}} \right)}$

[12] Unit values (export value divided by quantity), required to measure price and quantity margins, are computed at the eight-digit HS level. A small number of eight-digit HS codes, for which data on quantity are either zero or not reported, are excluded from the analysis.

5 Decomposition Results

Table 3 presents the decomposition results across partner groups for each year from 2000 to 2015. It can be seen that India's export penetration rate in high-income partner countries has declined significantly from 3.2 in 2000 to 1.7 in 2015 at the rate of −3.5%. During the same period, the growth rate of intensive margin was negative (−3.5%), declining from 3.2 to 1.8. On the other hand, the value of extensive margin has remained close to 1 during the entire period. That the value of extensive margin is almost 1 implies that India has been successful in penetrating into the high-income country markets by exporting almost the entire range of products. However, this high level of diversification is not associated with high intensive margin. Our results show that the decline in India's export penetration in high-income countries is driven entirely by the intensive margin. The decline in intensive margin, in turn, can be attributed to the quantity margin which declined from 2.9 in 2000 to 1.6 in 2015 at the rate of 4% per annum. During 2000–2015, India's price margin in high-income countries has averaged at a value of 1.1, implying that, as expected, Indian products fetch a higher price in high-income countries as compared to other country groups. In sum, despite high extensive margin and high price margin, India's market penetration

Table 3 Decomposition of India's merchandise exports across income groups

High-income partner countries					
Year	S_{ijt}	EM_{ijt}	IM_{ijt}	P_{ijt}	Q_{ijt}
2000	3.221	0.994	3.240	1.108	2.924
2015	1.748	0.991	1.765	1.136	1.553
r	−3.5	0.0	−3.5	0.5	−4.0
Low-income partner countries					
Year	S_{ijt}	EM_{ijt}	IM_{ijt}	P_{ijt}	Q_{ijt}
2000	0.021	0.893	0.024	1.005	0.024
2015	0.052	0.875	0.059	0.922	0.064
r	5.3	0.3	5.0	−0.5	5.6
Lower middle-income partner countries					
Year	S_{ijt}	EM_{ijt}	IM_{ijt}	P_{ijt}	Q_{ijt}
2000	0.110	0.963	0.114	0.958	0.119
2015	0.161	0.952	0.169	0.922	0.183
r	2.0	−0.1	2.0	1.1	1.0
Upper middle-income partner countries					
Year	S_{ijt}	EM_{ijt}	IM_{ijt}	P_{ijt}	Q_{ijt}
2000	0.133	0.970	0.137	1.109	0.123
2015	0.214	0.945	0.226	1.101	0.206
r	3.0	−0.2	3.2	0.2	2.9

Source Authors' estimation using DGCI&S data rates in high-income partner countries recorded a significant decline entirely due to a low-quantity margin. Thus, the lack of specialization and intensification, rather than a lack of product diversification, is primarily responsible for the decline in India's market penetration in high-income partner country markets.

Interestingly, the negative growth rate of intensive margin and export penetration is restricted to the group of high-income countries only. In contrast, the growth rates of intensive margin in low- and middle-income countries are positive. During 2000–2015, intensive margin recorded a growth rate of 5% in low-income countries, 3.2% in upper middle-income countries, and 2% in lower middle-income countries.

While the results reported above pertain to merchandise exports as whole, we also look at the decomposition results separately for the group of manufactured products across partner country groups.[13] We see that, as in aggregate merchandise exports, export penetration rate of manufactured exports in high-income countries witnessed a sharp decline from 2.8 in 2000 to 1.7 in 2015. Again, this decline is due to the fall in intensive margin from 2.8 in 2000 to 1.7 in 2015. The negative growth of intensive margin, in turn, is driven by a decline in quantity margin from 2.6 to 1.5 during 2000–2015. On the other hand, in low- and middle-income countries, the growth rates of export penetration, intensive margin, and quantity margin are positive.

Overall, our decomposition results are consistent with those reported in Veeramani et al. (2018). Using a different decomposition approach, Veeramani et al. (2018) observed that India lags significantly behind China in terms of intensive margin due to an abysmally low and stagnant quantity margin. As far as the extensive margin is concerned, the gap between the two countries is narrow and India is clearly catching up with China.

6 Conclusion

While India's merchandise exports in dollar terms grew moderately at about 8.1% per year during the first decade of economic reforms (1993–2001), the period from 2002 to 2011 stands apart for its strong growth rate of 21.3% per annum. Data for the more recent years, however, indicate a significant slow-down of export growth rate. The commodity composition of exports underwent consistent changes in favor of capital- and skill-intensive products. The lack of dynamism in labor-intensive manufacturing

[13] Manufactured goods include SITC codes 5–8 less 667 (Pearls and precious or semi-precious stones, unworked, or worked) and 68 (Non-ferrous metals): Chemicals (SITC 5), manufactured materials (SITC 6), machinery and transport equipment (SITC 7), and miscellaneous manufactured articles (SITC 8). The HS codes corresponding to these SITC codes are identified using the HS-SITC concordance table available in WITS. It should, however, be noted that during the entire period of our analysis, the nomenclatures used by the DGCI&S to classify products into HS codes have undergone changes. For instance, HS 1996 is used for product classification from 2000 to March 2003, HS 2002 is followed from April 2003 to March 2007, and HS 2007 is used thereafter. In order to maintain a uniform classification, we use the concordance between different HS series and SITC revision 2 and map each eight-digit HS product code to a one-digit SITC code.

is a matter of concern because it is this sector that holds the potential to absorb the large pools of surplus labor from India's agriculture sector. The experience of the successful East Asian countries showed that export-led industrialization based initially on labor-intensive industries is crucial for sustained employment generation and poverty reduction. The observed pattern of specialization is an anomaly given the fact that India's true comparative advantage lies in unskilled labor-intensive activities. Due to its idiosyncratic specialization, India has been locked out of the vertically integrated global supply chains in several manufacturing industries. India's export penetration to high-income OECD countries grew much slower compared to other market destinations, which is expected given the increasing bias in India's export specialization in skill- and capital-intensive products.

The sustainable solution to the problem of India's current account deficit lies in ensuring that export growth keeps pace with the growth of imports. What type of policy interventions would help achieve faster export growth? Should export promotion policies be targeted at accelerating export growth at the intensive or at the extensive margin? To help answer these questions, we have analyzed the role of extensive and intensive margins in India's export market penetration across partner country groups.

We analyze India's exports during 2000–2015 by decomposing overall bilateral export flows into extensive, intensive, price, and quantity margins, and draw inferences about the relative export performance across various partner country groups. The analysis is undertaken using highly disaggregated (eight-digit HS) export data. We find that there is a sharp contrast between India's relative performance in high-income countries and in other country groups. Our decomposition results show that while exports to low- and middle-income countries grew positively, there has been a significant decline in India's export penetration into high-income countries. The negative growth rate of export penetration in rich country markets is driven entirely by the intensive margin and not extensive margin.

A major misconception among the policy-makers in India is that the country should necessarily diversify to new markets in the developing world if it has to increase its export volume. Based on this perception, the Indian government had even announced an export incentive scheme providing explicit financial supports for market diversification. Our analysis suggests that the country can reap rich dividends by adopting policies aimed at accelerating export growth at the intensive margin. Contrary to the general perception, there exist a great potential for India to expand and intensify its export relationships with the traditional developed country partners. However, this would necessitate India's greater participation in the vertically integrated global supply chains and a realignment of its specialization in labor-intensive processes and product lines. To this end, it is important to make the labor market more flexible, promote investment in physical infrastructure, remove market distortions, and reduce the administrative costs on business.

Appendix: Decomposition Methodology—A Numerical Illustration

Suppose a country exports three products to a set of partner countries—A, B, C, and D.

Product	Country A	Country B	Country C	Country D
1	10	0	50	40
2	20	40	10	30
3	50	20	0	0
Column total	80	60	60	70

	Calculation of intensive margin	Calculation of extensive margin
Country A	$\frac{80}{60+60+70} = 0.42$	$\frac{60+60+70}{60+60+70} = 1.00$
Country B	$\frac{60}{70+10+30} = 0.55$	$\frac{70+10+30}{80+60+70} = 0.52$
Country C	$\frac{60}{30+40+70} = 0.43$	$\frac{30+40+70}{80+60+70} = 0.67$
Country D	$\frac{70}{30+40+60} = 0.54$	$\frac{30+40+60}{80+60+60} = 0.65$

From the above example, it is easy to understand that the value of the exporting country's extensive margin in country A is equal to 1, since it exports the entire set of products to A.

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Digitalization and India's Losing Export Competitiveness

Rashmi Banga and Karishma Banga

1 Introduction

The fourth digital industrial revolution is transforming production, consumption and distribution processes in ways that can drastically alter export competitiveness of developing countries. The use of Big Data analytics in the pre-production stage is helping forecast which products and services will be demanded and in which markets; robotics, 3D printing and artificial intelligence are being used to produce cost-effective products and services at a much higher speed than ever; and e-commerce and electronic transmissions are emerging as the new ways for distributing and delivering products and services. A study by Leering (2017)[1] estimates that of current growth of investments in 3D printing continues, 50% of the manufactured goods will be 'printed' by 2060, and if investment in 3D printing doubles, this target will be achieved in 2040. However, while developed countries are rapidly developing their digital capacities by increasing the use of digital technologies and digital services in their industrial production, developing countries are still in nascent stages. With the growing digital divide between developed and developing countries, the traditional patterns of trade are likely to undergo drastic changes with export competitiveness shifting in favour of the developed countries, even in the traditional export sectors of

[1]Leering (2017), "3D printing: a threat to global trade". https://www.ing.nl/media/ING_EBZ_3d-printing_tcm162-131996.pdf.

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the developing countries. In this context, this paper estimates the impact of growing digitalization on India's exports. India's exports have been rising in the last 3 years crossing $300 billion in 2018, and India's share in global exports has also been rising. However, the growth of Indian exports and growth of India's share in global exports have been erratic, especially since 2011. To estimate the impact of growing digitalization on India's export competitiveness, the paper undertakes analyses at the sectoral level and at the firm level. The sectoral-level analysis is undertaken by estimating the value added by digital services (computer programming, consultancy and related activities, information service activities and telecommunications) in India's traditional exports and comparing it with other developing and developed countries. The firm-level analysis is undertaken by estimating the impact of digital assets on export intensity of a firm, where digital assets is measured as the share of computer and IT systems in overall expenditure on plant and machinery, which includes plant and machinery, computer systems and electrical installations.

The rest of the paper is organised as follows: Sect. 2 highlights trends in India's exports at the aggregate level and at disaggregated sectoral level, highlighting India's changing export competitiveness; Sect. 3 presents the methodology for estimating the extent of digitalization of India's exports, comparing it with selected countries; Sect. 4 presents the results at the aggregate level as well as at the sectoral level of the extent of digitalization of India's exports; Sect. 5 presents review of empirical literature at the firm level on the impact of digitalization on export intensity of firms. Section 6 discusses the methodology of firm-level analysis and presents preliminary analysis; Sect. 7 presents firm-level empirical results of impact of digital assets on firm's export intensity; Sect. 8 concludes and provides the way forward.

2 India's Losing Export Competitiveness

India's exports of goods and services fell in absolute terms from US$448 billion in 2012 to US$434 billion in 2016, rising to US$495 in 2017, but its exports of goods and services as a share of GDP has declined steadily in this period, falling from 24.5% in 2012 to 19% in 2017 (Table 1).

While India's export of services has increased over time, its traditional exports comprise merchandise exports, which remain around 60% of India's total exports. There can be many indicators of export competitiveness of a country, but the direct indicator which captures changing export competitiveness of a country is its changing share in global exports.

Examining India's merchandise export in the period since 2003 (Table 2), it is seen that India's exports have grown steadily since 2003 rising from US$59 billion in 2003 to US$220 in 2010 and further to US$294 in 2017 reaching US$323 in 2018. This has led to rise in India's share in global exports from 0.9% in 2003 to 1.5% in 2010 and further to 1.9% in 2017. The average annual growth of exports has been impressive at 21% in the period 2003–2010. However, average annual growth of exports in the period 2011–2017 has declined from 21 to 5.5%. While it can be

Table 1 India's global exports of goods and services: 2012–2016

	Exports of goods and services (current USD)	Exports of goods and services (% of GDP)
2012	448	24.5
2013	472	25.4
2014	468	23.0
2015	421	19.9
2016	434	19.3
2017	495	19.1

Source World Integrated Trade Solutions (WITS): COMTRADE, World Bank

Table 2 Changing export competitiveness of India: 2003–2017

	India's global exports (US$ bn)	India's share of global exports (%)	Annual growth in exports (%)	Annual growth in India's share in global exports (%)
2003	59	0.9		
2004	75	0.9	27.9	2.5
2005	100	1.1	32.2	16.5
2006	121	1.1	20.8	2.4
2007	145	1.1	20.4	4.6
2008	181	1.2	24.6	7.4
2009	176	1.5	−2.8	25.2
2010	220	1.5	24.7	0.4
Average annual growth rate (2003–2010)			*21.1*	*8.4*
2011	301	1.7	36.8	14.0
2012	289	1.7	−4.0	−3.3
2013	336	1.9	16.2	11.9
2014	317	1.8	−5.7	−4.9
2015	264	1.7	−16.7	−3.8
2016	260	1.8	−1.5	1.4
2017	294	1.9	13.1	6.3
Average annual growth rate (2011–2017)			*5.5*	*3.1*

Source World Integrated Trade Solutions (WITS): COMTRADE, World Bank

argued that the global slowdown must have led to this slide in the average annual growth rate of exports in the period 2011–2017, the average annual growth of India's share in global exports has also experienced a drastic fall from 8.4% in the period 2003–2010 to 3.1% in the period 2011–2017.

Table 3 India's share in global exports, 2011–2017

	2011	2012	2013	2014	2015	2016	2017
Textile fibres, not manufactured and waste	8.9	10.1	12.7	9.5	8.5	7.3	7.8
Plastic materials, etc.	1.6	2.6	1.9	1.5	1.3	1.2	1.2
Leather, leather manufs., n.e.s and dressed fur	4.3	4.4	5.1	5.2	6.1	4.5	3.7
Textile yarn, fabrics, made up articles, etc.	5.4	5.6	6.4	6	6.6	5.9	5.2
Non-metallic mineral manufactures, n.e.s	12.8	9.6	11.6	9.7	10.6	11	10.5
Electrical machinery, apparatus	0.6	0.6	0.6	0.5	0.4	0.4	0.4
Sugar, sugar preparations and honey	4.1	4.4	2.4	3	3.9	3.9	2.9
Oil seeds, oil nuts and oil kernels	2.4	1.9	1.7	2.2	2	1.8	1.7
Fixed vegetable oils and fats	1.1	1	1.1	1	1.2	1	0.2
Crude chemicals from coal, petroleum, gas	3.8	3.7	6.8	2.2	0.8	1.1	1.1
Special transact. Not classified	6.3	1.1	1.6	0.3	0.5	0.2	0.1

Source World Integrated Trade Solutions (WITS): COMTRADE, World Bank

Table 3 reports the sectors which experienced a decline in India's share in global exports in the period 2011–2017. India's share in global exports has declined in textile fibres (1.1%), plastic materials (0.4%), leather manufacturers (0.6%), non-metallic minerals n.e.s (2.3%), crude chemicals (2.7%) and in special transactions not classified anywhere else (6.2%).

To investigate further the changing export competitiveness of India's merchandise exports, we compare the Revealed Comparative Advantage of India's exports in different sectors, as reported in World Bank's World Integrated Solutions (WITS), in the period 2015 to 2017. It is seen that out of 15 broad sectors, India lost its comparative advantage in 9 sectors. Most of these sectors contribute to India's top traditional exports like textiles and clothing, footwear, food products and chemicals (Table 4).

At a more disaggregated product level, as reported in World Bank's WITS, it is found that in the period 2011 to 2017 India has experienced a fall in its RCA in more than 75 products at the three-digit level. The top 25 products in terms of loss in RCA are reported in Table 5. Most of India's traditional export products are losing their comparative advantage including precious stones (which ranked second largest exports of India in 2017), spices, jewellery (ranking third largest export of India in 2017), cotton, tea, fabrics, clothing articles and leather. Most of these products also experienced a fall in their share in global exports in this period.

Trends in competitiveness over a longer period, i.e. 1995–2017, show that in some of India's traditional exports like tea, spices, clothing, jewellry and leather products, India is fast losing its comparative advantage (Fig. 1).

Table 4 India's sectoral revealed comparative advantage (RCA): 2015–2017

	Product code	Description	Revealed comparative advantage—2015	Revealed comparative advantage—2017
1	84–85_MachElec	Mach and elec	0.31	0.32
2	39–40_PlastiRub	Plastic or rubber	0.63	0.68
3	25–26_Minerals	Minerals	0.78	0.94
4	01–05_Animal	Animal	1.8	1.79
5	44–49_Wood	*Wood*	*0.31*	*0.29*
6	68–71_StoneGlas	Stone and glass	3.18	3.27
7	16–24_FoodProd	*Food products*	*0.66*	*0.62*
8	28–38_Chemicals	*Chemicals*	*1.36*	*1.35*
9	41–43_HidesSkin	*Hides and skins*	*1.86*	*1.66*
10	64–67_Footwear	*Footwear*	*1.22*	*1.09*
11	86–89_Transport	*Transportation*	*0.73*	*0.68*
12	72–83_Metals	Metals	1.2	1.4
13	06–15_Vegetable	*Vegetable*	*1.9*	*1.73*
14	27–27_Fuels	Fuels	1.2	1.32
15	90–99_Miscellan	*Miscellaneous*	*0.3*	*0.24*
16	50–63_TextCloth	*Textiles and clothing*	*2.94*	*2.85*

Source WITS, World Bank

Therefore, we can conclude that while India share in global exports has increased, there has been a gradual fall in the growth of its share and a steady decline in its export competitiveness (in terms of declining share in global exports and falling RCA), especially in key traditional labour-intensive products including tea, textile fabrics and apparels, leather manufacturers and spices.

3 Methodology to Estimate Extent of Digitalization of Manufacturing Exports

The fourth digital industrial revolution has witnessed a rise in digital content in manufactured products. Digital content in production can rise by either higher use of digital technologies like artificial intelligence, robotics or 3D printing or by higher use of digital services like ICT/software services and telecommunication services in the production process. The extent of digitalization used in the production processes can have far-reaching implications on the global competitiveness of manufacturing exports.

Table 5 India's revealed comparative Advantage (RCA) at three-digit product level: 2011–2017

		2011	2017
1	[667] Pearls, precious and semi-precious stones	11.6	10.4
2	[075] Spices	10.7	10.5
3	[897] Jewellery and articles of precious materia., n.e.s.	8.8	6.5
4	[263] Cotton	8.3	6.5
5	[074] Tea and mate	6.7	4.9
6	[516] Other organic chemicals	4.5	3.3
7	[686] Zinc	3.4	3.2
8	[334] Petroleum oils or bituminous minerals >70% oil	3.4	3.2
9	[842] Women's clothing of textile fabrics	3.2	2.4
10	[653] Fabrics, woven of man-made fabrics	3.1	2.4
11	[264] Jute, other textile bast fibre, n.e.s., not spun, tow	3.0	1.8
12	[612] Manufactures of leather, n.e.s., saddlery and harness	2.9	2.6
13	[061] Sugar, molasses and honey	2.7	1.7
14	[654] Other textile fabrics, woven	2.6	1.7
15	[611] Leather	2.6	2.1
16	[793] Ships, boats and floating structures	2.3	2.0
17	[266] Synthetic fibres suitable for spinning	2.2	2.2
18	[846] Clothing accessories of textile fabrics	2.0	1.8
19	[848] Articles of apparel, clothing access, excluding textile	1.9	1.8
20	[044] Maize (not including sweet corn), unmilled	1.9	0.3
21	[678] Wire of iron or steel	1.8	1.7
22	[325] Coke and semi-cokes of coal, lign, peat, retort carbon	1.8	0.1
23	[223] Oil seeds and oleaginous fruits (incl. flour, n.e.s.)	1.7	1.4
24	[281] Iron ore and concentrates	1.6	1.1
25	[697] Household equipment of base metal, n.e.s.	1.5	1.2

Source WITS, World Bank

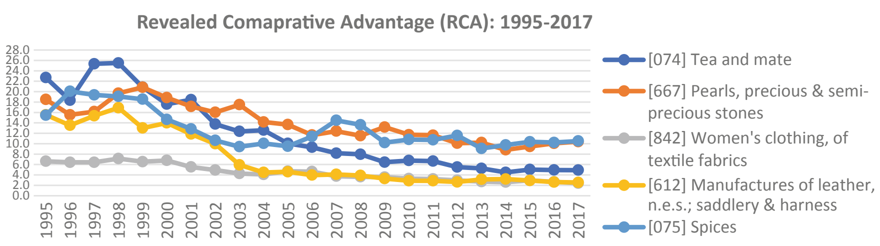

Fig. 1 India's competitive advantage in its traditional exports: 1995–2017. *Source* WITS, World Bank

To estimate the extent of the rise in digitalization of manufactured products in India and other selected countries for comparatives, we use two estimates. Firstly, the use of digital services (computer programing and information services and telecommunication services) in the production of manufactured products and secondly, value added by digital services (DS) in exports of manufactured products in different countries in the period 2000–2014.

DS as an input in manufacturing output is measured using national input–output tables (derived from World Input-Output Tables) and World Input-Output dataset (WIOD) for selected countries. For inter-country comparisons, this is taken as a percentage of total inputs used by manufacturing sectors; and the estimates for value added by DS in manufacturing exports are undertaken for 10 countries,[2] including India, for which the input–output tables are available in WIOD.

The value added by digital services (computer programing and information services and telecommunication services) in exports of manufactures is estimated using data from World Input-Output Dataset (WIOD) for the period 2000–2014. This dataset provides input–output data for 43 countries, including 15 developing economies, and 56 sectors. Using gross flows from WIOD and the 'decompr' package in R, developed by Quast and Kummritz (2015), Leontief's decomposition (1936) is applied, wherein the gross exports are decomposed into value-added flows between industries across countries.

The Leontief's decomposition can be expressed mathematically as

$VB = V(I - A)^{-1}$.

where V is an $N \times N$ matrix with the diagonal representing the direct value-added contribution of N industries, A is the input–output coefficient matrix with dimension $N \times N$, i.e. it gives the direct input flows between industries required for 1$ of output, and $B = (I - A)^{-1}$ is the Leontief inverse. VB gives an $N \times N$ matrix of called value-added multipliers, which denote the amount of value added that the production of an industry's 1$ of output or exports brings about in all other industries (Quast and Kummritz 2015).

Applying this to world input–output tables, V_{1XCN}. becomes the vector of direct value-added contributions of all industries across different countries, with C denoting number of countries and N denoting number of industries. A_{CNXCN}. gives the industry fls including cross-border relations. Since we are interested in the value-added origins of exports, A and V are multiplied by E_{CNXCN}. whose diagonal constitutes each industry's exports. This gives us the output of the Leontief's decomposition, mathematically expressed as E.

'Decompr' implements this algorithm into R to derive the matrix. The output is CNxCN matrix that gives for each country and industry the value-added origins of its exports by country and industry.

[2] Brazil, China, India, Indonesia, Russian Federation, Taiwan China, Turkey, United States, UK, Japan and ROW (rest of the World).

4 Extent of Digitalization of Manufacturing Exports: Results

4.1 Change in Intermediate Consumption of Digital Services as a Percentage of Total Intermediate Consumption in Manufacturing Sector: 2000–2014

Using the National Input-Output tables, DS used as an input in manufacturing output is compared for selected countries in the period 2000–2014. To normalise the variable, this is taken as a percentage of total inputs used in manufacturing output. It can be seen from Fig. 2 that the use of DS in manufacturing output has increased in developed countries like USA and the UK in the period 2000–2014, while it has declined in most of the developing countries. However, India has experienced a rise in this ratio. Although in terms of the ratio, the use of digital services as a percentage of total inputs used in manufacturing sector appears to be a small percentage in many countries, in absolute terms the digital services purchased for manufacturing production cross $50 billion in some developed countries. The maximum consumption of digital services in manufacturing production in absolute terms was done by USA in 2014, which surpassed $50 billion, followed by China ($30 billion) and Japan ($20 billion), while India consumed DS of US$18 billion. In the USA, the consumption increased from $15 billion in 2000 to $51 billion in 2014 and in Germany from $5 billion to $20 billion. India also experienced a rise in its use of digital services as an input in manufacturing output from US$3 billion to US$18 billion in this period.

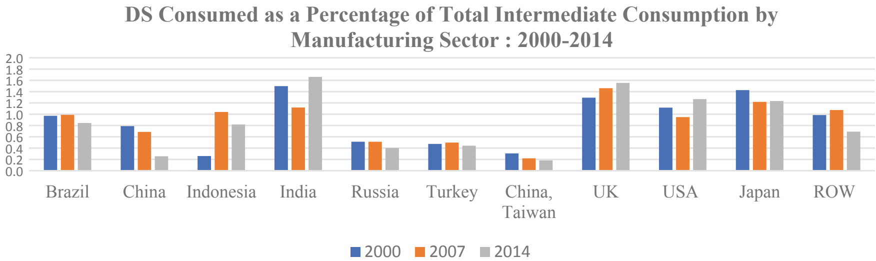

Fig. 2 Intermediate consumption of digital services as a percentage of total intermediate consumption in manufacturing output in developing and developed countries: 2000–2014. *Source* National input-output tables derived from world input-output tables, world input-output database (WIOD)

4.2 *Value Added by Digital Services in Manufacturing Exports: Results*

Using the above-discussed methodology, value added by digital services in total exports and in manufacturing exports is estimated for 10 selected countries for the year 2014. Table 6 reports the results, which show that in India, while intermediate consumption of digital services in manufacturing output was found to be US$18 billion, the value added by digital services to manufacturing exports amounted to US$4.8 billion only. In total exports of India, which includes merchandise exports as well as services exports, digital services contributed US$51.8 billion. Manufacturing exports therefore had a share of only 9% of total value added by DS in India's exports. The corresponding figure for other countries is much higher at 78% in Turkey, 60% in China, 57% in Indonesia and 54% in Brazil. This could be a plausible reason for sliding export competitiveness of India.

A closer look at the share of sectors in value added by DS to India's exports in Table 7 reveals that digital services contribute very little value added to manufacturing exports; the share of most manufacturing sectors is less than 1%. Most of the value added by digital services is contributed to exports of computer programing and telecommunication services which together account for 88% of total value added contributed by DS to total exports. This lopsided value addition by digital services to exports in India can have serious implications on its export competitiveness in the digital era. India is also found to lag behind other developing and developed countries in terms of other indicators of digital preparedness for international trade like ICT development index and digital infrastructure, as discussed in Banga (2019).

Table 6 Value added by digital services in total exports and manufacturing exports in 2014

	Value added by DS in manufacturing exports (US$ million)	Value added by DS in total exports (US$ million)	Value added by DS in manufacturing exports as a percentage of value added by DS in total exports
Brazil	1,805	3,340	54
China	18,789	31,148	60
India	*4,817*	*51,863*	*9*
Indonesia	1,596	2,804	57
Japan	12,220	17,553	70
Russian Federation	1,373	5,704	24
Taiwan, China	2,146	4,345	49
Turkey	2,246	2,867	78
United Kingdom	6,571	38,111	17
United States	16,606	58,509	28

Source Authors' estimates based on world input-output table

Table 7 Value added by digital services in sectoral exports of India: 2014

Sectors	Share of sectors in VA by DS in exports in India (%)
Manufacture of basic metals	0.4
Manufacture of basic pharmaceutical products and pharmaceutical preparations	0.1
Manufacture of chemicals and chemical products	1
Manufacture of coke and refined petroleum products	0.8
Manufacture of computer, electronic and optical products	0.7
Manufacture of electrical equipment	0.4
Manufacture of fabricated metal products	0.5
Manufacture of food products, beverages and tobacco	0.5
Manufacture of furniture; other manufacturing	0.8
Manufacture of machinery and equipment n.e.c.	0.6
Manufacture of motor vehicles, trailers and semi-trailers	0.7
Manufacture of other non-metallic mineral products	0.1
Manufacture of other transport equipment	0.9
Manufacture of paper and paper products	0
Manufacture of rubber and plastic products	0.2
Manufacture of textiles, wearing apparel and leather products	1.5
Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials	0
Total VA by digital services in manufacturing exports	*9.2*
Air transport	0.2
Architectural and engineering activities; technical testing	0.9
Computer programming, consultancy and related activities; information	*84.5*
Construction	0
Crop and animal production, hunting and related service	0.1
Insurance, reinsurance and pension funding, except compulsory social security	0.1
Land transport and transport via pipelines	0.2

(continued)

Table 7 (continued)

Sectors	Share of sectors in VA by DS in exports in India (%)
Legal and accounting activities; activities of head offices; management consultancy activities	0
Mining and quarrying	0.1
Other service activities	0.2
Printing and reproduction of recorded media	0
Retail trade, except of motor vehicles and motorcycles	0.1
Telecommunications	4
Warehousing and support activities for transportation	0.1
Water transport	0.1
Wholesale trade, except of motor vehicles and motorcycles	0.1
Others	0
Total VA by digital services in exports of non-manufacturing sectors	*90.7*

Source Authors' estimates based on national input-output table of India as reported in world input-output tables

The next sections analyse how digital assets employed by a firm affect its export intensity. Section 5 presents a review of literature on firm-level drivers of export intensity. Drawing from the literature review, Sect. 6 outlines the econometric model, empirical strategy and data used in the paper for estimating impact of digital assets firm-level firm's export intensity. Section 7 presents and discusses the empirical results.

5 Review of Existing Literature on Impact of Digitalization on Firm's Export Intensity

There exists an extensive literature which examines the drivers of export performance of Indian manufacturing firms, including impact of firm productivity on export status (Goldar and Kato 2009), R&D and technology (Kumar and Siddharthan 1994), firm size on export intensity (Kumar and Siddharthan 1994), financial variables, import competition (Goldar and Kato 2009) and imported services (Goldar et al. 2018). However, very few studies exist, especially for India, which estimates the impact of digitalization on firm's export intensity.

Majority of existing studies on export performance of Indian firms have used a 'self-selection' framework to analyse the relationship between export performance and productivity. As per the self-selection hypothesis, firms are heterogenous in nature and it is the 'better' firms that are more likely to start exporting. More productive firms may find it easier to enter into export market since they are better placed to deal with the sunk costs associated with exporting (Melitz 2003; Bernard et al. 2003), such as those related to identifying foreign customers, conducting inspections and meeting foreign standards (Wagner 2007). Several empirical studies have confirmed that a firm's decision to start exporting is positively and significantly impacted by its productivity in the previous period. In the Indian context, these studies include Haidar (2012), Gupta et al. (2013) and Thomas and Narayanan (2016).[3]

Some studies also find that once a firm enters into the export market, its productivity rises due to 'learning by exporting'. Exporters face international competition and cater to foreign buyers with higher demands, which create higher incentives to innovate, increase productivity and remain competitive. Ranjan and Raychaudhuri (2011), for instance, find empirical evidence of learning by exporting for the case of Indian manufacturing firms in the period 1990–2006.

Beyond firm productivity, the financial constraints faced by a firm can also play an important role in its decision to enter the export market. Firms that have a higher access to finance and credit from the banking sector are more likely to deal with sunk costs related to exporting. Several studies have therefore extended the Melitz (2003) model by incorporating financial constraints faced by firms as an additional factor determining firms' decision to enter export markets (see, for instance, Chaney 2005; Muuls 2008; Manova 2013) and its export intensity. For Indian firms, Nagaraj (2014) provides empirical evidence of financial constraints negatively impacting firms' decision to export in the period 1989–2008. The author further finds that financial health of firm is the cause of export performance and not the effect of exporting. Analysing Indian manufacturing in the period 2000–2014, Goldar et al. (2018) confirm that financial constraints faced by a firm, measured by its debt-to-equity ratio, negatively impact export intensity, and this impact is found to hold for both internal and external margins of exports in the study by Padmaja and Sasidharan (2015).

Firms that are both importing and exporting can benefit from the cost complementarities that arise from two-way trading. This is evidenced in Kasahara and Lapham's (2013) study which finds that Chilean firms engaging in both trading activities reduce per period fixed and sunk costs. Defining two-way traders as firms engaged in Global Value Chains, Baldwin and Yan (2014) show that joining a GVC improves firm productivity, which can also have a positive impact on export intensity as discussed above. For Indian firms, Banga (2017) finds that manufacturing firms involved in GVCs, i.e. firms which are both importing intermediate goods and exporting have more sophisticated product baskets. Focusing on services, and using firm-level data for 1994–2004, Bas (2013) finds that service reforms of energy, telecommunications

[3] See Goldar et al. (2018) for a recent review of studies examining the relationship between exporting status and productivity.

and transport services in India positively impacted export performance of manufacturing firms. Goldar et al. (2018) confirm the positive impact of services inputs, particularly imported services, on export intensity of Indian manufacturing firms in the period 2000–2014.

With recent advances in digital technologies, a number of studies have examined the impact of ICT adoption and use of digital services in manufacturing, with a growing consensus that digitalization at the firm level can contribute to significant improvements in firm performance. However, most of these studies are focussed on developed countries. Evidence of both adoption of digital technologies and its consequences in developing countries remains scant, largely due to problems of data availability required to construct estimates of digital capital. This includes information on 'hard' digital infrastructure such as computers, routers and sensors, and 'soft' digital infrastructure which refers to access to and quality of Internet, software, use of digital services and data, intellectual property, etc. (Banga and te Velde 2018a).

The developing country evidence that does exists tends to focus on the implications of digitalization on growth and productivity. For Chinese manufacturing firms in the period 1995–2002, Motohashi (2008) finds that ICT capital in Chinese firms contributes significantly to productivity, particularly in foreign-owned firms. Commander et al. (2011) analyse Indian and Brazilian manufacturing firms in the period 2001–2003 and find positive productivity gains associated with ICT adoption. For Indian manufacturing, Sharma and Singh (2013) find a positive association between ICT stock in industries and value added. Analysing Indian manufacturing firms in the period 1994–2010, Mitra et al. (2014) hold that infrastructure and ICT have a boost firm-level TFP, with firms in industries of transport equipment, textiles, chemicals and metal products being more sensitive to infrastructure endowments as a result of increased exposure to foreign competition. Joseph and Abraham (2007) confirm the positive impact of ICT investment on labour and total factor productivity in Indian firms; outsourced ICT is observed to have a higher impact on productivity than in-house ICT (Kite 2012, 2013).

Firm-level empirical literature on the direct impact of digital technologies or ICT on export intensity is limited. The existing evidence on developing countries suggests that there is heterogeneity in technological capability, and these differences are an important factor for international trade (Moreno 1997; Trefler 1993, 1995). By adopting modern technologies, these countries can strengthen their comparative advantages (Noland 1997). In line with this, Erumban and Das (2016) identify three channels through which digitalization can increase competitiveness of developing countries; (a) a production channel, in which ICT adoption can facilitate rapid technological changes; (b) an investment channel, in which firms investing in ICT can enhance the contribution of capital to growth; and (c) a productivity channel, in which firms using ICT can improve their productivity. Banga and te Velde (2018a) argue that comparative advantage is not static; it is a dynamic concept that can be shaped through appropriate policies, including on ICT adoption. Banga and te Velde (2018b) present the case study of New Wide garments—a garment manufacturing firm in Kenya that has invested in digital technologies of Computer-Aided Design and Manufacturing, and as a result has expanded into new production lines, met international standards, and increased exports and productivity. Another Kenyan firm, Megh Cushion Industries, invested heavily in multipurpose technologies such as CNC auto-cut and laser technology, and as a result was able to diversify from producing and supplying automotive parts into transport seating and complete van conversions (ibid). Portugal-Perez and Wilson (2012) report that ICT infrastructure positively impacts export performance of developing countries but is increasingly important the richer a country becomes.

In the context of developing countries, several studies have examined the adoption of e-business[4] by manufacturing firms (Goldstein 2002; Goldstein and O'Connor 2002; Moodley 2002). In addition to lowering export barriers and providing online sales channels, digital technologies present opportunities for increasing market access to manufacturing firms through information gathering on competitors (Borges et al. 2009), using valuable customer-related data in updating business models, establishing direct customer contact (Lohrke et al. 2006), relationship building, digital marketing and improving customer service.

Focusing on Indian firms, Lal (2004) uses a Tobit model to analyse 51 Indian garments manufacturing firms and finds that adoption of IT significantly boosts export performance. Export-oriented firms may have adopted more advanced digital technologies to achieve greater flexibility in garment designs and to manufacture international quality products. Bhat (2015) focuses on pharmaceutical firms in India, and also find a positive impact of IT investment export performance, along with other firm-level characteristics such as age and size. Regular exporters that invest in information technology for efficient storage, retrieval, analysis and distribution of data and information are found to have higher export intensities.

Moodley (2002), however, does not find sufficient evidence of e-business benefitting export-oriented apparel firms in South Africa, which may be because the impact of online activities on export sales are likely to depend on 'how' the Internet technologies are being used (Anna Morgan-Thomas and Bridgewater 2004). The absorptive capacity of online sellers in developing countries also matters for using digital technologies. Goldstein (2002) presents the case of Fiat, one of the top automobile firms, which has been able to optimise its supply-chain management in Brazil, but not in India where the use of Internet by the company (Fiat India) remains limited to knowledge management, R&D and marketing.

Digitalization can therefore directly increase export intensity or have an indirect impact through other firm-level characteristics such as productivity and R&D. The next section contributes to the existing literature by empirically estimating the impact of firm-level digital assets on export intensity of Indian manufacturing firms, controlling for other firm-level characteristics. Digital assets are measured as the share of computer/IT systems (including hardware and software) in overall plant and machinery expenditure of the firm. Digital assets can play an important role in determining

[4]E-business encompasses all business conducted online, and includes e-commerce, which refers to buying and selling online.

firm's export competitiveness in the digital era, especially the use of software. The impact of digital assets on export competitiveness of Indian firms is estimated using the methodology discussed in the next section.

6 Model Specification and Empirical Strategy

6.1 Model Specification

Drawing on the above review of literature, we analyse the impact of digital assets in Indian manufacturing firms on firm-level export intensity using the following baseline model specification for the period 2000/01–2014/15:

$$\begin{aligned}\text{Export intensity}_{it} &= \phi_1 \text{Export intensity}_{i,t-1} + \phi_2 \text{Export intensity}_{i,t-2} + \alpha \text{Log(labour productivity)}_{i,t-1} \\ &+ \beta \text{Log(Digital Assets)}_{i,t-1} + \sum \phi X_{i,t} + \sum \phi_2 Z_{i,t-1} + a_t + u_{it}\end{aligned} \tag{1}$$

where Export intensity$_{it}$. is the share of exports in sales of firm i. at time t. This is regressed on lagged values of export intensity to capture the influence of sunk cost (e, e.g. Padmaja and Sasidharan 2015, 2017). We follow Goldar et al. (2018) and introduce two lagged terms for export intensity as explanatory variables. Other explanatory variables include labour productivity and digital assets of the firms. $\sum X_{i,t}$ is a vector of firm-level control variables measured at time t, such as log(age) and log(size) of the firm, and $\sum Z_{i,t-1}$ is a vector of controls measured at time t-1 such as log (import intensity), log (R&D intensity), log (debt/equity ratio), etc.[5] The model controls for time and industry fixed effects through inclusion a_t and a_j, respectively, and u_{it} is the error term.

For estimating the above model, the study employs the System Generalised Method of Moments (GMM) estimator and a random effects panel Tobit model. The main issue in estimating the impact of digital assets on export intensity is that of endogeneity; unobserved firm characteristics such as unobserved productivity may be correlated to both export intensity and digital assets, which can lead to spurious regressions. The results can also be biased if there are unobserved time-invariant firm effects correlated with the regressors in the model. The possibility of endogeneity together with the presence of firm-fixed effects indicates that results from ordinary least squares regressions will be biased and inconsistent. Using the fixed effects estimator will also lead to inconsistent estimates due to the presence of lagged dependent variables as regressors in Eq. 1.

[5]Some of the control variables in estimations have also been taken with a 1-year lag in the model since the impact of a change in these variables on export intensity of firms may take some time to be realised.

GMM is therefore employed as an instrumental variable estimator that can deal with both persistency in the dependent variable and endogeneity in the model. It runs the model both in levels and first differences, using lagged values of first differences as instruments for the level equation and lagged values of levels as instruments for first differences (Arellano and Bover 1995). It also allows inclusion of lagged values of export intensity as explanatory variables, enabling us to deal with problems of (1) autocorrelation of disturbances in panel estimation, (2) time-invariant firm effects correlated with regressors and (3) the possibility that some variables may be pre-determined but may not be strictly exogenous.

To employ System GMM, Roodman's (2009) *xtabond2* command has been used, with two-step GMM estimation and robust standard errors, clustered at the firm level. This ensures maximum efficiency and robustness to heteroskedacity and autocorrelation. We also include time fixed effects in all our models and check robustness suing industry dummies in some models.

The validity of system GMM estimations is checked using Hansen's J test of over-identifying restrictions (Arellano and Bond 1991). A *p*-value greater than 0.05 ensures that the instruments are exogenous. We also check for no second-order serial correlation in the first differenced residuals, i.e. at the AR (2) level. Following Roodman's (2009) suggestions and rule-of-thumb, we ensure that the number of instruments remains below the number of groups in the panel.

The estimates are also undertaken using a random effects panel Tobit estimates. The logic in applying a random effects panel Tobit is that it considers the fact that the dependent variable is truncated at zero and in nearly half of the observations, the export intensity is zero.

6.2 Data and Variables

The main source of data for the econometric analysis of export performance of Indian manufacturing firms presented in the paper is Prowess (CMIE).[6] Data for 15 years 2000–2001 (hereafter 2001) to 2014–2015 (hereafter 2015) are used for the analysis.[7] We restrict ourselves to manufacturing firms and collect firm-level data on identification indicators, sales, output, value added, exports of goods and services, import capital goods, import of raw materials and store and spares, liquidity and leverage, purchase of services, net fixed assets, labour, materials, etc. The number of firms in the dataset varies from year to year. As part of data cleaning, we drop

[6]Compiled from annual reports, Prowess provides data on listed companies, as well as some unlisted public and private limited companies. It has a good coverage of the Indian firms with the output of manufacturing companies in Prowess covering around 60% of India's manufacturing output. In regard to international trade, Prowess covers around 50% of Indian exports and nearly 60% of imports (this is for the year 2013–2014).

[7]The number of firms in the dataset varies from year to year. It is mostly between 3000 and 5000 firms in different years, except for 2015 for which there are only about 2000 firms.

Table 8 Construction of variables

Variable	Construction	Data sources used
Export intensity	(Export of goods/total sales) * 100	Prowess
Labour productivity	GVA/number of people employed	Prowess, ASI
Size	Log (deflated sales) or log (deflated total assets)	Prowess
Digital asset	(Computer and IT systems expenditure)/(Expenditure on plant and machinery, computers and IT, electrical installations) * 100	
Age of the firm	Reporting year—year of incorporation	Prowess
Service input intensity	(Services purchased/sales) * 100	Prowess
Imported services intensity	(Imported services/total services) * 100	Prowess
R&D intensity	(R&D expenditure/sales) * 100	Prowess
Debt/equity ratio	Total debt of the firm/total equity of firm	Prowess

observations with negative values of value added and remove observations with real value added to labour or value added to capital ratio in the 1st or 99th percentile.

Table 8 explains the variables used in regression analysis. The key variable of interest is Digital Assets, measured as the share of computer/IT systems in overall plant and machinery expenditure of the firm, which includes expenditure on plant and machinery, electrical installations and computer systems. Computer systems capture the overall hardware and software required in the operation of a computer.[8]

Labour productivity is measured as the gross value added (GVA) divided by number of people employed. GVA is calculated as the nominal output minus nominal value of intermediate inputs (materials, energy and services), deflated using three-digit industry-level price deflators constructed from WPI series, obtained from Office of Economic Advisor (Ministry of Commerce and industry), spliced and rebased to 2004–2005. Prowess provides employment data only for a limited number of firms. Following the literature, we construct firm-level labour input using the Annual Survey of Industries in India. We first calculate the Average Wage Rate (AWR) for National Industrial Classification (NIC) three-digit industries in ASI using total emolument/total employees. We then match five-digit NIC industries in Prowess (which follow 2008 classification) to three-digit industry in ASI. Wages and salaries in Prowess are divided by the industrial wage rate to get labour employed.

The summary statistics are presented in Table 9. The average export intensity in our sample is roughly 12%.[9] The share of digital assets ranges from 0 to 100%, with an average of 6.5%. It is observed that only 5% of the sample is classified as foreign firms, defined in Goldar and Banga (2018) as firms with more than 10% of foreign

[8]In line with earlier sections, a firm-level indicator on the use of digital services in manufacturing would have been a useful indicator; however, Prowess does not report this information.

[9]Missing values of export intensity are treated as zero; this is common practice among econometric studies on export intensity of Indian firms using Prowess database.

Table 9 Summary statistics

Variable	Obv.	Mean	STD	Min	Max
Export intensity	29,657	11.89	22.85	0.00	123.83
Labour productivity	16,404	0.07	0.288	0.00	3.86
R&D intensity	29,657	0.15	0.81	0.00	28.57
Digital assets share	29,631	6.51	15.53	0.00	100.00
Debt/equity	26,635	2.73	48.35	0.00	5792.00
Real sales	29,349	31.03	325.00	0.00	23367.03
Service input intensity	29,657	11.60	8.55	0.01	143.68
Foreign firm	29,657	0.05	0.23	0.00	1.00
Foreign shares	29,657	1.81	9.51	0.00	96.80
Age	29,393	23.65	16.90	1.00	132.00
Labour employed	16,631	925	4925	1	19,3628

Note Real sales are in Rs. million

equity. Foreign shares range from 0 to 97%, with a low average of 1.8%. On an average, a firm is employing 925 workers.

6.3 Preliminary Analysis: Descriptive Statistics

Comparing average share of digital assets across two-digit industries in the period 2001–2015, Fig. 3 shows that motor vehicles and trailers, coke and refined petroleum, machinery and equipment, computer and electronics, and electrical equipment are the top five digitalised industries in Indian manufacturing. Manufacturing industries of furniture, leather products, food and beverages, wood products, basic metals and wearing apparel are found to be relatively less digitalised. These results are in line with findings of Krishna et al. (2018). Calculating ICT investment in Indian industries, Krishna et al. (2018) show that in early 1990s, 22% of total ICT investment was in chemicals, 18% in textile and 9% in food products. However, the share of textiles dropped substantially over the years, particularly until mid-1990s, and stood at a low of 6% in 2013–2014. The share of machinery, transport and electrical and optical equipment, on the other hand, increased, respectively, from 6% to 13%, from 7% to 17% and from 8% to 18% (ibid). The authors conclude that together these three industries constitute almost half of the total ICT investment in India's organised manufacturing sector in 2013–2014.

It is also key to note that industries identified in Fig. 3 as being more digitalised, i.e. machinery and equipment, computer and electronics and pharmaceuticals, also rank higher in terms of export intensity in our sample. On the other hand, less digitalised sectors of leather, wearing apparels, food and beverages relate to sectors identified in Fig. 1 as losing export competitiveness (tea, spices, clothing, leather, etc.).

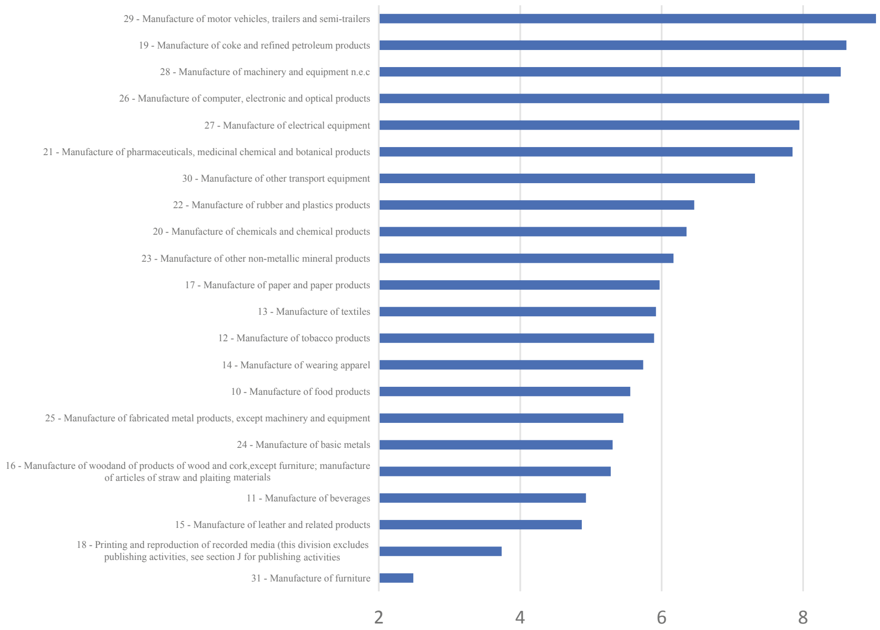

Fig. 3 Share of digital assets in two-digit NIC industries, average % in 2001–2015. *Source* Constructed from Prowess

Comparison of the share of digital assets of exporters and non-exporters (Fig. 4) shows that although exporters are more digital, i.e. they have a higher share of digital assets, this share has been consistently declining, going down from roughly 8.5% in 2001 to 5.8% in 2013. While the share of digital assets has also declined in non-exporting firms during the period 2001–2005, it has steadily increased in the period 2005–2010.

Figure 5 observes average export intensity and digital assets over 2001–2014 for the sample of Indian manufacturing firms and finds that export intensity increased in the period 2004/05–2008/09, but declined thereafter. Overtime, the average share of digital assets has also experienced a declining trend. This could be due to declining

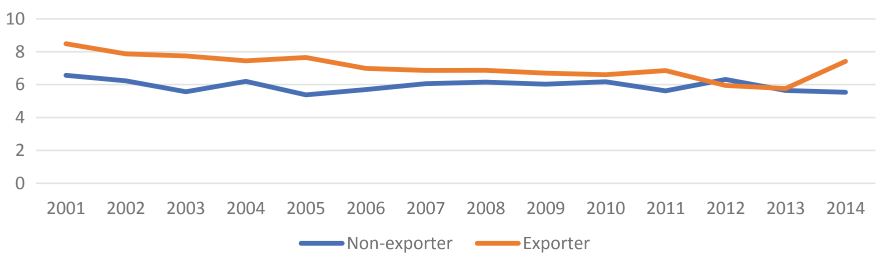

Fig. 4 Share of digital assets, exporter versus non-exporter. *Source* Prowess

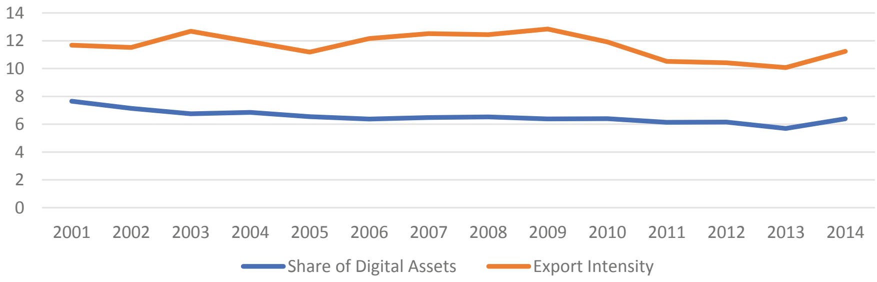

Fig. 5 Export intensity and share of digital assets. *Source* Prowess

share of digital assets in exporting firms (as observed in Fig. 4), which form 51.25% of the sample.

We further test if export intensity significantly differs across firm characteristics. Table 10 presents results of difference-in-mean tests for examining if the average export intensity is significantly different across firms with a higher share of digital assets (i.e. firms in which the share of digital assets is above the median industry level) as compared to firms with a low share, as well as across domestic and foreign firms. Results indicate that average export intensity is significantly higher in firms which are more digitalised, and in foreign firms as compared to domestic firms.

Table 10 Testing differences in export intensity across digital assets

Variable	Obs.	Average export intensity	SE	Standard dev.	95% confidence interval		T stat for H(0): Diff in means = 0	Significantly different means across groups
Low digital cap	14,816	11.47	0.18	22.66	11.11	11.84	−3.1***	Yes
High digital cap	14,815	12.30	0.18	23.03	11.93	12.67		
Domestic	28,037	11.53	0.13	22.62	11.26	11.79	−11.22***	Yes
Foreign	1620	18.07	0.63	25.68	16.82	19.32		

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
Source Prowess

Table 11 System GMM results: dependent variable = export intensity

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
L.export intensity	0.682*** (0.03)	0.685*** (0.03)	0.739*** (0.04)	0.738*** (0.04)	0.739*** (0.04)	0.733*** (0.04)	0.735*** (0.04)	0.738*** (0.04)
L2.export intensity	0.108** (0.04)	0.096** (0.04)	0.168*** (0.05)	0.169*** (0.05)	0.159*** (0.05)	0.160*** (0.05)	0.160*** (0.05)	0.174*** (0.05)
L.log digital assets	0.322* (0.18)	0.359* (0.18)	0.489** (0.22)	0.473** (0.22)	0.458** (0.22)	0.470** (0.22)	0.456** (0.22)	0.610*** (0.22)
L.log labour prod			0.317* (0.18)	0.340* (0.19)	0.346* (0.19)	0.331* (0.20)	0.385* (0.21)	0.236 (0.21)
L.log R&D inten.		0.016 (0.03)	−0.052 (0.03)	−0.056 (0.03)	−0.054 (0.03)	−0.056 (0.03)	−0.054 (0.03)	−0.036 (0.03)
L.log debt/equity	−0.120 (0.08)	−0.127 (0.08)	−0.084 (0.08)	−0.106 (0.09)	−0.106 (0.11)	−0.110 (0.11)	−0.113 (0.11)	−0.068 (0.11)
L.log service input				0.299 (0.39)	0.359 (0.38)	0.390 (0.37)	0.402 (0.38)	0.0320 (0.30)
L.foreign share					−0.006 (0.04)	−0.008 (0.04)	−0.008 (0.04)	0.005 (0.04)
Log age						0.0300 (0.23)	−0.003 (0.22)	−0.054 (0.21)
Log real sales							0.0418 (0.14)	0.0653 (0.16)
Constant	0 (0)	2.321** (0.97)	0 (0)	0 (0)	0 (0)	0.591 (1.51)	0.818 (1.76)	0 (0)
Times FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	No	No	Yes

(continued)

Table 11 (continued)

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Hansen p val	0.15	0.23	0.35	0.35	0.26	0.27	0.25 0.51	0.34 0.44
AR (2)	0.80	0.93	0.44	0.44	0.59	0.51		
Observations	13,627	13,627	7,846	7,846	7,846	7,785	7,785	7,785
Number of firms	3,568	3,568	2,330	2,330	2,330	2,305	2,305	2,305

Standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

7 Empirical Results

Table 11 reports the empirical results using GMM. Model 1 reports the results of regressing export intensity on lagged export intensity, digital assets and firm leverage, captured by the debt-to-equity ratio. It is expected that lagged values of export intensity will yield a positive impact on export intensity in the current period, since these lagged variables are capturing sunk costs associated with exporting. Model 2 adds a control for R&D intensity, measured as share of R&D expenditure in total sales of the firm. To this, Model 3 adds a control for labour productivity. Together labour productivity and R&D intensity can capture important elements of firm-level internal absorptive capacity and are expected to boost export intensity. Model 4 adds a control for use of services in manufacturing firms, measured as services purchased divided by firm-level sales. Following Mukherjee (2015) and Goldar et al. (2018), it is expected that higher use of services will have a positive impact on export intensity. Models 5–7, respectively, add controls for foreign ownership, age and firm size. Models 1–7 control for time fixed effects through inclusion of time dummies. Models 8 further controls for industry fixed effects. Across all models, the Hansen *p*-value is above 0.05, indicating that the null hypothesis that the instrument set is exogenous cannot be rejected at 5%. Similarly, the null hypothesis of no autocorrelation in second differences residuals also cannot be rejected—the AR(2) test statistic is greater than 0.05. The GMM estimations are therefore valid for interpretation.

Across the models, it is observed that the coefficient of one-period and two-period lagged export intensity is positive and significant. This confirms persistency in export intensity and renders support to the choice of GMM estimator.

Coming to the main variable of interest-digital assets, we find that digital assets have a positive and significant impact on export intensity of a firm across all estimated models. Firms with higher share computer and IT systems' expenditure in their total plant and machinery expenditures are found to have higher export intensity in the period 2000–2015 in India, other things remaining the same. Digitalization is therefore found to have provided a competitive edge to firms in the export markets.

The coefficient of labour productivity is also positive as expected and statistically significant, indicating that a higher level of labour productivity leads to higher export intensity, ceteris paribus. This empirical result is consistent with the self-selection hypothesis. We further observe that the financial leverage and firm age affect export intensity negatively; however, the impact of these variables is not found to be significant. Similar to Goldar et al. (2018), the impact of firm size on export intensity is not found to be significant. In line with, no significant impact is found for foreign ownership impacting export intensity of Indian firms. This is in line with the results of Ghosh and Roy (2018) for the case of exports in machinery, transport equipment and textile industries (Table 12).

Appendix Table 13 checks robustness of results to alternate lag specification for endogenous variables (model 1), measurement of firm size (using total assets in model 2), alternate variable specification and addition of other controls (in models 3 and 4) and one-step GMM (model 5). Similar to Goldar et al. (2018), it is observed

Table 12 Panel Tobit model results with left censoring in export intensity

Variables	Model 1	Model 2	Model 3
L.export intensity	0.932*** (0.0109)	0.913*** (0.0117)	0.728*** (0.0155)
L2. Export intensity			0.245*** (0.0146)
L.log productivity	0.961*** (0.198)	0.705*** (0.204)	0.769*** (0.223)
L.log_service_input_intensity	3.021*** (0.303)	2.773*** (0.315)	2.467*** (0.331)
L.log digital assets	0.365*** (0.124)	0.285** (0.125)	0.365*** (0.132)
L. log R&D inten	0.144*** (0.0287)	0.0990*** (0.0300)	0.0993*** (0.0311)
L.foreign shares	0.0193 (0.0191)	0.0119 (0.0192)	0.00680 (0.0193)
Log total assets	2.100*** (0.146)	2.297*** (0.150)	1.836*** (0.150)
Log age	0.357 (0.336)	0.429 (0.344)	0.475 (0.368)
Constant	−11.67*** (1.714)	−16.68*** (1.964)	−13.45*** (2.072)
Prob >=chibar2	0	0	0
No. of left censored obv.	5668	5668	4081
Year FE	Yes	Yes	Yes
Industry FE	No	yes	Yes
Observations	12,064	12,064	9,025
Number of firms	3,069	3,069	2,575

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

that the share of raw materials and stores and spares in total sales (RMSS) of the firm has a significant and positive impact on exporting intensity. Increasing capital intensity of the firm, captured through capital-to-labour ratio, also has a positive impact, while import intensity is not found to affect export intensity in Indian firms significantly. Across all the models, the coefficient on share of digital assets remains positive and significant, indicating the robustness in the impact of digital assets on export intensity. Some additional evidence of financial leverage negatively impacting export intensity is also found.

Table 12 reports further estimates of Eq. 1 using random effects panel Tobit model, which accounts for the fact that export intensity is truncated at zero. We find that qualitatively the results remain similar; lagged export intensity, productivity and digital assets have a significant and positive impact. Additionally, a positive impact is found for service input intensity, similar to Goldar et al. (2018), R&D intensity and firm size.

The results arrived from the firm-level analyses corroborate the results arrived at the sectoral level as well as the aggregate level. The extent to which a firm's production process uses digital assets, including computer software, can impact the firm's export intensity. At the sector -level also it was found that sectors which are losing their export competitiveness in terms of fall in growth of their share in global exports are also the sectors which use much lower value added by the digital services.

8 Summary and Way Forward

India's exports of goods and services as a share of GDP have declined steadily since 2012, falling from 24.5% in 2012 to 19% in 2017. But India's merchandise exports have been rising in the last 3 years crossing $300 billion in 2018. This has led to a rise in India's share in global merchandise exports from 1.5% in 2010 to 1.9% in 2017. Examining further it is found that there has also been a steady and sharp decline in the growth of merchandise exports and growth of India's share in global merchandise exports overtime. The average annual growth of merchandise exports was impressive at 21% in the period 2003–2010. This fell to 5.5% in the period 2011–2017. While it can be argued that global slowdown may have caused this fall, this decline has also been accompanied by a drastic fall in the average annual growth of India's share in global merchandise exports from 8.4% in the period 2003–2010 to 3.1% in the period 2011–2017. The sectors which experienced a fall in India's share in global exports include some of its traditional exports sectors, namely, textiles fibres, textiles fabrics and made up articles, and leather and leather manufactures. At the product level, it is found that in the period 2011–2017 India has experienced a fall in its RCA in more than 75 products at the three-digit level. Most of India's traditional export products are therefore found to be losing their comparative advantage including precious stones, spices, jewellery, cotton, tea, fabrics, clothing articles and leather. Most of these products also experienced a fall in their share in global exports in this period.

In this context of a falling export competitiveness of India, this paper estimates the impact of digitalization on India's merchandise exports by undertaking analyses at sectoral level as well as at the firm level. Four different methodologies have been adopted, which are (i) use of digital services (Computer programming and information services and telecommunication services) in the production of manufactured products at the sectoral level, (ii) value added by digital services (DS) in exports of manufactured products at the sector level, (iii) impact of share of digital assets in total expenditure on plant and machinery on export intensity using system Generalised Method of Moments (GMM) estimator at the firm level and (iv) impact of digital assets on export intensity using random effects panel Tobit estimations at the firm level.

The results using different methodologies at the sectoral and at the firm level show that the extent of digitalization is playing an important role in determining a country's export competitiveness. India is found to have increased its use of digital services in manufacturing production in the period 2000–2014, but value added by digital services to India's manufacturing exports remains at only 9% and 91% of the total value added by digital services goes to India's exports of services. Value added by DS in manufacturing exports of India is found to be much lower than in other developing countries, e.g. it is 78% in Turkey, 60% in China, 57% in Indonesia and 54% in Brazil. A closer examination reveals that most of the value added by digital services is contributed to India's exports of computer programming and telecommunication services, which together account for 88% of total value added contributed by DS to total exports. This lopsided digitalization of India's exports may have been the reason for declining growth of India's exports in the period 2011–2017 as compared to 2000–2010 and also responsible for sliding share of India in global merchandise exports in this period.

To further investigate the impact of digitalization on exports, the paper undertakes a firm-level unbalanced panel data analysis for the period 2000–2015. The impact of share of digital assets in total expenditure on plant and machinery of a firm is estimated, controlling for other firm-specific variables. Digital assets of a firm are estimated by its expenditure on computer/IT systems, where computer systems include all the hardware and software required to make it functional for a user. The impact of digital assets on firm's export intensity is estimated using system Generalised Method of Moments (GMM) estimator and a random effects panel Tobit estimation. The results of both the models show that the higher the share of digital assets in total plant and machinery expenditure of a firm, the higher will be the firm's export intensity, ceteris paribus. Other determinants of firm's export intensity found significant by the models include its lagged export intensity and labour productivity.

The analysis in the paper provides empirical evidence of India's sliding export competitiveness. The growing digitalization of manufacturing exports in the world is not matched by digitalization of India's manufacturing exports, which may be a plausible reason for India's losing export competitiveness. Banga (2019) also shows that India lags behind many other developing countries when its digital preparedness for international trade is compared using different indicators. Although India has put in place many initiatives for progressing on digitalization under *Digital India* programme, these initiatives focus on providing digital services to the citizens, building digital infrastructure and e-governance for delivering these services and digital empowerment of the citizens. There are no digital initiatives focused on increasing digitalisation of India's exports. Banga (2019) proposes a *Digitally-Informed Foreign Trade Policy* with the objective of improving India's digital infrastructure for trade, enhancing digital content of its exports, building digital skills in tradeable sectors, promoting use of digital technologies in manufacturing exports, and using big data analytics to inform foreign trade policy on ways of improving trade competitiveness.

There is a need for targeted policies and strategies for increasing digitalization of India's exportable sectors, especially traditional exports like textiles and clothing and leather and leather products as these sectors generate large-scale employment for low-skilled workers. Digital start-ups in India are mainly focused on digital solutions. These start-ups need to be harnessed for innovations for the manufacturing sector. Many countries like China and Korea have set up digital innovation hubs within their existing special economic zones so that these innovations could help further digital transformation of their manufacturing sectors (Mayer and Banga 2019). Use of digital technologies like big data analytics, robotics and artificial intelligence need to be promoted in manufacturing sectors to give a competitive edge to India's manufacturing exports.

Appendix

See Table 13.

Table 13 Robustness checks for Table 11. Dependent variable: export intensity

Variables	Model 1 Two-step	Model 2 Two-step	Model 3 Two-step	Model 4 Two-step	Model 5 One-step
L. export intensity	0.756*** (0.0383)	0.734*** (0.0418)	0.733*** (0.0412)	0.706*** (0.0363)	0.658*** (0.0429)
L2. Export intensity	0.165*** (0.0520)	0.160*** (0.0586)	0.164*** (0.0594)	0.144*** (0.0427)	0.156** (0.0689)
L log digital assets	0.487*** (0.187)	0.455** (0.226)	0.453** (0.221)	0.405** (0.178)	0.707* (0.371)
L.log R&D inten	−0.0398 (0.0385)	−0.0544 (0.0373)	−0.0141 (0.0684)	−0.0335 (0.0350)	−0.0561 (0.0581)
L. log debt/equity	−0.127 (0.110)	−0.114 (0.114)	−0.121 (0.109)	−0.229** (0.106)	−0.334** (0.135)
L.log service input int.	0.238 (0.277)	0.393 (0.383)	0.350 (0.395)	0.0116 (0.237)	0.733 (0.475)
L. foreign shares	−0.0188 (0.0384)	−0.00794 (0.0423)			−0.0272 (0.0459)
L. foreign firm			−1.087 (1.918)		
L.log labour prod	0.252 (0.202)	0.389* (0.202)	0.382* (0.212)	−0.316 (0.314)	0.0879 (0.317)
L. log capital/labour				0.693** (0.346)	
L. log imported RM sh.				0.0561*** (0.0210)	
Log age	−0.0499 (0.191)	−0.00888 (0.219)	−0.0935 (0.262)		−0.114 (0.257)
L.log real sales	0.1000 (0.145)		0.00733 (0.151)		
Log total assets		0.0462 (0.140)			0.258 (0.205)

(continued)

Table 13 (continued)

Variables	Model 1 Two-step	Model 2 Two-step	Model 3 Two-step	Model 4 Two-step	Model 5 One-step
L.log import intensity					0.0457 (0.0680)
Constant	0 (0)	0.893 (1.622)	0 (0)	−0.886 (1.706)	0 (0)
Hansen	0.30	0.24	0.22	0.61	0.24
AR(2)	0.49	0.51	0.49	0.54	0.30
Time FE Industry FE	Yes Yes	Yes No	Yes No	Yes Yes	Yes No
Observations	7,785	7,785	7,785	7,846	7,785
Number of firms	2,305	2,305	2,305	2,330	2,305

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

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Firm-Level Productivity and Exports: *The Case of Manufacturing Sector in India*

K. Narayanan and Santosh Kumar Sahu

1 Introduction

Apart from many other features, literature on productivity growth has also focused on the possible link between efficiency and export both at the aggregate and disaggregate levels. The general findings are supported by sets of literature that are related to the significant differences in productivity among firms. Further, it is also observed that these differences persist over time (for example, Griliches and Regev 1995; Tybout 1997 and others). Entry condition of firms is one of the important factors that explain export market participation and export behaviour of firms. Closeness to the efficiency frontier as one of the behaviours of exporting firms is explained in studies such as Aw et al. (2000) and others.[1]

Firm size is considered as one of the important factors in explaining export intensity or propensity at firm level as explained in both empirical and theoretical researches. Yet empirical results on this hypothesis have been mixed based on the type of data in use. For instance, few studies found positive cross-sectional relationship between firm size and export intensity (Perkett 1963), but other studies have found no meaningful relationship (Doyle and Schommer 1976).

[1]Related studies are Aw and Hwang (1995), Bernard and Jensen (1995), Jensen and Wagner (1997), Aw et al. (1997) and Clerides et al. (1998).

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Cavusgil (1976) explains that very small firms tend not to export. Further, he explains that beyond some point of exporting behaviour is not correlated with firm size; however, till the threshold point export behaviour is correlated with firm size. In an attempt using Indian data, Narayanan (1998) studies the effects of deregulation policy of Indian economy that was initiated during the mid-1980s. He studies the impact on technology acquisition and competitiveness in the automobile industries of India. Further, Sahu and Narayanan (2015) focused on the export patterns of automobile sector with an emphasis on the technology and R&D capabilities of automobile firms in Indian economy. This study also uses a parametric approach in determining factors affecting export intensity of sample firms in consideration based on the technological efforts and R&D participation. In general, therefore, to understand the export performance of firms, it is important to analyse the productivity and size of firms. There are several studies focused on difference in labour productivity (Baldwin et al. 2002); however, barring a few exceptions (Van Biesebroeck 2005) evidence for total factor productivity (TFP) is relatively scarce.

The purpose of this work is to estimate total factor productivity (TFP) and measure the TFP differentials for the firms that participate in the export market and the domestic firms. This productivity differentiate is examined for the sample of manufacturing firms in India from 2003 to 2015. This period is after a decade of New Economic Policy of 1991. Hence, this will add in the literature of the policy impact of industrial deregulation and efficiency of firms in export market. This paper will also investigate if export makes difference in productivity differentials. While the research question is related to if exporting has any relation with the TFP, the method used in this paper is different compared most of the works carried out earlier for the Indian context. As against the marginal movements in the TFP, this paper compares the entire distribution of productivity. In particular, we are interested in observing the cumulative distribution function of TFP for firms in different groups such as exporters versus non-exporters and entering to the export market versus continuing exporters. Based on the recent development in quantitative economics, we rank the distributions using stochastic dominance, and their differences using Kolmogorov–Smirnov tests,[2] which are consistent in the direction of general non-parametric alternatives.

Assuming different trajectories between export and domestic markets in case of the productivity growth, we explore the difference between these sets of firms. Our results confirm higher level of productivity for the exporting firms as against the domestic firms. Further, results are in line with the existing literature on learning by exporting; meaning firms with higher productivity level do enter to the export markets as compared to the lesser productive ones, catering only for the domestic market. This validates our hypothesis that there are indeed different trajectories of productivity growth for domestic and the export markets. Having stated the results on the learning-by-exporting hypothesis, we conclude that this hypothesis do exists for

[2]The Kolmogorov–Smirnov test is a non-parametric test of the equality of continuous, one-dimensional probability distribution that can be used to compare a sample with a reference probability distribution. This can be either of one-sample or two-sample test. For more details, see Darling (1957).

the Indian manufacturing firms, however, weak and limited to the younger exporters. In the context of international experiences, our results are in line with works such as Clerides et al. (1998), Bernard and Jensen (1999) and Aw et al. (2000).

The remainder of the paper is as follows. Next section explains review of existing literature from international and domestic experiences. This section also explains the analytical arguments related to the research hypothesis and links productivity distribution and exports for the select sample of firms in manufacturing sector of India. Data and index used in this study are presented in the next section. Section 4 presents results and discussions on the empirical estimation, and Sect. 5 concludes the paper.

2 Literature Review

As reported in the analytical literature, the international markets are exposed to more intensive competition and exporters have high sunk entry cost as compared to the domestic firms. These two arguments are used to indicate why exporters are efficient than the non-exporters. Both explanations above indicate that export market selects the most efficient firms among the domestic firms as entrants to the export market. Hence, the product market competition is greater in the export market and a positive relationship can be established between competition and productivity in general. However, as studies are not unanimously concluded similarly, it will be interesting to see these phenomena in the context of an emerging economy such as India.

The idea of industry dynamics as explained in Jovanovic (1982) and further by Ericson and Pakes (1995) also plays an important role in linking productivity and exports at firm level. In the literature related to industry dynamics, existence of a clear relationship exists between patterns of enter and exit of firms in an economy and productivity. However, Aw et al. (1997) argue that differences in sunk costs can explain productivity differentials between exporters and domestic firms assuming the competitive pressures between the domestic and foreign market are similar. This argument relays on the fact that non-exporter must incur sunk entry cost in order to enter to the export market. In a parallel setup, Roberts and Tybout (1997) explain that previous export status of a firm becomes one of the major factors in explaining future decision to export. This also helps firms favourable to the existence of sunk entry cost in the export market.

In the context of industry dynamics, if higher entry costs for export market are there with respect to the firms that operate in the domestic markets, the productivity growth of the exporting firms has to be much higher. Therefore, enrty and exit patterns of firms are related to productivity growth differentials in the export market. The differences lie between the continuous exporters and the rest in any given economy, and hence it is ideal to assume that the probability distribution of productivity for the continuous exporters should stochastically dominant over the rest. This argument calls for a classification between the continuously exporting firms and for those who are new entrants to the markets and the existing exporters. Therefore, productivity distributions should be different for continuous exporters and that enter to the export market and exit from the export market. These two arguments can be linked with the hypothesis of selection. Similarly, the other argument can also hold true that exporting as a learning mechanism allows firms to improve productivity over time. This result is highly accepted in the management literature that explains exporting as a learning process due to innovation and better management practices. Based on the above understanding of link between productivity and export behaviour of firms, we suggest the following hypothesis to be tested for the manufacturing firms in India.

1. The productivity distribution of exporting firms, entering exporters and continuing exporters should dominate the productivity distribution of non-exporting firms, and
2. Productivity growth between exporting and non-exporting firms should be statistically different and should increase after a new export firm enter to the market for those firms that are already in the export market.

As stated in the hypothesis above, we have to test the productivity distributions between group of firms identified as exporters and non-exporters, which can be done with the panel structure of firms. The idea of such an exercise is motivated from Delgado et al. (2002).[3] We use a similar approach related to first-order stochastic dominance. This allows us to establish a rank for a comparison purpose.

As explained in Delgado et al. (2002), let F and D denote the cumulative distribution functions of productivity corresponding to multi groups of firms (more than one), then the first-order stochastic dominance of F that is relative to D can be defined either as (1) in case of a two-sided test or (2) in case of one-sided test:

$$H_0 : F(z) - D(z) = 0 \text{ all } z \in \mathbb{R} \quad \text{versus} \quad H_1 : F(z) - D(z) \neq 0 \text{ some } z \in \mathbb{R}, \\ \text{cannot be rejected} \tag{1}$$

$$H_0 : F(z) - D(z) \leq 0 \text{ all } z \in \mathbb{R} \quad \text{versus} \quad H_1 : F(z) - D(z) > 0 \text{ some } z \in \mathbb{R}, \\ \text{cannot be rejected} \tag{2}$$

Similarly, one- and two-sided test can be also formulated as

$$H_0 \sup_{z\in\mathbb{R}} |F(z) - D(z)| = 0 \quad \text{versus} \quad H_1 \sup_{z\in\mathbb{R}} |F(z) - D(z)| \neq 0$$
and
$$H_0 \sup_{z\in\mathbb{R}} \{F(z) - D(z)\} = 0 \quad \text{versus} \quad H_1 \sup_{z\in\mathbb{R}} \{F(z) - D(z)\} > 0, \tag{3}$$

respectively.

As presented above, if F and D represent the productivity distributions for the firms that are exporting and the non-exporters, we can compare their respective distribution to validate our assumption of dominance. In case of the two-sided test, we

[3] For a detail methodological review, refer to Degado et al. (2002).

can conclude if both distributions are identical, whereas one-sided test will conclude the dominance characteristics of respective distributions. Hence, if two-sided test is accepted, one-sided test has to be accepted, and hence, the distribution of F has to be on the right of D. This argument implies that the productivity distribution of the exporters stochastically dominates that productivity distribution of the non-exporters. For the one-sided test, the Kolmogorov–Smirnov test statistics can be explained as

$$\delta_N = \sqrt{\frac{n.m}{N}} \max_{1 \le i \le N} |T_N(Z_i)| \quad \text{and} \quad \eta_N = \sqrt{\frac{n.m}{N}} \max_{1 \le i \le N} \{T_N(Z_i)\}, \tag{4}$$

3 Descriptive Statistics, Measurement and Estimation

The data set considered in this study is drawn from the Center for Monitoring Indian Economy Prowess IQ database, an annual survey that refers to a representative sample of Indian manufacturing firms. The base year of the dataset used for this research starts from 2003. We have collected information from 2003 to 2015 annual series for the manufacturing sector in India. We categorized dataset based on firm size, where firm size is defined as a natural log of the net sales. Due to entry and exit of firms in the dataset, our data is unbalanced panel in nature. From 2003 to 2015, we have collected 54,139 firm-year observations that has an average of 4,164 firms. This data set has a maximum observation of 4,817 for 2005 and minimum of 2,053 for 2015.

Observing the export intensity patterns of firms in our sample, the average sample mean is 0.43 with minimum export intensity of zero (no export participation). Therefore, we have classified firms in two sets: (1) small exporting firms and (2) large exporting firms. This classification is based on the average export intensity of firms that are exporting. This gives 650 firms in the category of large exporting firms and rest in the category of small exporting firms. Export intensity of these two groups is found to be statistically different (given the t-test result to be −2.91***). The average turnover of the large exporting firms is smaller than that of the small exporting firms. This may be due to the fact that only 1.3% of sample firms are engaged in export activities.

Few data characteristics can be noted from the descriptive analysis of the sample. First, there is a high turnover rate in terms of entering and exiting from the export market. The computed annual average turnover rate is 26 for the small firms and 21 for the large firms. Second observation from the data set is that the average entry rate is higher than the average exit rate of firms in the export market. Therefore, it can be concluded that the export share of the manufacturing firms in India is due to the net increase in the number of new exporters. In a parallel statistics, we can also see the patterns of the switchers (both entering and exiting in some years) in the data set. 27% of small firms are the switchers, whereas 15% firms are switchers in case of large firms in the sample. Hence, entering and exiting happens for few years more in case of the small firms as compared to the large firms in this sample. This can also explain partly the productivity differentials of small firms compared to the large firms those are in the export market. Further here, we provide information on the estimation of the production function and the productivity of the sample firms. Total factor productivity is estimated using one of the standard recent methods of parametric estimation of a homogenous production function. The estimate of firm productivity (TFP) is crucial and important as this is the most important indicator that distinguishes between the exporters and non-exporters. Variables of interest in computing TFP are presented in Table 1. As stated earlier, information on the firm-specific variables are collected from the Center for Monitoring Indian Economy's Prowess IQ database. The estimation of TFP will be important to link the export behaviour of firms related to its productivity growth.

There are various methodological approaches to estimate TFP. In this case, we use the residual from the production function at firm level as total factor productivity. Both theoretical and empirical works have pointed out that use of ordinary least squares generates an inconsistent and biased estimator of TFP. Information asymmetry related to firm behaviour other than the factor inputs may create the biasness of the estimator; these can be listed as nature of industry, time, sample, region, etc. Other than the factor inputs, these information asymmetries may influence the estimator and hence create endogeneity in estimating productivity at firm level. In

Table 1 Definition and measurement of variables[a]

Sl. no.	Variable(s)	Definition and measurement
1	Output (Y)	Output at firm level is obtained by adding plus changes in stocks to sales. We deflate nominal output at three-digit industry-level price deflators. Deflation is constructed using Wholesale Price Index (WPI) series from the Office of the Economic Advisor, Ministry of Commerce and Industry, Government of India
2	Labour (L)	Prowess provides data on wages and salaries given to employees. We arrive at firm-level employment figure using emoluments and total persons engaged data from Annual Survey of Industries (ASI), Central Statistics Office, Government of India
3	Capital (K)	Following Banga and Goldar (2007), we use the blanket deflation method
4	Material (M)	The raw material expenses include the value of raw materials consumed. The nominal value of the raw material cost was deflated using raw material price indices. In this case, the base year is taken as 2004–05 = 100
5	Energy (E)	We first calculate the nominal energy input for a firm as the sum of its expenses on power and fuel, in current prices, obtained from Prowess IQ. To construct the energy deflator, we use price indices of coal, petroleum products, natural gas and electricity for industrial use from the official WPI series and other sources

[a]All the variables used to calculate TFP using a production function are of 2004–05 prices. This is obtained by deflating each series reported in current prices with appropriate price indices. These information are collected from 'Index Numbers of Wholesale Prices in India' that is published by the Economic Adviser, Ministry of Commerce and Industry, Government of India

such a scenario, Levinsohn and Petrin (2003) presented an alternative way to estimate a production function using intermediate inputs other than the factor inputs. The intermediate inputs identified are related to energy or electricity use of a firm. This variable helps in addressing the simultaneity problem and keeps the sample size intact. To address the non-convex adjustment cost investment proxy can also be used in this method of estimating productivity. "If adjustment costs lead to kink points in the investment demand function, plants may not entirely respond to some productivity shocks, and correlation between the regressors and error can remain. If it is less costly to adjust the intermediate input, it may respond more fully to the entire productivity term (Levinsohn and Petrin 2003)".

In this study, we use Levinsohn and Petrin (2003) to estimate the production function as in (5).

$$y_t = \alpha + \beta_l l_t + \beta_k k_t + \beta_m m_t + \beta_e e_t + \omega_t + \mu_t \tag{5}$$

where y_t, k_t, l_t, m_t and e_t are logarithm of output, capital stock, labour, raw materials and energy, respectively, ω_t denotes productivity of the firm and μ_t stands for the measurement error in output, which is uncorrelated with input choices. In most of the existing studies, material inputs or energy consumed are used as a proxy to take care of endogeneity problem arising out of unobserved shocks. In this paper, we take energy as a proxy. Given that LP assumes that firm's intermediate inputs demand function, is monotonically increasing in productivity given its capital stock, the unobservable productivity term w_t depends solely on two observed inputs, e_t and k_t. Hence, we can rewrite the Eq. (5) as

$$y_t = \beta_l l_t + \beta_m m_t + \beta_e e_t + \phi(k_t + e_t) + \omega_t + \mu_t \tag{6}$$

where $\phi(k_t, e_t) = \alpha + \beta_k k_t + \beta_e e_t + \omega_t(k_t, e_t) + \mu_t$ and the error term μ_t are not correlated with inputs. From this, we can calculate productivity of the firms as the difference between actual and predicted output using Eq. (7).

$$TFP_{ijt} = y_{ijt} - \beta_k k_t - \beta_l l_t - \beta_m m_t - \beta_e e_t \tag{7}$$

Once the TFP are computed at firm level, the next methodological issue is related to the non-linear estimation of productivity distributions for different groups of firms. As explained in the previous section, we can differentiate the distributions using two-sided and one-sided Kolmogorov–Smirnov tests. To use such a test in the data set, we have the following assumptions. First, the test application requires independence of observations. As the data used in this research is an unbalance panel or large scale firm-year observations and many firms are repeated over years, it will be not possible to arrive at independent or stationary series of the sample. Statistically, the unit-root tests of the panel data also reject the hypothesis that the sample is stationary. Hence, we have applied the test statistics each year separately for each time period. Second, cumulative distribution of productivity at firm level is considered to test the stochastic dominance between group of sub-sample in this case small and large firms.[4] In a parallel exercise, we also compare exporters and non-exported related to firm size and firm age. Third, it should be noticed that our productivity measure can be interpreted as an estimate of a non-observable measure, where the Kolmogorov–Smirnov test is directly applicable.[5] Fourth, we provide two *P*-values for each of the statistics: one based on the limiting distribution and the other on the bootstrap approximation.[6] These *P*-values can be approximated, as accurately as desired, by Monte Carlo.

4 Empirical Results

We explain the empirical result in this section. This section is followed by the descriptive inference and theoretical argument of the previous section on establishing link between productivity and export behaviour at firm level. As classified earlier, the sample of firms is classified into exporters and non-exporters. First, we examine differences of TFP between these two groups. Further, we establish a possible source of observed differences between firms that are in export market and those are not. Basically, this is to observe the differences between export and non-exporting firms in case of the estimated productivity. To arrive at the differences between the set of firms, we establish two comparisons in terms of ex-ante differences in productivity for firms that are entering in the export market and the non-exporters. The second comparison is carried out between exiting exporting firms with the continuing exporters. Finally, the larger set of firms in terms of domestic and exporting firms is compared in terms of productivity differentials.

For comparison purpose instead of using standard parametric approach, we use non-parametric methods as described in previous section. This is carried out by computing a smooth sample distribution function, instead of a sample distribution function. The reason is that the smooth sample distribution gives a nice and smooth estimate as compared to the sample distribution. Figure 1 presents the distribution function for the full sample that permits us to compare visual comparison of the distribution functions. As noted in the methodology section, exporting firms' distribution of TFP growth is to the left of the non-exporters distribution and presented in Fig. 1. This accepts the hypothesis that exporter smooth distribution stochastically dominates the non-exporters' distribution. Also, as visible from the graphs there is a higher growth rate of TFP for the exporters as against the non-exporters.

[4] Comparisons between distribution functions for the whole population are avoided since this would have required the estimation of a mixture of two distributions.

[5] See Bai (1996) and Delgado and Mora (2000) for a similar argument.

[6] We arrive at good accuracy of asymptotic approximation as the asymptotic and bootstrap *P*-values are fairly close. For detail, see Gine and Zinn (1990).

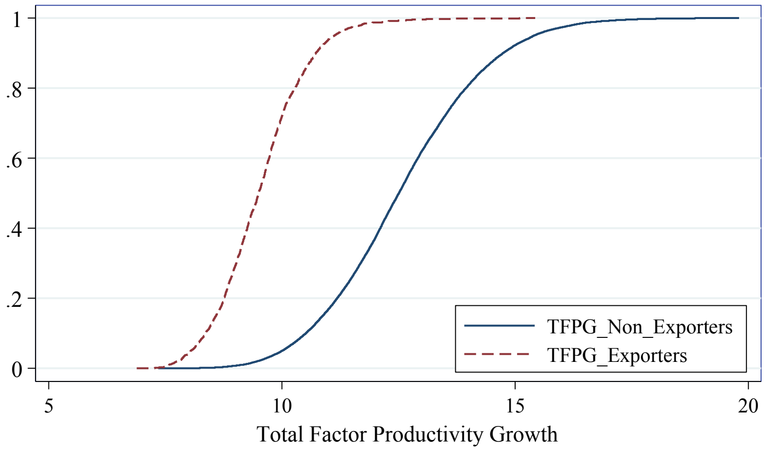

Fig. 1 Smooth distribution function of TFP. *Source* Authors' representation from Prowess IQ database

Next, we present the results from the formal statistical tests for the differences in productivity for firms classified in different groups. The first step in analysis is carried out to see the productivity differences between exporting and non-exporting firms in the sample. We define exporting firms as those participate in export market at period *t*, and non-exporters are the firms that only participate in the domestic market. In both the cases, we have not considered the switchers.[7] The differences in productivity are presented for exporting and non-exporting firms in Fig. 1. The position of the distribution for exporting firms with respect to the distribution of non-exporting firms indicates higher levels of productivity for exporters versus non-exporters.[8]

We present the hypothesis test statistics on productivity differentials between the firms in export market and domestic market. These sets of tests are applied separately for the small and the large exporting firms. First, for the group of exporters and non-exporters, the null hypothesis of equality between both distributions can be rejected at one per cent level for all years (column-1, Table 2). A similar result is drawn for the large exporters and non-exporters for all years. These two results are consistent for the full sample and whole period of study. As accepted the sign of difference is also arrived at as presented in Table 2. A slightly different but interesting result is arrived at between (1) small and non-exporters, and (2) large and small exporters. Except for few years such as 2009, 2013 and 2014, there is no statistical relationship of productivity growth differentials between the small and non-exporters. Interestingly,

[7]Switchers are exporting firm that participate in the export market intermittently, in time intervals that is greater than 1 year.

[8]Productivity distributions are also higher in all quartiles for firms in the export market as compared to the non-exporting firms. The median productivity of the former is 26% higher than the productivity of the latter. Similarly, productivity differences are greater at the lower part of the distribution, 7% in favour of exporting firms at the lower quartile, and smaller in the upper part, 5% in favour of exporting firms at the upper quartile.

Table 2 Productivity differences between exporters and non-exporters

Year	Exporters–non-exporters	Large exporters–non-exporters	Small exporters–non-exporters	Large exporters–small exporters
2003	13.882***	13.724***	−2.037***	0.203
2004	16.913***	16.290***	−4.482***	−1.487
2005	15.706***	15.290***	−3.485***	−0.199
2006	15.591***	14.880***	−4.552***	−0.856
2007	14.734***	14.301***	−3.467***	1.069
2008	15.610***	15.526***	−1.803*	2.328**
2009	14.416***	14.636***	−0.338	4.350***
2010	12.830***	12.636***	−2.662***	2.392**
2011	13.476***	13.094***	−3.361***	2.106**
2012	11.511***	11.068***	−3.396***	2.139***
2013	10.866***	10.866***	−0.765	3.437***
2014	6.034***	6.237***	1.681	2.710***
2015	6.946***	7.050***	−2.037***	1.919**
Full sample	47.951***	3.180***	−9.221***	4.388***

Note Statistically significant of the t-test is presented in table based on limiting the distributions. Significant levels based on the bootstrap approximation (10,000 replications) are presented as *** for 1%, ** for 5% and * for 10%.
Source Authors' calculation from Prowess IQ database

as we can see the productivity growth of non-exporters is better for all other year having a negative sign of the coefficient as against the small exporters. Given the status of activity is restricted to 3 years of export activity, the small exporters may be those who used to be non-exporters and yet to arrive at a higher productivity level due to competition and economics of scale. On the contrary, the difference between the large and small exporters' statistical relationship is not arrived at for observations from 2003 to 2007. However, from 2008 as accepted, the differences between the large and the small exporters are clearly visible as depicted in Table 2.[9] This result is in line with the earlier results of exporters and non-exporters, large exporters and non-exporters.

Conclusions from the above analysis can be classified in two major parts. The first is productivity distribution of firms in export market stochastically dominates the productivity distribution of firms that are in the domestic market. The second conclusion is that the productivity distribution of large exporting firms lies above the productivity of non-exporting firms. Further, we also confirm on the parameters weighing the linear combination to be positive. Hence, we conclude that for the larger sample of firms in the manufacturing sector of India, the productivity of exporters stochastically dominates the productivity of the non-exporters.

[9] *P*-values on limiting the distribution and on bootstrap approximation lead to same results.

Once the conclusion on the differences of exporters and non-exporters are arrived at we now consider the productivity and transition between domestic and the export market. In doing so, we classify firms based on entry of firms in the export market, exit of firms from the export market and firms that are in continuous in the export market. This refers to the selection of firms in either staying/leaving/entering to the export market. On the other hand from this analysis, we can also conclude if the export market considers the most efficient firms as against the inefficient firms in the market. This selection mechanism can work at both enter and exit patterns.[10] On the second discussion on the entry side behaviour of the exporting firms in the sample, we further compare two group of firms as stated earlier; one being the non-exporters and the firms that have newly entered to the export market. The reference case in this case for the non-export-oriented firms being the year, 2003. If a firm has entered any point between 2004 and 2015, they are considered as the entering exporting firms. Rest of firms in the sample are defined as non-exporters.[11] Three years of entry period are considered to enlarge the number of observations. A variation of the selection of year gap is also tried, however; the number of observation drastically falls if we increase the number of years to more than 3. In these cases, however, the behaviour of the sample firms do not change; hence, we allow a larger observation for a best fit for the non-linear analysis to get the differential impacts in case of productivity change for firms in export market and those are not in the export market. Therefore, in this setup, the productivity levels of both groups of firms are compared for the year 2003 before entry for the entering exporters.

Table 3 reports test statistics on the comparison of both productivity distributions. We can observe that individual time effect each year is not statistically established for the full sample in case of enter and exit pattern. However, a decadal effect is quite established (column-1, Table 3, row representing result for the full sample across years). Further, an inconsistency result is arrived at for the differences favourable to entry for the firms in the data set for the Indian economy. For example, if firms have entered in the years either 2003/2004/2009 they have gained productivity growth as compared to the counterparts; for all other years, we are not able to arrive at the statistical relationship of the distribution. Similarly, for existing patterns, if firms exited in the years 2003/2006/2013, they have a higher productivity growth and for all other years, distributional impact is not statistically arrived at. For the continuous exporters, years such as 2004/2008 and 2014 are favourable statistically as compared to other years. However, the decadal effect is quite visible and positively explains the distributional differences for all the categories of firms when taken together.

Now we plot the distributions of small and large exporters and arrive a similar distribution as shown in Fig. 1. For the cohort of 2003–2015, the cumulative distribution functions of productivity of large and small exporters are presented in Fig. 2.

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[10]On the entry side, the implication of selection is that only firms with higher productivity should enter the export market. On the exit side, if selection is at work, low productivity exporters should leave the export market.

[11]Switchers are excluded from the comparison.

Table 3 Self-selection to export market and TFP

Year	Equality of distribution		Difference favourable to entering exports		Difference favourable to exiting exports		Difference favourable to continuous exports	
	Full sample	*P*-value	Enter	*P*-value	Exiting	*P*-value	Continuous	*P*-value
2003	0.058	0.945	0.295	0.097*	0.443	0.036**	0.164	0.930
2004	0.052	0.974	0.351	0.011**	0.172	0.644	0.325	0.070**
2005	0.063	0.876	0.216	0.266	0.171	0.692	0.311	0.181
2006	0.053	0.985	0.275	0.135	0.316	0.061**	0.200	0.786
2007	0.066	0.953	0.174	0.742	0.171	0.877	0.231	0.524
2008	0.076	0.825	0.252	0.295	0.196	0.576	0.404	0.015**
2009	0.116	0.465	0.439	0.011**	0.318	0.190	0.505	0.061**
2010	0.094	0.783	0.232	0.527	0.206	0.770	0.319	0.442
2011	0.105	0.716	0.241	0.595	0.236	0.689	0.172	0.931
2012	0.131	0.550	0.307	0.361	0.144	0.995	0.336	0.478
2013	0.165	0.645	0.429	0.423	0.596	0.059**	0.467	0.388
2014	0.115	0.996	0.548	0.287	0.194	0.899	0.800	0.104*
2015	0.125	0.973	0.446	0.446	0.250	0.741	0.568	0.300
Full sample	0.056	0.026***	0.213	0.000***	0.155	0.002***	0.197	0.000***

Note Statistically significant of the t-test is presented in table based on limiting the distributions. Significant levels based on the bootstrap approximation (10,000 replications) are presented as *** for 1%, ** for 5% and * for 10%. *Source* Authors' calculation from Prowess IQ database

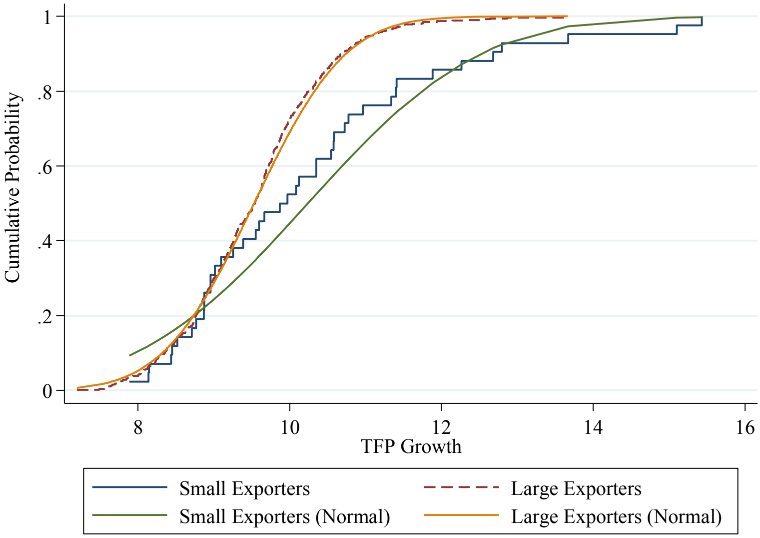

Fig. 2 Cumulative distribution of TFP growth for small and large exporters. *Source* Authors' representation from Prowess IQ database

Table 4 Self-selection to exports market and TFP weighted for firm size

Year	Difference favourable to entering exports		Difference favourable to exiting exports		Difference favourable to continuous exports	
	Enter	*P*-value	Exiting	*P*-value	Continuous	*P*-value
2003	0.540	0.008***	0.183	0.589	0.253	0.179
2004	0.454	0.002***	0.334	0.052*	0.155	0.785
2005	0.361	0.094*	0.308	0.075*	0.216	0.361
2006	0.504	0.003***	0.247	0.461	0.411	0.007***
2007	0.399	0.112	0.416	0.028**	0.383	0.116
2008	0.386	0.018**	0.397	0.013**	0.306	0.108*
2009	0.744	0.000***	0.190	0.830	0.333	0.139
2010	0.583	0.003***	0.519	0.012**	0.548	0.002***
2011	0.510	0.021**	0.394	0.154	0.454	0.046**
2012	0.624	0.002***	0.304	0.472	0.471	0.047**
2013	0.600	0.055*	0.385	0.511	0.707	0.014**
2014	0.400	0.854	0.556	0.360	0.500	0.425
2015	0.917	0.035**	0.464	0.397	0.333	0.819
Full sample	0.394	0.000***	0.217	0.000***	0.237	0.000***

Note Statistically significant of the t-test is presented in table based on limiting the distributions. Significant levels based on the bootstrap approximation (10,000 replications) are presented as *** for 1%, ** for 5% and * for 10%. *Source* Authors' calculation from Prowess IQ database

From the figure, this is evident from the distribution that small exporters have lower productivity growth as compared to the large exporters.

We now present a similar exercise as reported in Table 3; however, in this case, the entry–exit and continuous exporters are weighted with firm size. From the result presented in Table 4, it is quite clear that entering to the export market for the big firms is stochastically different and better as compared to the small exporters. As evidenced from the table, except for 2007 and 2014, entering to export market from the big firms have resulted higher TFP as compared to the small size firm that entered to the export market. The full sample, however, has a similar result of higher TFP for firms that are big in size and entered the export market during 2003–2015. Similarly, we exercised for the exiting and continuous firms. For those who existed either during 2003/2006/2009/2003–2015, statistical significant of TFP distribution is not arrived at; however, for all other years, decision to exit from the export market for the big firms resulted in increase in TFP as compared to the small firms. Firms that are continuing in the export market are having an advantage over time as given in Table 4; however, year-wise analysis shows that those continued even during 2006/2010/2013 have higher TFP compared to others. When we analyse this phenomenon in relation to other results of the same table, we can see that for the year 2006 enter to export market was a good decision to increase TFP, or firms that are efficient self-selected to enter in export market that is in line with the behaviour of the continuous exporters.

However, in the same year 2006 exiting from the market was not favourable. This case continuously happens for other 2 years of study period for both 2010 and 2013. Therefore, those entered in these periods if stayed/continued in the market enjoyed higher TFP. This behaviour can be linked to learning by exporting and increasing TFP at firm level for the big firms. However, the exact channels of increase in TFP growth are difficult to establish.

On a similar exercise, Table 5 presents results with firm age. Firms that are old in export market (not old based on the year of incorporation) have favourable result in increase in TFP only for the entry pattern for years 2005/2007/2010/2011/2013–2015. For other two analyses in case of exiting and continuous exporting, we are not able to arrive at the statistical relationship. However, the sign of the coefficient as reported in Table 5 remains positive and signifies that there is a positive gain for the TFP for the old exporter by not stochastically determined as different from the young exporters. Hence, the young exporter enjoys higher TFP by continuing in the export market along with the old exporters.

Table 5 Self-selection to exports market and TFP weighted for firm age

Year	Difference favourable to entering exports		Difference favourable to exiting exports		Difference favourable to continuous exports	
	Enter	*P*-value	Exiting	*P*-value	Continuous	*P*-value
2003	0.359	0.031**	0.259	0.149	0.159	0.711
2004	0.387	0.003***	0.126	0.839	0.138	0.825
2005	0.214	0.322	0.143	0.774	0.147	0.773
2006	0.341	0.036**	0.187	0.577	0.277	0.124
2007	0.114	0.993	0.232	0.377	0.149	0.881
2008	0.190	0.613	0.210	0.442	0.217	0.422
2009	0.518	0.018**	0.227	0.511	0.118	0.993
2010	0.238	0.537	0.288	0.265	0.286	0.281
2011	0.304	0.305	0.242	0.552	0.185	0.867
2012	0.496	0.092*	0.197	0.912	0.248	0.656
2013	0.208	0.985	0.357	0.658	0.208	0.985
2014	0.528	0.528	0.286	0.955	0.381	0.736
2015	0.227	0.998	0.250	0.974	0.750	0.030***
Full sample	0.204	0.000***	0.063	0.501	0.052	0.738

Note Statistically significant of the t-test is presented in table based on limiting the distributions. Significant levels based on the bootstrap approximation (10,000 replications) are presented as *** for 1%, ** for 5% and * for 10%. *Source* Authors' calculation from Prowess IQ database

5 Conclusions

This paper tries to establish the TFP growth differences between set of exporting and non-exporting firms in the manufacturing sector of India. The sample period of this study is considered to be from 2003 to 2015 drawn from the Prowess IQ corporate database of Center for Monitoring Indian Economy. The underlying hypothesis of this paper is that the exporting firm has higher productivity growth as compared to the firms that are non-exporters. In understanding the productivity differentials, we use a non-linear method of statistical approach instead of a standard linear approach. The possible complementary explanations for greater productivity of exporting firms are linked with either market selection hypothesis or the learning-by-exporting hypothesis. Within the set of exporting and non-exporting firms, our paper differs from the existing research by creating transition patterns between export and non-export firms.

The finding of this paper confirms that there is an identifiable higher level of productivity difference exists between the exporting and non-exporting firms in case of the Indian economy, which is in line of market selection, and learning hypothesis. Hence, we conclude that more efficient firms self-select to the export market in India. Similarly, in case of the entry side argument to the export market, we find evidence in favour of selection. Meaning, firms entering to the export market eventually have higher productivity as compared to the non-exporters in the period prior to their entry. When we look at the exit side of the export market, we see that the ex-ante productivity distribution of continuing exporters stochastically dominates the productivity distribution of the existing firms. Hence, firms that are not able to have higher level of productivity are forced to exit from the export market. Even if we validate the self-selection hypothesis, we are not able to strongly conclude the learning-by-exporting hypothesis in this case. As the productivity growth seems to be similar for exports and non-exporters, we see the entire sample for the sample period of this study. Therefore, the leaning hypothesis is not conclusive for the full sample in this case. Further, weightage based on firm size and firm age are also considered, as firm size and firm age are one of the important variables that explains the export decision and intensity at firm level. This is basically done as a robustness check of the existing empirical result. These results do not explicitly explain the yearly effect, but the aggregate effect is quietly visible from the analysis. The firm size seems to have higher role in export market as against the firm age. The learning from the export market is clearly seen with higher increase in TFP and hence, points out that firms that enter into exports market are more efficient and also bigger in size.

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FDI and Export Spillovers: A Case Study of India

Sanghita Mondal and Manoj Pant

1 Introduction

Since liberalisation, India's most important policy focus has been the promotion of exports. The main reasons behind the export promotion were earning foreign exchange to finance import, to gain economies of scale through the larger market, to learn from the export experiences and most importantly to gain knowledge and internationally available technology.

As has been pointed out by Prasanna (2010), most of the developing countries possess comparative advantage in low-technology, labour-intensive primary products. However, with the increasing competition among developing countries, this comparative advantage can change and eventually disappear. This leads to the importance of technology and knowledge base in creating comparative advantage in products other than the primary products. The countries can attain this technology-based comparative advantage either by improving local technological capabilities or by importing technology or by encouraging foreign direct investment (FDI hereafter) in the domestic export sector. Innovation of new technologies and import of technology require adequate financial backup and human capital which most of the developing countries lack. Another important concern that has been mentioned in many studies is with the quality of the imported technology. Pant (1995) has showed that in 1980s, India was importing technologies which were mostly obsolete in the world market. His study also pointed out that, during 1970–80s, Indian firms relied on the import of technology and had restrictive policies towards technical collaborations with TNCs

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which raised the payments for royalty and technical know-how to 50% of total remittances. According to the study, a very small portion of the total payment went to the actual import of drawings and designs for production while most of the payments went for the royalty and payment for technicians which means that actual transfer of technology was very little. Thus, FDI was considered as the most reliable channel for gaining technology and knowledge as FDI is believed to have command over the assets which include superior technology and knowledge, distribution networks, product diversification and credit advantages (Hymer 1976).

In the context of recent liberalisation and globalisation, the role of FDI on the export performance of the domestic firms has become an important consideration. A cross-country study by UNCTAD (1999) on 52 countries has shown that there is a strong relationship between FDI and manufacturing exports, especially in the developing countries. According to Dunning (1993), FDI promotes specialisation and improves resource allocation playing an important role in international comparative advantage in trade. Sun (2001) also pointed out the importance of FDI in relocation of global resources and international division of labour which eventually alters the productive capacity of the countries and in turn the comparative advantage. While export from the foreign firms increases the export capacity of the country, indirect benefits in terms of spillover effects not only build the export capacity of the domestic firms but also improve the export competitiveness by improving the productive capacity with necessary technology and information about the international market. Keeping these facts in mind India, like many other developing countries, also started opening up the domestic market to foreign investors since 1991. The 1991 Industrial Policy of India clearly mentioned that:

> …Foreign investment would bring attendant advantages of technology transfer, marketing expertise, introduction of modern managerial techniques and new possibilities for promotion of exports…. The government will therefore welcome foreign investment which is in the interest of the country's industrial development… (Rao and Dhar 2011).

These spillover benefits from FDI are discussed vividly in the literature. In the case of export spillovers, the most important channels are mentioned as information spillover, imitation spillovers, competition spillovers and skill spillovers. Information spillover occurs through the export activity of the foreign firms; competition spillovers take place from foreign firms' domestic market activities; spillovers associated with technology occurs when domestic firms imitate foreign technology and their R&D activities; and lastly, skill spillovers commence through the labour turnover from foreign to domestic firms. The competition, imitation and skill spillovers have induced effects on the export performance of the domestic firms through the enhancement of the firm productivity. There exists a large body of empirical literature, and most of the studies have shown that there are positive spillover effects of FDI on the export propensity of the domestic firms.

In the present study, we focus on the impact of above-mentioned FDI spillover channels on the export performance of Indian manufacturing firms. Previous studies by Franco and Sasidharan (2010) and Joseph and Reddy (2009) have disentangled the spillover channels and tried to find out their impacts on the export performance of Indian manufacturing firms. Though Franco and Sasidharan (op cit.) disentangled most of the channels they did not consider one of the most important facts that competition from the foreign firms in the domestic market may have impact on the export performance of the domestic firms. On the other hand, while Joseph and Reddy (op cit.) considered the FDI impact on export performance of Indian manufacturing firms, they fail to incorporate various intra-industry spillover channels. We try to bridge the gap between the studies in three ways: first, we disentangle spillover channels focusing on horizontal spillover channels as mentioned in the previous literature, to find out the impact on export performance which incorporates both the export decision of the non-exporting firms and also the export propensity of the exporting firms. Second, the study removes the bias of the Joseph and Reddy (op cit) paper by considering not only the exporting firms but also the non-exporting firms as well. Third, the study divides the period 1994–2010 into two sub-periods (1994–2001 and 2002–2010) according to the inflow of FDI which we think has large influence on export performance. Moreover, as it also takes care of the absorption time, we expect interesting results of FDI in these two sub-periods. We use Heckman selection method to estimate the two-stage effects of export performance of domestic firms: in the first step the firms decides whether to export and in the second step the self-selected firms decide how much to export. Our study covers more than 6000 Indian manufacturing firms over 17 years (1994–2010).

The paper is organised into six sections. The next section provides a brief review of the previous theoretical and empirical research on export spillovers and FDI especially focusing on India, followed, in section three by a brief discussion on the FDI and trade activity of India since liberalisation. The fourth section is dedicated to the methodological issues, while the econometric results are explained in the fifth section. Section six concludes the paper.

2 Review of Literature

Previous literature has mentioned about four intra-industry spillover channels through which export activities can be influenced by foreign investment. The spillover channels are named as imitation spillovers, competition spillovers, skill spillovers and informational spillovers. The first three channels are considered as the induced channels of export spillovers as the induced effects on exports occur through the productivity enhancement of the firms. The last channels influence export performance by providing international information to the domestic firms.

As suggested by studies (see, Ruane and Sutherland 2005; Greenaway et al. 2004; Anwar and Nguyen 2011; Franco and Sasidharan 2010), imitation of foreign R&D activity and technology enhances technological capability of the domestic firms. The reverse engineering of the technologies used by foreign firms generally reduces the cost of import and implementation and in turn reduces overall production cost. Moreover, it is believed that foreign firm employees get better training and work in a better organisational and managerial environment, which makes them more productive and efficient than the corresponding local firms. In a scenario of labour turnover from foreign to local firms, embodied skills transmit to the domestic labour which improves the productive capacity of local labour. Imitation and skill spillovers thus can improve the export performance of the domestic firms by improving the product quality and production competence.

Many studies (for example, Haddad and Harrison 1993; Aitken and Harrison 1999) have argued that competition from the foreign firms is the main source of productivity spillovers. For fear of losing the market share to their foreign counterpart, local firms tend to upgrade their production technology base or find ways to use their available resources more efficiently. It is also argued that competition from foreign firms forces least efficient firms to leave the market and thus relocate the resources towards the firms with comparative advantage. Therefore, in the process of winning the competition with the foreign firms, domestic firms gain productive capability and increase product quality which are considered as the major factors of export competitiveness inducing export activity of domestic firms. According to Greenaway et al. (2004) and Franco (2013), competition from the foreign firms also induces local firms to look for new market outside, thus encouraging non-exporters to become exporters.

These effects are generally considered as induced effects of FDI on export performance through the improvement of productive capacity. On the contrary, export activity of the foreign firms improves export performance of the domestic firms through positive information spillover (Karpaty and Kneller 2011). MNCs indirectly convey information about the international market through their connection with the international distributors and networks, their knowledge about the taste and demand of the consumers, servicing facilities and higher marketing capabilities. These reduce the cost of attaining information and advertising, leaving productivity unchanged (Franco and Sasidharan 2010). This effect is known as the “learning by seeing” or information spillover (Aitken et al. 1997; Sun 2001; Franco and Sasidharan 2010).

There are a number of studies which investigated the FDI spillover effects on export propensity or export performance of the domestic firms. Most of the studies have found positive spillover effects of FDI on the domestic export performance. For example, Sun (2001), Wang et al. (2007), Xuan and Xing (2008), Sun (2012) and Chen et al. (2013) have found out that FDI has positive spillover effects on the export activity of the Chinese manufacturing firms. Similarly, Johnson (2006) has shown a significant positive effect of FDI on the export activities of the East Asian countries. However, none of the above studies disentangled the spillover channels. The studies which have segregated the export spillover channels from FDI have found contradicting results. While Greenaway et al. (2004) found positive effects on export performance from competition, information and imitation spillovers from FDI for UK, Ruane and Sutherland (2005) found negative effect of foreign export activities (negative information spillovers) on the export performance of the Irish firms. According to Ruane and Sutherland (2005), foreign firms used Ireland as the export platform reducing domestic firms’ foreign market share.

Export spillover studies are relatively less explored in India. Earlier studies by Kumar and Siddharthan (1994) could not find any significant difference in export performance between foreign affiliates and domestic firms in restrictive policy regime. However, a number of studies for post-liberalisation period suggested that foreign firms have shown significantly higher export performance as compared to domestic firms (Aggarwal 2002; Kumar and Pradhan 2003). Using Tobit model, Aggarwal (2002) found that MNEs' export performance is better than domestic firms during late 1990s. However, she did not find any evidence of positive relationship between foreign equity share and export performance in high-technology domestic firms. She argued that India could not attract efficiency-seeking outward-oriented FDI in the high-technology sector. Banga (2003) found a significant impact of FDI on the export intensity of non-traditional export industries in India. Contradicting this finding, Prasanna (2010) found that between 1991–1992 and 2006–2007, India's export performance (especially exports of high-tech products) has been highly influenced by the presence of FDI. Similar to the previous studies, these studies also did not mention the channels of export spillovers.

In recent studies, Joseph and Reddy (2009) and Franco and Sasidharan (2010) have formally investigated FDI spillover effects on export performance of Indian manufacturing firms. Joseph and Reddy (2009) have shown that spillover can occur through the export and sales of the foreign affiliates. According to the study, horizontal and vertical spillovers in terms of export intensity of the foreign firms did not have any spillover effect on domestic firms' export activity. They argued that economic liberalisation did not attract much of export-oriented FDI to India. Contrary to the foreign firms' export activity, foreign firms' domestic activity (sales in the domestic market which is mentioned as competition spillovers in earlier literature) was found to be a significant factor in raising export activity of domestic firms in the same industry groups except for the period 1997–2000 when industry characteristics were controlled for using industry dummy. Franco and Sasidharan (2010) considered various horizontal channels (mentioned above) for export spillover from foreign presence. They showed that Indian firms' decision to export was highly influenced by the R&D activity and skill of the foreign firms; however, there was no evidence of information spillover. Interestingly, the result changes when firms' internal R&D activity interacts with all these spillover variables. The result shows that with internal R&D activity, the domestic firms can absorb the positive effects of FDI presence. Domestic firms' export intensity is also found to be positively influenced by the export activity of the foreign firms. The result remains the same for the export decision of the non-exporting domestic firms as well. Export spillovers and R&D spillovers were found to be more effective in the presence of domestic R&D activity. The result reinforces the fact that domestic R&D activity is highly relevant to gather any benefit from foreign presence in any form.

3 FDI and Export Activity in India

3.1 FDI in India

Since liberalisation, India has been experiencing inflows of FDI. The policy change in the post-reform period brought a major alteration in terms of inflow of actual FDI through various channels. The total FDI inflow has gone up to $ 44 billion in 2016 from merely $129 million in 1991–1992. During the same period, India has also grown as an investor in the world market. As we see, India's outbound investment has increased from $0.7 billion in 2000 (data is not available before 2000) to around $4 billion in 2016. As we see from the graph below (Fig. 1), even after liberalisation, FDI inflow was not that high till 2002. The policy change to allow FDI up to 100% foreign equity under the automatic route in townships, housing, built-up infrastructure and construction development projects in 2004 can be observed from the surge in FDI inflow. However, economic slowdown has shown an impact on the FDI inflow in India as we see that FDI inflow has decreased after 2007–2008 which has again increased since 2012.

3.2 Export Activity of India

In Fig. 2, we present the major exported items of India during 1995–2010. There have been some notable changes in the commodity composition of India's exports. As seen from the figure, the importance of agricultural/primary products has noticeably declined as the share in total exports has declined from 23% in 1995 to 14% by 2010. In contrast, the manufacturing sector has been a major constituent of merchandise

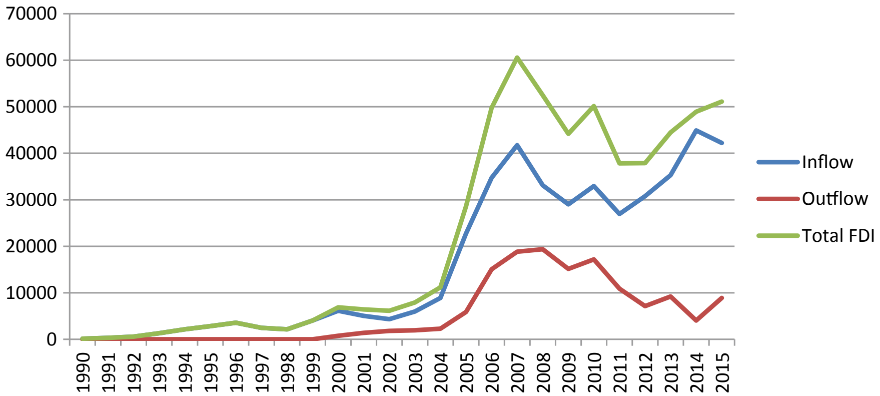

Fig. 1 Inflow, outflow and total FDI since 1990–1991 ($ Million). *Source* Handbook of statistics on Indian economy, Reserve Bank of India

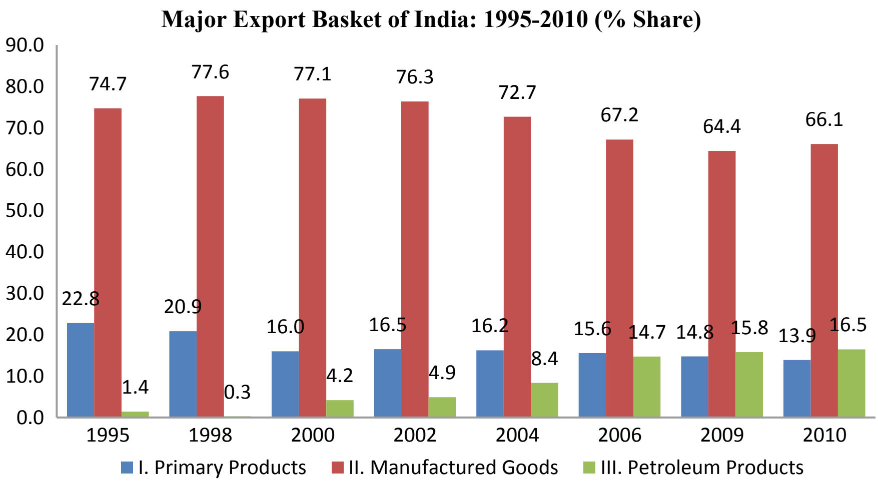

Fig. 2 Major export basket of India: 1995–2010 (% share). *Source* Author's calculation from World Development Indicators (WDI)

exports in recent decade (around 66%). The manufacturing sector recorded the fastest growth of 9.6% per annum since 1995, whereas agricultural export commodities grew at a much lower rate of 6.2%. In what follows, we examine a detailed descriptive analysis of manufacturing exports of India since reform.

We further examined the direction of India's export during 1990–2010. Table 1 shows that OECD is the largest market for Indian exports. However, since the mid-2000, there has been gradual decline as the share came down to 36% by 2010. Notably, the importance of Asian markets has increased during the same period. For instance, from 21% share in 1990, the market share of Asian region has gone up to 32% by 2010. Further, there have been significant exports of Indian manufacturing products to the developing countries during this period. In terms of countries, the importance of USA has declined. The share of exports has reduced from 22% in 2000 to 17% by 2005 and further down to 11% by 2010. On the other hand, the preference for Chinese market has increased as it is seen that the share has improved from marginal 2% in 2000 to 8% by 2010.

Table 1 Region/country-wise direction of India's export (% share)

Year	OECD	Developing countries	LDC	Africa	Asia	China	USA
1990	46.6	5.4	3.2	3.1	20.6	0.1	14.5
1995	53.9	10.8	5.9	5.6	26.2	1.1	17.0
2000	55.8	11.2	4.1	6.0	21.8	1.8	21.6
2005	46.7	18.7	5.2	7.2	30.2	7.2	16.5
2010	36.2	22.4	5.5	8.6	31.5	8.1	10.8

Source Author's calculation based on UN Comtrade (WITS)

4 Data Source, Definition of the Variables and Econometric Methodology

4.1 Data Source

The data for the study has been collected from PROWESS database provided by Centre for Monitoring Indian Economy (CMIE). Although the database provides financial activities since 1989–1990, we have considered the data since 1994 due to the availability of observations for most of the firms. The present study covers the study period of 1994–2010. The key indicators for which we have collected data are sales revenue, imports of capital goods, imports of raw material and finished goods, R&D expenditure, foreign promoters' share, exports of goods, profit after tax, etc. We cleaned the data using various criteria. First, we dropped firms that do not have continuous sales figure for at least 5 years. We further excluded firms with no data on wages and salaries, gross fixed assets and raw materials from the sample. In this process, we dropped almost 3000 firms due to non-availability of data. To mention, we define foreign firms as those firms with greater than or equal to 10% foreign equity share for at least 3 years in the study period.

4.2 Econometric Methodology: Heckman Selection Model

We capture the impact of FDI on export spillover by examining two aspects of export performance of the domestic firm: (i) non-exporter firm's decision to export and (ii) export propensity of the exporting firms. Underlying this behaviour is the issue of sunk cost associated with exporting activity. Due to this problem of self-selection, the OLS estimation can provide biased estimates. For capturing these two activities of the domestic firms, we use the Heckman two-stage selection model (Heckman 1979). This model treats the selection problem as the omitted variable problem. As the model takes into account firms' decision to enter export market or not, it removes the problem associated with the selectivity bias that occurs when we consider only the exporting firms.

The Heckman selection model involves two steps. In the first step, the firms self-select to the exporting activity and in the second step, the model explores the outcome of these self-selected firms. The selection equation is given in Eq. (1)

$$\begin{aligned} DEXP_{ijt} &= \alpha + \beta_1 DEXP_{ijt-1} + \beta_2 PROFIT_{ijt} + \beta_3 K/L_{ijt} + \beta_4 RD_{ijt-1} + \beta_5 TECH_{ijt-1} \\ &\quad + \beta_6 RAWIMP_{ijt-1} + \beta_7 WAGE_{ijt} + \beta_8 Sei_{jt} + \beta_9 S\sec t_{jt} + \beta_{10} AGE_{ijt} + \beta_{11} AGE^2_{ijt} \\ &\quad + \beta_{12} SIZE_{ijt} + \beta_{13} SIZE^2_{ijt} + +\beta_{14} SP_{jt-1} + v_i \end{aligned} \tag{1}$$

The outcome equation of the model is given in Eq. (2)

$$EXPINT_{ijt} = \alpha + \beta_1 K/L_{ijt} + \beta_2 RD_{ijt-1} + \beta_3 TECH_{ijt-1} + \beta_4 RAWIMP_{ijt-1} + \beta_5 WAGE_{ijt} + \beta_6 Sei_{jt} + \beta_7 S\sec t_{jt} + \beta_8 AGE_{ijt} + \beta_9 AGE^2_{ijt} + \beta_{10} SIZE_{ijt} + \beta_{11} SIZE^2_{ijt} + + \beta_{12} SP_{jt-1} + u_i \quad (2)$$

Subscript i refers to firm, j to sectors and t to time. u_i and v_i represent the random errors in the outcome and selection equations, respectively. There are two methods to estimate the Heckman selection model: the two-step method and the maximum likelihood method. As we are following the MLE model,[1] we assume that $v_i \sim N(0, 1)$, $u_i \sim N\left(0, \sigma^2\right)$. The distribution of the error terms of the equations is assumed to be bivariate normal with correlation $\rho \neq 0$. Since we analyse the export behaviour of all firms including non-exporters, estimating only export intensity would lead to a sample selection bias. If $\rho = 0$, then the OLS estimates would provide consistent and unbiased estimates of the outcome variable.

SP_{jt-1} represents the lag of FDI spillover variables which a competition spillover (*CompSpill*), information spillover (*ExpSpill*), imitation spillover (*RDSpill* and *TechSpill*) and skill spillover (*SkillSpill*). $DEXP_{ijt}$ of the Eq. (1) is a binary-dependant variable which takes the value 1 if the firm reports positive exports and 0 otherwise. In the next Eq. (2), the dependent variable is measured as export intensity ($EXPINT_{ijt}$) of the domestic firms. Lagged values of the spillover variables and technology variables have been added considering the fact that time lag is needed to influence export performance of the domestic firms. It would deal with the endogeneity problem as well. We measured all variables on annual basis (t). We also include industry and time dummies to account for possible industry and time-invariant effects.

To analyse our research question, we have also incorporated a few firm-level and industry-level control variables along with the spillover variables. As we see from the above two equations, both equations include same regressors except two variables in the selection Eq. (1) in order to identify the complete model as required by the selection models (Heckman 1979). One of the two is the lagged export status ($DEXP_{ijt-1}$) to take into account the fact that the decision to export depends on the previous export status of the firms. This means that if a firm exports at time *t* it would export at time *t + 1* as well. The second regressor is lag profitability ($PROFIT_{ijt-1}$) of the firm, which is the proxy for the capacity of the firm to meet the start-up cost associated with the exporting activity (Franco and Sasidharan 2010).

In our model, we have included five *firm-specific* variables to control spillover effects. Capital–labour ratio (*K/L*) and wage intensity (*WAGE*) represent the capital accumulation and the skill accrued in the production process, respectively. Increasing capital–labour ratio and higher skill enhance productivity and in turn quality of the products, improving export competitiveness in the international market (Roberts and

[1] In the Heckman two-step procedure, the inverse mills ratio is included as the independent variable in the second step of the regression analysis. Often, the inclusion of inverse mills ratio results in multicollinearity, which can have adverse effect on the model estimates. Therefore, we prefer the Heckman maximum likelihood method.

Tybout 1997). The recent shift of the export concentration from LT sector to other sectors indicates that India is slowly growing in export of skill-intensive products. India's LT sector's export share in world LT exports has remained stagnant over the study period (share increased marginally from 2.42 to 2.57), while the share of the medium- and high-technology sectors has increased from 1.11 to 2.47.[2] Thus, we add these two variables to investigate the influence of capital and labour skill on the export activity of the domestic firms.

Pant (1995) has discussed the import-induced export activity of Indian firms. According to the study, developing countries generally import domestically scarce and relatively high-quality materials. Thus, we can expect that import of raw material and intermediate inputs (*RAWIMP*) by firms would allow them to improve the quality of export products and thus in turn export competitiveness.

To compete and to achieve competitive advantage in the international market, firms need to innovate and diversify their products constantly and also need to improve the quality of the products. To capture the effects of innovative ability of the firms, internal R&D activities of domestic firms (*RD*), a proxy for the innovative capacity is added which we expect to influence the export performances positively. Along with R&D activity, firms in the developing countries also import technology to improve their technological capabilities. It is seen that Indian firms spend more on import of technology than internal R&D activities. As productivity and competitiveness improve due to the incorporation of advanced technology, we expect technology imports (*TECH*) to have positive impact on export activities of the domestic firms.

Among other firm-specific variables, we have added age (*AGE*) and size (*SIZE*) as control variables. Size can be seen as the indicator of efficiency of the firm (Willmore 1992) or economies of scale achieved by the firm (Pant 1995). Thus after a certain threshold level, the firm gains efficiency to cover the sunk cost and export more. However, the positive association may hold till the coordination costs are less than the profitability of the firm (Franco and Sasidharan 2010). Similarly, older firms are more knowledgeable and more efficient to compete in the international market. Thus, we expect AGE to have a positive impact on export activity although Power (1998) found an inverted U-shaped relationship between age and export activity. Our model tries to capture that by including the square term of the variable.

To accommodate the importance of the economic activities of the industries where the potential exporter or the exporting firms belong to, we incorporate two *sectoral variables*, sectoral export (*Sei*) and domestic market activity (*Ssect*). The *Sei* variable controls the factors that affect overall export performance of the industry (Greenaway et al. 2004). We expect a positive sign for the variable because firms located in an export-oriented industry would have positive impact on the export performance through information assimilation from other domestic firms. The *Ssect* variable accounts for the possible general spillover effects not associated with the export activities (Greenaway et al. 2004; Franco and Sasidharan 2010). It captures the fact that firms serving for the larger domestic market would have lower export

[2]Ratios are calculated using PROWESS CMIE database. Technology sectors are separated according to the OECD (2011) definition.

activity and thus we expect a negative association between export activity and *Ssect* variable.

We have already mentioned the spillover variables that we have added in the models. The *CompSill* variable captures the importance of foreign firms in the domestic market. The higher the competition from the foreign firms, the higher is the possibility that domestic firms turn into exporters either by improving their technology base or by relocating resources to the sectors according to their comparative advantages or just by force to leave the domestic market. Imitation of foreign technology and R&D activities reduces the cost of acquiring technology and implementing it in the production process. Therefore, *RDSpill* and *TechSpill* variables are included to incorporate the impact of imitation on export performance of the firms. In the end, to take into account the impact of labour mobility on skill enhancement of the domestic firms, we have included *SkillSpill.* As already mentioned before, these channels improve export performance through improvement of productivity of the firms. On the other hand, domestic firms gain from established networks and marketing knowledge of the foreign exporting firms, and, therefore, we expect a positive information spillover (*ExpSpill*) on the export performance of the domestic firms. The definition and expected signs are provided in Table 2.

5 Econometric Results

The results of the Heckman selection model are shown in Table 3.

5.1 Manufacturing Sector (1994–2010)

5.1.1 Export Decision of Domestic Firms

Firm-Specific Variables

As can be seen in Table 3, starting with the firm-level variables, we find that profit (*PROFIT*) and previous export status of the firms (*DEXP*) are very important deciding factors for future export decision of the domestic firms. Both of these variables show significant positive coefficients which follow the previous studies on India (Franco and Sasidharan 2010) as well as the theory that profitable firms can overcome the sunk cost associated with exporting.

For a non-exporting domestic firm, internal R&D activity is found to be an important factor for the exporting decision, while import of technology shows negative effect. As argued already, imported technology needs human capital and time to get adapted with the process of production. Thus, it increases cost of production and

Table 2 Definition and symbol of the explanatory variables with expected signs

Variables	Symbol	Definition	Expected sign (export decision)	Expected sign (export intensity)
Export intensity	*EXPINT*	Ratio of FOB value of export and sales turnover of the firm		
Decision to export	*DEXP*	DEXP = 1 if the firm has exported during the year; 0 otherwise	+	
Profitability	*PROFIT*	Profit after tax divided by sales turnover of the firm	+	
Capital–labour ratio	*K/L*	Calculated with perpetual inventory method using gross fixed assets. Labour is measured by deflating wages and salaries with three-digit industry wages. A ratio of capital to labour is used as capital–labour ratio	+/?	+/?
Wage intensity	*WAGE*	Expenditure on wages and salaries divided by sales turnover of the firm	+/?	+/?
R&D intensity	*RD*	Expenditure on R&D divided by sales turnover of the firm	+/?	+/?
Technology import intensity	*TECH*	Expenditure on (capital goods import + Royalty and technical fee payment made abroad) divided by sales turnover of the firm	+/?	+/?

(continued)

Table 2 (continued)

Variables	Symbol	Definition	Expected sign (export decision)	Expected sign (export intensity)
Material input import intensity	*RAWIMP*	Expenditure on import of raw and intermediate inputs divided by sales turnover of the firm	+	+
Age	*AGE*	Difference between the year of incorporation and the year in the study	+	+
Size	*SIZE*	Ratio of the firm output to the median output of the industry	±	±
Size of the sector	*Ssect*	Share of domestic sales in each sector to total manufacturing sales	–	–
Sectoral exports	*Sei*	Share of the domestic exports in each sector on total manufacturing export	+	+
Export spillover	*ExpSpill*	Share of the MNE's export in total exports of the sector	+	+
R&D spillover	*RDspill*	Share of the MNE's R&D expenditure on total R&D expenditure of the sector	+	+
Skill spillover	*SkillSpill*	Share of the MNEs' expenditure on wages and salaries on total expenditure on wages and salaries of the sector	+	+

(continued)

Table 2 (continued)

Variables	Symbol	Definition	Expected sign (export decision)	Expected sign (export intensity)
Technology import spillover	*TechSpill*	Share of the MNEs' expenditure on royalty and technical fees made abroad on total expenditure on royalty and technical fee payment of the sector	+	+
Competition spillover	*CompSpill*	Share of the MNEs' sales in total sales of the sector	+	+

reduces the competitiveness in the international market. However, this finding contradicts the previous studies by Joseph and Reddy (2009) and Franco and Sasidharan (2010) where they found imported technology boosts exports of Indian firms.

Contrary to our expectations, we find negative effect of capital–labour ratio (*K/L*) on the decision to export. This result is not very surprising for a developing country like India where adequate skill is also limited to couple with available technology and capital. Negative significant coefficient of the skill variable (*WAGE*) complements the previous result showing that India still has not reached that threshold level of competitive advantage in capital and skill-intensive products to enter the international market (Bhat and Narayanan 2009). Import of inputs (*RAWIMP*) has significant positive impact on export promotion in Indian manufacturing firms. It shows that the claim during the export promotion policies to open the import of raw and intermediate materials has actually been successful.

Our study shows that old but small-sized Indian firms are successful in entering export market. It seems that large firms with oligopolistic power in the domestic market enjoy the profit rather than taking the risk associated with exporting activities (Kumar and Siddharthan 1994; Pant 1995). The result also confirms the non-linearity of the size (*SIZE* and *SQSIZE*) variable. The square term for age (*SQAGE*) variables is found to be insignificant. The significant positive sign of the *AGE* variable confirms that firms which are operating in the market for some time are able to gather the knowledge of international market and thus it is easier for the older firms to enter the export market.

Sectoral Variables

Among the sector-specific variables, export orientation of the sector (*Sei*) indicates that firms in a more export-oriented sector are more likely to become exporters. We can term this as positive information spillovers from domestic firms' export activity.

Table 3 Heckman Selection (MLE) model for Indian manufacturing firms

Variables	Model 1		Model 2		Model 3		Model 4		Model 5	
	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity
PROFIT	0.0015 (2.01)[b]		0.0015 (2.00)[b]		0.0015 (2.01)[b]		0.0015 (1.99)[b]		0.0015 (1.95)[b]	
DEXP	2.6291 (169.99)[b]		2.6286 (169.71)[b]		2.6285 (169.92)[b]		2.6290 (169.9)[a]		2.6290 (169.69)[b]	
K/L	−0.00001 (6.45)[a]	0.00000 (2.58)[a]	−0.00001 (−6.45)[a]	0.00000 (−2.56)[b]	−0.00001 (−6.42)[a]	0.00000 (−2.49)[b]	−0.00001 (−6.45)[a]	0.00000 (−2.56)[b]	−0.00001 (−6.43)[a]	0.00000 (−2.53)[b]
RD	0.5603 (2.52)[b]	−0.0871 (−2.22)[b]	0.5612 (2.53)[b]	−0.0880 (−2.24)[b]	0.5635 (2.54)[b]	−0.0869 (−2.21)[b]	0.5563 (2.50)[b]	−0.0884 (−2.25)[b]	0.5529 (2.48)[b]	−0.0867 (−2.22)[b]
TECH	−0.8587 (−4.52)[a]	−1.4129 (5.68)[a]	−0.8566 (−4.52)[a]	−1.3491 (−5.40)[a]	−0.8673 (−4.57)[a]	−1.4096 (−5.66)[a]	−0.8581 (−4.52)[a]	−1.4143 (−5.68)[a]	−0.8458 (−4.45)[a]	−1.4237 (−5.74)[a]
RAWIMP	0.1254 (6.21)[a]	0.6266 (44.9)[a]	0.1252 (6.20)[a]	0.6262 (44.69)[a]	0.1264 (6.26)[a]	0.6270 (44.84)[a]	0.1253 (6.21)[a]	0.6289 (44.96)[a]	0.1237 (6.12)[a]	0.6136 (3.69)[a]
WAGE	−0.3177 (−11.11)[a]	0.0884 (8.18)[a]	−0.3178 (−11.10)[a]	0.0909 (8.37)[a]	−0.3183 (−11.12)[a]	0.0891 (8.23)[a]	−0.3180 (−11.11)[a]	0.0882 (8.15)[a]	−0.3160 (−11.05)[a]	0.0876 (8.14)[a]
SEI	1.3574 (2.95)[a]	1.4120 (12.36)[a]	1.3981 (3.00)[a]	1.5516 (13.48)[a]	1.5083 (3.26)[a]	1.5962 (13.96)[a]	1.2856 (2.75)[a]	1.4416 (12.36)[a]	1.4034 (3.01)[a]	1.5777 (13.80)[a]
SSECT	0.1940 (1.23)	−1.6423 (−7.58)[a]	0.1288 (1.15)	−1.9770 (−9.07)[a]	0.2208 (1.26)	−1.9176 (−8.89)[a]	0.1880 (1.22)	−1.9349 (−8.98)[a]	0.1863 (1.10)	−2.1532 (−9.65)[a]
AGE	0.0046 (2.49)[b]	−0.0015 (−3.19)[a]	0.0046 (2.49)[b]	−0.0014 (−2.97)[a]	0.0046 (2.50)[b]	−0.0014 (−2.95)[a]	0.0045 (2.48)[b]	−0.0015 (−3.15)[a]	0.0047 (2.55)[b]	−0.0014 (−2.96)[a]
SQAGE	−0.00002 (−1.09)	−0.00001 (−1.18)	−0.00002 (−1.09)	−0.00001 (−1.34)	−0.00002 (−1.08)	−0.00001 (−1.37)	−0.00002 (−1.08)	−0.00001 (−1.17)	−0.00003 (−1.07)	−0.00001 (−1.37)

(continued)

Table 3 (continued)

Variables	Model 1		Model 2		Model 3		Model 4		Model 5	
	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity
SIZE	−0.0049 (−6.42)[a]	0.0112 (16.81)[a]	−0.0049 (−6.41)[a]	0.0110 (16.58)[a]	−0.0049 (−6.42)[a]	0.0111 (16.67)[a]	−0.0049 (−6.42)[a]	0.0111 (16.68)[a]	−0.0049 (−6.42)[a]	0.0111 (16.85)[a]
SQSIZE	0.00000 (9.62)[a]	−0.00001 (−7.83)[a]	0.00000 (9.61)[a]	−0.00001 (−7.67)[a]	0.00000 (9.63)[a]	−0.00001 (−7.71)[a]	0.00000 (9.62)[a]	−0.00001 (−7.73)[a]	0.00000 (9.59)[a]	−0.00001 (−7.85)[a]
CompSpill	−0.1042 (−1.44)	−0.5716 (−11.47)[a]								
RDSPill			0.0391 (1.49)	−0.0013 (−1.07)						
ExpSpill					−0.4012 (−2.29)[b]	−0.1705 (−3.81)[a]				
WageSpill							−0.2745 (−1.58)	−0.3421 (−4.34)[a]		
TechSpill									−0.0082 (−1.17)	−0.0383 (−2.97)[a]
Constant	−0.1158 (−13.20)[a]	0.5229 (29.37)[a]	−1.1728 (−14.47)[a]	0.5493 (31.02)[a]	−1.1740 (−14.50)[a]	0.5489 (31.03)[a]	−1.1548 (−13.81)[a]	0.5704 (31.05)[a]	−1.1582 (−13.60)[a]	0.5625 (30.87)[a]
Log likelihood	−25634.47		−25642.94		−25690.21		−25690.53		−25452.42	
Rho	−0.1158045		−0.1137094		−0.1136412		−0.1136677		−0.1135843	

(continued)

Table 3 (continued)

Variables	Model 1		Model 2		Model 3		Model 4		Model 5	
	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity
Wald Chisq (47)	8663.71		8386.23		8513.2		8518.99		8188.6	
LR test	157.06[a]		154.57[a]		154.57[a]		154.44[a]		155.21	
Observation	64538		64538		64538		64538		64538	

[a, b, c] stand for significance at 1, 5 and 10% levels. Error-corrected z ratios are in the parenthesis

On the other hand, domestic market concentration of the sectors (*Ssect*) does not have any impact on the decision to export of the firms.

Spillover Variables

Now we move to our main focus of the study, the spillover variables. Except the information spillover (*ExpSpill*) variable, all other variables are found to be insignificant. The significant negative coefficient of the *ExpSpill* variable suggests that Indian market is probably being used as an export platform and thus the information does not filter to the domestic firms (Kneller and Pisu 2007). Moreover, due to the higher export competitiveness of the foreign firms, the domestic counterparts are unable to cater to the export market from the sectors where foreign firms are strong exporters. India's close competitor for FDI, China, seems to have seen a positive impact from foreign export activity (Buck et al. 2007). It seems that the motives of FDI investment are different for these two countries. The coefficients of skill spillover (*WageSpill*), technology spillover (*TechSpill*) and competition spillover (*CompSpill*) are negative but insignificant.

5.1.2 Export Intensity of Domestic Firms

Firm-Specific Variables

Once again, as shown in Table 3, in the case of export intensity, capital–labour ratio (*K/L*) follows the results of export decision. The result confirms that India does not have competitive advantage in technology-intensive products. In contrast to the export decision, skill intensity (*WAGE*) is found to have positive influence on the export activity of the exporting firms. Around 60% of the domestic export activity is concentrated in the LT and MLT sectors which use semi-skilled labour and less of capital. Knowledge acquired from the exporting activity improves the production skill of the labour enhancing the export activity of the manufacturing firms. Along with these variables, *RAWIMP* is also found to be an important factor influencing export intensity of the Indian firms.

Although R&D activity (*RD*) has a positive impact on the export decision, in the case of export intensity this variable shows just the opposite result. The main contributors (LT and MLT sectors) to the exporting activity in India do not share much of the R&D activity, and moreover expenditure incurred on R&D activity is so small that this result is not surprising. In addition, the lack of coordination between the production process and R&D activity increases the cost of production reducing effective productivity gain. Similar to R&D activity, import of technology (*TECH*) has significantly negative impact on export activity.

Unlike the export decision, our result finds that young and large-sized firms (*SIZE*) are more export intensive. This indicates that the economies of scale achieved by the Indian firms have significant influence on export performance (Kumar and Pradhan 2003). The non-linearity is fairly visible for the variable suggesting that after a certain size the coordination cost becomes higher than the profit earned reducing their export activity (Franco and Sasidharan 2010).

Sector-Specific Variables

Among the sectoral variables, exporting activity of the industry (*Sei*) is found to be an export-enhancing factor for the domestic exporting firms. However, domestic market size of the sector (*Ssect*) shows significant negative impact on the export intensity of the domestic firms. Firms within large domestic market sector encounter huge competition from other firms in the sector. In fear of losing market share, firms generally are not able to concentrate in exporting which in turn reduces the international activity of the domestic firms.

Spillover Variables

Spillover variables have significant impacts on export intensity of domestic firms. Contradicting Greenaway et al. (2004) and Ruane and Sutherland (2005), we find significantly negative competition spillover effects on export activity of the domestic firms. As already mentioned, due to competition domestic firms in general lose market share to their foreign counterparts losing economies of scale in the production process. Moreover, in the process of upgrading production technology to diversify products, domestic firms tend to increase their production cost (Aitken and Harrison 1999). Due to these effects, domestic firms lose their cost competitiveness both in domestic and international markets.

The study also does not find any imitation spillover among manufacturing firms. Both of the imitation spillover variables (*RDSpill* and *TechSpill*) are negative and insignificant. It is a fact that only 14% of total R&D stock in manufacturing industry is possessed by the foreign firms. As it seems, to remain competitive and to reduce the technology diffusion, foreign firms prefer to undertake the R&D activity at the headquarters and import them back. Therefore, the effect does not seem unexpected. Buck et al. (2007) pointed out correctly that Chinese firms have delocalised the foreign R&D activity more than Indian firms to accumulate higher spillover potentials. *TechSpill* variable is found to be significantly negative. The result confirms that quality of the domestic absorptive capacity is not high enough to capture the benefit of foreign technology import.

The coefficient of the skill variable (*WageSpill*) is also negative and significant. Foreign firms not only create a significant skill gap between domestic and foreign firms by hiring the best available skilled labour from the domestic market (Globerman 1979), it also increases the wage bill of the domestic firms (Saggi 2002; Poole 2007). Therefore, increasing cost and reduced availability of the skilled labour hinders the export competitiveness in the world market reducing export activities.

Significant negative coefficient of the *ExpSpill* variable supports the result we found for the export decision of the domestic firms, indicating that foreign firms have used India as export platform and have reduced share of domestic export in international market. Technologically advanced and skill-oriented foreign firms diversify products faster than domestic competitors, thus reducing domestic export market share (Ruane and Sutherland 2005).

The above econometric analysis brings out important aspects of export spillovers from FDI during the time period 1994–2010. However, the study period has a very distinct feature; while the 1990s had a relatively controlled FDI regime, 2000s were more liberal. Therefore, the inflow of FDI was significantly high during 2000s. We expect the spillover effects would also be different in these two regimes. The next subsection provides a detailed discussion of econometric results for two sub-periods, 1994–2001 and 2002–2010.

5.2 *FDI Spillover and Manufacturing Export Performance: Sub-period Analysis (1994–2001 and 2002–2010)*

The complete estimation results are provided in Table 5. Table 4 presents the results of spillover variables.

5.2.1 Export Decision of Domestic Firms

Spillover Variables

In general, the decision to export is not influenced by any of the activities of MNCs in India during the first phase (1994–2001). The increasing competitive pressure from FDI is evident from the positive (although insignificant) coefficient of *CompSpill* variable in the second period (2002–2010). Though insignificant, foreign R&D activity (*RDSpill*) shows positive coefficient in both the sub-periods. The negative coefficient of the *ExpSpill* variable provides further support for the export-platform theory of Ruane and Sutherland (2005). Significantly negative coefficient of the variable during 2002–2010 sub-periods explains that the foreign firms were attracted to India as they could use the country as the export platform for the southern region of the globe which obstructed the export decision of the domestic firms. In addition, there is no evidence of skill spillover on export decision of domestic firms (*SkillSpill*) in any of these sub-periods. Interestingly, the coefficients of *TechSpill* variable along with *CompSpill* and *RDSpill* become positive though insignificant in the second period of analysis.

Sectoral and Firm-Specific Variables

Export activity of the sector (*Sei*) and domestic market orientation of the sector (*Ssect*) are not significant in the first sub-period (1994–2001) while both of these variables become significant in the second sub-period (2002–2010). While sectoral export activity (*Sei*) has significant positive impact on the export decision of the domestic firms during 2002–2010, domestic market activity of the industry (*Ssect*) poses negative impact on the domestic firms' export decision. During this period, due to increased export activities of the domestic firms, the non-exporting firms were able to get necessary information about the foreign market, reducing the entry cost.

Table 4 FDI and export spillovers on domestic firms in aggregate manufacturing sector (1994–2001 and 2002–2010): Results from Heckman selection model (MLE)

Period	Variables	Model 1		Model 2		Model 3		Model 4		Model 5	
		Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity
1994–2001	CompSpill	−0.1698 (−1.24)	−0.1516 (−1.22)								
	RDSPill			0.2304 (1.34)	0.1856 (1.07)						
	ExpSpill					−0.5529 (−1.50)	0.3216 (1.36)				
	WageSpill							−0.6872 (−1.13)	−0.0371 (−0.43)		
	TechSpill									−0.0799 (−1.09)	−0.0313 (−1.73)[a]
	Constant	−1.3303 (−10.31)[c]	0.2884 (9.33)[c]	−1.3948 (−14.43)[c]	0.2790 (12.47)[c]	−1.2643 (−11.58)[c]	0.2753 (10.04)[c]	−1.2171 (−8.05)[c]	0.2820 (8.00)[c]	−1.2887 (−11.83)[c]	0.3076 (11.63)[c]
	Log likelihood	−10878.55		−10826.09		−10877.47		−10878		−10876.45	
	Rho	−0.1161511		−0.1158807		−0.1159506		−0.1160577		−0.1162772	
	Wald Chisq (36)	3256.66		3102.43		3256.73		3256.52		3260.14	
	LR test	74.42[c]		74.09[c]		74.13[c]		74.31[c]		74.64[c]	
	Observation	25963									
2002–2010	CompSpill	0.0230 (1.08)	−0.4899 (−2.58)[b]								
	RDSPill			0.3187 (1.08)	0.1101 (0.43)						

(continued)

Table 4 (continued)

Period	Variables	Model 1		Model 2		Model 3		Model 4		Model 5	
		Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity
	ExpSpill					−0.1692 (−1.75)[a]	−0.1739 (−1.90)[a]				
	WageSpill							−0.7744 (−1.22)	−0.3886 (−3.12)[c]		
	TechSpill									0.0520 (1.04)	−0.0480 (−1.78)[a]
	Constant	−1.5614 (−10.27)[c]	0.3388 (10.80)[c]	−1.4914 (−11.84)[c]	0.2903 (10.99)[c]	−1.4605 (−11.56)[c]	0.3044 (11.49)[c]	−1.2927 (−6.91)[c]	0.3842 (9.86)[c]	−1.4613 (−10.98)[c]	0.3105 (11.41)[c]
	Log likelihood	−10217.27		−10220.35		−10219.1		−10214.99		−10216.68	
	Rho	−0.2257916		−0.2257543		−0.2255993		−0.2262024		−0.2259323	
	Wald Chisq (35)	5487.46		5478.97		5483.53		5491.94		5482.09	
	LR test	223.42[c]		223.43[c]		222.9[c]		224.11[c]		223.65[c]	
	Observation	38575									

Note [a, b, c]represent the 10, 5 and 1% level of significance. The values in the parentheses are z-values

On the other hand, domestic competition reduced the domestic market and profit share increasing the difficulty of covering the sunk costs associated with entering new market.

PROFIT is found be significantly important determinant of export activity in the phase-I (1994–2001) but not during the phase -II (2002–2010). This might be due to the fact that gathering information, advertising and building networks (sunk cost associated with exporting activity) were costlier during the first phase of liberalisation as compared to the second phase when industries are relatively more connected with the world through Internet. Capital intensity (*K/L*), skill intensity (*WAGE*) and technology intensity (*TECH*) of the firms show significant negative impacts on export decision in both the sub-periods. This result confirms the fact that India always has comparative advantage in less-capital-intensive, less-skill-intensive or less-technology-intensive products. Increase in significance of *TECH* variable in the second sub-period proves that increased technology import could not be coupled with complementary R&D activities or skills. Therefore, firms were worse off from imported technology. However, R&D intensity (*RD*) variable is significant and positive during the first phase but turned out to be insignificant during the second phase. Age (*AGE*) variable does not seem to have important impact in the phase-II though it is found to be an important deciding factor for export decision for the period prior to 2002. On the other hand, size of the domestic firms (*SIZE*) followed the same non-linearity in both of these phases.

5.2.2 Export Intensity of Domestic Firms

Spillover Variables

Domestic activity of the foreign firms (*CompSpill*) shows significantly negative impact on export propensity of domestic firms in the second sub-periods, while this variable is insignificant in the first half of the study period (1994–2001). Similarly, if we look at the *ExpSpill* variable, we see that domestic export activities are adversely affected only during 2002–2010. This is interesting because since 2002, 100% FDI was approved in almost all industries in manufacturing sectors. The aim was to promote export, limit the possibility of financial crunch and improve productivity. However, the result shows that India has only attracted FDI which primarily catered into the domestic market during this period. Skill spillover (*SkillSpill*) variable is also significantly negative during 2002–2010, while it is negative but insignificant during the previous period. While *RDSpill* variable is positive but insignificant in both the periods, the other imitation spillover variable (*TechSpill*) is significantly negative in both sub-periods. The result points out to the requirement of domestic absorptive capacity in terms of human capital, physical capital and R&D activities to successfully imitate the imported technology.

Sectoral & Firm-Specific variables

Among the sectoral variables, *Sei* has positive and significant effect on export propensity, while *Ssect* variable has negative impact during both the sub-periods. Firms which are already exporting are benefitted from the import of inputs (*RAWIMP*) and skill intensity (*WAGE*) of the firms. Capital–labour ratio (*K/L*) and R&D intensity (*RD*) are both negative and significant during 1994–2001. On the other hand, during 2002–2010 periods, exporting firms are benefitted from the higher capital–labour ratio (*K/L*). The result in this period shows that though for the start-up exporting firms it is beneficial to export labour-intensive products (*K/L* ratio is negative in the export decision), firms which are already exporting have gained some comparative advantage in capital-intensive products. R&D intensity (*RD*) is also becoming positive in this period although the variable is not significant. Technology intensity (*TECH*) variable follows the previous results. Age (*AGE*) does not show any significant impact on export intensity of the domestic firms during 2002–2010. However, size (*SIZE*) of the firms show an inverted U-shaped relationship in the first period, while only the larger firms seemed to export more in the second period.

The sub-period analysis brings out few interesting observations. First, Indian firms have not gained comparative advantage in the technology-intensive and skill-intensive products in the export market over the study period, although it has been the prime motive of the Indian export promotion policies. Second, during the second half (2002–2010) of the study, Indian manufacturing sector mainly received domestic market-oriented or export-platform FDI which did not have positive influence on the export performance of the domestic firms. Most importantly, Indian firms could not build much internal technological capabilities over the time to capture the benefits from foreign firms in the export production.

6 Conclusion

Since the economic liberalisation policy reforms of 1991, the major thrust has been towards improving the export orientation of manufacturing sector so that economy attains faster economic progress. In this regard, the liberal FDI policies aim to facilitate more foreign investment in manufacturing sector so that the overall exports improve both directly and indirectly. The role of TNCs in expanding exports of host developing countries derives from their access to global, regional and especially home-country (or, third country) markets along with the additional capital, technology and managerial know-how they bring with them. TNCs, with their resources and market access, complement a country's own capabilities and reduce the obstacles of the host country firms in entering the world trading system (Honglin Zhang 2005). This study is relevant in the recent days as since 2002, India has experiences a huge surge in FDI inflow. Therefore, a study was needed to see how effective the FDI has been in Indian manufacturing sector.

In this paper, using econometric tools, we examined the spillover effects from FDI on the export performance of the Indian manufacturing firms during 1994–2010. Our study focused on two aspects: first, the impact of FDI spillovers on export performance of the domestic firms and second, the difference in the FDI spillovers on export performance during the two sub-periods, 1994–2001 and 2002–2010. Based on the theoretical literature, we incorporated four intra-industry FDI-induced spillover channels, i.e. information spillover, competition spillover, imitation spillover and skill spillover. For the empirical estimation, we have employed the Heckman Selection (Maximum Likelihood) model, which distinguishes export performance into two stages. In the first stage, the model examines the FDI spillover effects on the export decision of non-exporting firms and in the second stage the impact on export intensity of the self-selected firms from FDI is estimated. Apart from the spillover variables, we have also incorporated various sectoral and firm-specific control variables, for example, R&D activities, import of technology, capital–labour ratio, etc., which are often considered as some of the major determinant factors of export performance at the firm level.

The empirical analysis based on export decision and export intensity revealed that both technology and non-technology variables in various sector-specific categories have differential impact on export performance. In the case of technology variables, internal R&D was found to have significant influence on the probability of firms' decision. However, the internal R&D and skill intensity did not show any impact on export propensity of the Indian exporters. In the case of technology import, it seems that Indian firms are not able to utilise imported technology due to lack of innovative capability and human capital at the firm level. Capital–labour ratios of the firms have also adversely affected the decision to export and the export intensity of the firms which we can argue that India being capital scarce country, the comparative advantage lies in the export of labour-intensive products. Among the non-technology variables, the profitability of the firm, previous export status and raw material inputs are the most influential factors for the export decision of the domestic firms. We find a non-linear relationship with export decision, thus confirming the small size of the newly exporting firms. Contrary to the export decision model, we found a higher export intensity among larger size firms. Variables which control for the sectoral characteristics of the sample firms show that firms within the highly export-intensive sectors have higher probability to be exporters and moreover, exporting firms within these industries are more successful in the export market.

Looking at the spillover variables, we find that in general, Indian firms are not benefitted from the foreign activities in the domestic market. In contrast to the earlier studies on Indian manufacturing, we do not find any evidence of information spillover from the export activity of the foreign firms. This may be due the large domestic market bias for which foreign firms invest in India and the preference of foreign firms to use India as their export platform. The study also did not find any evidence of competition spillover in Indian manufacturing firms. High sunk cost associated with exporting and loss of competitive advantage due to high production cost disallows the firms to enter the foreign market. Similarly, skill spillover from foreign labour and limitation spillover through the technology import by foreign firms are also found to have adverse effects on the export decision and intensity of the domestic firms. Lastly, imitation spillovers through R&D activities of the foreign firms have shown negative impacts on export performance of the domestic firms. Due to lower internal R&D activity and human capital (absorptive capacity), domestic firms cannot imitate the technology used in the foreign production or absorb embodied skills.

The sub-period study reveals that Indian firms are in general adversely affected from foreign activities during 2002–2010. During 1994–2001, FDI inflow was low and therefore, most of the FDI spillover channels are found insignificant. However, it is interesting to notice that the export activities or the domestic market activities of the foreign firms reduced the export activities of the domestic firms during 2002–2010, while it was assumed that foreign investment would improve export activities of the foreign firms. The motive of the foreign firms seems to be the most important factor in generating spillover benefits. Although it is difficult to look into all investments, through policy it may be recommended that the foreign investors should undertake R&D activities within the country and export oriented foreign firms should share the information regarding their export destinations and the networks of their exports. In the study, the importance of the internal R&D activities and human capital on export performance came into light which must be encouraged through proper infrastructural facilities and training for sustainable export performance.

Appendix

Table 5 FDI and export spillovers on domestic firms in aggregate manufacturing sector (1994–2001 and 2002–2010): Results from Heckman selection model (MLE)

Sub-period	Variables	Model 1		Model 2		Model 3		Model 4		Model 5	
		Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity
1994–2001	PROFIT	0.0022 (1.90)[a]		0.0022 (1.90)[a]		0.0022 (1.91)[a]		0.0022 (1.90)[a]		0.0022 (1.90)[a]	
	DEXP	2.474 (110.85)[c]		2.475 (110.73)[c]		2.475 (110.86)[c]		2.474 (110.87)[c]		2.474 (110.87)[b]	
	K/L	−0.000009 (−3.15)[c]	−0.000003 (−3.67)[c]	−0.000009 (−3.17)[c]	−0.000003 (−3.69)[c]	−0.000009 (−3.10)[c]	−0.000003 (−3.68)[c]	−0.000009 (−3.16)[c]	−0.000003 (−3.67)[c]	−0.000009 (−3.13)[c]	−0.000003 (−3.67)[c]
	RD	1.3164 (2.72)[c]	−0.1125 (−3.12)[c]	1.3194 (2.72)[c]	−0.1126 (−3.12)[c]	1.3145 (2.72)[c]	−0.1125 (−3.12)[c]	1.3062 (2.70)[c]	−0.1125 (−3.12)[c]	1.3067 (2.70)[c]	−0.1128 (−3.13)[c]
	TECH	−0.3638 (−1.72)[a]	−1.1324 (−4.30)[c]	−0.3646 (−1.73)[a]	−1.0411 (−3.94)[c]	−0.3727 (−1.76)[a]	−1.1302 (−4.29)[c]	−0.3634 (−1.72)[a]	−1.1320 (−4.30)[c]	−0.3643 (−1.72)[a]	−1.1438 (−4.34)[c]
	RAW	0.0600 (2.72)[c]	0.3991 (21.57)[c]	0.0601 (2.72)[c]	0.3960 (21.35)[c]	0.0611 (2.76)[c]	0.3990 (21.56)[c]	0.0600 (2.72)[c]	0.3991 (21.57)[c]	0.0600 (2.72)[c]	0.3990 (21.57)[c]
	WAGE	−0.2553 (−6.16)[c]	0.0385 (2.66)[c]	−0.2561 (−6.18)[c]	0.0430 (2.96)[c]	−0.2556 (−6.17)[c]	0.0386 (2.67)[c]	−0.2558 (−6.17)[c]	0.0385 (2.67)[c]	−0.2553 (−6.16)[c]	0.0384 (2.66)[c]
	SEI	0.6720 (1.39)	1.0584 (4.73)[c]	0.6369 (1.33)	1.0874 (4.69)[c]	0.6843 (1.41)	1.0568 (4.72)[c]	0.7253 (1.47)	1.0614 (4.75)[c]	0.6802 (1.45)	1.0622 (4.75)[c]
	SSECT	0.6654 (1.35)	−1.0672 (−3.52)[c]	0.3804 (1.20)	−1.1164 (−3.62)[c]	0.3798 (1.20)	−1.0484 (−3.37)[c]	0.7365 (1.41)	−1.0730 (−3.54)[c]	0.4139 (1.23)	−1.1658 (−3.80)[c]
	AGE	0.0071 (2.66)[c]	−0.0032 (−5.11)[c]	0.0073 (2.71)[c]	−0.0031 (−5.06)[c]	0.0071 (2.65)[c]	−0.0031 (−5.09)[c]	0.0071 (2.65)[c]	−0.0032 (−5.10)[c]	0.0071 (2.66)[c]	−0.0032 (−5.11)[c]
	SQAGE	−0.0001 (−1.22)	0.0000 (1.96)[b]	−0.0001 (−1.29)	0.0000 (1.90)[b]	−0.0001 (−1.21)	0.0000 (1.95)[b]	−0.0001 (−1.22)	0.0000 (1.96)[b]	−0.0001 (−1.22)	0.0000 (1.96)[b]
	SIZE	−0.0067 (−5.48)[c]	0.0187 (20.17)[c]	−0.0067 (−5.47)[c]	0.0185 (19.97)[c]	−0.0067 (−5.48)[c]	0.0186 (20.17)[c]	−0.0067 (−5.47)[c]	0.0186 (20.17)[c]	−0.0068 (−5.49)[c]	0.0186 (20.16)[c]

(continued)

Table 5 (continued)

Sub-period	Variables	Model 1		Model 2		Model 3		Model 4		Model 5	
		Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity
	SQSIZE	0.0000 (5.50)[c]	0.0000 (−16.95)[c]	0.0000 (5.49)[c]	0.0000 (−16.81)[c]	0.0000 (5.50)[c]	0.0000 (−16.95)[c]	0.0000 (5.49)[c]	0.0000 (−16.95)[c]	0.0000 (5.51)[c]	0.0000 (−16.95)[c]
	CompSpill	−0.1698 (−1.24)	−0.1516 (−1.22)								
	RDSPill			0.2304 (1.34)	0.1856 (1.07)						
	ExpSpill					−0.5529 (−1.50)	0.3216 (1.36)				
	WageSpill							−0.6872 (−1.13)	−0.0371 (−0.43)		
	TechSpill									−0.0799 (−1.09)	−0.0313 (−1.73)[a]
	Constant	−1.3303 (−10.31)[c]	0.2884 (9.33)[c]	−1.3948 (−14.43)[c]	0.2790 (12.47)[c]	−1.2643 (−11.58)[c]	0.2753 (10.04)[c]	−1.2171 (−8.05)[c]	0.2820 (8.00)[c]	−1.2887 (−11.83)[c]	0.3076 (11.63)[c]
	Log likelihood	−10878.55		−10826.09		−10877.47		−10878		−10876.45	
	Rho	−0.1161511		−0.1158807		−0.1159506		−0.1160577		−0.1162772	
	Wald Chisq (36)	3256.66		3102.43		3256.73		3256.52		3260.14	
	LR test	74.42[c]		74.09[c]		74.13[c]		74.31[c]		74.64[c]	
	Observation	25963		25963		25963		25963		25963	

(continued)

Table 5 (continued)

Sub-period	Variables	Model 1		Model 2		Model 3		Model 4		Model 5	
		Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity
2002–2010	PROFIT	0.0011 (0.55)		0.0011 (0.53)		0.0011 (0.54)		0.0011 (0.54)		0.0011 (0.55)	
	DEXP	2.7461 (126.11)[c]		2.7464 (126.09)[c]		2.7460 (126.10)[c]		2.7462 (126.10)[c]		2.7462 (126.08)[c]	
	K/L	−0.000022 (−5.73)[c]	0.000002 (1.89)[a]	−0.000022 (−5.72)[c]	0.000002 (1.90)[a]	−0.000022 (−5.73)[c]	0.000002 (1.89)[a]	−0.000022 (−5.72)[c]	0.000002 (1.89)[a]	−0.000022 (−5.73)[c]	0.000002 (1.90)[a]
	RD	0.3644 (1.33)	0.1980 (1.41)	0.3635 (1.32)	0.1992 (1.41)	0.3627 (1.32)	0.1998 (1.42)	0.3601 (1.31)	0.1914 (1.36)	0.3611 (1.31)	0.2016 (1.43)
	TECH	−0.4742 (−3.48)[c]	−1.1966 (−3.48)[c]	−0.4729 (−3.47)[c]	−1.1967 (−3.48)[c]	−0.4730 (−3.47)[c]	−1.2035 (−3.50)[c]	−0.4721 (−3.47)[c]	−1.1998 (−3.49)[c]	−0.4739 (−3.48)[c]	−1.2027 (−3.50)[c]
	RAW	1.3180 (14.44)[c]	0.6593 (37.18)[c]	1.3160 (14.42)[c]	0.6601 (37.22)[c]	1.3161 (14.41)[c]	0.6596 (37.20)[c]	1.3162 (14.42)[c]	0.6605 (37.26)[c]	1.3169 (14.42)[c]	0.6594 (37.18)[c]
	WAGE	−0.3117 (−7.94)[c]	0.0384 (3.31)[c]	−0.3120 (−7.95)[c]	0.0386 (3.33)[c]	−0.3122 (−7.95)[c]	0.0389 (3.35)[c]	−0.3131 (−7.97)[c]	0.0380 (3.28)[c]	−0.3111 (−7.92)[c]	0.0388 (3.34)[c]
	SEI	1.287 (2.33)[b]	0.826 (4.01)[c]	1.110 (2.17)[b]	0.891 (4.36)[c]	1.145 (2.21)[b]	0.897 (4.39)[c]	1.130 (1.96)[b]	0.774 (3.72)[c]	1.121 (2.17)[b]	0.929 (4.53)[c]
	SSECT	−0.709 (−1.83)[a]	−0.889 (−1.87)[a]	−0.878 (−1.71)[a]	−1.120 (−2.40)[b]	−0.741 (−1.65)[a]	−1.079 (−2.31)[b]	−0.643 (−1.51)	−1.006 (−2.15)[b]	−0.882 (−1.62)	−1.370 (−2.84)[c]
	AGE	0.003 (1.02)	0.000 (−0.05)	0.003 (1.02)	0.000 (−0.04)	0.003 (1.02)	0.000 (−0.03)	0.003 (1.01)	0.000 (−0.12)	0.003 (1.04)	0.000 (0.01)
	SQAGE	−0.000003 (−0.17)	−0.000027 (−3.44)[c]	−0.000003 (−0.17)	−0.000027 (−3.45)[c]	−0.000003 (−0.18)	−0.000027 (−3.47)[c]	−0.000002 (−0.16)	−0.000026 (−3.38)[c]	−0.000003 (−0.19)	−0.000027 (−3.50)[c]

(continued)

Table 5 (continued)

Sub-period	Variables	Model 1		Model 2		Model 3		Model 4		Model 5	
		Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity	Export decision	Export intensity
	SIZE	−0.005 (−3.79)[c]	−0.001 (−1.86)[a]	−0.005 (−3.78)[c]	−0.001 (−1.89)[a]	−0.005 (−3.79)[c]	−0.001 (−1.91)[a]	−0.005 (−3.77)[c]	−0.001 (−1.87)[a]	−0.005 (−3.80)[c]	−0.001 (−1.89)[a]
	SQSIZE	0.00000 (5.55)[c]	0.00004 (22.92)[c]	0.00000 (5.54)[c]	0.00004 (22.95)[c]	0.00000 (5.55)[c]	0.00004 (22.97)[c]	0.00000 (5.54)[c]	0.00004 (22.95)[c]	0.00000 (5.56)[c]	0.00004 (22.95)[c]
	CompSpill	0.0230 (1.08)	−0.4899 (−2.58)[b]								
	RDSPill			0.3187 (1.08)	0.1101 (0.43)						
	ExpSpill					−0.1692 (−1.75)[a]	−0.1739 (−1.90)[a]				
	WageSpill							−0.7744 (−1.22)	−0.3886 (−3.12)[c]		
	TechSpill									0.0520 (1.04)	−0.0480 (−1.78)[a]
	Constant	−1.5614 (−10.27)[c]	0.3388 (10.80)[c]	−1.4914 (−11.84)[c]	0.2903 (10.99)[c]	−1.4605 (−11.56)[c]	0.3044 (11.49)[c]	−1.2927 (−6.91)[c]	0.3842 (9.86)[c]	−1.4613 (−10.98)[c]	0.3105 (11.41)[c]
	Log likelihood	−10217.27		−10220.35		−10219.1		−10214.99		−10216.68	
	Rho	−0.2257916		−0.2257543		−0.2255993		−0.2262024		−0.2259323	
	Wald Chisq (35)	5487.46		5478.97		5483.53		5491.94		5482.09	
	LR test	223.42[c]		223.43[c]		222.9[c]		224.11[c]		223.65[c]	
	Observation	38575		38575		38575		38575		38575	

Note [a, b, c]represent the 10, 5 and 1% levels of significance. The values in the parentheses are z-values

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Foreign Involvement and Firm Productivity: An Analysis for Indian Manufacturing, Service, Construction and Mining Sectors

Isha Chawla

1 Introduction

In recent years, there have been important changes in the nature of firms. The dramatic rise in trade, outward foreign direct investment (OFDI), offshoring and outsourcing reflect the new way firms organize their activities (Gattai 2006). Firms are investing abroad in an increasing range of markets, industries and products, experiencing changes in their technology sourcing, contractual patterns and asset structures. Foreign production/activities range from the export substituting, horizontal or market-seeking OFDI (Markusen 1984; Brainard 1997; Helpman et al. 2004 (hereon HMY)), to vertical or resource-seeking OFDI (Helpman 1984), to complex integration strategies (Yeaple 2003). Although there has been an impressive increase in both the *intensive* and *extensive margins* of trade and OFDI,[1] Bernard et al. (2012) among others document that micro-level empirical studies have shown that international activity is concentrated among a few very large firms that are active in more than one

[1] *Extensive margin* for exports is the number of firms involved in exports, while *intensive margin* is the average firm-level exports conditional on exporting. Likewise, for OFDI, *extensive margin* is the number of firms involved in OFDI, while *intensive margin* is the average firm-level OFDI flows conditional on doing OFDI.

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country and in more than one industry.[2] In explaining the observed *heterogeneity* in the foreign involvement decision of firms, empirical insights from the trade literature (Bernard and Jensen 1995, 1999, 2004) placed within-industry *heterogeneity* in firm productivity (e.g. Bartlesman and Doms 2000) in a dominant position. Further, within theoretical constructs of the *new new trade theory* (Melitz 2003; HMY) firm productivity explains the *self-selection* of firms into foreign markets. Firm productivity has also been taken as an important result of the *learning effects* from foreign contact, following Clerides et al. (1998).

Indian FDI outflows have increased noticeably from \$.119 billion in 1995 to \$11.304 billion (1.6% of gross fixed capital formation) in 2017, while OFDI stock has increased from \$.495 billion in 1995 to \$155.340 billion (6.3% of gross domestic product) in 2017.[3] Based on a large sample of Indian firm-level data obtained from the Centre for Monitoring the Indian Economy (CMIE) *Prowess* database for 1995–2010, for the *mining*, *manufacturing*, *construction* and *services* (information and communication) sectors, this paper seeks to establish if there is a positive link between firm productivity and organization of international activities through exports and/or OFDI. Although the positive link could be due to the most productive firms self-selecting themselves into foreign markets (e.g. Goldar 2016; Thomas and Narayanan 2017; Chawla 2019), it could also reflect learning effects through foreign engagements (e.g. EXIM Bank 2017).

Estimates of firm productivity are obtained from applying two alternative specifications of the production function, and two methodologies, namely, gross output (GO) specification based on the Levinsohn and Petrin (2003) (hereon LP) approach and value-added (VA) specification based on a modification of the LP approach, proposed by Wooldridge (2009) (hereon WLP). Within each of these two approaches, productivity estimates are also compared for two alternative classifications of exporters, and outward investing firms (S1 and S2, respectively, refer Sect. 4).

This paper begins in Sect. 2 by reviewing the related theoretical literature on firm productivity and multinational firms. Section 3 highlights the important contributions of the empirical firm productivity, exports and OFDI literature. Section 4 describes the sample and outlines the construction of real output and input series required for estimating firm productivity. Section 5 discusses methodological issues and the alternative productivity estimation approaches. Section 6 presents descriptive statistics. Section 7 compares distributions of firm productivity for firms that export as well as invest abroad, pure exporters and firms that serve the domestic market only. Section 8 concludes. The appendices present additional tables and figure.

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[2]In support, the present study finds that Indian foreign investment activity is very much concentrated. In 2009 and 2010, of the sampled firms, the top 1% outward investors from manufacturing account for 64.5% and 68% of the total investment outside India, respectively (*Prowess4* database and own calculations).

[3]World Investment Report (WIR), Annex Tables, UNCTAD 2018.

2 Theoretical Considerations

Early empirical findings on firm heterogeneity and trade, Bernard and Jensen (1995, 1999) observed that only a few firms export, and others in the same industry do not, and exporters are marked by clear defining characteristics in terms of size, productivity, capital intensity, skill and wages. On the theoretical side, this was at odds with the *new trade theory* (Krugman 1979) where all firms export. Theoretical research on the firm and international trade in the *new new trade theory* framework associated with Melitz (2003), and Bernard et al. (2003) introduce firm heterogeneity that underlies comparative advantage. The productivity ordering pattern between exporters and purely domestic firms in trade (Melitz 2003) has been extended to outward investing firms (HMY; Head and Ries 2003 (hereon HR)).

In HMY, firms face the ‘proximity-concentration’ trade-off. Self-selection entails the least productive firms to exit from the industry, less productive firms cater only to the domestic market and more productive firms choose to export as they can cover the higher cost of export. At some point, these firms are able to afford the sunk costs of OFDI and make the transition to the next level and invest abroad. The model predicts the sorting of firms into different organizational forms based on their productivity draw. The HMY model with its focus on firm heterogeneity can be related to a wider literature on firm-specific advantages and firm-level determinants of OFDI.

An alternative model to get the HMY predictions is developed by HR, which also consider the empirical complementarity between exports and OFDI to extend the choice from exports *or* OFDI to exports *and* OFDI, that could result with differences in fixed costs across destinations. The prediction of the productivity ordering between domestic firms, exporters and firms that export and invest abroad is closer to the empirical literature in developing economies that suggests that it is exporters that graduate to the next level and invest overseas. In the context of the literature on emerging market MNEs, while the asset-seeking motive may dominate over asset exploitation, some firm-level capacity to absorb resources is required.

Next, for the services industries, Oldenski (2012) argues that the standard predictors of the export versus OFDI decision do not hold, as they do for manufacturing. The traditional ‘proximity-concentration’ models that emphasize physical transportation costs and market size are augmented to a task-based framework, wherein each industry is decomposed into the tasks required for production. Considering the costs of transmitting information, it is predicted that industries requiring direct communication with consumers, such as services, are more likely to be produced in the destination market. However, the hidden cost of OFDI, namely, the difficulty of contracting nonroutine activities to foreign affiliates suggests that services (that are more intensive in nonroutine activities) are more likely to be produced at multinationals’ headquarters for export, partially offsetting the communication effect. That manufacturing and services differ in these two task measures is likely to generate different export to OFDI proportions at the industry level. Empirical support is found for these predictions using firm-level data from the US.

3 Related Empirical Literature

3.1 Exports and Productivity

On the empirical side, the bulk of the early studies established the superior performance of exporters of *manufactured goods* over domestic producers using estimated export premia, tested for differences in average productivity, and tested for stochastic dominance of productivity distributions (e.g. Delgado et al. 2002; ISGEP 2008). Early theoretical inquiries into trade in producer *services* (e.g. Markusen 1989) characterize these services as intermediates with significant degrees of scale economies (due to high knowledge intensity of many producer services) and/or product differentiation. A recent literature examines the link between exports of services and firm productivity. Breinlich and Criscuolo (2011) for UK, Love and Mansury (2009) for business service firms in US, Temouri, Vogel and Wagner (2013) for business services firms in France, Germany and the United Kingdom, and Minondo (2014)[4] for Spain find that as in manufacturing, trade in services is characterized by strong heterogeneity at the firm level. There is a positive link between productivity and export status,[5] and the *self-selection* hypothesis is confirmed for services firms as well.[6]

It has thus been suggested as in Breinlich and Criscuolo (2011) that the existing heterogeneous models for goods trade seem to be a good starting point also for the interpretation of trade in services. Unlike goods trade, however, Chang and Marrewijk (2013) for a study of 15 developing countries in Latin America find that the export productivity premium is negative for the services sector in contrast to the manufacturing sector. Lööf (2010) instead finds the premium to be larger than in manufacturing.

3.2 Exports, OFDI and Productivity

HMY find support for their model in their analysis of the relationship between exports-to-OFDI ratio of four-digit US manufacturing industries. Regressing log of productivity (VA per worker) on a set of controls, HMY find that an export firm has a productivity advantage of around 39% over non-exporters, while an outward

[4] Minondo (2014) further finds that the productivity premium is higher in services not related with the internet than in Internet-related services.

[5] Grubliešić and Damijan (2011), however, note that firm size seems to be related to the strong concentration of trade in services on a small number of firms as most exports of services are a function of the number of employees. On the other hand, external trade in knowledge-based services is concentrated with the small- and medium-sized firms (SMEs).

[6] Most of these studies consider trade in business services that represents the tradable component of services.

investing firm has a productivity advantage of around 15% over an average export firm.

The scope of the coverage of the microeconometric evidence on testing the predictions of HMY is wide. HR replicate the HMY prediction without imposing constant-elasticity-of-substitution (CES) preferences and 'iceberg' transportation costs. For 1,070 large Japanese firms in 1991, the study shows that there exists a hierarchy in productivity levels of firms investing abroad, exporting firms and purely domestic firms, although the differences tend to be statistically insignificant and there is weak correlation between firm size and productivity.

Girma et al. (2004), for Ireland in 2000, find that while the most productive firms engage in OFDI, no significant differences are discernible between exporters and domestic firms. Kimura and Kiyota (2006) for Japan in 1996–2002 also find similar patterns. Wagner (2006) for Germany in 1995, Bogheas and Gorg (2008) for Ireland,[7] and Arnold and Hussinger (2010) for Germany find support for HMY. Damijan et al. (2007) for Slovenia find no statistically significant advantage of firms with foreign affiliates over exporting firms although firms that export and engage in OFDI are twenty percent more productive than firms that serve only domestic markets.[8]

Tian and Yu (2012) for firms in the Zhejiang Province of China[9] find that over 2006–2008, there is positive correlation between firm productivity and OFDI, higher productivity firms are more likely to undertake OFDI and the greater is their OFDI. Castellani and Zanfei (2007) for Italy find that productivity is highest for firms with manufacturing activities abroad, followed by firms with only non-manufacturing activities abroad (an intermediate category, considered to have lower commitment to foreign markets), followed by exporters and then domestic producers. Tomiura (2007) for Japanese manufacturing firms in 1998 sorts productivity by the modes (combination) of foreign activities and finds that firms engaged in OFDI or in multiple globalization modes are more productive than foreign outsourcers and exporters, which are in turn more productive than domestic firms.

Yeaple (2009) demonstrates that the HMY sorting extends to the scale and scope of multinational enterprises and finds that the most productive US firms invest in a larger number of foreign countries and sell more in each country in which they operate. Aw and Lee (2008) focus on the production location decision of Taiwanese electronic multinationals in 2000 and find that more productive firms engage in OFDI, and firms that invest in US have higher productivity than those that invest in China as well as those that have no overseas assets.

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[7]Bogheas and Gorg (2008), however, note that studies that focus on only a couple of the many alternative strategies for global engagement may potentially yield wrong predictions and demonstrate the superiority of capturing a greater variety of organizational forms.

[8]That the HMY prediction does not hold in the comparison between firms with foreign affiliates and exporters is, however, traced to transition-specific transitory factors related to inherited foreign investments of large inefficient firms. TFP nevertheless has a positive effect on the probability of investing in the first-ever foreign affiliate.

[9]Zhejiang Province being the largest province in the number of OFDI firms in 2007 and the largest in OFDI in 2010.

Engel and Procher (2012) note that while theoretically the HMY model applies to market-driven OFDI, empirically it is difficult to disentangle between different motives for OFDI.[10] For a large sample of French firms from all business sectors that include manufacturing and services sectors, with the exception of the construction industry, the HMY model is confirmed, with MNEs exhibiting the highest productivity followed by exporters and domestic companies. Findings support the HR prediction in Europe with more market-driven outward investing firms exhibiting higher productivity than comparatively less market-driven ones. That MNEs with investments in high-wage countries do not outperform MNEs with investments in low-wage countries in firm productivity is taken as evidence that high-wage countries are also targets of substantial vertical OFDI (for R&D seeking, for instance).

For India, Bhattacharya et al. (2012) (hereon BPS), for 2000–2008, find differences between manufacturing and services industries with regard to the productivity ordering between exporters and OFDI. While the HMY predictions hold for a manufacturing industry, namely, chemicals where firms with OFDI are more productive than exporters, a symmetric analysis for software services industry reverses the predictions with the least productive firms self-selecting themselves into OFDI.

Using German services firms' data, Wagner (2013) finds support for BPS. However, Kox and Rojas-Romagso (2010) for Netherlands find that only the most productive Dutch service firms participate in exports and FDI. Also, Federico and Tosti (2017) for Italy find that as in HMY, smaller and less productive firms are more likely to export than to sell through foreign affiliates. Using labour productivity data on nine service product groups that include six producer services, namely, construction, transport, auxiliary transport, post and telecommunication, data processing, and R&D, and three business services, namely, management services, advertising and personnel services, Kelle et al. (2013) show that for Germany in 2005, the more productive service sector firms are more likely to export and more likely to choose foreign-affiliate sales instead of cross-border sales.[11] Further, Tanaka (2011) for Japan finds that OFDI firms are more productive than non-OFDI services firms, as in manufacturing, suggesting that the standard firm heterogeneity model can well explain OFDI by firms in the services sector.[12]

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[10]Two alternative approaches for classifying firms' foreign investments into resource-driven and market-driven OFDI can, however, be used to enhance the empirical precision of the HMY hypothesis. The study distinguishes between the *host country approach* of HR, whereby low productive firms enter only low-wage but not high-wage countries and the *NACE approach* that requires similar industry affiliation of the parent company and its subsidiary for market-driven OFDI, and vertical subsidiaries active in upstream (or downstream) industries from their parent's industry for resource-driven OFDI.

[11]As studies on exports, OFDI and productivity in services are fewer than in manufacturing, some studies that relate productivity to the likelihood of OFDI are included in this review, even if they do not compare the productivity distributions of firms.

[12]Service sector firms are, however, assumed to only have the choice of domestic production or OFDI as the dataset does not contain services exports, while manufacturing firms can choose between exports and OFDI. It is also demonstrated theoretically that none of the services firms can exceed the export cut-off productivity level that is sufficiently high enough for them.

4 Sample Description

4.1 Criteria for Firm Categorization

Following Narayanan and Bhat (2011) among others, for this study, identification of firms with foreign investments (that may also export) is done on the basis of the *investment outside India* data field in *Prowess*. The outward investing firm's industrial classification by National Industrial Classification (NIC)-2008 is based only on its activity, not that of its affiliates outside India. As in HR, among others, firms are categorized into D, DX, DXI and DI. These are, namely, firms that only serve the domestic market (D), firms that also export (DX),[13] firms that export and invest abroad (DXI), and firms that invest abroad but do not export (DI). In this study, the DXI and DI categories are merged to form the OFDI firms' category (hereon DIDXI).

Further, in the absence of information in the *investment outside India* data field in *Prowess* about the percentage holding by Indian firms in their affiliates abroad, while some studies identify an OFDI firm on the basis of the existence of positive overseas assets, some use cut-offs on the fraction of OFDI to total assets (as, for instance, >1%). In making the cross-sectional comparisons of the productivity distributions, an attempt is made to see whether the stricter basis for classifying foreign investors affects the nature of productivity rankings by firm categories. For this purpose, two specifications are used: S1, where DX represents firm-years where firms' export/sales ratio (*export intensity*) is positive, while DXI represents firm-years where firms' export intensity, and investment outside India/total assets ratio (*foreign investment intensity*) is positive, and S2, where a 1% cut-off on firms' export intensity is imposed to define firm-years as DX, while in addition to the 1% cut-off on firms' export intensity, a 1% cut-off on firms' foreign investment intensity is required to define firm-years as DXI. Likewise, DI covers non-exporter firms with foreign investment intensity of 1% and above.

4.2 Data and Construction of Variables[14]

Using *Prowess* data, a panel of 127 firms (1,196 observations) for mining and quarrying (NIC 05 to 09), 6,068 firms (57,698 observations) for manufacturing (NIC 10 to 32), 247 firms (2,036 observations) for construction (NIC 41, 42) and 683 firms (5,145 observations) for services sector (NIC 58, 61, 62, 63) is constructed, after data cleaning (Table 1). To reduce potential bias due to sample selection, the data or

[13]DX covers continuing exporters (firms that export continuously over the sample period) but also firms that switch their export status from domestic to exporter in the current year.

[14]For details on data sources, data cleaning, variable construction, econometric issues, and methodology of TFP estimation (based on LP), refer to Goldar et al. (2019).

Table 1 Number of firms in the sample, 1994/95 to 2009/10

Panel 1a: by year		Panel 1b: by industry							
		Two-digit NIC code	NIC-2008 description	No. of three-digit industries	Firms		Firm-year count[b] (All)	Firm-year count (DXI)[c]	
								S1	S2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Year	**Count**		**Mining and quarrying**		**No.**	**Share of sector (%)**			
1995	41	05	Mining of coal and lignite	2	11	08.2	154	–	–
1996	58	06	Extraction of crude petroleum and natural gas	2	02	01.54	29	–	–
1997	54	07	Mining of metal ores	2	17	13.4	149	01	–
1998	61	08	Other mining and quarrying	2	89	70.3	768	52	–
1999	58	09	Mining support service activities	1	08	06.56	96	05	–
2000	65			**09**	**127**	**100**	**1,196**	**58**	–
2001	68								
2002	73								
2003	88								
2004	98								
2005	101								
2006	96								
2007	98								
2008	93								
2009	75								
2010	69								
	1,196								
Year	**Count**		**Manufacturing[a]**						

(continued)

Table 1 (continued)

Panel 1a: by year		Panel 1b: by industry							
		Two-digit NIC code	NIC-2008 description	No. of three-digit industries	Firms		Firm-year count[b] (All)	Firm-year count (DXI)[c]	
								S1	S2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1995	2,503	10	Food products	8	695	11.45	6,408	200	90
1996	2,758	11	Beverages	1	124	2.04	1,068	20	4
1997	2,925	12	Tobacco products	1	08	.13	105	14	–
1998	3,054	13	Textiles	2	696	11.47	6,527	265	87
1999	3,253	14	Wearing apparels	1	107	1.76	844	42	16
2000	3,371	15	Leather and related products	2	64	1.05	558	62	24
2001	3,402	16	Wood and products of wood and cork, except furniture	1	32	.52	318	07	–
2002	3,486	17	Paper and paper products	1	228	3.75	2,057	18	07
2003	3,842	18	Printing and reproduction of recorded media	2	23	.37	164	03	02
2004	4,035	19	Coke and refined petroleum products	2	41	.67	292	22	04
2005	4,222	20	Chemicals and chemical products	3	802	13.21	7,934	478	211
2006	4,353	21	Pharmaceuticals, medicinal chemical and botanical products	1	437	7.20	4,267	471	298
2007	4,378	22	Rubber and plastics products	2	362	5.96	3,550	265	124

(continued)

Table 1 (continued)

Panel 1a: by year		Panel 1b: by industry							
		Two-digit NIC code	NIC-2008 description	No. of three-digit industries	Firms		Firm-year count[b] (All)	Firm-year count (DXI)[c]	
								S1	S2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
2008	4,303	23	Other non-metallic mineral products	2	225	3.70	2,312	143	52
2009	4,106	24	Basic metals	3	695	11.45	6,427	232	94
2010	3,707	25	Fabricated metal products, except machinery and equipment	2	195	3.21	1,767	67	40
	57,698	26	Computer, electronic and optical products	5	224	3.69	1,937	159	82
		27	Electrical equipment	6	299	4.92	2,884	115	39
		28	Machinery and equipment n.e.c.	2	360	5.93	3,692	222	81
		29	Motor vehicles, trailers and semi-trailers	1	15	.24	159	37	13
		30	Other transport equipment	4	335	5.52	3,558	203	111
		32	Other manufacturing	5	101	1.69	870	124	72
				57	**6,068**	**100**	**57,698**	**3,169**	**1,451**
Year	**Count**		**Services: information and communication**		**No.**	**Share of sector (%)**			
1995	74	58	Publishing activities	1	42	06	395	31	10
1996	98	61	Telecommunications	4	89	13	594	48	33

(continued)

Table 1 (continued)

Panel 1a: by year		Panel 1b: by industry							
		Two-digit NIC code	NIC-2008 description	No. of three-digit industries	Firms		Firm-year count[b] (All)	Firm-year count (DXI)[c]	
								S1	S2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1997	116	62	Computer programming, consultancy and related activities	1	446	65	3,514	1009	900
1998	129	63	Information service activities	2	106	16	642	132	108
1999	184			**08**	**683**	**100**	**5,145**	**1,220**	**1,051**
2000	235								
2001	299								
2002	318								
2003	392								
2004	433								
2005	469								
2006	497								
2007	507								
2008	504								
2009	465								
2010	425								
	5,145								

(continued)

Table 1 (continued)

Panel 1a: by year		Panel 1b: by industry							
		Two-digit NIC code	NIC-2008 description	No. of three-digit industries	Firms		Firm-year count[b] (All)	Firm-year count (DXI)[c]	
								S1	S2
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Year	**Count**		**Construction**						
1995	81	41	Construction of buildings	1	54	22	474	28	–
1996	86	42	Civil engineering	3	193	78	1576	144	–
1997	94			**04**	**247**	**100**	**2,036**	**172**	–
1998	95								
1999	103								
2000	102								
2001	110								
2002	120								
2003	136								
2004	150								
2005	160								
2006	174								
2007	184								
2008	167								
2009	148								
2010	126								
	2,036								

Notes
[a]Excluding NIC 31 (Manufacture of furniture), NIC 33 (Repair and installation of machinery and equipment)
[b]Firm-year count at each 2-digit level is based on the sample for which LP estimates are obtained
[c]Firm-year count for DXI
Source Prowess 4 and own calculations

firm coverage is not restricted to large firms alone. Wider industry coverage allows cross-industry heterogeneity.

Some modifications are applied towards the construction of real output (GO, VA) and input series (intermediate inputs, namely, raw materials, energy and services; labour and capital) required for estimating firm productivity. The 'combined' intermediate input series is formed using separate three-digit-specific price deflators for raw materials, energy and services using Input–Output Transactions Tables (IOTT) 1993–94 and 2003–04. Incomplete coverage of the labour input in the database leads to the need for imputation of the labour input (also see Chawla 2012). Given the widely noted heterogeneity in wages across firms, the Annual Survey of Industries (ASI)-based method of imputing firm employment[15] has been criticized for its implicit assumption of a uniform wage rate among all firms belonging to an industry (Goldar et al. 2004; Siddharthan and Lal 2004, among others). An adjustment is made to the imputed estimates of the labour input following the 'ASI-based approach' for a 'wage premium' based on firms' ownership categories.[16] Physical real capital stock is constructed following the Perpetual Income Method (PIM), allowing for disaggregated growth of investment, and is combined with 'knowledge' or R&D 'capital' stock.

5 Estimation of Firm Productivity

For the GO specification of the Cobb–Douglas production function (in logs), with output (y_{it}) as function of capital (k_{it}), labour (l_{it}) and intermediate inputs (m_{it}), log total factor productivity (TFP) is the estimated residual:

$$\widehat{\omega}_{it} = (y_{it} - \widehat{\beta}_k k_{it} - \widehat{\beta}_l l_{it} - \widehat{\beta}_m m_{it})$$

In the VA specification, with VA (v_{it}) as function of primary inputs of capital (k_{it}) and labour (l_{it}), estimated log TFP is

$$\widehat{\omega}_{it} = (v_{it} - \widehat{\beta}_k k_{it} - \widehat{\beta}_l l_{it})$$

[15]The 'ASI-based approach' involves the computation of an average wage rate (emoluments per employee, at the 2-digit or 3-digit industry level), obtained by dividing Annual Survey of Industries (ASI) data on total emoluments by the total persons engaged. Subsequently, by dividing each firm's wage bill obtained from the company database by this computed average wage rate, an imputed measure of the employment in the firm is arrived at.

[16]For consistency with the wage adjustment as performed for manufacturing firms, the reported compensation to labour for group, government and foreign firms is adjusted downwards (by the same percentage as worked out for manufacturing) before imputing employment.

5.1 Methodological Issues

5.1.1 'Simultaneity Bias' Due to Correlation Between Observed Input Levels and Unobserved Productivity

In the context of productivity measurement, comparisons are drawn between the alternative methods that attempt to overcome 'simultaneity bias', namely, LP and WLP. The *semi-parametric, proxy variables* LP approach shows that when the demand for an observed input decision of the firm, that is, intermediate inputs (a function of state variables of the firm, namely, productivity and capital), is strictly positive, and the invertibility condition is satisfied, unobserved productivity can be expressed only as a function of the observable inputs (that is, capital and the proxy variable), and can thus control for 'simultaneity bias'. The estimation algorithm in the *first stage* involves the identification of the labour coefficient, while the *second stage* involves the identification of the capital and materials coefficients.

Ackerberg et al. (2015) (hereon ACF), however, point out that under the assumption that labour and materials are both chosen simultaneously, they are likely to be functions of the same state variables, namely, productivity and capital. Under the LP invertibility condition, $l_{it} = f_t\,(g_t\,(k_{it}, m_{it}), k_{it})$ where $g_t = m_t^{-1}$, such that in the first stage, the coefficients on the variable inputs are non-parametrically unidentified due to collinearity with the inverted function. ACF attempt to recover the input coefficients by modifying the timing assumption, wherein, as in LP, capital k_{it} is assumed to be chosen at time $t-1$, intermediate inputs m_{it} at time t, but adjustment time for hiring and firing labour allows labour to be chosen by the firm at time $t-b$, where $0 < b < 1$ so that it is 'less variable' than intermediate inputs, and being determined prior to intermediate inputs enters the set of variables that affect the choice of the intermediate inputs ($m_{it} = f_t\,(\omega_{it}, k_{it}, l_{it})$).

WLP modifies the LP estimator to address the collinearity issues raised above by a joint GMM estimation of the system, such that the first stage of LP provides identifying information for parameters on the variable inputs (such as labour) and efficiently accounts for serial correlation and heteroscedasticity in the errors. The contemporaneous state variable, k_{it}, any lagged inputs and functions of these are taken as instrumental variables in estimation.

5.1.2 Value-Added Bias

Some studies point out that the relative superiority of exporters in comparison to purely domestic firms may result from several sources of potential bias in productivity estimates, also related to the selection of the functional form of the production function, namely, GO vs.VA (Gandhi et al. 2011, 2013; Rivers 2013).[17] Output heterogeneity among firms thus reflects not only variation in productivity, but that in

[17]For Indian manufacturing, Pradhan and Barik (1998) find through a statistical test that primary and intermediate inputs are not separable in the production function, thus weakening the option of using VA for TFP estimation.

excluded inputs (intermediate inputs) as well. As intermediate input usage is likely to be correlated with productivity, it could overstate the true degree of productivity heterogeneity. Also, the correlation between intermediate input usage and inputs that are controlled for (capital and labour) may cause biased output elasticity estimates for these inputs, the bias consisting of two components: (i) 'transmission bias' that results from the correlation between productivity and primary inputs and (ii) 'value-added bias' that results from the failure to subtract intermediate inputs from GO to fully control for the contribution of intermediate inputs to output (Gandhi et al. 2011).

5.2 Empirical Specification: Production Function Estimation

Two sets of input coefficients are estimated in an attempt to explore whether similar concerns are of importance when investigating the relative superiority of OFDI firms (that also export). Estimates of firm productivity and relative firm productivity index (following Pavcnik 2002) are obtained from applying GO–LP,[18] and VA–WLP,[19] at the two-digit industry/industry group level. For the revenue production function (GO–LP), estimated input coefficients are bounded away from zero, with the materials input coefficient being higher than those of labour and capital. For VA–WLP, vectors of the exogenous, endogenous and instrumental variables follow Petrin et al. (2011). The production function coefficients obtained by WLP are mostly significant at the 1% level. Results of the overidentification tests of the joint null hypothesis that the instruments are valid, that is, they are orthogonal to the error term, and the excluded instruments are correctly excluded from the estimated equation (as given by the p-values for the Hansen J statistic test), indicate that for most cases, the validity cannot be rejected at a cut-off of 10%. The WLP procedure yields TFP estimates from 1997 onwards as inputs used during the first 2 years of the sample period are used as lagged inputs.

[18]The LP approach is implemented using the levpet command (Petrin et al. 2004).

[19]The WLP method is implemented using the program available at http://www.econ.umn.edu/~petrin/programs.html using (ivreg2.do). Under ivreg2, the estimator option gmm2s (that produces the IV/2SLS estimator, standard errors consistent under homoscedasticity) when combined with the cluster option, generates two-step efficient GMM (EGMM) estimates (that is statistics robust to heteroscedasticity and clustering at the firm level). cluster standard errors are robust to both arbitrary heteroskedasticity and arbitrary intra-group correlation. The ivreg2 Stata module developed by Baum et al. (2012), available at http://ideas.repec.org/c/boc/bocode/s425401.html, is used for estimation.

6 Descriptive Statistics

6.1 Sectoral Classification and Broad Features by Firm Category

Table 2 shows that in *manufacturing*, only a small fraction of observations (5.84% S1, 2.9% S2) correspond to foreign investors,[20] while a large proportion (51.89% S1, 45.82% S2) correspond to exporters.[21]

Also, in 2009/10, DIDXI accounted for 53% of sales of all firms in the sample (by S1) and 19.67% (by S2). For *construction* firms, DIDXI accounted for 62.75% of sales in the same year. The export and foreign investment intensity varies greatly between firms. For instance, in 2009/10, for *manufacturing*, among the 1,771 exporters, about 18.4% export less than 1% of their sales, while another 34.5% export between 1 and 10% of their sales, 32.9% export 10 and 50% of their sales, 7.5% export 50 and 75% of their sales and 6.5% export 75 and 100% of their sales. Also, of the 444 outward investors, 48.4% hold less than 1% assets abroad and 35.6% hold 1–10% assets abroad; another 15% invest between 10 and 50% assets abroad, while .006% hold 50–75% assets abroad. In the *construction* sector, for the same year, of the 40 firms that export (DX + DXI) around 30% export less than 1% of sales, 37.5% export between 1 and 10% of sales, 27.5% export between 10 and 50% of sales and 6.66% export between 50 and 100% of sales. Also, 73.3% firms have a foreign investment intensity of less than 1%, while the remaining 26.6% invest between 1 and 10% of their assets abroad. Several empirical studies have shown that exporting and foreign investing firms are generally larger in size (e.g. Bernard et al. 2007). Characterizing the data along the size dimension, Chawla (2015) indicates that firm size (by sales) is positively related with the percentage of firms participating in overseas investment in *manufacturing* and *construction*, while the overseas investors in *services* are less concentrated in the largest size class.

Table 4 in Appendix A for *manufacturing* shows broad features of the structure of firms with foreign operations compared to those that do not. For both specifications (S1 and S2), as in the literature, the median firm in outward investing firms' categories (DI and DXI) is more productive than firms not engaged in OFDI (DX and D), while the median DX firm is more productive than the D firm. The median firm in the D sample is smaller (in sales/total assets/number of employees) than firms in the DX sample, while DXI firms are much larger. The median DX or DI/DXI firm produces more output and has higher VA than the D firm. DXI firms have

[20]Following S2, however, may cause a firm's classification to change to a non-exporter and/or a non-overseas investor firm if a change in exports (and/or investment outside India) and/or in sales/total assets causes these ratios to fall below 1% (as for *Videocon Industries* in 2006) among others, instead of an actual change in the firm's trajectory between export and/or overseas investment and the domestic market over any given period.

[21]Unlike the empirical findings wherein *few* firms export (e.g. Bernard et al. 2007 for US, where exporters represent only 18% of the total population), the relatively large share of exporting firms in the sample reflects the oversampling of the relatively large and medium firms in the database.

Table 2 Firm-years (in percentages), by foreign involvement, 1995–2010

	S1					S2				
	D	DX	DXI	DI	DIDXI	D	DX	DXI	DI	DIDXI
Manufacturing	42.26	51.89	5.49	.35	5.84	51.27	45.82	2.51	.39	2.9
Services	33.43	40.58	23.71	2.27	25.99	39.75	37.8	20.43	2.02	22.45
Mining	48.24	46.66	4.85	.42	5.10					
Construction	65.71	23.23	8.44	2.6	11.05					

Note For the *mining* and *construction* sub-samples, percentages of observations are reported only for specification S1 due to the small absolute number of firm-years in the DIDXI category using specification S2
Source Prowess 4 and own calculations

Table 3 Mean productivity (*ln* TFP index) of OFDI firms, pre- and post-OFDI

(*a*)							
Time periods	$t-3$	$t-2$	$t-1$	$t0$	$t+1$	$t+2$	$t+3$
Ln TFP index	.0323	.0545	.0557	.0659	.0718	.0725	.0731

(*b*)			
	Pre-OFDI (merging time periods $t-3$, $t-2$, $t-1$)	Post-OFDI (merging time periods $t+1$, $t+2$, $t+3$)	*t*-test Post > Pre (*p*-value)
Mean *ln* TFP index (No. of obs.)	.0477 ($n = 1520$)	.0724 ($n = 1560$)	.0143

Source Prowess 4 and own calculations

higher export intensity than DX firms (reflecting market-seeking export behaviour and interdependencies across modes of internationalization). DXI firms also spend more on R&D, indicating creation of 'knowledge' capital.[22] This evidence from manufacturing is in line with Narayanan and Bhat (2011) that for 2000–2005 find multinational firms from the information technology (IT) industry having higher export intensity, and making more technological effort than other IT firms in the sample. There is also slight difference in DXI and DI qualitatively (for both S1 and S2) as regards overall characteristics of firm categories.

Further, for manufacturing, it is examined whether there is any change in the mean productivity of OFDI firms over time, that is, in comparing pre- and post-OFDI time periods. For this, using productivity estimates for GO–LP, for S1, if $t = 0$ is the year in which a firm *i* switches into becoming an OFDI firm by investing abroad for the first time, for 599 OFDI entries over various years of the sample period, Table 3 shows the mean productivity (*ln* TFP index) of DIDXI firms at time $t \pm s$, where $s = 1, 2, 3$, that is, *s* years pre- and post-OFDI entries, respectively.

Merging pre- and post-OFDI time periods ($t-3$, $t-2$, $t-1$) and ($t+1$, $t+2$, $t+3$), respectively, mean productivity for the post-OFDI time period is significantly higher (at the 5% level) for the one-sided *t*-test, that is, the average of the post-OFDI time period is higher than that for the pre-OFDI time period.

6.2 *Inter-sectoral and Inter-industry Comparison*

Comparison of the *inter-sectoral* foreign investment intensities, conditional on outward investment (Fig. 1), shows that firms in the services and manufacturing sectors are much more internationalized than those in the construction and mining sectors.

[22]Chawla (2015) shows that DXI category has slightly lower capital–output ratio, combined material, raw material and energy intensity although their services intensity is slightly higher than of D category.

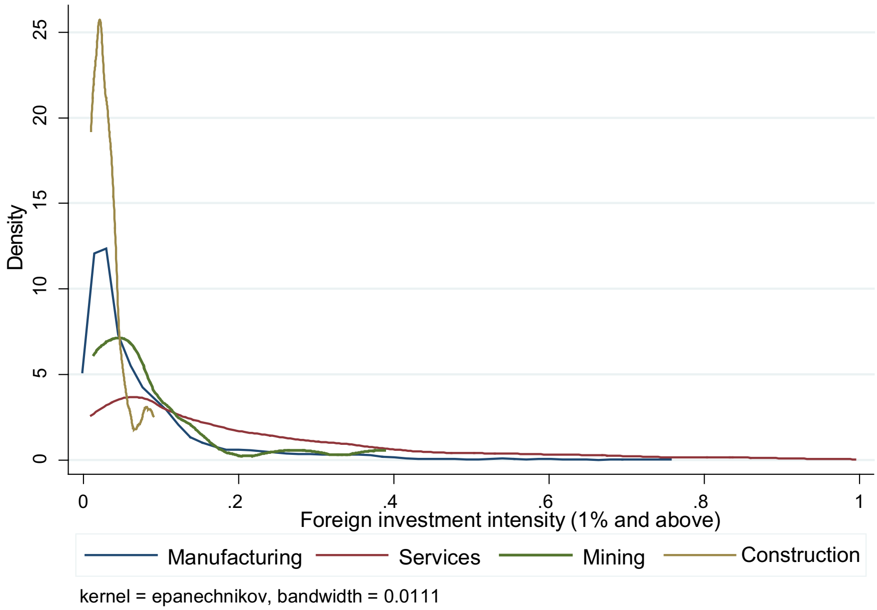

Fig. 1 Density plots of foreign investment intensity by sector, for S2, 1995–2010 *Source Prowess* 4 and own calculations

At the two-digit level, in manufacturing, Table 1 shows substantial variation in the extent of internationalization across industries within manufacturing. For instance, in 2009/10, the wood products industry is much less internationalized than the chemicals/pharmaceuticals industries that are strongly involved in OFDI.[23] *Inter-industry* comparison for manufacturing (Fig. 2) is indicative of considerable heterogeneity in the outward orientation of firms at the three-digit industry level. Industry-specific effects, partly attributable to the nature of products produced, are suggestive of the outward orientation of firms belonging to the industry groups.

[23]However, the largest home-based transnational corporations (TNCs) for 2010 as in *India country sheet*, WIR, UNCTAD (2013) represent manufacturing industries with varying degrees of technological sophistication: Reliance Industries Ltd., Essar Oil Ltd. (coke, petroleum and nuclear fuel), Tata Steel Ltd., Hindalco Industries Ltd., MMTC Ltd., JSW Steel Ltd., Ispat Industries Ltd. (metals and metal products), Tata Motors Ltd., Mahindra and Mahindra Ltd., Bajaj Auto Ltd. (motor vehicles and other transport equipment), Suzlon Energy Ltd. (machinery and equipment), ITC Ltd. (food, beverages and tobacco), Hindustan Unilever Ltd., Ranbaxy Laboratories Ltd., Tata Chemicals Ltd., Dr. Reddy's Laboratories Ltd. (chemicals and chemical products), Videocon Industries Ltd., Siemens Ltd., Crompton Greaves Ltd. (electrical and electronic equipment), Apollo Tyres Ltd. (rubber and plastic products) and Ambuja Cements Ltd., Ultratech Cement Ltd. (non-metallic mineral products).

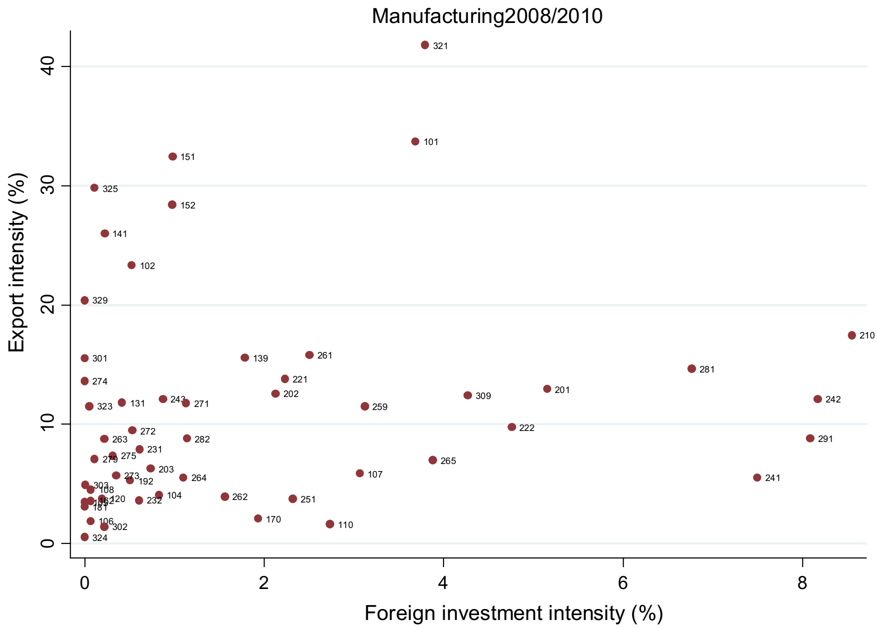

Fig. 2 Scatter plots: average export and foreign investment intensity by three-digit industry, manufacturing, for S1, 2008–2010. *Notes* NIC191 and NIC103 are excluded as the number of outward investing firms is below five. *Source Prowess* 4 and own calculations

7 Productivity Comparisons

7.1 Testing Procedure: Kolmogorov–Smirnov (KS) Test

To assess if there are any significant differences between distributions of productivities of firms based on their foreign engagements, Sect. 7.2 employs the non-parametric test of first-order stochastic dominance (FOSD) that makes no assumption about the sample distributions,[24] and tests for differences in all moments of the distributions. Differences in marginal moments such as mean and standard deviation do not reflect the entire distribution of productivities. Following Girma et al. (2004), Engel and Procher (2012), and Wakasugi and Natsuhara (2012) among others, these are comparisons of unconditional distributions, that is, are not controlled for other covariates such as size, age, innovation, group and industry fixed effects.

The hypothesis to be tested is that if productivity differences between firms at any point in time reflect *self-selection* and/or *learning effects*, the productivity distribution of the outward investing firms (that may export as well) should dominate that of the pure exporting firms that should in turn dominate the productivity distribution of

[24]The test is more robust than the *t*-test that requires the normality assumption.

the purely domestic firms.[25] FOSD of the cumulative distribution function (CDF) of productivity, F_{DIDXI} relative to F_{DX} requires $F_{DIDXI} - F_{DX} \leq 0$ uniformly in $z \in$ R, with strict inequality for some z. The test requires that the null hypothesis of the *two-sided* test:

H_0: F_{DIDXI} $(z) - F_{DX}$ $(z) = 0$ for all $z \in$ R versus H_1: F_{DIDXI} $(z) - F_{DX}$ $(z) \neq 0$ for some $z \in$ R can be rejected while that of the *one-sided* test:

H_0: F_{DIDXI} $(z) - F_{DX}$ $(z) \leq 0$ for all $z \in$ R versus H_1: F_{DIDXI} $(z) - F_{DX}$ $(z) > 0$ for some $z \in$ R cannot be rejected.

This allows us to conclude (1) that the two distributions are not identical, and (2) that one distribution dominates the other. Graphically, F_{DIDXI} is to the right of F_{DX}, that is, is on the higher productivity side, or that overseas investors' productivity distribution stochastically dominates that of exporters. Further, to maintain the independence assumption, the hypothesis is tested separately for each year of the sample period. Table 5 in Appendix A reports the *D-statistic* and the *p*-value (the probability that the two distributions are the same) for manufacturing (by S1).[26,27]

7.2 Results

7.2.1 Manufacturing Sector

Figure 3 compares the productivity differences among firm types (DIDXI, DX, D) for the two alternative productivity measures, for S1. Column (1) depicts GO–LP for 1995–2010, while column (2) depicts VA–WLP for 1997–2010.

A comparison of the graphs in panel (a) for trend in mean productivity (*ln* TFP index)[28] for foreign investors (DIDXI), exporters (DX) and purely domestic firms

[25] As Girma et al. (2004, p. 319) note, 'although these tests encompass the possibility that firms of the same productivity level may choose different forms of commerce, the degree of uncertainty in behaviour cannot be too large such that the structure of commerce and firm heterogeneity are no longer meaningfully related'.

[26] 'The directional hypotheses are evaluated with the statistics: $D^+ = \max_x\{F(z) - G(z)\}$, $D^- = \max_x\{F(z) - G(z)\}$ where F(x) and G(x) are the empirical distribution functions for the samples being compared. The combined statistic is: $D = \max(|D^+|,|D^-|)$ which identifies the maximum vertical difference between the two empirical cumulative distribution functions. The *p*-value for this statistic may be obtained by evaluating the asymptotic limiting distributions' (*Stata Base Reference Manual Vol. 2, Release 10, p. 109*).

[27] Similar tables (reporting KS test results), for manufacturing (S2), services (S1, S2), construction (S1) and mining (S1) not reported here, are available in Chawla (2015), results discussed below.

[28] The mean productivity for the sample DIDXI is not shown for 1995–1999, as due to the small number of firms in this time period, the mean values are subject to larger variations.

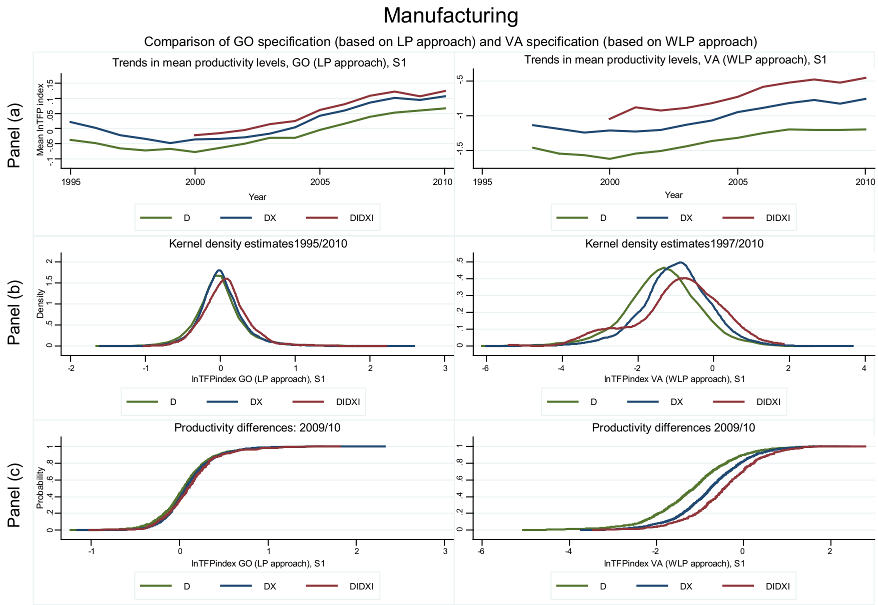

Fig. 3 Differences among firm types (DIDXI, DX, D), based on TFP estimates, comparing methods, manufacturing, S1, 1995–2010. *Source Prowess* 4 and own calculations

(D) displays stronger differences across firm types under VA rather than GO specification.[29] Panel (b) shows that kernel density estimate[30] of the productivity distribution for DIDXI lies to the right of the distribution for DX, and even further to the right from the distribution for D, consistent with HMY (and HR) prediction.[31] For 2009/10, panel (c) shows that the CDF of firm productivity for DIDXI lies to the right of that for DX and more so for D, indicating FOSD. Productivity rankings thus favour DIDXI over DX, DX over D and DIDXI over D (which also follows by transitivity). Firms that invest abroad have higher productivity than firms that export only or that only operate domestically.

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[29]Both columns, however, show that the impact of the negative demand shock for Indian firms in 2008 (Q2) to 2009 (Q2) has been more so for firms with foreign engagements than purely domestic firms.

[30]Epanechnikov kernel, with varying bandwidth.

[31]As the HMY model deals with horizontal FDI alone, and although a large fraction of FDI by Indian firms goes to the developed countries for market access (RBI *Bulletins*), it seems reasonable to test the HMY predictions. Nunnenkamp et al. (2012) also find that the location choice of Indian direct investors is dominated by the motive of market-related factors, much less so for access to raw materials or for superior technologies. In so far as OFDI is also guided by vertical or complex integration strategies, also related to the internationalization of R&D, in the absence of the fraction of OFDI directed by the underlying motives, testing the HMY predictions, may, however yield partial insights.

The differences across firms are, however, more pronounced for VA specification indicating a 'value-added bias' that remains even after controlling for the 'transmission bias' with WLP productivity estimation technique that is robust to the ACF (2015) criticism (Gandhi et al. 2013; Rivers 2013). Density plots of estimated productivity at the two-digit level/combined groups (Fig. 10 in Appendix B) indicate that the relationship between firm productivity and foreign involvement is stronger in some industries, for instance, in textiles (NIC 13), coke and refined petroleum products, chemicals (NIC 19, 20), pharmaceuticals (NIC 21), basic metal and fabricated metal (NIC 24, 25), and machinery and equipment n.e.c. (NIC 28) than in the rest.

Table 5 in Appendix A presents the number of firms by each firm type for each year of the sample period, in columns (2) to (4),[32] with mean values of productivity (*ln* TFP index) in columns (5) to (7). KS test statistics of productivity differentials are presented for exporters and non-exporters (DX vs. D) in columns (8) to (10), outward investors and exporters (DIDXI vs. DX) in columns (11) to (13), firms that export and invest abroad, and exporters (DXI vs. DX) in columns (14) to (16), and outward investors and domestic firms (DIDXI vs. D) in columns (17) to (19), respectively, for GO–LP. Rest of the columns correspond to VA–WLP for corresponding comparisons. Tests are applied separately to each category for every year of the sample period.

DX versus D: The null hypothesis of equality between both distributions can be rejected at the 1% level for several years (mainly after the year 2000). The null hypothesis that the direction of the difference is as expected, that is, DX have greater productivity than D, cannot be rejected at any reasonable significance level for most years. **DIDXI versus DX**: The equality of both productivity distributions cannot be rejected at any reasonable significance level in the earlier years of the sample period 1995–2000. Although productivity differences between DIDXI and DX are rather modest in GO specification, it is only after 2001 that they favour DIDXI over DX as suggested by the test statistics for the one-sided test, column (12).[33] Qualitatively similar results obtain in comparing DXI with DX, i.e. DXI > DX, columns (14) and (15). **DIDXI versus D**: For 2001 onwards, DIDXI stochastically dominate D firms. Chawla (2015) reports KS test results that show that limiting the lower bound for qualifying as an exporter and foreign investing firm (S2), lend support to HMY (and HR) models for most but not all years of the sample period. Graphically, differences in firm categories are, however, less pronounced for S2 than for S1 (Fig. 4).

[32]The number of observations is reported for GO–LP approach. Under WLP, as noted above, the overall sample size is smaller.

[33]The year 2001 onwards has also witnessed a significant increase in the number of outward investing firms.

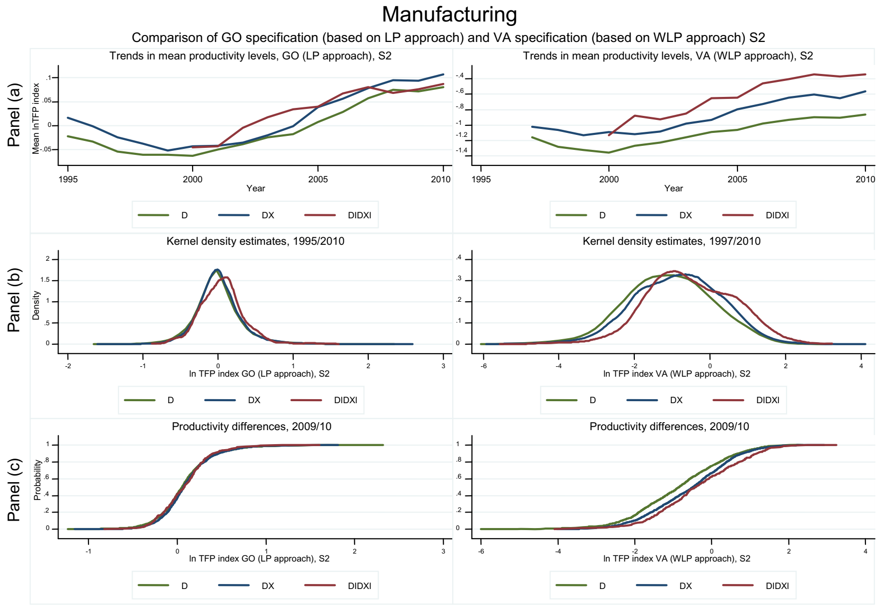

Fig. 4 Differences among firm types (DIDXI, DX, D), based on TFP estimates, comparing methods, manufacturing, S2, 1995–2010. *Source Prowess* 4 and own calculations

7.2.2 *Services Sector*[34]

Figure 5 shows similar comparisons for service sector firms (analysis restricted to NIC 61, 62 and 63) for S1.[35] Panel (a) shows that as in manufacturing, the trend

[34]DXI and DX firms are engaged in industries such as 'basic telecom services, internet access by the operator of the wireless infrastructure, other wireless telecommunications activities, other telecommunications activities, providing software support and maintenance to the clients (software service and consultancy), news agency activities (television broadcasting media, cable television broadcasting media (DX only), other information service activities n.e.c. (information technology enabled service/BPO), activities of maintaining and operating paging, cellular and other telecommunication networks (DX only)' (based on *Prowess 4*). Several firms in the services sector have established large overseas positions, for instance, in 2009/10, while the largest stock of overseas assets was held by Bharti Airtel Ltd., Silverline Technologies Ltd, H O V Services Ltd., Four Soft Ltd. and Mindteck (India) Ltd. had a foreign investment intensity of over 80%. Further, Bharti Airtel Ltd., Reliance Communications Ltd., Tata Communications Ltd., United Breweries Holdings Ltd. (transport, storage and communications), Tata Consultancy Services Ltd., Wipro Ltd., Infosys Ltd., HCL Technologies Ltd., Satyam Computer Services Ltd., Mphasis Ltd., Tech Mahindra Ltd. (business services, the high-skill intensive category of services) list in the largest home-based TNCs for 2010 (WIR, *Investment Country Profiles*, India, UNCTAD, 2013). Tata Consultancy Services Ltd., Infosys Ltd., Wipro Ltd., Tech Mahindra Ltd., HCL Technologies Ltd. were also the largest service exporters in 2010.

[35]NIC 58 is not included in the graphical display to bring out any distinct features of this group that is dominated by NIC 62 in terms of firm coverage.

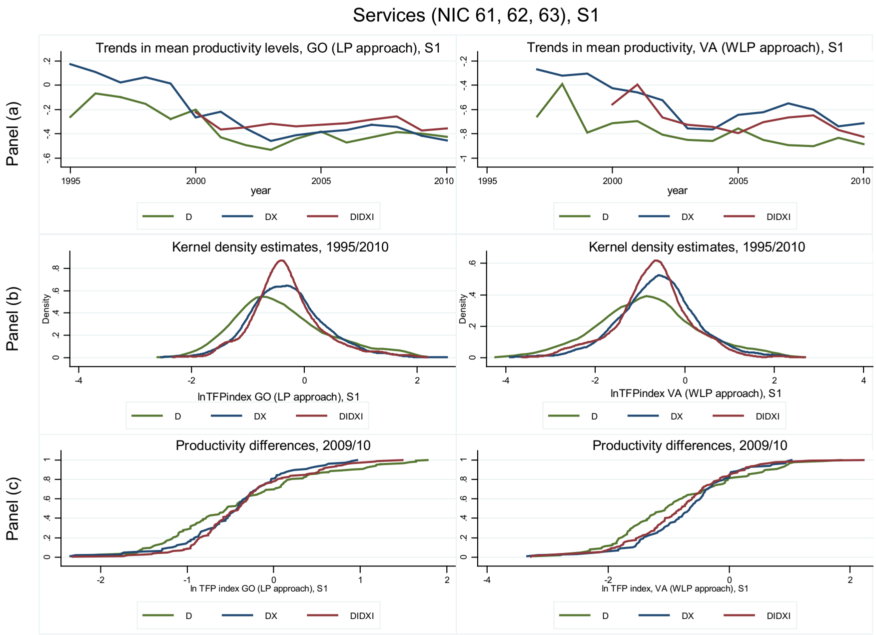

Fig. 5 Differences among firm types (DIDXI, DX, D) based on TFP estimates, comparing methods, services, S1, 1995–2010. *Source Prowess* 4 and own calculations

in mean productivity (*ln* TFP index)[36] for DIDXI, DX and D displays stronger differences under VA–WLP than under GO–LP.[37] While mean productivity (*ln* TFP index) for D consistently lies below that for DX for both productivity measures, the left column for GO shows that DIDXI lie above the other two categories for most time periods while the right column is more in line with BPS theorising.

Panel (b) shows that the density plots for DX lie to the right of that for D for both productivity measures although there is a small overlap with D towards the right tail. Further, due to the crisscrossing of DIDXI and DX plots, and the CDFs (for 2009/10) in panel (c), graphically, the dominance of one group over the others is not very obvious over the whole distribution, although CDFs in the left panel seemingly favour DIDXI over DX, while the right panel favours DX over DIDXI.[38]

DX versus D: Year-wise results of the KS test indicate that the hypothesis of identical distribution of productivity for DX relative to D can be rejected for most years of

[36]The mean productivity for the sample DIDXI is not shown for 1995–1999, as due to the small number of firms in this time period, the mean values are subject to larger variations.

[37]Due to the relatively small number of firms in the services sector for which productivity could be estimated in the 1995–1999 period, the broad trends for this sector are more meaningful for the 2001 onwards time period.

[38]The density plot for DXI (not shown in the plot) is close to that of DIDXI.

the sample period for both productivity estimation methodologies and specifications. The one-sided test supports the view that DX category has higher productivity than D, in line with several studies for other countries. The KS test methodology followed in this study, however, does not allow for comparison of the productivity advantage of exporters of services vis-à-vis that of exporters of manufactures over domestic producers.

Minondo (2014) refers to Francois and Hoekman (2010) in making the argument that since services face much larger barriers to trade than manufactures, as they require the coincidence of suppliers and customers in space and time, it is expected that there would be a very strong link between exporting and productivity in services. However, a weaker link is expected in services where the movement of the supplier is inherent to the activity, as in transport services, and in services that can be supplied through the internet (e.g. call centres), or whose final output can be digitized and transferred through the Internet. As the present sample under services mainly consists of IT, this reasoning could be relevant. Based on the same methodology, results for services and manufacturing firms are qualitatively similar. In such cases, Breinlich and Criscuolo (2011) note that the existing goods trade models might be suitable for firm-level services trade as well.[39]

DIDXI versus DX: The equality of productivity distributions for these two categories could not be rejected at standard significance levels.[40] Unlike manufacturing where there are significant productivity differentials between DIDXI and DX (especially under VA), and BPS wherein TFP distribution for DX dominates over that for DXI,[41] in the present study, the productivity ranking of DX lying to the right of DIDXI indicating stochastic dominance could not be established in the information and communication sector.

For 2009/10, the VA approach in Panel (c), however, suggests DX domination, although not for the entire distribution. Part of the difference in results between BPS and the present study could be due to production function specification. For software services, BPS adopt a two-input GO production function. On another view, the HMY model deals with horizontal OFDI alone, motivated by market-seeking considerations. As a large fraction of OFDI by Indian IT firms goes to developed countries, OFDI could also be guided by vertical or complex integration strategies, related to the internationalization of R&D with firms investing abroad for technology-seeking motives, or agglomeration economies (due to clustering in specific regions). These considerations could also have a bearing on the observed relationship between

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[39]BPS compares DXI to DX but not DX to D.

[40]Comparisons of DIDXI with DX and D, respectively, for 1995–99 are not presented due to the small number of DIDXI firms in the same time period.

[41]Two key characteristics that identify software service companies are near-zero transportation costs for software services that are posited to encourage production at home while software services being non-commoditized, with a range of intangible characteristics, are posited to make customers feel it is risky to buy software services from a distant country, considered to encourage FDI.

firm productivity and foreign involvement. These results also differ from Engel and Procher (2012) that finds HMY ranking for French firms in manufacturing, wholesale and retail trade, transport, financial intermediation, real estate, IT services and services for companies. **DIDXI versus D**: Even while DX does not differ significantly from DIDXI, the KS test confirms that DIDXI is significantly more productive than D. These results support the findings of Tanaka (2011) for Japan. Figure 6 for S2 conveys a similar picture, although several firms that are now classified as D raise the productivity of this category, so that its domination by DIDXI and DX is now less clear-cut, more so in the left panel.

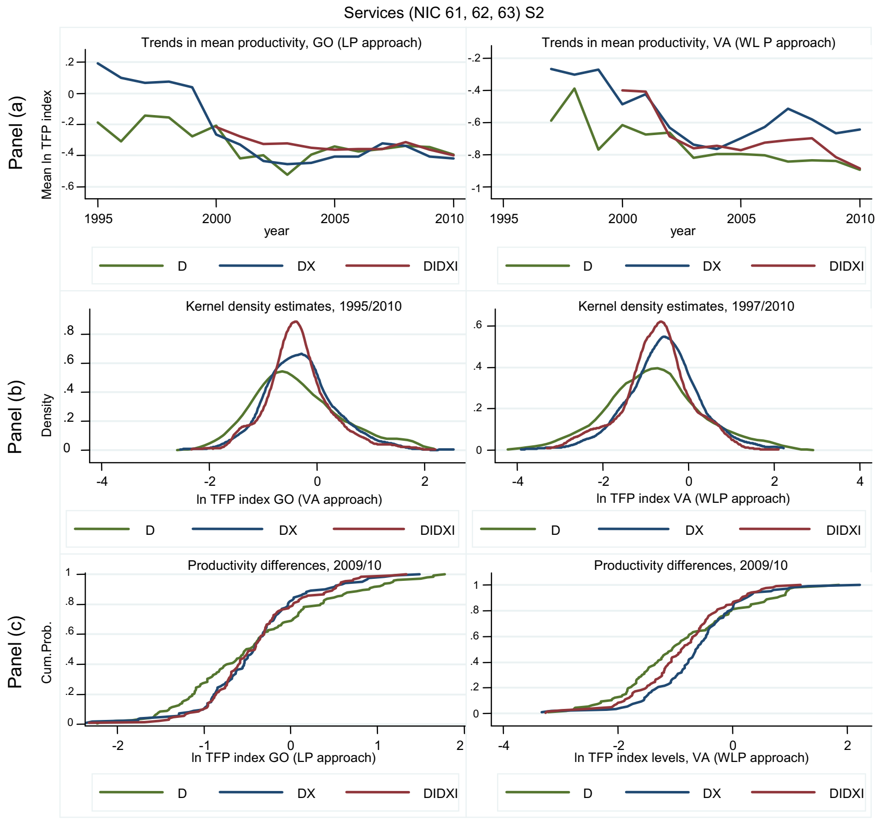

Fig. 6 Differences among firm types (DIDXI, DX, D), based on TFP estimates, comparing methods, services, S2, 1995–2010. *Source Prowess* 4 and own calculations

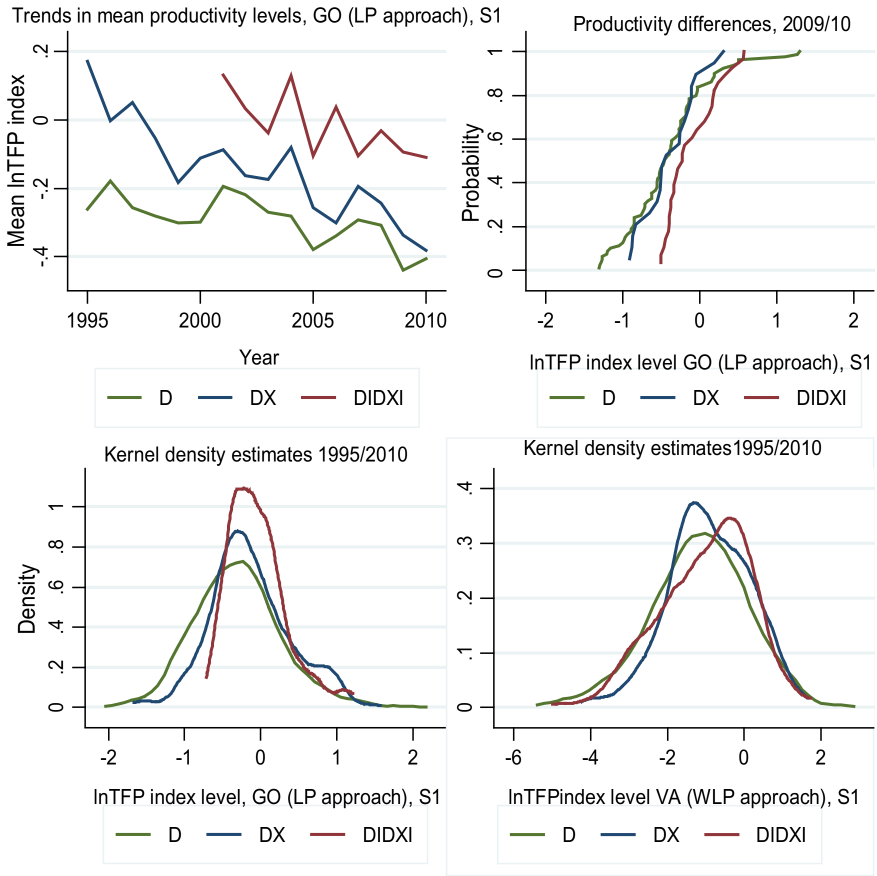

Fig. 7 Differences among firm types (DIDXI, DX, D), based on TFP estimates, comparing methods, construction, S1, 1995–2010. *Source Prowess* 4 and own calculations

7.2.3 *Construction Sector*[42]

Figure 7 illustrates productivity comparisons for construction firms, for S1. Due to the relatively small number of outward investing firms from this sector, results are not presented for S2. For comparison, VA–WLP is shown in the right bottom panel only. Trends in mean productivity for the three firm categories suggest an ordering of

[42]Construction firms involved in exports and outward investment belong to industries such as 'construction of buildings carried out on own-account basis or on a fee or contract basis, construction and maintenance of motorways, streets, roads, other vehicular and pedestrian ways, highways, bridges, tunnels and subways, construction of utility projects n.e.c., and other civil engineering projects n.e.c.' (based on *Prowess4*). For 2010, Larsen and Toubro Ltd., Punj Lloyd Ltd. and Gammon India Ltd. are the largest home-based TNCs from the construction sector (WIR, UNCTAD 2013).

DIDXI, DX and D, respectively.[43] Density plot for DX lies to the right of D for both productivity measures, and for DIDXI even further to the right (for GO–LP) although there is an overlap with DX towards the right tail. The CDFs (for 2009/10) suggest the stochastic dominance of DIDXI. Comparison of DIDXI with DX for VA–WLP is less marked. Both productivity measures suggest the productivity advantage of DIDXI over D.

DX versus D: For some years, the two-sided and one-sided test for both productivity specifications supports the view that DX firms have higher productivity than D. **DIDXI versus DX**: Similar results are revealed in the comparison of DIDXI/DXI with DX. **DIDXI versus D**: For several years in the sample period, the KS test confirms that DIDXI is significantly more productive than D, but mainly for GO–LP. As the sample size under VA–WLP is smaller than that under GO–LP, the number of DIDXI firms in the WLP sample may be considerably less for a meaningful comparison of the two productivity methods. The results for the construction sector in the present study are at odds with those for construction firms in France in the study of Engel and Procher (2012) that does not find any clear productivity patterns between foreign investors, exporters and domestic firms. Engel and Procher (2012, pp. 15–16) point out:

> The two-sided KS test regarding the equality of distribution between DX and DI and both one-sided tests between D and DX (i.e., D < DX and DX > D) do not lead to the null hypotheses being rejected. Two considerations might help to explain these results. The construction and building market is dominated by local players and transport costs play a fundamental role because of typically bulk-sized and low-margin products. Closeness to the customer is of utmost importance. Hence, transnational expansion in this industry might be governed by different motivations compared to other industries. In addition, temporally project-oriented co-operations with the involvement of a large number of consortium partners are quite common in the construction industry. Here, sunk costs of OFDI might be comparatively low so that the difference between exporters and multinational becomes negligible.

Results of this study are consistent with HMY (and HR) models for most but not all years in the sample period. In 2009/10, for instance, according to the RBI dataset on 'Overseas Investments by Indian Companies',[44] construction firms have mainly invested in several developing countries with major investments in Mauritius (likely due to round-tripping), United Arab Emirates, Spain, Cyprus and Singapore. These infrastructure and real estate developments indicate that Indian overseas investors could be providing appropriate level technology at a reasonable cost, an idea associated with an earlier literature (e.g. UNCTAD, 1993) on the ownership advantages of firms from developing countries and as in the product cycle model of Vernon (1966).

[43] Over 1995–2010, the estimated average annual growth rate of the real physical capital stock (real NFA) for this sector is comparatively higher (Chawla 2015). If output has not risen in accordance, higher growth of the capital input could partly explain the downward slant in the mean TFP over the years. The yearly fluctuations in mean productivity could reflect the small sample size in each category for which the mean has been computed.

[44] https://rbi.org.in/Scripts/Data_Overseas_Investment.aspx.

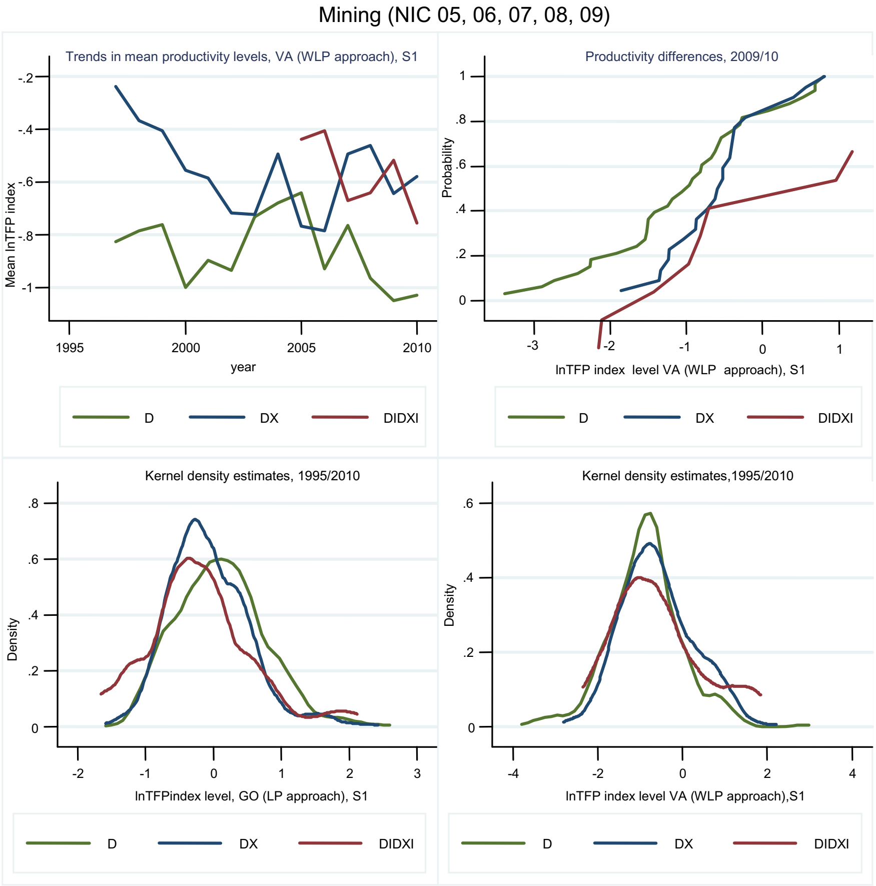

Fig. 8 Differences among firm types (DIDXI, DX, D), based on TFP estimates, comparing methods, mining, S1, 1995–2010. *Source Prowess* 4 database and own calculations

7.2.4 Mining Sector

Overseas investments (mainly acquisitions of oil and gas assets) by Indian natural resource-based firms have mainly been directed at the extractive sector of Africa and elsewhere as a source for energy and raw material supplies.[45] Figure 8 shows that the trend of mean productivity for DX is higher for most years than for D, and

[45]DX and DXI firms in the mining sector belong to industries such as 'on shore extraction of crude petroleum and natural gas, mining of iron and other ores, quarrying of granite, mining of clays, salt mining, quarrying, screening, etc., extraction and agglomeration of peat, services incidental to off shore oil extraction, and other operations relating to mining and agglomeration of hard coal' (e.g. Oil and Natural Gas Corp. Ltd. (ONGC), Sterlite Industries (India) Ltd.). TFP estimates for ONGC could, however, not be obtained as its raw material data is not available. Even though the firm has large overseas stakes in exploration, it is thus not part of the sample of firms.

although that of DIDXI and DX categories is not perceptibly higher or lower than the other, that for DIDXI is higher than that for the D category. Kernel density plots show that GO–LP suggests that the productivity distribution of D lies to the right of DX that in turn lies to the right of DIDXI. The VA specification, however, shows no clear pattern except in the right tail. CDF based on VA–WLP also suggests that DX dominates the other two categories but not over the entire distribution.

Results of the KS test for the three firm categories (reported in Chawla 2015) indicate that in comparison to the other three sectors considered for analysis, the number of outward investing firms is considerably smaller in mining. DX that includes relatively more observations is thus more indicative of the productivity characteristics of the internationalized firms. Although the fact that there are only a small number of outward investing firms in mining severely restricts checking the validity of HMY (and HR) models, the hypothesis may nevertheless not hold good as the underlying motives for OFDI may be mixed, resource-driven as well as market-driven. **DX versus D**: From 2003 onwards, GO–LP supports the view that the productivity distribution of DX dominates that of D. For the years for which the two-sided KS test hypothesis can be rejected for VA–WLP, the one-sided test favours the FOSD of DX over D. **DIDXI versus DX**: The number of firms in the DIDXI category is fewer than five before 2005 that restricts the acceptance of the KS test results. From 2005 onwards, the KS test does not support the hypothesis that the productivity distributions of DIDXI and DX differ, for both productivity specifications. **DIDXI versus D**: Similar considerations as in the comparison above are relevant here as well. From 2005 onwards, for GO–LP, the null hypothesis of the two-sided KS test can be rejected for only 3 years, for which the one-sided test supports FOSD of D over DIDXI. Part of the explanation for this result could be identification concerns associated with a GO production function. With VA–WLP no clear-cut differences between productivity distributions of DIDXI and D could be established.

7.3 Robustness Analysis

For the manufacturing sector, this section discusses whether results are sensitive to the choice of data set, choice of TFP measure (GO vs. VA) and choice of methodology of production function estimation, respectively. First, examining the choice of data set (comparing S1 and S2), Chawla (2015) and Figs. 3 and 4, it is observed that irrespective of whether LP or WLP are employed, the same pattern of productivity rankings is obtained. Results are thus robust to covering the data set that includes firms with small overseas positions. Second, in examining the choice of TFP measure, even for the same methodology of production function estimation (say, LP), comparing distributions based on GO specification (Fig. 3, left-hand panel) and VA specification (Fig. 9) shows that the 'pecking order' as in HMY is obtained for both specifications of the production function although VA-based distributions suggest stronger differences among firm categories. Results are thus robust to the choice of TFP measure (GO vs. VA). Third, for the same productivity measure (say, VA) and specification (say,

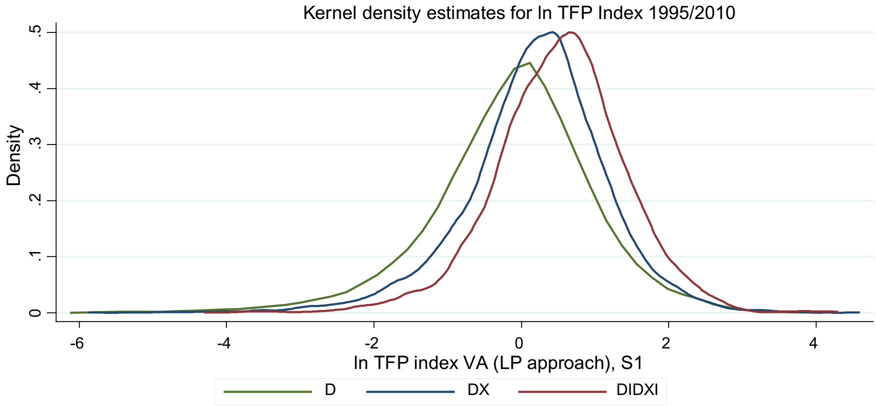

Fig. 9 Kernel density estimates for *ln* TFP index, VA specification (for LP), S1, 1995–2010. *Source Prowess* 4 and own calculations

S1) comparing distributions based on LP and WLP approaches (Fig. 9, and Fig. 3, right-hand panel) confirms that results are robust to choice of method of production function estimation.

8 Conclusions

Using firm-level data for the period 1995 to 2010, based on two methodologies and two specifications of the production function to estimate TFP, non-parametric methods were used to examine the nature of productivity differentials between firm categories (based on foreign involvement). Attempts were also made to refine the criterion for firm classification as OFDI firms. For firms in the *manufacturing* sector, it was found that overseas investing firms (DIDXI) are more productive than the other firm categories, while pure export firms (DX) have intermediate productivity levels. These results are in agreement with such results from similar studies for several countries including Tian and Yu (2012) for China that also finds a positive correlation between firm productivity and OFDI. Cross-sectional findings of a positive link between firm productivity and foreign involvement could be due to the most productive firms self-selecting into foreign markets, and/or learning effects through foreign engagements.

Although DIDXI and DX categories dominate over the purely domestic firms (D) for both production function specifications, the gross output (GO) specification based on Levinsohn and Petrin 2003 (LP) approach suggests quantitatively smaller differences in productivity between firm categories. The value-added (VA) specification based on Wooldridge 2009 (WLP) approach thus validates the Helpman et al. 2004 (HMY), and Head and Ries 2003 (HR) hypothesis more strongly than the GO specification (based on LP approach). These results compared with Gandhi et al.

(2013) and Rivers (2013) show that accounting for intermediate inputs using the GO specification substantially reduces the estimated productivity advantage of exporters over non-exporters. This suggests that controlling the 'value-added bias' is important and it is not sufficient to control only for the 'transmission bias'.

Further, productivity differentials vary, sometimes considerably by two-digit industry/industry groups. In manufacturing, the HMY (and HR) pattern obtains, more so in textiles (NIC 13), coke and refined petroleum products, chemicals (NIC 19, 20), pharmaceuticals (NIC 21), basic metal and fabricated metal (NIC 24, 25), and machinery and equipment n.e.c. (NIC 28) than in the rest. Also, although similar patterns obtain, yet graphically, differences in firm categories are less pronounced for S2 than for S1.[46]

For the *services* sector, for both productivity approaches and specifications, DX firms were found to have higher productivity than D firms as found in several other studies. However, unlike the results for the manufacturing sector and unlike the findings of Bhattacharya et al. 2012 (BPS) for software services, the study did not find any clear differences in firm productivity between pure exporters (DX) and OFDI firms that also export (DIDXI). The stochastic dominance of DX over DIDXI as suggested for software services in BPS could not be established. This suggests that Indian IT firms' OFDI that is mainly located in developed countries could also be guided by vertical or complex integration strategies, related to the technology-seeking motives and agglomeration economies (due to clustering in specific regions). DIDXI firms, however, come out to be more productive than the D category. Furthermore, expanding the sample of outward-oriented firms to include firms with small international positions does not qualitatively alter the nature of the relationship between firm productivity and foreign involvement.

For the *construction* sector, unlike Engel and Procher (2012) that does not find any clear productivity patterns between foreign investors (DI), exporters (DX) and domestic firms (D), the above results, presented for S1 only, suggest the HMY (and HR) ordering of DIDXI, DX and D, respectively, for most years in the sample period. This could mainly reflect advantages built at home. DX dominate D, DIDXI dominate DX and DIDXI dominate D. Demirbas et al. (2013) do not include the construction firms in their sample as they point out that the concepts of exporting versus OFDI are blurred in the construction industry. Further, as a limitation of the present exercise, Hall and Mairesse (1995) note that the concepts of both labour productivity and total factor productivity are better measured and more meaningful in manufacturing than in other sectors such as construction and business services.

For firms in the *mining* sector, graphically, the GO specification (based on LP approach) and VA specification (based on WLP approach) suggest a different ranking pattern. As the number of outward investing firms is considerably smaller in

[46]Specification S1: DX if export intensity is positive, DIDXI if export intensity is positive and foreign investment intensity is positive. Specification S2: DX if export intensity $\geq 1\%$, DXI if export intensity $\geq 1\%$ and foreign investment intensity $\geq 1\%$, DI non-exporter firms with foreign investment intensity $\geq 1\%$.

mining, the DX category that includes relatively more observations is more indicative of the productivity characteristics of internationalized firms. Also, the underlying motives for OFDI in mining may be both resource-driven and for market access. For both production function specifications, while from 2003, DX dominate D, yet the dominance of DIDXI over DX could not be established. From 2005 onwards, for the GO specification (based on LP approach) for only 3 years, it is suggested that D dominate DIDXI. The VA specification (based on WLP approach) could not establish any clear-cut differences between the productivity distribution of DIDXI and D firms.

Qualified support is thus found for the 'pecking order' as predicted by heterogeneous firms' theories. As the productivity and other firm characteristics of OFDI firms that initially start small are observed to be similar to those with larger positions abroad, if a constraint on financing is found to be an issue for these firms, the government should support a more liberal financial system for OFDI that could also aim specifically at firms with initially small OFDI. EXIM Bank (2017), for instance, indicates that there is a range over which it is possible to increase firms' OFDI intensity and increase the benefits from OFDI.

Acknowledgements I am extremely indebted to Prof. Aditya Bhattacharjea and Prof. Bishwanath Goldar for invaluable guidance. I am grateful to Prof. K. L. Krishna and Prof. J. V. Meenakshi for insightful comments and suggestions. I am also grateful to the editors of this book for giving me the opportunity to contribute. All errors are my own.

Appendix A: Additional Tables

See Tables 4 and 5.

Appendix B: Additional Figure

See Fig. 10.

Table 4 Descriptive statistics by foreign involvement (after data cleaning), manufacturing, 1995–2010

	S1								S2							
	D		DX		DI		DXI		D		DX		DI		DXI	
Variable	Median	IQ range	Median	IQ range	Median	IQ range	Median	IQ range	Median	IQ range	Median	IQ range	Median	IQ range	Median	IQ range
Ln TFP index	–.028	–.189/.139	.0005	–.151/.166	.068	–.078/.294	.061	–.114/.227	–.018	–.176/.150	–.0004	–.155/.165	.150	–.051/.360	.042	–.149/.189
Ln TFP	.170	–.04/.43	.249	.027/.489	.259	.048/.473	.306	.06/.541	.181	–.029/.443	.257	.029/.496	.343	.063/.543	.255	.049/.474
Sales (in Rs. cr)	21	7/ 55	65	24/173	117	30/772	385	133/1027	26	9/74	69	25/191	212	41/961	408	121/1137
Total assets (in Rs. cr)	18	8/44	60	24/166	143	41/610	414	145/1183	22	9/61	64	25/189	189	50/731	541	141/1421
R&D expenditure (in Rs. cr)	.1	.04/.4	.4	.1/1.4	1	.2/3	2.7	.7/13	.2	.1/.7	.5	.1/2	3	.44/8	4	.8/23
Export intensity (in %)	–	–	8.5	2/28	–	–	17.6	6/42	0	0/0	13	5/35	0	0/.4	22	9/48
Foreign investment intensity (in %)	–	–	–	–	1	.4/4	.9	.1/.4	.2	0/.5	.1	0/.4	3	1/8	4.4	2/10
Output (in 1999/00 rupees)	19	7/49	59	23/157	103	25.4/560	314	112/810	24	8/65	62	23/171	198	31/773	325	100/888
Value added (in 1999/00 rupees)	5	2/13	17	6/52	33	8.5/15	111	37/307	6	2/19	18	6/57	52	15/297	122	34/336
R and D stock (in 1999/00 rupees)	0	0/0	0	0/.3	0	0/.1	.4	0/5	0	0/0	0	0/.3	0	0/.9	.4	0/8
Number of employees (imputed)	127	46/381	450	171/1227	529	216/1569	2074.5	776/5105	165	56/498	484	176/135	704	243/300	2031	744/5593
No. of observations	24,383		29,940		206		3,169		29,580		26,440		227		1,451	

Note Specification S1: DX if export intensity is positive, DIDXI if export intensity is positive and foreign investment intensity is positive. Specification S2: DX if export intensity ≥1%, DXI if export intensity ≥1% and foreign investment intensity ≥1%, DI non-exporter firms with foreign investment intensity ≥1%
Source *Prowess* 4 and own calculations

Table 5 Productivity level differences between outward investors, exporters and domestic firms; hypotheses test statistics, manufacturing, S1, 1995–2010

							GO specification (based on LP approach), S1											
	DIDXI	DX	D	DIDXI	DX	D	DX versus. D			DIDXI versus. DX			DXI versus. DX			DIDXI versus. D		
Year	No. of observations			Mean (SD)	Mean (SD)	Mean (SD)	Two -way	DX >D	D >DX	Two -way	DIDXI >DX	DX >DIDXI	Two -way	DXI >DX	DX >DXI	Two -way	DIDXI> D	D >DIDXI
							D- Statistic (*p*-value)			*D- Statistic* (*p*-value)			*D- Statistic* (*p*-value)			*D-Statistic* (*p*-value)		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
1995	11	1483	1009	–.060	.021	–.038	.107	.003	–.107	.184	.184	–.099	.184	.184	–.099	.189	.119	–.189
				(.212)	(.275)	(.281)	(.000)	(.989)	(.000)	(.768)	(.476)	(.807)	(.768)	(.476)	(.807)	(.738)	(.734)	(.457)
1996	7	1657	1094	–.057	.002	–.047	.103	.005	–.103	.336	.336	–.252	.336	.336	–.252	.330	.255	–.330
				(.077)	(.277)	(.277)	(.000)	(.960)	(.000)	(.278)	(.207)	(.412)	(.278)	(.207)	(.412)	(.300)	(.402)	(.220)
1997	12	1744	1169	.009	–.022	–.065	.102	.003	–.102	.242	.130	–.242	.242	.129	–.242	.317	.070	–.317
				(.196)	(.268)	(.287)	(.000)	(.978)	(.000)	(.367)	(.668)	(.247)	(.368)	(.669)	(.247)	(.114)	(.888)	(.092)
1998	20	1773	1261	–.064	–.034	–.071	.057	.000	–.057	.125	.125	–.082	.125	.125	–.082	.119	.089	–.119
				(.195)	(.284)	(.288)	(.014)	(1.000)	(.008)	(.868)	(.536)	(.764)	(.868)	(.536)	(.764)	(.905)	(.729)	(.569)
1999	19	1850	1384	–.127	–.047	–.067	.048	.002	–.048	.261	.261	–.064	.246	.246	–.057	.230	.230	–.073
				(-248)	(.287)	(.296)	(.044)	(.994)	(.024)	(.100)	(.076)	(.853)	(.204)	(.146)	(.899)	(.194)	(.136)	(.817)
2000	57	1816	1498	–.022	–.036	–.077	.071	.002	–.071	.100	.084	–.100	.112	.106	–.112	.121	.058	–.121
				(.322)	(.290)	(.287)	(.000)	(.993)	(.000)	(.572)	(.457)	(.329)	(.503)	(.333)	(.293)	(.334)	(.684)	(.199)
2001	160	1771	1471	–.015	–.034	–.063	.042	.000	–.042	.075	.022	–.075	.069	.020	–.069	.109	.010	–.109
				(.278)	(.295)	(.298)	(.099)	.(999)	(.054)	(.337)	(.865)	(.189)	(.496)	(.891)	(.275)	(.052)	(.968)	(.032)
2002	206	1772	1508	–.004	–.029	–.049	.031	.003	–.031	.101	.011	–.101	.100	.012	–.100	.105	.011	–.105
				(.274)	(.288)	(.304)	(.386)	(.983)	(.203)	(.037)	(.950)	(.023)	(.054)	(.951)	(.033)	(.030)	(.951)	(.018)
2003	228	1950	1664	.015	–.016	–.031	.036	.022	–.036	.086	.019	–.086	.088	.020	–.088	.114	.009	–.114
				(.293)	(.284)	(.305)	(.176)	(.416)	(.094)	(.078)	(.855)	(.046)	(.089)	(.859)	(.053)	(.011)	(.966)	(.007)
2004	245	2039	1751	.025	.005	–.030	.066	.005	–.066	.081	.031	–.081	.084	.032	–.085	.121	.009	–.121
				(.295)	(.291)	(.332)	(.000)	(.941)	(.000)	(.097)	(.652)	(.056)	(.085)	(.649)	(.050)	(.003)	(.962)	(.002)
2005	275	2067	1880	.061	.043	–.004	.079	.007	.079	.074	.041	–.079	.077	.047	–.077	.134	.004	–.134
				(.306)	(.286)	(.325)	(.000)	(.907)	(.000)	(.114)	(.426)	(.065)	(.113)	(.353)	(.065)	(.000)	(.989)	(.000)
2006	342	2108	1903	.080	.060	.016	.081	.011	–.081	.069	.008	–.069	.067	.010	–.067	.135	.011	.135
				(.294)	(.300)	(.327)	(.000)	(.776)	(.000)	(.101)	(.956)	(.059)	(.130)	(.936)	(.074)	(.000)	(.931)	(.000)
2007	403	2093	1882	.108	.086	.039	.099	.010	–.099	.066	.015	–.066	.063	.017	–.063	.147	.024	–.147
				(.282)	(.299)	(.330)	(.000)	(.821)	(.000)	(.089)	(.857)	(.050)	(.126)	(.829)	(.071)	(.000)	(.669)	(.000)
2008	447	2064	1792	.122	.102	.052	.096	.013	–.096	.063	.019	–.063	.051	.026	–.051	.131	.021	–.131
				(.312)	(.305)	(.347)	(.000)	(.701)	(.000)	(.092)	(.747)	(.052)	(.280)	(.614)	(.153)	(.000)	(.715)	(.000)
2009	471	1983	1652	.107	.095	.060	.061	.012	–.061	.065	.021	.065	.067	.019	–.067	.097	.013	–.097
				(.325)	(.318)	(.345)	(.002)	(.770)	(.001)	(.067)	(.711)	(.038)	(.063)	(.760)	(.036)	(.002)	(.870)	(.001)
2010	472	1771	1464	.124	.107	.066	.065	.006	–.065	.065	.033	–.065	.060	.030	–.060	.107	.001	–.107
				(.333)	(.307)	(.330)	(.002)	(.926)	(.001)	(.069)	(.442)	(.039)	(.136)	(.525)	(.076)	(.000)	(.998)	(.000)

(continued)

Table 5 (continued)

	VA specification (based on W–LP approach), S1											
	DIDXI	DX	D	DX versus. D			DIDXI versus. DX			DIDXI versus. D		
Year	Mean (SD)	Mean (SD)	Mean (SD)	Two –way	DX >D	D >DX	Two –way	DIDXI >DX	DX >DIDXI	Two –way	DIDXI >D	D >DIDXI
				D– Statistic(*p*–value)			*D– Statistic*(*p*–value)			*D–Statistic*(*p*–value)		
(1)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)
1997	–.854	–1.133	–1.459	.180	.000	–.180	.264	.124(	–.264	.417	.064	–.417
	(.617)	(.920)	(.944)	(.000)	(.999)	(.000)	(.499)	(.783)	(.329)	(.069)	(.937)	(.064)
1998	–1.195	–1.187	–1.542	.179	.000	–.179	.180	.180	–.129	.283	.054	–.283
	(.633)	(.934)	(1.02)	(.000)	(.999)	(.000)	(.541)	(.335)	(.568)	(.088)	(.905)	(.069)
1999	–1.570	–1.242	–1.570	.191	.002	–.191	.277	.277	–.053	.171	.171	–.168
	(1.00)	(.946)	(.930)	(.000)	(.993)	(.000)	(.135)	(.102)	(.918)	(.691)	(.422)	(.432)
2000	–1.048	–1.213	–1.623	.220	.001	–.220	.181	.058	–.181	.329	.002	–.329
	(.978)	(.881)	(.993)	(.000)	(.998)	(.000)	(.088)	(.744)	(.060)	(.000)	(1.00)	(.000)
2001	–.881	–1.226	–1.545	.152	.000	–.152	.209	.004	–.209	.358	.000	–.358
	(.742)	(.917)	(.954)	(.000)	(1)	(.000)	(.000)	(.995)	(.000)	(.000)	(1.00)	(.000)
2002	–.924	–1.206	–1.509	.170	.000	–.170	.193	.003	–.193	.329	.001	–.329
	(.816)	(.900)	(.956)	(.000)	(.999)	(.000)	(.000)	(.996)	(.000)	(.000)	(.999)	(.000)
2003	–.883	–1.129	–1.437	.165	.002	–.165	.208	.011	–.208	.316	.010	–.316
	(.971)	(.870)	(.915)	(.000)	(.991)	(.000)	(.000)	(.949)	(.000)	(.000)	(.963)	(.000)
2004	–.821	–1.071	–1.366	.155	.003	–.155	.156	.009	–.156	.292	.006	–.292
	(.945)	(.948)	(.946)	(.000)	(.988)	(.000)	(.000)	(.968)	(.000)	(.000)	(.983)	(.000)
2005	–.727	–.944	–1.316	.179	.000	–.179	.139	.009	–.139	.316	.003	–.316
	(.975)	(.914)	(1.00)	(.000)	(1)	(.000)	(.000)	(.957)	(.000)	(.000)	(.993)	(.000)
2006	–.581	–.888	–1.249	.178	.001	–.178	.158	.000	–.158	.327	.000	–.327
	(.855)	(.902)	(1.04)	(.000)	(.995)	(.000)	(.000)	(1.00)	(.000)	(.000)	(1.00)	(0.00)
2007	–.519	–.817	–1.199	.208	.000	–.208	.166	.000	–.166	.361	.000	–.361
	(.839)	(.924)	(.955)	(.000)	(.999)	(.000)	(.000)	(1.00)	(.000)	(.000)	(1.00)	(0.00)
2008	–.476	–.773	–1.207	.224	.000	–.224	.173	.001	–.173	..379	.000	–.379
	(.885)	(.911)	(1.01)	(.000)	(.999)	(.000)	(.000)	(.998)	(.000)	(.000)	(.999)	(.000)
2009	–.519	–.828	–1.207	.186	.002	–.186	.165	.0.00	–.165	.329	.000	–.329
	(.857)	(.935)	(1.02)	(.000)	(.992)	(.000)	(.000)	(1.00)	(.000)	(.000)	(1.00)	(.000)
2010	–.455	–.758	–1.195	.210	.000	–.210	.186	.003	.186	.362	.000	–.362
	(.865)	(.855)	(1.02)	(.000)	(1)	(.000)	(.000)	(.994)	(.000)	(.000)	(1.00)	(.000)

Notes Corrected *p*-values in parentheses. Two-way stands for combined K-S
Source *Prowess* 4 and own calculations

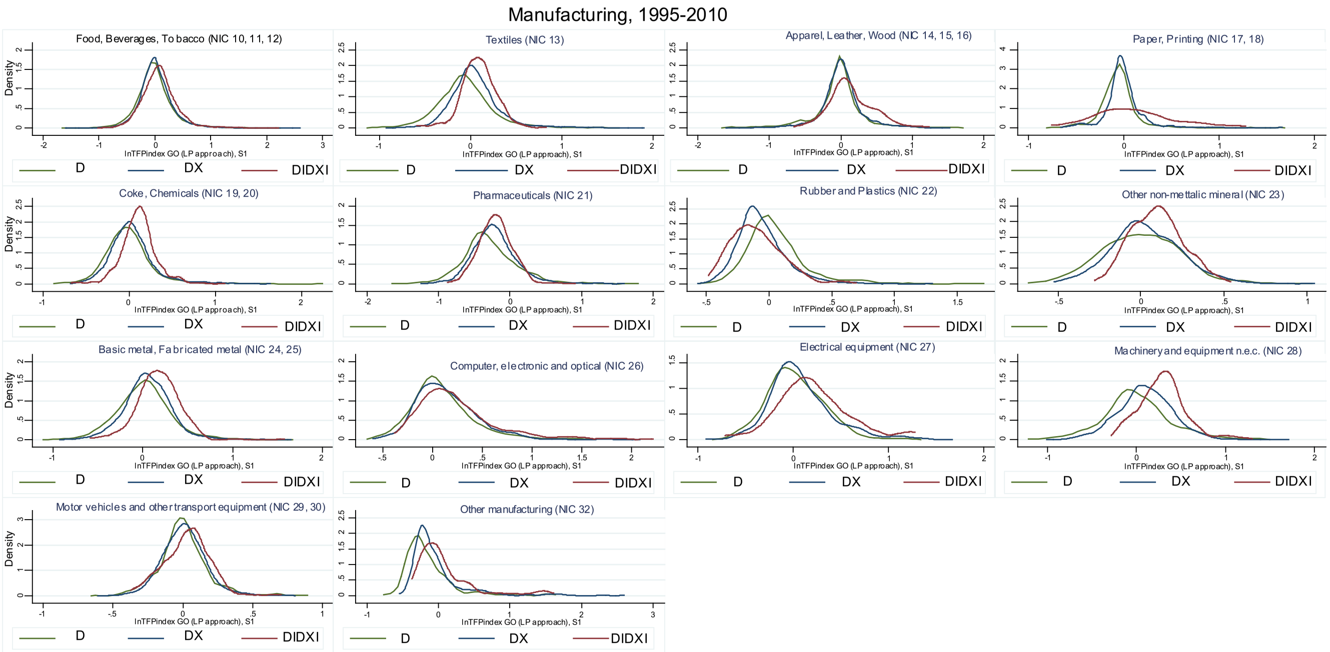

Fig. 10 Density plots of *ln* (TFP) index at two-digit level, manufacturing, 1995–2010. The distribution for DIDXI firms is more shifted to the right for Machinery and equipment n.e.c. (NIC 28). The figure shows the same direction of result for all industries except rubber and plastics (NIC 22). *Source Prowess* 4 and own calculations

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Growth Accompanied with Employment Generation: Challenges and Way Forward

Informal Sector in National Accounts Estimation: Importance of Workforce and Productivity

T. C. A. Anant

1 Introduction

Informal or Unorganised Sector in National Accounts is a domain that has created considerable challenges to official statisticians. To start with there is a problem of what exactly do we mean by this segment of the economy. The System of National Accounts (SNA 2008) defines two broad categories of institutional categories. Households and Legal Entities. Legal entities are either entities created for purposes of production, mainly corporations and non-profit institutions (NPIs), or entities created by political processes, specifically government units. One defining characteristic of legal entities is the fact that they invariable capture their economic activities through books of accounts. Further, as these accounts are usually reported to statutory authorities, they become available in some manner to official statisticians. In contrast, the household sector is marked by the absence of such observable accounting data. This is the approach which has been adopted by India in the recent 2011–12 revision of National Accounts. Earlier, this segment was conflated with what was called the Unorganised Sector. The definition of what is unorganised was different in different categories of economic activity. The details are captured in the NAS publications on 'Sources and Methods'.

This paper is written as an effort to outline the contribution of Prof. Goldar in introducing productivity computations in Indian National Accounts. The paper draws extensively on the 'Report of the Sub Committee On Unorganised Manufacturing & Services Sectors for Compilation of National Accounts Statistics With Base Year 2011–12' National Accounts Division, Central Statistics Office, Ministry of Statistics and Programme Implementation, Government of India, New Delhi and on a Note on 'Measuring Effective Labour Input in Manufacturing Industries' by Prof Goldar for subcommittee.

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Table 1 Share of unorganised/household sector in India

Year	Percentage share of NDP[a]
1980–81	70.0
1993–94	63.1
1999–2000	59.2
2004–05	58.7
2011–12	43.0

Compiled from different Issues of National Account Statistics
[a]The estimates for the informal sector across different base years are not strictly comparable due to small differences in the definition of informal activity adopted

The statistical challenge posed by the informal sector is further amplified by the share of this sector in the national accounts (Table 1).

This aggregate contribution of the Informal sector was made up of different sectoral shares, with agriculture being almost entirely in the unorganised segment, and the share in manufacturing and services being highly varied. The measurement also follows different approaches. In agriculture, the value added is measured by combining production data and cost data obtained through separate measurement protocols. In manufacturing and services, the estimates are typically derived by combining value-added estimates derived from sample surveys with workforce estimates derived from censuses and surveys. The exact approach has varied over the years and we will briefly review these efforts in the next two sections before turning to the issue of estimating value added.

2 Workforce Measurement in India

The basic conceptual framework of measuring employment in India is as per the definition given by the International Labour Organisation, which considers a person as employed if they contribute to the production of goods and services within as defined by the System of National Accounts. This way of defining employment suggests two ways of measuring the size of the workforce. The first is to canvass individuals directly through a population census or sample survey and examine their engagement in economic activity. The second is to canvas 'Institutions controlling Economic Activity' to determine their employment profile. These two approaches yield different results for two reasons. First, the establishment count will typically exclude workers engaged in production for home consumption and secondly, the estimates will diverge on account of people undertaking multiple economic activities in different institutional settings.[1] The general practise, therefore, has been to treat

[1]"Exploring Differences in Employment Between Household and establishment Data" Abraham, Katharine, G., Haltiwanger, John C., Sandusky, Kristin and Spletzer, James. Journal of Labor Economics, Vol. 31, No. 2, Pt 2, 2013, pp. S129–S172.

Table 2 Work participation ratio for usually employed (PS + SS) (per 1000)

Round (year)	Male	Female	Person
38th (1983)	538	296	420
50th (1993–94)	545	286	420
55th (1999–2000)	527	259	397
61 (2004–05)	547	287	420
68 (2011–12)	544	219	386

Source NSS Report No 554: Employment and Unemployment Situation in India, 2011–12

measures of employment derived from censuses and labour force surveys as more reliable indicators of workforce.

In keeping with this assessment, Indian National Accounts have been deriving the workforce estimates from these sources. Till the 1980–81 base years, census data was the principle source for workforce estimation. Concerned with sectoral biases in the census workforce estimates, from 1993–94 revision the census Population estimate was combined with WPR ratios derived from the NSS Surveys. This approach was then broadly continued in later revisions as well. The WPR as measured by NSS had remained broadly stable at the all India level from the early eighties till the 61st round of the NSS in 2004–05. However, Employment surveys after 2004–05 started revealing a decline in the WPR, we can see from the table below that the WPR declines from 42% in 2004–05 to 38.6% in 2011–12 (Table 2).

The reasons for the secular decline in WPR have been extensively discussed in the literature[2] and need not concern us here. However, combined with the declining population growth implied that the national accounts estimate for the unorganised sector after 2004–05 suffered from a significant upward bias. This bias needed to be investigated in detail and was analysed by the committee on unorganised sector setup for the base revision exercise of 2011–12.[3]

The change in the WPR between 2004–05 and 2011–12 were not the only characteristics of importance, Employment in India has been undergoing a variety of structural shifts. The table below shows that there has been a secular decline in the self-employed and an increase in the proportion of the workforce working for wages. This pattern is sharpest amongst rural males and urban females (Table 3).

In addition to these changes, there are also changes in the education and skill levels of the workforce. To properly assess the likely dimension of bias in National Accounts it is necessary therefore to also duly account for these changes in the structure of the workforce.

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[2] See for instance 'India Employment Report 2016: Challenges and the Imperative of Manufacturing-Led Growth' Ajit Ghose, 2016, Oxford University Press.

[3] 'Report of the Sub Committee on Unorganised Manufacturing & Services Sectors for Compilation of National Accounts Statistics with Base Year 2011–12' National Accounts Division, Central Statistics Office, Ministry of Statistics and Programme Implementation, Government of India, New Delhi.

Table 3 Per 1000 distribution of usually employed (PS + SS) by category of employment

		1983	1993–94	1999–2000	2004–05	2011–12
Rural males	Self employed	605	577	550	581	545
	Regular salary wage	103	85	88	90	100
	Casual	292	338	362	329	355
Rural females	Self employed	619	586	573	637	593
	Regular salary wage	28	27	31	37	56
	Casual	353	387	396	326	351
Urban males	Self employed	409	417	415	448	417
	Regular salary wage	437	420	417	406	434
	Casual	154	163	168	146	149
Urban females	Self employed	458	458	453	477	428
	Regular salary wage	258	284	333	356	428
	Casual	284	258	214	167	143

Source NSS Report No 554: Employment and Unemployment Situation in India, 2011–12

3 Estimating Value Added for the Informal Sector: Traditional Approaches

The valued added in the informal sector has till the 2011–12 base revision been estimated by the labour input method which computes value-added per worker (VAPW)from the NSS survey of establishments and combines it with estimates of workforce obtained from employment surveys and the population census. The approach in simple terms proceeds in the following manner estimates of VAPW are derived from the estimate of value added and number of workers in an establishment from the establishment survey. This is used to compute VAPW computed for the various activity categories used for compiling national accounts. These are then combined with labour force estimates obtained from surveys. There are essentially three major elements in the approach which are

(i) Estimating workforce aggregates for the base year,
(ii) Projecting estimates of labour input to subsequent years,
(iii) Netting out the workforce engaged in organised segment of the economy from the estimates of total labour input.[4]

[4]For a complete description of the approach see 'Report of the Working Group on Workforce Estimation for Compilation of National Accounts Statistics with Base Year 1999–2000' National Accounts Division, Central Statistics Office, Ministry of Statistics and Programme Implementation, Government of India, New Delhi.

The workforce estimation from the time the first estimates of the National Income Committee till the 1980–81 revision were based on the workforce estimates from the population census. In the 1993–94 estimates WPR estimates from the NSS employment survey were combined with census population estimates. These estimates were then adjusted for the unorganised segment by netting out the employment estimates derived from the Annual Survey of Industries (ASI) estimates for manufacturing and EMI data of DGE&T for the other industries.[5] This is then used as the workforce in the unorganised sector. Since the labour force surveys were done once every 5 years the requirements of value-added estimations in years after the base year were done by projecting the workforce estimate by an estimate of labour force growth. Till 1980–81 this was done using the intercensal growth rates. From the 1993–94 onwards the growth rate derived from the estimates of successive employment surveys were used.

This approach has some fundamental limitations as was noted by the subcommittee reviewing value-added estimation in the unorganised sector. Firstly, while compiling GVAPW from the ES, it is assumed that there is equal contribution from all categories of workers engaged in an economic activity, i.e., the contribution of an employer, unpaid family member, regular employee on salary or Casual wage worker is the same. Second issue is that in projecting the LI for subsequent years CAGR concept based on past two rounds of EUS will overestimate the LI in all those activity categories where employment growth is less. On the average since WPR is falling this approach will overestimate the labour input and hence value added in years after the base year. The subcommittee estimated that if the estimation approach of the 2004–05 series were applied to the NSS establishment survey of 2010–11 and Employment Survey of 2011–12, we would see an estimation bias of 108% in aggregate. Further, the sharper decline in female WPR suggests that the gender composition of the workforce has also changed, if there are productivity differences across male and female workers then that will also be a source of bias.

These factors led the committee to review the approach taken to compute value added in the informal sector.

4 Estimating Value Added for the Informal Sector: 2011–12 Revisions

For the 2011–12 revision an effort was made to examine the productivity differentials between different categories of workers engaged in the Informal Sector. This exercise was based on a note prepared by Prof Goldar ‘Measuring Effective Labour Input in manufacturing industries’ for the subcommittee.[6] This note showed using ASI data that there could be significant productivity differentials across different types of

[5] This is essentially the approach followed in the revision exercises between 1980–81 and 2004–05. For a complete discussion see the above cited report of the Working Group.

[6] ‘Measuring effective labour input in manufacturing industries: A note’ Bishwanath Goldar, Institute of Economic Growth, Delhi, September 2014.

workers measured by the ASI. The committee decided to adapt this approach to the data canvassed in the NSS Establishment survey. The NSS 67th Round (2010–11) defined a worker as all persons working within the premises of the enterprise who are in the payroll of the enterprise as also the working owners and unpaid family workers.[7] The survey classified workers as working owners, formal hired workers, informal hired workers, and other workers. These were further categorised as full-time or part-time and male or female.

For the purposes of the survey working owner referred to owners or partners who were working with the enterprise on a fairly regular basis (Correspond to Codes 11 and 12 in the employment survey). Formal Hired workers is one having continuity of job and eligible for paid annual leave and also eligible for social security benefits like provident fund or insurance provided by the employer, this corresponds somewhat to the category of regular salary wage worker (code 31) in the employment survey, Informal Hired worker is not having continuity of job and/or not eligible for paid annual leave and/or not eligible for social security benefits like provident fund or insurance provided by the employer. This category corresponds to the Casual labour in the Employment Survey. Finally, the other workers include unpaid family Workers captured in Code 21 of the employment survey.[8]

The subcommittee in attempting to implement the Goldar note treated all hired workers in a single category. While from the viewpoint of an establishment, a formal worker with wage and non-wage benefits is likely to have a different productivity from an informal worker. This is borne out by Prof. Goldar's study using ASI data which showed that such regular workers have higher productivity compared to contract workers (Approximately 7:10). The problem in the case of the informal sector is that while establishment data readily permits identification of workers who receive non-salary benefits, the ability to determine this in a household survey is limited. A regular salary wage worker in the EUS survey is one who is *working in other's farm or non-farm enterprises (both household and non-household) and getting in return salary or wages on a regular basis (and not on the basis of daily or periodic renewal of work contract) are the regular wage/salaried employees. This category not only includes persons getting time wage but also persons receiving piece wage or salary and paid apprentices, both full time and part-time*. Note the emphasis here is on the regularity and predictability of employment. The availability of benefits is not part of the definition. The EUS does have additional questions on benefits but the response rate here is much poorer. In part, this is due to the inability of the respondent to reply effectively to such questions. Therefore, on the margin, for a regular salary wage worker who gets no benefits, the likely differential in productivity with a casual labour is likely to be small. Therefore, the Subcommittee decided to club formally

[7] See 'Instruction to Field Staff, Vol. I: NSS 67th round' Survey on Unincorporated Non-Agricultural Enterprises (Excluding Construction) July–June 2010–11, NSS 67th Round. http://microdata.gov.in/nada43/index.php/catalog/125.

[8] It may be noted that in aggregate labour force survey estimates the category self employed refers to all three codes 11, 12 and 21. The decline in self employment is more marked in the category of 21. It is this group that withdraws from the LF in order to attend to family or school.

hired and informally hired into a single category of wage labour. Thus, the definitional differences across the two surveys are eliminated.

Of the different functional forms investigated by Prof. Goldar, it was decided to work with the nested Cobb–Douglas function. The results reveal significant productivity differentials across the different categories. Typically working owners had two-third of the productivity of hired workers and unpaid other workers were only one-third to one-fourth of the productivity of hired workers.[9]

The effect of incorporating productivity differential was to partly ameliorate the overestimation implicit in the old series. The exact effect is difficult to quantify because ideally, we should recompute the older series.

The second concern about the LI method was about using the growth rate in Labour Force between two surveys to project value-added growth in the years after the base year. This become particularly problematic when we are in period of effectively decreasing labour force due to rising family incomes.[10] The paradox of falling employment and rising Incomes is explained by the increase in labour productivity. The subcommittee recommended replacing the LI indicator with other contemporaneous indicators. The indicators are derived from sales tax for retail trade, service tax for some services, and indicators derived from sectoral attributes. The details of these changes are contained in the report of the subcommittee.

5 Conclusion

The shift from undifferentiated labour to effective labour was a major methodological innovation in In the Indian System of National Accounts. The SNA 2008[11] does note that 'It is possible to produce a quality-adjusted measure of the labour inputs that takes account of changes in the mix of workers over time by weighting together indicators of quality for different grades of workers'. Quality is likely to be dependent on education level, age, experience etc. The suggestion is that the different labour types could be aggregates using weights determined by appropriate wage rates. The implementation in the Indian revision is in the spirit of the SNA recommendation. However, it becomes clear from this limited exercise that the quality of estimation in the informal sector can be improved if data for more refined productivity estimation is collected in establishment and employment surveys. A small step in this direction was classifying workers as skilled or unskilled in the establishment survey of the NSS 73rd round (2015–16). The recently launched PLFS survey also has information on wages and earning canvassed in both first visits and revisits. Thus, the possibility

[9]For details of the results see the report of the subcommittee cited earlier.

[10]The decline in labour force is accounted for to a large measure due to the increase enrolment in Higher Education. The period has seen Gross Enrolment rise from 13% to about 25%. A second factor is rising household incomes has made women's workforce participation an inferior good due to prevailing sociocultural norms.

[11]SNA 2008 (Chapter 19, para 19.55, 19.56).

of a richer measure of labour quality is now worth exploring. Because like with the organised sector it is likely that productivity changes may play a bigger role in Value added growth than simple growth in volumetric measures. 2011–12 base year revision has laid the foundation for a more methodologically precise estimate of the contribution of the informal sector.

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Who Creates Large Number of Good Jobs in India's Organized Manufacturing? Small Versus Large and Start-Ups Versus Old

Jitender Singh and Arup Mitra

1 Introduction

There are two general perceptions about employment in the small-scale sector. First, this sector provides large number of jobs thus require special policy attention. Based on this, policies are in place to promote small-scale industries in India. Second, the quality of jobs in this sector is not highly productive, therefore, generally, labour force aspires to work in larger firms. These popular perceptions are easily extended to employment in small-scale unorganized manufacturing sector, and taken for granted in small-scale organized manufacturing sector too.

Evidence for low quality (wages and employment benefits) of new jobs created in the formal/organized component of the Indian manufacturing sector during 1995–2005 is taken to argue that India's organized manufacturing has not been doing well (Maiti and Mitra 2010; Goldar and Agrawal 2010). However within the organized manufacturing sector the employment and its quality dynamics may be different as per size-structure and age of the firms.

The literature dealing with size-structure characteristics of manufacturing (Vaidyanathan and Eapen 1984; Nagaraj 1985; Little 1987; Mazumdar 2001; Mazumdar and Sarkar 2008; Hasan and Jandoc 2013; and Hsieh and Olken 2014) helps understand the constraints and requirements of various sizes of firms and the designing of policies to optimize the potential of the manufacturing sector.

However, most of these studies are either very old or they explored only a few characteristics of size category. Similarly, it is difficult to find studies in case of India which examined the characteristics of employment as per age-structure of firms. In

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view of this, the present study proposes to use sets of simple criteria examining employment characteristics by age and size structure of organized manufacturing firms in India.

2 Data and Methodology

The study uses evidence from other studies along with aggregate and unit-level data from Annual Survey of Industries (ASI) for 2012–13 and 2011–12. The plant size is categorized as 'small' if the employment size is less than 49.[1] The rest are categorized as 'medium' (50–499 employees), 'large' (500–4999 employees), and 'ultra-large' (>5000)—the classification which is also followed in earlier studies. The age is measured from the date of commencement of the production by the plant.

The criteria used are size of employment, its growth, quality (regular/contract, wages), and sustainability (diversification/concentration of jobs, and vulnerability to business cycles). Using these criteria we prepare a scorecard of manufacturing firms by age and size class in order to gauge the potential of manufacturing firms for creating ample quality and sustainable jobs.

The Herfindahl Index (HI), is one of the commonly used measures for estimating concentration. The index is defined as $\mathrm{H} = \sum_{i=1}^{n} \mathrm{pi2}$, where p is the share of each 'i' industry at 5-digit of NIC. The value of the index ranges between 0 and 1. The lower the value, the higher is the diversification of employment in the category and vice versa.

3 Data Analysis

(i) *Size and growth*

Size of employment

Before nineties reforms, there was a consensus that either small or large factories employed mostly manufacturing workers in India, while employment in medium-sized units was very less. Dhar and Lyndall (1961) found high level of concentration in employment in the highest size group while middle was somewhat thin. More precisely, as per Little (1987) medium size factories (50–500) workers accounted for less than one-third of employment in the organized manufacturing during 1960s and 1970s. Mazumdar (2001) and Mazumdar and Sarkar (2008) examining the overall manufacturing sector (organized and unorganized) found bipolar distribution of employment during 1989–90. While employment was found concentrated in categories below 10 workers or above 1000 workers, the middle was almost missing. This phenomenon was also called as 'missing middle'. Economic reasoning is said to be

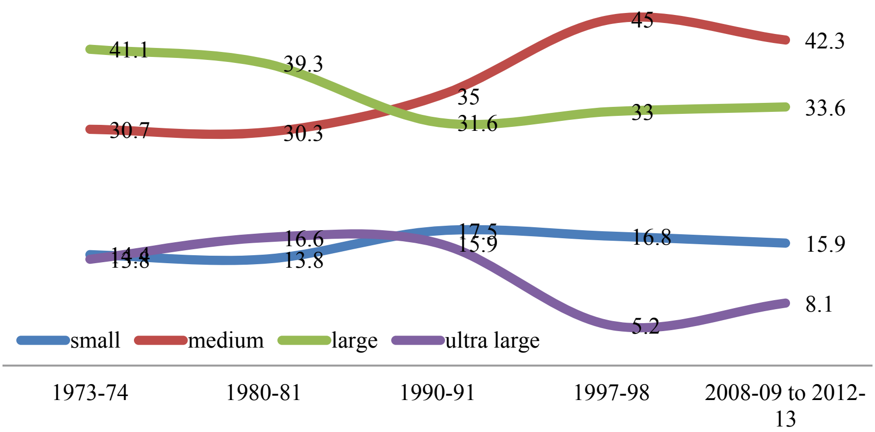
[1] Little (1987) argues that in developing countries average plant size is smaller, so small is taken as 1–49 workers.

working behind this phenomenon which stems from policy incentives and regulation prevalent in India.

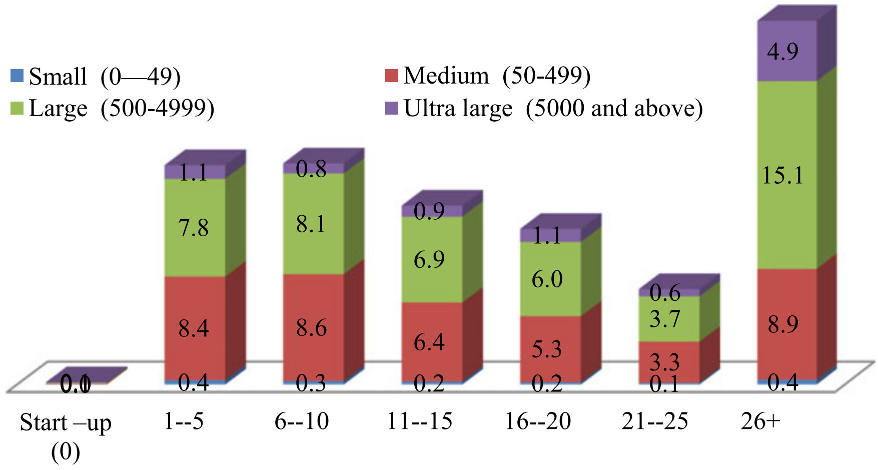
In other words, the factor responsible for 'missing middle' before 1990s was mainly related to industrial policy. Little (1987), Goldar (2000), Nagaraj (1994) argued that the policy promoting large-scale public enterprises and policies promoting small-scale industries might have created this bipolar concentration of employment in the manufacturing sector. Mazumdar and Sarkar (2008) concluded that differential application of labour legislations, biased education policy towards promotion of tertiary and neglecting primary and secondary education, protection to small-scale industries, and hysteresis (persistence of old phenomenon in economic agents and institutions) have been responsible for this distribution. Hasan et al. (2012) urged that the labour legislations have contributed to size distribution of employment.

The distribution of employment in organized manufacturing since 1973–74 to 2012–13 is presented in Graph-1. It shows that the situation has changed gradually after the 1990s reforms. During 2008–09 to 2011–12, it is the medium and large firms which employed about 75% of total employment in organized manufacturing. The share of medium firms has increased significantly especially subsequent to 1990 reforms. The share of small factories has been more or less stable between 14 and 17% and that of ultra-large projects has declined considerably.

The liberalization policies of the nineties, comprising de-licensing of industries, de-reservation of industries from public sector and small sector, firms' access to capital market due to financial liberalization, opening up of economy for foreign investment, economic integration of economy pushed by the trade agreements, and policies promoting industrial infrastructure and investment through Special Economic Zones and industrial clusters, have probably improved the scale in the sector.



Graph 1 Distribution of organised manufacturing employment. *Source* Goldar (2000) and from 2008–09 to 2012–13 compiled from ASI reports. *Note* The plant size is categorized as small (<49 employees); medium (50–499 employees), large (500–4999 employees) and ultra-large (>5000)



Graph 2 Share of Employment by age and size in 2012. *Source* Calculated from Unit-Level data of ASI

These liberalization policies have been able to remove considerable institutional constraints as argued by Nagaraj (1985).

The Graph-2 presents the share of employment by age and size of a plant in 2011–12. The young firms, i.e., 1–10 years old, account for the largest share of employment in the organized manufacturing except the plants with an age of 26 years and above. In general, the employment share of the plants declines as age increases till the firms reach the threshold limit of 25 years. Turning to size, young (1–10 years age), medium, and large plants accounted for much of the employment. On the other hand, the contribution of start-ups is seen to be less than one percent.

Growth of Employment

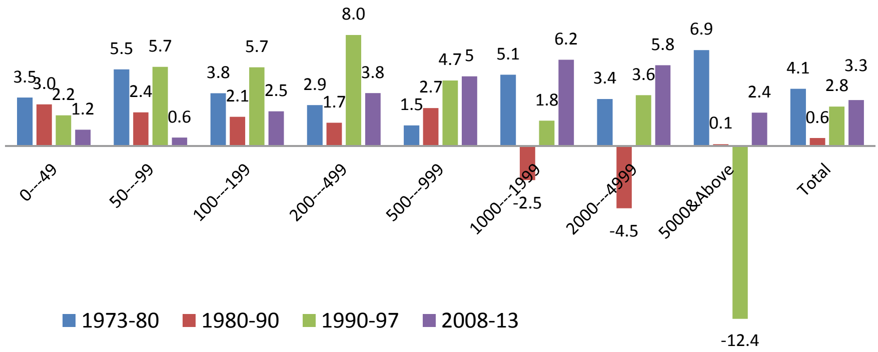
The employment growth across size category is presented in Graph-3. The overall growth in employment in organized manufacturing increased during 1990s and 2008–13. However, it varies across categories. The growth in small factories declined continuously during 1990s and 2008–13. On the other hand, the growth in employment in large factories, i.e., 500–999, has continuously increased.

The Graph-4 plots the change in the share of employment in 2012 over 2011. It may be seen that most of the increase in employment is reported by young medium and large plants. The increase in employment in ultra-large and small plants is small. On the other hand, maximum destruction of employment is reported to have taken place in the old plants (age group of 10–25 years). The role of start-ups in creating employment does not appear to be significant.

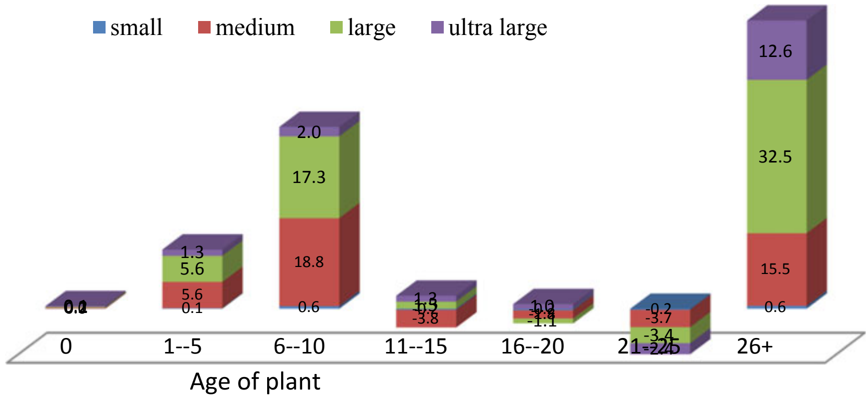
(ii) ***Quality of Employment***

Intensity of Contract workers

The quality of employment here is measured in terms of two indicators: one, the intensity of contract worker, and another, average wage rate paid by firms in a size/age



Graph 3 Growth of Employment (%). *Source* Goldar (2000) and 2008–09 to 2012–13 compiled from ASI reports



Graph 4 Share of employment changed in 2012 over 2011 (%)

class. Though both are not independent, generally the contract workers are paid lower wages in comparison to the regular workers. However, there are other factors also which influence the demand for contractual workers and wage rate in the size group. The contention is that intensity of contract worker decreases with an increase in firm size and age. But economic reasoning works both ways. First, as the firm grows in size, the marginal productivity of hired worker also declines. So the firm tends to hire workers with low wage, who are preferably contract workers. If this reasoning has to yield, the technology should remain the same for all firms, which is not the case. Second, both marginal and average productivity are relatively high in large firms compared to small firms mainly due to their high capital intensity. Thus, large firms tend to pay better to hired workers. In addition, the deployment of higher levels of capital and superior technology in a relatively large firm creates the need for relatively better skilled workers who can be attracted through regular and high wage jobs. In addition, in India, the labour regulation, Industrial Dispute Act (IDA),

Table 1 Share of contract workers in total workers in 2012 (%)

Age (years)	Small	Medium	Large	Ultra-large	All
0	40.2	43.1	14.5		25.0
1–5	39.1	49.7	33.7	76.4	43.7
6–10	36.6	45.3	30.4	26.7	38.3
11–15	34.7	41.3	33.3	41.9	37.3
16–20	34.9	39.6	27.4	15.6	31.9
21–25	33.0	41.4	30.3	12.5	33.7
26+	34.1	36.7	27.0	52.6	34.7
All	35.9	42.3	29.4	44.0	36.6

Source Computed from ASI unit-level data

tends to create threshold effect, according to which firms directly employing 100 and more workers need prior government permission (which generally rarely granted) for retrenchment, layoff of workers and closure of firms. As a result of IDA, firms wish to remain small in terms of directly employed workers by employing more and more contractual workers (Ramaswamy 1994).

Srivastva (2015) infers, though the contractualization has increased and the growth of contract workers has been much higher than the growth of total workforce in organized manufacturing in India, protection laws are not the binding constraint and have not deterred employment growth. These trends of rising contractualization in organized manufacturing have also been confirmed in other studies (Mitra 2013), which may have been pursued with a view to reducing the labour cost.

Table 1 presents contract intensity (measured as percentage of contract worker in total person engaged) across firms by age and size. It is observed that intensity of contract workers is much higher in medium and ultra-large factories, lower in small and lowest in large factories. These observations conform to the findings of Srivastva (2015) that contract intensity is not higher in small factories.

Further, intensity of contract workers is found to be lowest at 25%, in start-ups, which peaks at 43.7% in young factories (1–5 years of age of firms) and declines thereafter with an increase in age of the factory up to 20 years. It appears to be increasing in start-ups with a decrease in size of the plant. It is also found high in ultra-large factories: among these factories those with 6–10 and 16–25 years of age tend to employ very low percentage of contract workers compared to the others.

Wages

There are two important propositions one, that the older firms pay higher wages, and second larger firms pay higher wages.

First strand of literature argues that older manufacturing plants pay higher wages to their workers include Dunne and Roberts (1990), Davis and Haltiwanger (1991), Troske (1998). However, Blanchflower and Oswald (1994), Brown and Medoff (2003) could not confirm the relationship statistically. The argument of worker quality (seen in Brown and Medoff 2003) propagated that older firms can pay higher wages because their workers are more experienced and have longer tenure. This view is also supported by the ability to pay argument propagated by Pakes and Ericson (1998) who argued that wages are likely to be higher in an established firm.

The second argument is that the younger firms have a higher probability of closing down without being able to stay in the market, which is a negative job characteristic. This implies that young firms would have to offer higher wages in order to attract a given quality of worker (seen in Brown and Medoff 2003). Further, since non-wage benefits to workers such as pension, health insurance, flexibility in working times and locations and housing facilities are better in old firms, they can attract good quality workers even at lower wages (Table 2).

Table 3 presents wage in Rs. per day for a person employed in Indian organized manufacturing by age and size. The wages are reported to be highest at Rs. 590 in start-ups and then declines to Rs. 338 in young factories (1–5 years) and recorded the lowest at Rs 318 per person in firms with 6–10 years of age. Thereafter, beyond 10 years of age, wage increases as the unit gets older. The start-ups pay the highest wage which is consistent with the argument that their probability to close down being

Table 2 Wage for contract workers (Rs. per day)

Age (years)	Small	Medium	Large	Ultra-large	All
Start-ups (0)	411	242	188	–	339
1–5	286	233	263	192	260
6–10	234	224	242	306	230
11–15	218	285	273	261	251
16–20	212	230	292	390	225
21–25	227	227	247	200	228
26+	253	256	267	148	255
all	245	242	264	201	245

Source Computed from ASI unit-level data

Table 3 Wage for persons employed (Rs. per day)

Age	Small	Medium	Large	Ultra-large	All
Start-ups (0)	648	489	457	–	590
1–5	276	381	442	284	328
6–10	268	364	429	326	318
11–15	274	378	477	569	330
16–20	282	386	458	459	339
21–25	296	395	474	857	352
26+	263	398	606	698	361
All	275	383	509	617	338

Source Computed from ASI unit-level data very high they have to offer higher wages in order to attract a given quality of worker (Brown and Medoff 2003). The low survival rate of start-ups may not be permitting them to commit on non-wage benefits to workers; therefore, to attract workers they may be required to pay relatively higher wages. Another observation is that a smaller size start-up needs to pay relatively higher wages than a larger start-up.

Further, a relatively larger size factory pays higher wage as reflected in Table 3. The results show that small factory paid Rs. 275, medium Rs. 383, large Rs. 509 and ultra-large Rs. 617.

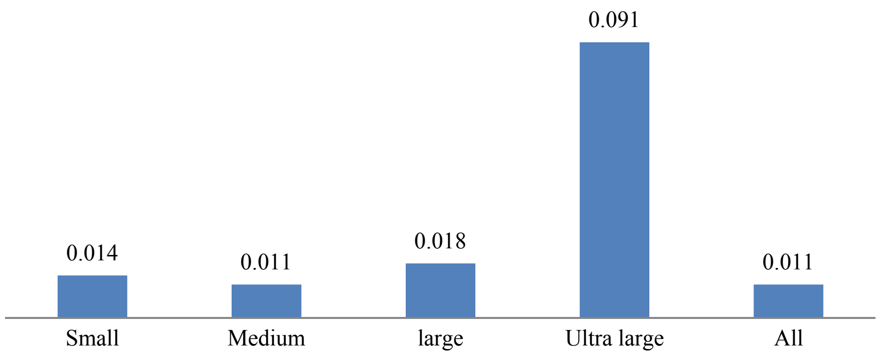
(iii) ***Sustainability***

Diversity
The sustainability of employment is measured in terms of two indicators. The first one is diversification of employment over age and size. And, the second indicator is the vulnerability of employment to the business cycles. The diversity of employment is measured in terms of Herfindahl Index and the vulnerability to business cycle is measured in terms of share of exports of a plant.

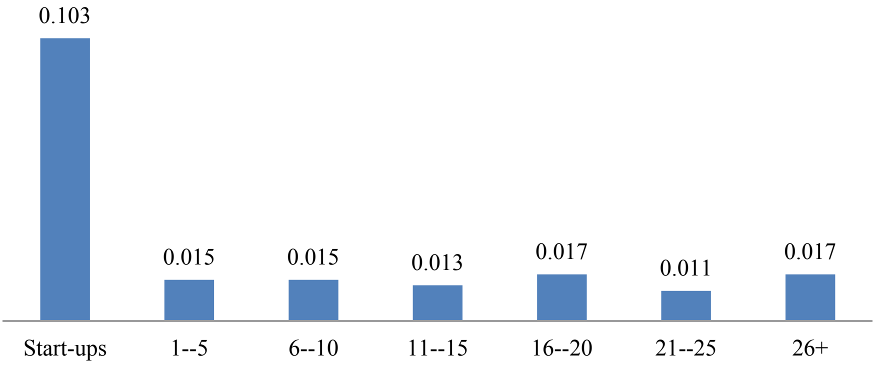
The Graph-5 presents the results of Herfindahl index, which shows that the employment is most diversified in medium-sized plants followed by their small and large counterparts. It is most concentrated in the ultra-large plants.

The Graph-6 presents the Herfindahl index by age of the plant. It is observed that the highest concentration of employment is in the start-ups. The diversity tends to rise as the plant gets older.

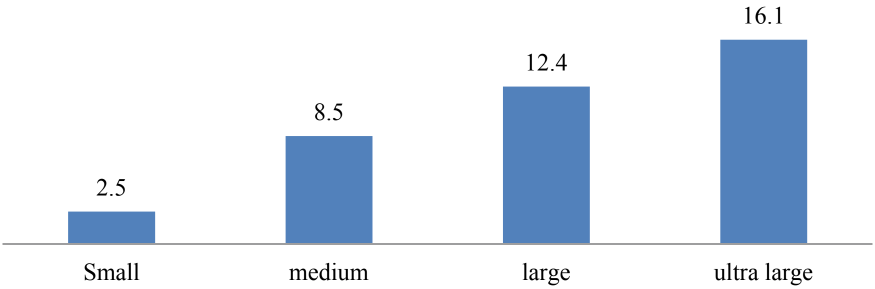
Vulnerability
The vulnerability to business cycles as measured in terms of share of product directly exported by a plant is presented in the Graph-7. It is observed that the share of export rises with the increase in the plant size. However, no such trend is witnessed in the share of export by age group. The vulnerability is observed lowest for the start-ups and the oldest plants (26 plus) while it is on the higher side for the older plants (Table 4).



Graph 5 Herfindahl Index by size



Graph 6 Herfindahl Index by age



Graph 7 Share of product directly exported (%)

Table 4 Share of product directly Exported (%)

Age	Small	Medium	Large	Ultra-large	All
0	1.0	0.0	15.0		1.7
5	3.0	9.0	10.0	5.0	5.6
6	3.0	10.0	16.0	25.0	6.7
11	3.0	9.0	15.0	4.0	5.8
16	3.0	10.0	16.0	20.0	6.7
21	3.0	9.0	16.0	13.0	6.4
26	2.0	6.0	9.0	9.0	4.3
All	2.5	8.5	12.4	16.1	5.8

Scorecard
The score for each indicator based on its value broadly infers three extremes: lowest (L), highest (H), and medium (M). These categories facilitated gross comparison and helped in drawing broad conclusions from the above discussion. Size and age wise scoreboard is presented in Table 5.

Table 5 Age and size wise scoreboard of plants characteristics

S. No.	Indicator	Small	Medium	Large	Start-up	Young	Mature
1	Share	L	H	M	L	M	H
2	Growth	L	H	M	–	–	–
3	Contract intensity	L	M	H	L	H	M
4	Wages	L	M	H	H	L	M
5	Diversity	H	M	L	L	H	M
6	Vulnerability	L	M	H	L	H	M

L = lowest; M = medium, H = highest: assigned comparing. Contrary to the perception, both the share and the growth of employment in small-scale sector of organized manufacturing in India is the lowest. It simply indicates that the small-scale organized manufacturing plants are neither the dominant employer nor the highest job generator. On quality of jobs, the wages are also low. However, it is good to see that contractualization is low along with highest diversity of jobs and lowest vulnerability to export cycles makes the jobs in this sector relatively sustainable.

Instead, the medium-scale plants are the dominant employer and are also creating the largest number of jobs in organized manufacturing. This fact emphasizes that at least in organized manufacturing sector the 'missing middle' is no more a phenomenon. The wages paid are also relatively better than small-scale sector, though, intensity of contract worker is relatively higher. However, the sector stands in the middle on diversity and vulnerability fronts.

Although, the contribution of start-ups in terms of employment is very low, they create quality jobs in terms of wage payment, contract workers intensity, and vulnerability to export cycles.

The employment provided by young plants is significant and very diverse. However, the quality is low and most vulnerable to the export cycles. The mature plant contributes the most in terms of employment with average quality and sustainability.

Regression analysis

In order to assess the sensitivity of employment with respect to growth and wages across units of various sizes and ages a regression equation, is estimated. Employment is taken to be a function of value added, wage rate and number of days worked per person in a year along with several slope dummies representing size and age groups of the units.

The results (Table 6) show that the growth elasticity of employment, wage elasticity, and elasticity with respect to the number of days worked per person tend to vary across size and age of plants. In comparison to plants which are very old (more than 50 years) and very large in size (employing 500 and more employees) the employment elasticity with respect to growth tends to decline across lower size categories and relatively younger firms. The new comers and the small ones seem to be generating least employment in relation to growth. Similarly, the wage sensitivity

Table 6 Regression Results on employment elasticity across units of different size and age

Age is in years and size is measured in terms of number of person engaged; gva = Gross Value Added	Dep. Var.: ln_person	Coef.	Std. Err.	t	P > t
	ln_gva	0.511	0.014	36.420	0.000
	ln_days worked by a person in a year	−0.150	0.010	−15.300	0.000
	ln_wage	−0.444	0.045	−9.830	0.000
Interaction with ln_GVA					
D1 = age_5*size up to 50	ln_gva*D1	−0.230	0.015	−15.500	0.000
D2 = age_5*size51_99	ln_gva*D2	−0.258	0.017	−14.920	0.000
D3 = age_5*size100_499	ln_gva*D3	−0.206	0.016	−13.200	0.000
D4 = age_5*size 500+	ln_gva*D4	−0.126	0.019	−6.480	0.000
D5 = age6_10*size up to 50	ln_gva*D5	−0.202	0.015	−13.330	0.000
D6 = age6_10*size51_99	ln_gva*D6	−0.243	0.018	−13.490	0.000
D7 = age6_10*size100_499	ln_gva*D7	−0.176	0.016	−11.250	0.000
D8 = age6_10*size500+	ln_gva*D8	−0.073	0.020	−3.720	0.000
D9 = age11_20*size up to 50	ln_gva*D9	−0.175	0.015	−11.880	0.000
D10 = age11_20*size51_99	ln_gva*D10	−0.193	0.017	−11.140	0.000
D11 = age11_20*size100_499	ln_gva*D11	−0.141	0.015	−9.310	0.000
D12 = age11_20*size500+	ln_gva*D12	−0.035	0.017	−2.010	0.044
D13 = age21_50*size up to 50	ln_gva*D13	−0.144	0.015	−9.690	0.000
D14 = age21_50*size51_99	ln_gva*D14	−0.182	0.018	−9.990	0.000
D15 = age21_50*size100_499	ln_gva*D15	−0.145	0.015	−9.610	0.000
D16 = age21_50*size500+	ln_gva*D16	−0.026	0.016	−1.610	0.107
D17 = age > 50*size up to 50	ln_gva*D17	−0.081	0.021	−3.820	0.000
D18 = age > 50*size51_99	ln_gva*D18	−0.246	0.028	−8.770	0.000

(continued)

Table 6 (continued)

D19 = age > 50*size100_499	ln_gva*D19	−0.161	0.017	−9.530	0.000
Interaction with ln_Wage					
D1 = age_5*size up to 50	ln_wage*D1	0.230	0.047	4.840	0.000
D2 = age_5*size51_99	ln_wage*D2	0.503	0.054	9.280	0.000
D3 = age_5*size100_499	ln_wage*D3	0.466	0.050	9.300	0.000
D4 = age_5*size500+	ln_wage*D4	0.362	0.064	5.660	0.000
D5 = age6_10*size up to 50	ln_wage*D5	0.161	0.048	3.350	0.001
D6 = age6_10*size51_99	ln_wage*D6	0.458	0.056	8.120	0.000
D7 = age6_10*size100_499	ln_wage*D7	0.377	0.050	7.480	0.000
D8 = age6_10*size500+	ln_wage*D8	0.195	0.064	3.020	0.003
D9 = age11_20*size up to 50	ln_wage*D9	0.081	0.047	1.710	0.087
D10 = age11_20*size51_99	ln_wage*D10	0.319	0.054	5.880	0.000
D11 = age11_20*size100_499	ln_wage*D11	0.273	0.049	5.600	0.000
D12 = age11_20*size500+	ln_wage*D12	0.071	0.056	1.270	0.206
D13 = age21_50*size up to 50	ln_wage*D13	−0.012	0.047	−0.250	0.804
D14 = age21_50*size51_99	ln_wage*D14	0.288	0.057	5.080	0.000
D15 = age21_50*size100_499	ln_wage*D15	0.297	0.049	6.100	0.000
D16 = age21_50*size500+	ln_wage*D16	0.056	0.052	1.080	0.281
D17 = age > 50*size up to 50	ln_wage*D17	−0.193	0.062	−3.090	0.002
D18 = age > 50*size51_99	ln_wage*D18	0.486	0.086	5.630	0.000
D19 = age > 50*size100_499	ln_wage*D19	0.350	0.054	6.440	0.000
	Constant	0.532	0.054	9.820	0.000
	Statistics				
	Number of obs	41946			

(continued)

Table 6 (continued)

	R-squared	0.892			
	Adj R-squared	0.891			
	Root MSE	0.522			
	F(21, 41924)	8399.710			
	Prob > F	0.000			

Note Firms very old (more than 50 years) and very large in size (employing 500 and more employees) comprise the comparison category
Source Based on unit-level data of ASI

of very large and the oldest firms is the maximum and it tends to decline (with a few exceptions) as size and age fall.

This would mean that labour deregulations may have favourable impact in very large and old firms whereas the small and new comers do not have much scope to enhance employment with a reduction in wage rate. This latter category in the face of capital intensive technology seems to be engaging the least required labour which does not show much flexibility in the sense of declining in response to wage increase or vice versa. In fact, in some of the relatively young and medium-sized units employment and wage go hand in hand, which could be a reflection of engaging highly skilled employees with higher wages.

4 Summary of Observations

The first observation is that the missing middle as highlighted in the literature is on the decline after the liberalization period as the employment share of medium-sized plants has increased significantly subsequent to the reforms of the 1990s. The employment shares of small and large units have been more or less constant while the share of ultra-large firms has declined. In addition, it is the young plants which employ the most in the organized manufacturing in India, and employment share declines as firms grow older.

Second, it is the medium and large young plants which create most of the new jobs in the organized manufacturing in India. Most of the jobs are destroyed in the plants in the age group of 11–25 years and the contribution of start-ups in creation of new jobs is very low.

Third, the intensity of contract workers is much higher in medium and ultra-large factories, lower in small and lowest in large factories. Among young factories, it is the medium and ultra-large factories which employ contract workers even more than half of their total workers. The intensity of contract workers is found lowest in start-ups, which peaks when plant is young and declines thereafter with an increase in age of the factory up to 20 years. Further, the wages are reported to be at the highest level in start-ups, then they decline as plants grow young and reach the lowest level in the older plants. However, beyond 10 years of age, wage rate increases as the factory gets older.

Fourth, employment is most diversified in medium-sized plants followed by their small and large counterparts. It is most concentrated in the ultra-large plants. Further, the highest concentration of employment is observed in the start-ups. The diversity tends to rise as the plants get older. In addition, the share of export rises with the increase in the plant size which could be an indicator of susceptibility to the influence of business cycles. However, no such trends are witnessed in the share of export by age group. The vulnerability is found at the lowest for start-ups as most of them are catering to the domestic markers. Surprisingly for the oldest plants as well (26 plus) the export share dwindles at a low level. It is on the higher side for the older plants.

In brief, it is the young middle and large-sized plants which not only account for most of the employment but also create most of the new jobs in the organized manufacturing sector. These jobs are although relatively low in terms of quality as measured through contract intensity, wages paid are relatively better by young firms. This group is also generating sustainable jobs as the diversity of jobs in this segment is high and vulnerability to business cycle is also relatively low. In view of these observations, it is suggested that the policy promoting employment in organized manufacturing in India should focus on the most dynamic group, which comprises middle-sized young factories, to generate the largest number of new and sustainable jobs. These are, however, preliminary and the observations and results are tentative. Further, the study is limited to the unit-level data of the organized manufacturing (provided by ASI) for two years 2011 and 2012 only. The regression exercise also brings out very interesting results, indicating that the employment elasticity is the highest in the largest and the oldest firms. Given the large volume of employment in these units, it is equally important that employment growth is encouraged in large industries alongside the medium-sized units.

Annexure

See Tables 7, 8, 9, 10, 11, 12, and 13.

Table 7 Share of employment as per plant size

Employment range (persons)	Total persons engaged	1973–74	1980–81	1990–91	1997–98	2008–09 to 2012–13
0–49	1876686	14.4	13.8	17.5	16.8	15.9
50–99	1237320	8.2	9	10.8	13.1	10.6

(continued)

Table 7 (continued)

Employment range (persons)	Total persons engaged	1973–74	1980–81	1990–91	1997–98	2008–09 to 2012–13
100–199	1566216	9.4	9.2	10.7	12.9	13
200–499	2358880	13.1	12.1	13.5	19	18.7
500–999	1764538	11.6	9.7	12	13.6	13.7
1000–1999	1416130	12.8	13.7	10.1	9.4	10.5
2000–4999	1218717	16.7	15.9	9.5	10	9.4
5000 and above	***979356***	***13.8***	***16.6***	***15.9***	***5.2***	***8.1***
Total	12417843	100	100	100	100	100

Source Goldar (2000). 2008–09 to 2012–13 is compiled from various ASI reports

Table 8 Change in employment in 2012 over 2011 (persons)

Age (years)	Small	Medium	Large	Ultra-large	All
>1	1,228	8,415	9,329	7,076	26048
1–5	6116	267573	263665	63430	600784
6–10	26706	891468	819327	94742	1832243
11–15	−9870	−180155	72378	60411	−57236
16–20	−11637	−86872	−49863	47156	−101216
21–25	−8774	−177928	−162562	−113154	−462418
26+	29485	736035	1541557	599542	2906619
All	33254	1458536	2493831	759203	4744824

Source Computed from unit-level data from ASI

Table 9 Growth and share of employment in organized manufacturing industries in India (%)

Employment range (persons)	2012–13					
	Total persons engaged	1973–74	1980–81	1990–91	1997–98	Average of 2008–09 to 2012–13
0–14	480466					3.8
15–19	261786					2.3
20–29	432418					3.7
30–49	702016	14.4	13.8	17.5	16.8	6.1
50–99	1237320	8.2	9.0	10.8	13.1	10.6
100–199	1566216	9.4	9.2	10.7	12.9	13.0
200–499	2358880	13.1	12.1	13.5	19.0	18.7
500–999	1764538	11.6	9.7	12.0	13.6	13.7

(continued)

Table 9 (continued)

Employment range (persons)	2012–13 Total persons engaged	1973–74	1980–81	1990–91	1997–98	Average of 2008–09 to 2012–13
1000–1999	1416130	12.8	13.7	10.1	9.4	10.5
2000–4999	1218717	16.7	15.9	9.5	10.0	9.4
5000 and above	***979356***	***13.8***	***16.6***	***15.9***	***5.2***	***8.1***
Total	12417843					100.0

Source Calculated from Annual Survey of Industries (ASI)

Table 10 Growth of employment in organized manufacturing industries in India (%)

Employment range	19973–80	1980–90	1990–97	2008–13
0–49	3.5	3.0	2.2	1.2
50–99	5.5	2.4	5.7	0.6
100–199	3.8	2.1	5.7	2.5
200–499	2.9	1.7	8.0	3.8
500–999	1.5	2.7	4.7	5
1000–1999	5.1	−2.5	1.8	6.2
2000–4999	3.4	−4.5	3.6	5.8
5000 and above	6.9	0.1	−12.4	***2.4***
Total	4.1	0.6	2.8	3.3

Table 11 Share of employment by age and size

Age	Small (0–49)	Medium (50−499)	Large (500–4999)	Ultra-large (5000 and above)	All
Start-up (0)	0.01	0.06	0.07	0.05	0.19
1–5	0.36	8.36	7.83	1.09	17.64
6–10	0.28	8.63	8.07	0.80	17.77
11–15	0.24	6.39	6.88	0.89	14.40
16–20	0.19	5.34	5.96	1.05	12.54
21–25	0.14	3.33	3.66	0.58	7.70
26+	0.39	8.94	15.05	4.85	29.23
Others (nec)	0.01	0.23	0.22	0.07	0.52
All	1.61	41.29	47.73	9.38	100.00

Source Computed from unit-level data ASI 2012

Table 12 Share of employment change in 2012 over 2011 (%)

	Small	Medium	Large	Ultra-large	All
0	0.0	0.2	0.2	0.1	0.5
1–5	0.1	5.6	5.6	1.3	12.7
6–10	0.6	18.8	17.3	2.0	38.6
11–15	−0.2	−3.8	1.5	1.3	−1.2
16–20	−0.2	−1.8	−1.1	1.0	−2.1
21–25	−0.2	−3.7	−3.4	−2.4	−9.7
26+	0.6	15.5	32.5	12.6	61.3
All	0.7	30.7	52.6	16.0	100.0

Source Computed from unit-level data ASI 2012

Table 13 Herfindahl Index

Size of plant	*Herfindahl Index*
Small	0.014
Medium	0.011
Large	0.018
Ultra-large	0.091
All	0.011
Age of plant	*Herfindahl Index*
Start-ups	0.103
1–5	0.015
6–10	0.015
11–15	0.013
16–20	0.017
21–25	0.011
26+	0.017

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Increasing Dualism in Indian Wage Labour Market

Sandip Sarkar and Balwant Singh Mehta

1 Introduction

The patterns of globalization and changes in technology have profound impact on the status of labour. The labour market in developing countries like India has been multifaceted—influenced by regional diversity, differences in rural and urban locations, status of workers, education and skill level, caste and religion, industry and institutional basis of labour regulations etc. If we consider the work status, regular work is considered to be better quality work compared to self-employed and casual work. The regular work often considered as better work due to its features of regularity in salary, long-term job tenure, and other social security benefits.

In India, a large proportion of workers are still involved in self-employment activities followed by casual and regular workers. Over the years, the positive aspect of the Indian economy is the growing share of regular workers. However, it is argued that this increment in regular workers comes with mostly contractual and informal jobs having similar characteristics as casual workers. The share of informal jobs within the formal sector has also increased by more than 9 percentage points from 48% in 2004–05 to 57% in 2011–12. In this process, the difference between regular jobs and casual jobs is narrowing, which may be due faster growth of casual wage compared to regular wage (Mazumdar et al. 2017; Sarkar 2015). This may be originating from increasing demand of casual or informal workers in non-farm activities particularly in construction sector, increasing migration of people from rural to urban areas, this process of rising informalisation of regular jobs is considered as the wage labour

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market is becoming dichotomous—with two poles, one with high end well paid regular workers and another with low paid informal regular/contractual/casual workers (Sarkar 2015).

These pattern and trends of nature and quality of employment in the country may suggests two simultaneous and contradictory processes: informalisation or casualisatioin of formal/regular employment as well as improvements in the wage level of low paid workers. Evidence of the rise in contractualisation, outsourcing and flexibility of jobs in services and industries suggests a process of increasing informalisation of regular or formal jobs and deterioration of job quality (ILER 2014). On the other hand, the evidence of the changes within regular jobs such as the increase of casual or informal jobs means shift of casual or informal jobs in the regular job category, which are better than casual or informal jobs means movement towards better quality of jobs with higher wages or salary.

However, most of the recent empirical research work (Mitra 2006a, b; Ghose 2016; Kannan 2009; NCEUS 2007; CII 2014; Mehta 2018) in India was mostly conceptually informed by the dichotomy between the formal and the informal economy and standards of work. It mostly took 'standard employment relation' as a frame of reference and an ideal model to list and detail the lack of minimum conditions of work; policy research was largely prescriptive in nature directed towards improving the working conditions in the informal sector through provision of social protection and other welfare schemes. The previous studies largely overlooked the dynamism within formal sector or regular employment and existing wage differentials.

Policymakers and scholars are currently debating on these dichotomy related to the linkages of casual/informal and regular/formal employment with thin and anecdotal evidences at aggregate levels. As Ghose (2016) suggests there is scope for improvements in quality of employment if the frame of analysis goes beyond the simple sectoral dichotomy—formal and informal sector—and presumed quality of work within these sectors.

In this context, there is need to understand how and what factors are responsible for this emerging dichotomy in Indian wage labour market. This paper is an attempt to unravel the factors and to understand the phenomenon through the available data and information. In this paper, three rounds of NSSO data 1999–00; 2004–05 and 2011–12 have been analysed to examine the objective.

2 Segmentation in Indian Labour Market

Indian labour market is characterized by numerous types of differentiation among groups of workers.

Segmentation originates from various factors such as geographical and rural/urban location, status of workers, gender, level of education and skill, caste & religion, industry and institutional basis of labour regulation, etc.

A brief analysis of various segmentation of Indian labour market is undertaken in the following sections.

2.1 Employment Status

Self-employed is the largest form of employment in rural areas. It still constitutes more than half of all employment (Fig. 1). The other form of employment is casual wage labour who does not necessarily work throughout the week but paid for the days for which he/she has worked. The share of regular worker (often considered as better jobs) is much less in rural areas as it constitutes around one-fifth of wage labourer. But it increased particularly between 2004–5 and 2011–12.

The job market scenario is quite different in urban areas. Self-employed share in total employed continue to fluctuate around 40% (Fig. 2). Wage labour includes both casual and regular worker, the latter is the dominant form of employment in urban areas. Unlike in rural areas, the regular workers constituted the largest form (45.9%)

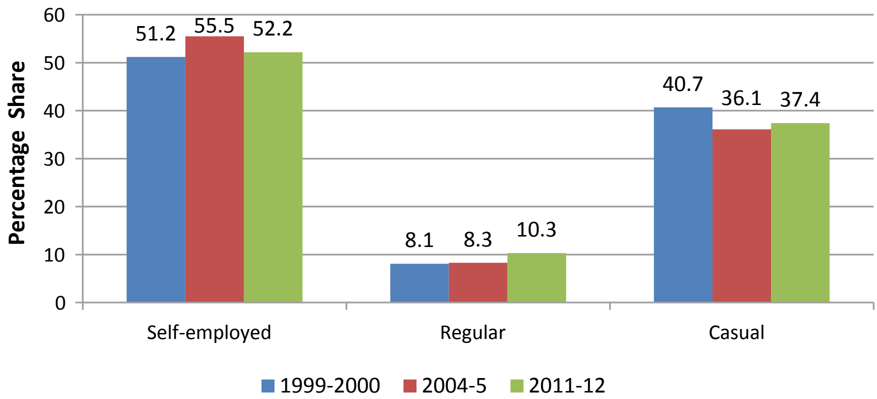

Fig. 1 Status of employment in rural areas. *Note* Usual Principal Status (UPS) workers aged 15 years and above. *Source* Unit level data of different rounds of NSS employment and unemployment

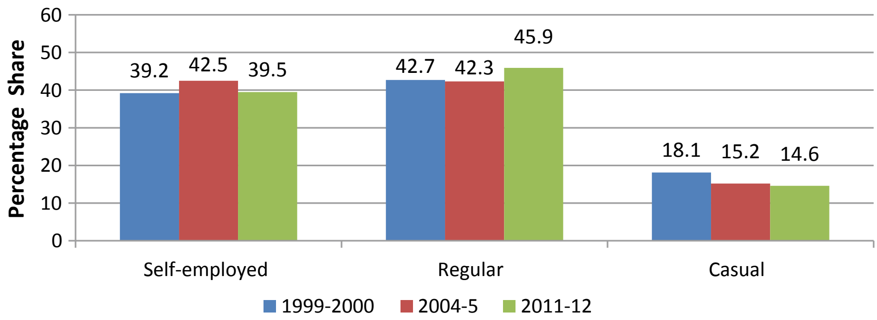

Fig. 2 Status of employment in urban areas. *Note* Usual Principal Status (UPS) workers aged 15 years and above. *Source* Unit level data of different rounds of NSS employment and unemployment

of employment in urban areas, while the share of casual wage labour was around of one-fourth of wage labour workers in 2011–12. The share of regular worker was substantially higher in urban areas and it increased between 2004–5 and 2011–12.

2.2 Formal/Informal Sector

Another important segmentation of Indian labour market is in the form of formal and informal sector. NCEUS highlighted this aspect of segmentation of labour market. But it considered all self-employed in the informal sector. In the present analysis, we included part of self-employed who are graduate and above as working in formal sector. It is a crude estimation under the assumption that a graduate self-employed would be part of formal sector. In addition, in the formal sector, we include all wage workers whether regular or casual who works in corporate or public sector and workers who work in enterprises employing 10 or more workers.

The comparison of 2011–12 over 1999–2000 shows marginal increase in the share of self-employed and casual workers in the formal sector at the cost of regular workers (Fig. 3). It goes against the common notion that with economic development the larger proportion of regular workers are likely to work in formal sector. However, the share of regular workers in formal sector was still more than half but it declined between 1999–2000 and 2011–12.

In the informal sector, self-employed constitutes more than half of all informal workers, followed by casual workers whose share is more than one-third. The share of regular workers is around one-tenth (Fig. 4). The share of both self-employed and regular workers went up in between 1999–2000 and 2011–12 at the cost of casual workers.

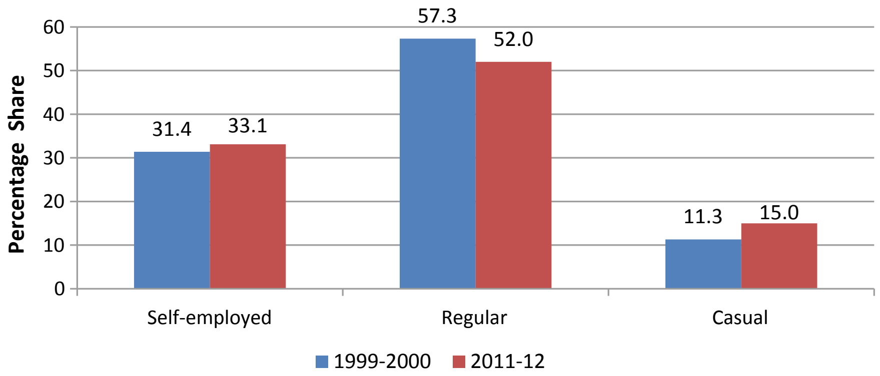

Fig. 3 Status of employment in formal sector. *Note* 1. Formal sector includes all workers working in public and corporate sector, workers working in enterprises with 10 or more workers and graduate self-employed. 2. Usual Principal Status (UPS) workers aged 15 years and above. *Source* Unit level data of different rounds of NSS employment and unemployment

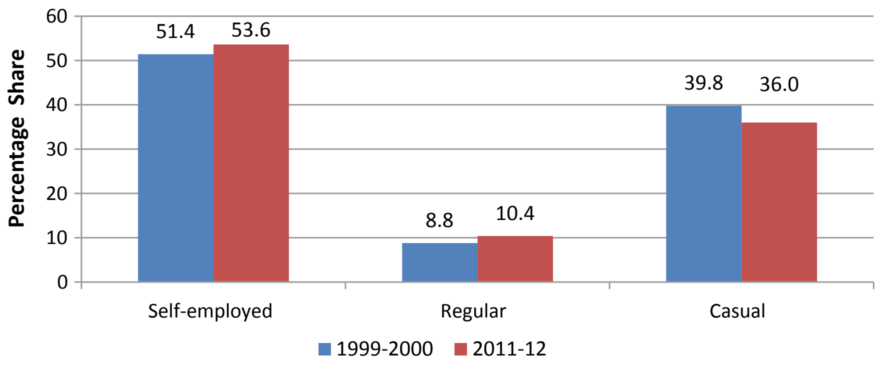

Fig. 4 Status of employment in informal sector. *Note* Same as Fig. 3. *Source* Same as Fig. 3

Table 1 Formal sector employment across social groups

Share of formal sector employment in total, 2011–12 (UPS), 15+						
Sector	Scheduled caste	Scheduled tribe	Other backward classes	Muslim	Dominant group	Total
Rural	12.07	8.39	10.95	11.29	17.89	12.09
Urban	36.13	45.68	37.81	22.63	55.95	41.40
All	17.26	11.91	17.60	15.52	33.97	20.25

Include public, corporate and >10 workers and graduate self-employed
Source NSS unit level data, 2011–12
Note All workers included

The analysis in Table 1 showed formal-informal break up across status of workers over the last one decade.

There is substantial difference in the spread of formal sector between rural and urban areas. In urban areas, over two-fifth of all employment was formal in 2011–12 but in rural areas formal sector constituted only one-twelfth of all employment. Even with this broad definition of formal sector, the share of formal sector employment in India was only one-fifth.

There was substantial variation in formal sector employment across various social groups. The share of the scheduled tribes (STs) in the formal sector was lowest but for other social groups also like scheduled caste (SCs), other backward class (OBCs) and Muslim it was not substantially higher than STs. The dominant group constituting forward caste—Hindu and religious minorities like Sikh, Jain, Christian, and Buddhist reported much higher share of formal sector employment. In the urban areas more than half of employment of dominant group was in formal sector but in rural areas, it was much lower. Interestingly, in urban areas the share of formal sector jobs for STs was much higher with 45% share of all urban jobs. The overall presence

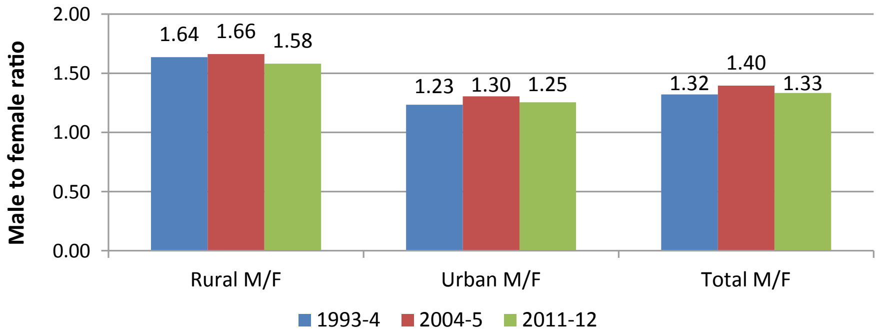

Fig. 5 Gender differential in regular wage. *Note* Usual Principal Status (UPS) workers aged 15 years and above. *Source* Unit level data of different rounds of NSS employment and unemployment

of STs is much lower in urban areas but their higher share in urban formal jobs is due to benefits of reservation in public jobs (ILER 2014).

Other labour market segmentation would be examined on the basis of wages/earnings.

2.3 Gender Differential in Wages

Gender differential in regular wage rates widened between 1993–94 and 2004–5 but it narrowed thereafter (Fig. 5). But hardly any change in the last two decades. There is marginal difference in rural and urban areas. Rural areas showed some decline in gender gap whereas urban areas showed marginal increase. Gender gap in wages for regular workers is substantially higher in rural areas compared to urban areas. The main factor seems to be much larger presence of government and public sector jobs in urban areas where gender wage discrimination is comparatively less.

Gender gap in wage rate for casual workers is much higher in urban areas compared to rural areas. Gender differential in casual wage rate has shrunk substantially in the last decade in both rural and urban areas (Fig. 6). One possible reason could be MGNREGA (Mahatma Gandhi National Rural Employment Guarantee Act) that raised reservation wage of female workers more compared to male workers.

Taking both regular and casual workers, it can be safely said that gender gap for wage workers has declined in the last two decades.

2.4 Regular-Casual Wage Differentials

Regular wage continue to be more than double of casual workers in both rural and urban areas (Fig. 7). Regular- casual wage differential narrowed in the last decade

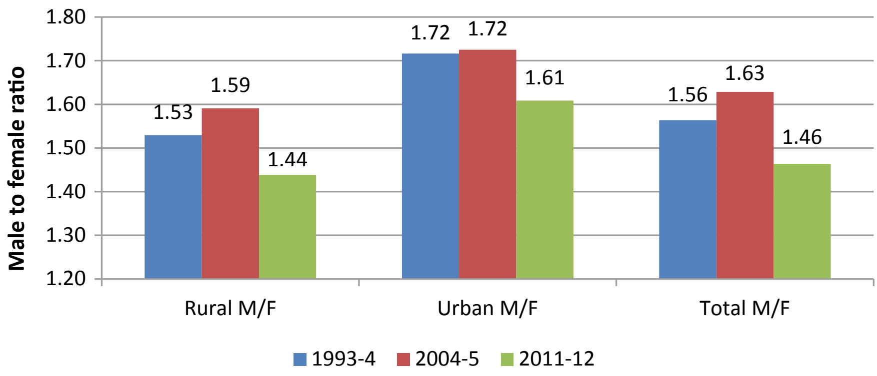

Fig. 6 Gender differential in casual wage. *Note* Usual Principal Status (UPS) workers aged 15 years and above. *Source* Unit level data of different rounds of NSS employment and unemployment

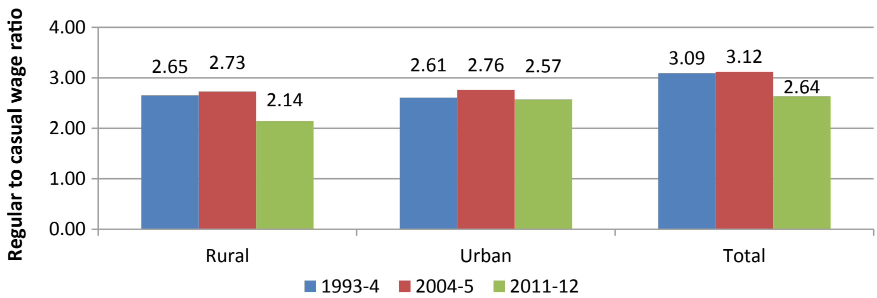

Fig. 7 Regular to casual wage differential. *Note* Same as Fig. 6. *Source* Same as Fig. 6

because of faster growth of casual wages compared to regular, which originated from increasing demand of casual work in non-agricultural activities particularly in the construction sector. The decline in wage differential was much larger in rural areas and in urban areas, it showed only marginal decline in the last two decades. The reason lies in increase in reservation wage of rural casual workers.

2.5 Urban-Rural Wage Differential

Urban to rural wage differential showed marginal increase for regular workers in the last two decades (Fig. 8). But urban-rural wage differential for casual workers showed continuous and substantial decline during the same period. It could be the consequence of increase in reservation wage in the rural areas and rise in the proportion of commuters for job from rural to urban areas.

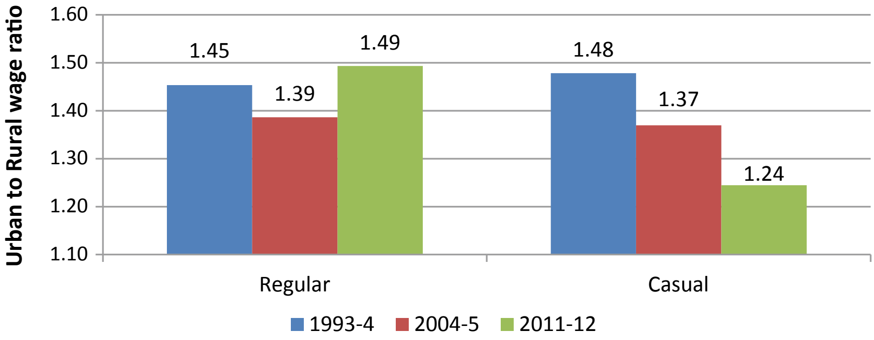

Fig. 8 Urban to rural wage differential. *Note* Same as Fig. 6. *Source* Same as Fig. 6

2.6 *Wage Differentials Across Social Groups*

It is clear from Table 2 that graduates belonging to all socio-economic groups earned substantially higher salary than high school pass regular workers. But there exists substantial wage differential between 'Dominant Group' (mostly upper-caste Hindu) and all other socio-economic groups for graduate & above regular workers. Their wage premium at this level of education was at least 40% from the average even when one-third of 'Dominant Group' category workers were at least graduates in urban areas (Table not presented). The difference in quality of education across socio-economic groups is unlikely to explain such large premium on the average earnings.

As a whole, across broad groups, wage differentials did not increase over time across gender, work status, urban-rural residence and social groups except for increasing gap within tertiary educated regular wage workers. As the analysis across various segmentation of labour market did not clearly indicate incidence of increasing dualism in the labour market, we extend our analysis to earning inequality among wage workers in its various characteristics.

Table 2 Daily wage differential across social groups for regular workers (2011–12)

Education	ST	SC	OBC	Muslim	Dominant group	Total
Not literate	135	169	176	165	172	169
Up to primary	186	197	191	168	208	191
Up to middle	201	211	223	206	242	222
Up to higher secondary	417	334	321	315	398	354
Graduate and above	585	548	573	552	816	690
Total	353	302	341	272	530	392

Note Usual Principal Status (UPS) workers aged 15 years and above
Source Unit level data of different rounds of NSS employment and unemployment

3 Earning Inequality Among Wage Earners

Overall earnings inequality [Gini, GE(0) and GE(1)] has increased between 1999–2000 and 2004–5 but substantial decline was observed between 2004–5 and 2011–12 (Table 3). The contribution to the decline in overall inequality in the latter period came largely from decline in inequality in lower half of the earnings distribution that is captured through GE(0). Reflection of this phenomenon was observed in the analysis of the previous section. The analysis in forthcoming sections would show two related phenomena. First, earning distribution of casual and regular wage earners was getting closer over time and it showed up clearly in 2011–12. Second, this is caused by higher growth of casual wage earners earnings and bifurcation of formal sector regular wage earners distribution between informal workers and formal workers. It also would be observed that earning distribution of informal sector regular workers and formal sector informal regular workers substantially narrowed.

GE(2) that captures inequality in the upper half of the earning distribution rose continuously for the whole period. It would be observed later that incremental net earnings of graduates rose continuously over time.

3.1 Earning Inequality Between Regular and Casual Wage Earners

Figure 9 shows the KDF distributions of weekly earnings per day for the casual and regular workers—taking both the urban and rural areas and the formal and informal sectors together. The distribution of earnings of casual workers over the years was less unequal and inequality did not show any increase. Earnings of regular workers were substantially unequal (Mazumdar et al. 2017). A major reason for the difference is that regular wage workers have much greater variation in human attributes, particularly in education that we have already observed. There is a big difference between manual and non-manual wage differences for regular workers, but not for the casual, reflecting dispersion by skill and education for the former category (Sarkar and Mehta 2010). It portrays vividly the nature of the relative increase in casual wages over time. The casual earning distributions had a much more prominent

Table 3 Trends of earnings inequality of wage workers

Period	Gini	GE(0)	GE(1)	GE(2)
1999–2000	0.540	0.510	0.551	1.005
2004–5	0.557	0.548	0.594	1.057
2011–12	0.510	0.454	0.514	1.072

Source Various rounds of NSS unit level data

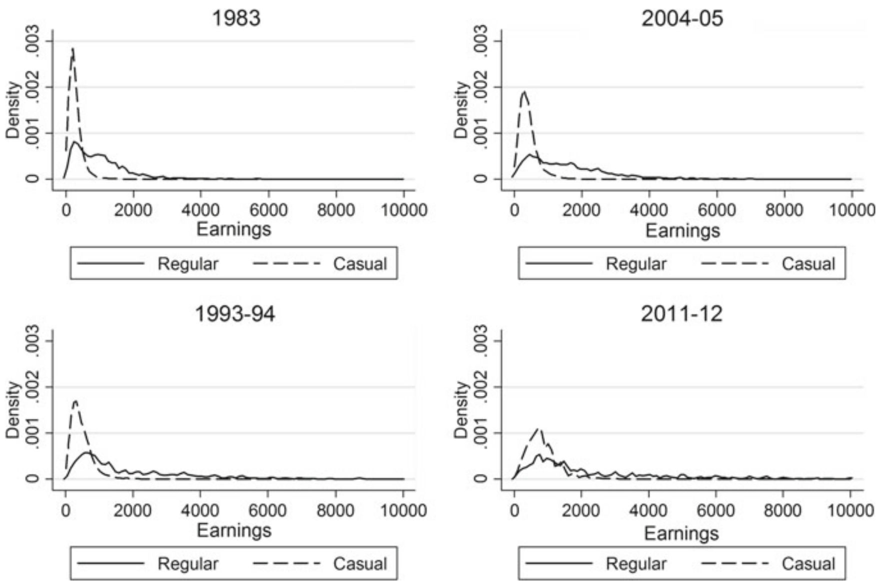

Fig. 9 KDF distributions for casual and regular wage earners (weekly earnings in Rs.), various NSS rounds. *Source* Mazumdar et al. (2017)

mode, but the mode had diminished in value over time and the decline in mode was substantial in pre-reform period of 1980s.

Earlier studies (Mazumdar and Sarkar 2008) of the working of casual wage market have noticed the strong mode for the earnings distribution of casuals. The only variable which seemed to be significant in the explanation of whatever variance existed was the socio-economic region. Casual labour earnings are generally higher in more prosperous regions. Although a great deal of more research remains to be done on the wages in the casual labour market in recent years we can hypothesize that part of the increase in relative earnings noticed in Fig. 9 are due to the growth of new prosperous regions. This could be due to the effect of the enhanced public employment programmes in rural areas, shift of labour to urban areas, as well as the decentralization of urban growth which has supported to growth of new urban centres.

The distribution of earnings of casual workers had also been spread out as the earnings of an increasing proportion of the casuals had come nearer the regulars, particularly in the region between the mode and the median. It had been approaching the distribution of regular wage earners over the successive rounds of the NSS surveys, until it more or less coincided with the latter in this particular segment in the year 2011–12.

We explore two factors that could be responsible for the earning inequality—these are examined one by one.

3.2 *Earnings Differentials Among Regular Wage Workers by Education*

It is analysed at two levels. First, we present wage differential among regular wage workers at mean and at different points of the wage distribution. As these are gross returns to education, in the next level we control influence of other factors and present net returns to education.

3.2.1 Earning Differential by Education Level for Regular Workers

The information presented in Table 4 are striking in revealing that for the whole economy (all sectors taken together) in the first post-reform period (from 1993–94 to 2004–5), mean wage differentials rose marginally at secondary level but it increased substantially at graduate and above level from ratio of 1:3.6 in 1993–94 to 1:4.6 in 2004–05. It gives credence to the argument of the skilled demand bias of technological change. To the extent, the employment of regular workers reflects the demand-side of labour market, the distribution of regular workers should shift to educated ones. In the second post-reform period between 2004–5 and 2011–12, there was some reduction in the mean wage differential across all education levels. It is quite likely that in urban areas where major section of regular workers reside, less educated (educated up to school level) experienced higher wage growth. They mostly belong to the lower part of the earning distribution of regular workers that led to the narrowing of wage differentiation across various education levels. Interestingly, overall wage differential at mean in the second post-reform period also increased when mean differences between various levels of education showed either clear decline or stagnancy. It is quite possible that distribution of earnings within different levels of education worsened over time.

Table 5 presents the distribution of wage earnings within each educational level. It gives a rough summary of the distribution of wage earnings within each educational group, and its changes over time. Thus the index of the median wage relative to the first quartile gives some idea of the distribution in the lower part of the distribution,

Table 4 Wage differential at mean between groups for regular workers

Level of schooling	1993–94	2004–05	2011–12
Not literate	1.0	1.0	1.0
Up to primary	1.3	1.3	1.1
Up to middle	1.4	1.3	1.3
Up to secondary and higher secondary	2.1	2.3	2.1
Graduate and above	3.6	4.6	4.1
Total	2.0	2.4	2.6

Source Mazumdar et al. (2017)

Table 5 Daily wage differential within education group for regular wage earners

Schooling	Percentile	1993–94	2004–05	2011–12
Not literate	25th	1	1	1
	50th	2.2	2.2	1.5
	75th	2.9	2.6	2.3
Up to primary	25th	1	1	1
	50th	2	2.1	1.4
	75th	2.8	2.5	2.1
Up to middle	25th	1	1	1
	50th	1.9	1.9	1.5
	75th	2.6	2.2	2.3
Up to higher secondary	25th	1	1	1
	50th	1.9	2.5	1.6
	75th	2.6	3.5	3.1
Graduate and above	25th	1	1	1
	50th	1.6	2.3	2.0
	75th	2.0	3.0	3.3

Source Mazumdar et al. (2017)

while the index of the third quartile relative to the median would be an indicator of the distribution at the top half of the distribution.

The major point which stands out from Table 5 is that the changes over the three NSS surveys covering the post-reform years had been quite significant. The changes in the first decade of post-reform and second decade of post-reform period are quite divergent. First, 50th/25th ratio either increased or stagnated in between 1993–4 and 2004–5 whereas in between 2004–5 and 2011–12 it showed sharp decline in all education classes. Second, the 75th/25th ratio showed sharp decline in the whole period for all educational groups up to middle education level. But for the upper two educational classes in the whole period, perceptible increase was observed. Third, only within graduates & above, wage differential between 25th and 75th percentile had increased in both decades. Examining the data for individual education groups, we can conclude that the major increase in inequality at the upper end had been due to changes within the top two education groups—higher secondary and graduate wage earners that was observed in G(2) values in Table 3.

3.2.2 Returns to Education

We now present results on the returns to education at various levels from estimated earnings functions for the three rounds of the NSS, 1999–2000, 2004–05 and 2011–12. For this exercise, all wage workers—regular and casual were included. It allowed us to look at the net effect of education on earnings at various levels, controlling for other measurable factors like gender, rural-urban location, industry, days of work and formality. These variables including education explained around two-third of the variance in earnings. It is interesting to note that for the latest year of 2011–12 that represent the fuller results to date of the reform process, there had been a substantial fall in the proportion of variance explained (not tabulated). Evidently, other factors affecting the quality of labour and/or institutional variables had a large and increasing effect on wage earnings of regular workers. The incremental impact of successive levels of education on regular earnings can be observed in Fig. 10.

A major difference is seen in the differentials returns for 1999–2000 and those for the subsequent NSS rounds. The incremental earnings from 'some primary education' had been unusually large for all three NSS rounds, moderating a little in 2011–12. After this level, there is clear indication of increasing returns to education for the successive stages. But the big difference is that from 1999–2000 to 2011–12 the incremental returns up to the higher education level consistently declined up to the level of the higher secondary. But the big difference is that while after 1999–2000 the increasing returns stopped at the level of higher secondary, they go on strongly through college (graduate +) levels. It supports the evidence of higher returns to education at graduation & above level that was shown in Tables 4 and 5.

One of the main factors that increased its importance in the net return to education regression was formality of employment among the regular wage earners. In the following section, we expand this analysis.

3.3 Formality and Informality Among Regular Workers

An issue much discussed in the literature is the relative importance of formality of employment (or the impact of the formal sector) relative to that of education. There are indeed two alternative definitions of the formal-informal distinction. We can make the distinction either on the basis of the type of enterprise in which the worker works (called the *sector* definition) or on the criterion if the worker receives some social security payment (which can be called the *type of worker*).

Following NCEUS conception, the formality-informality distribution has been examined in two perspectives. First one is formal and informal sector employment where formal sector is defined as consists of workers who work in enterprises employing 10 or more workers with power. Second one is formal employment has been defined as regular workers having any form of social security.

The alternative definitions give quite different pictures of wage distribution for the formal and informal classification, as can be seen in Fig. 11. It is clear that already in 1999–2000 the KDF from informal *workers* (based on the social security criterion) was pulled more to the right compared to the distribution based on the sector classification. This difference was clearly accentuated in the later NSS surveys. In the 2011–12 round, the mode of the distribution for the formal sector was the same as that for the informal sector (on the enterprise based classification). But in the alternative classification the mode for the formal *workers* (in receipt of some social

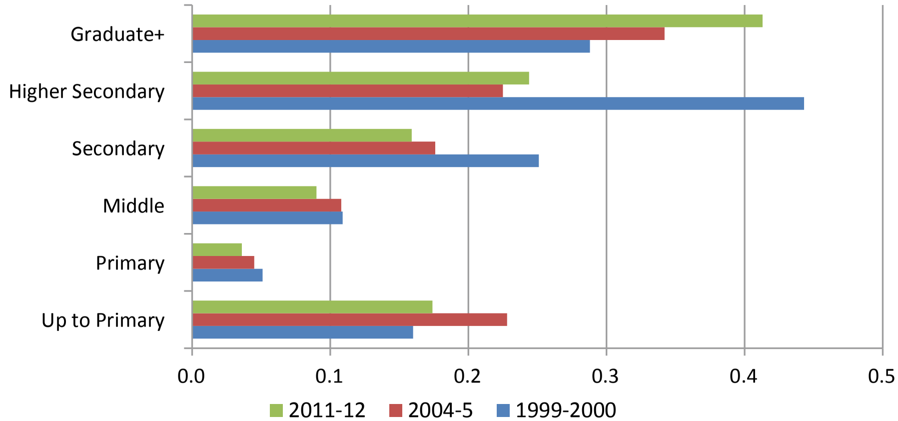

Fig. 10 Incremental net additions to log earnings for successive levels of education for all workers (casual and regular). *Source* Adapted from Mazumdar et al. (2017)

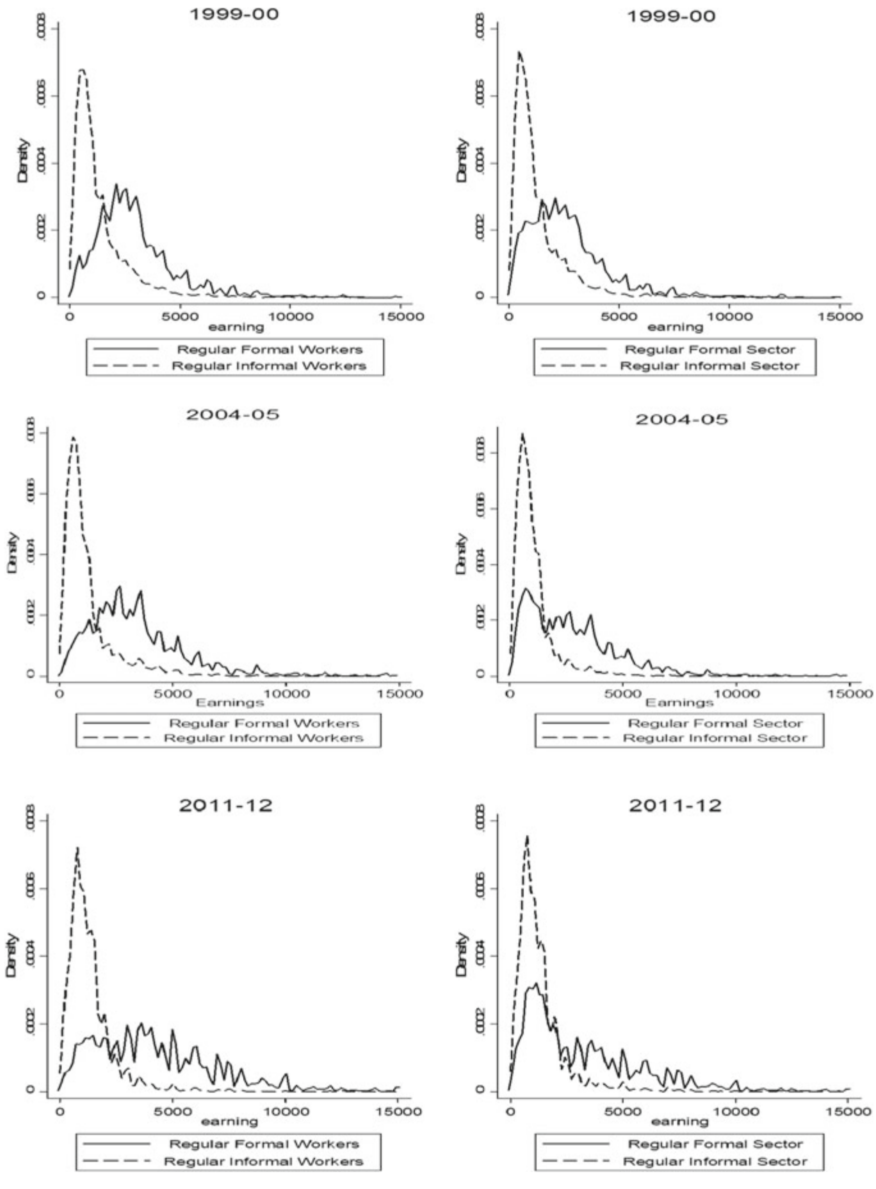

Fig. 11 Wage distribution for the formal-informal types, 1999–00, 2004–05 and 2011–12. *Source* Mazumdar et al. (2017)

Table 6 Cross classification of formal sector and formal worker among regular workers, 2011–12

		Formal workers	Informal workers	Total
Formal sector	Row (%)	61.8	38.2	100.0
	Col (%)	91.6	40.8	61.8
Informal sector	Row (%)	9.0	91.0	100.0
	Col (%)	8.4	59.2	38.2
Total	Row (%)	41.2	58.8	100.0
	Col (%)	100.0	100.0	100.0

Source Calculated from unit level data of NSSO, 2011–12

security payment) shifted to the right. In fact, the whole distribution was significantly above that of informal *workers*—whose earnings were bunched strongly at the low mode. It appears that the formal–informal wage differential is much more when the formal workers are defined as those with some social security payments, and this phenomenon has become stronger with the recent accelerated growth of the economy.

Table 6 gives the cross classification of workers based on these two alternative definitions.

The cross classification in Table 6 shows that over two-third of regular workers belong to the formal sector whereas little over two-fifth of workers can be termed as formal workers. It means that a substantial proportion of formal sector workers are informal workers. This line of analysis is expanded further in the next section.

3.4 Formality-Informality Earning Differential Among Regular Workers

The discussion in previous section raised interesting issues. We saw in Table 6 that formal and informal workers constituted substantial part of workforce in the formal sector. Formal workers in the informal sector also exist but these constituted less that 10% of informal sector workforce.

It would be useful to distinguish formal and informal workers in the formal sector. Figure 12 makes it clear. In between 1999–2000 and 2004–5, the share of formal sector worker marginally went up but the share of formal workers in the formal sector came down leading to 7 percentage point decline in the share of formal workers. Between 2004–5 and 2011–12, the share of formal sector workers among regular workers increased by more than 6 percentage points but it was accompanied by even larger decline in the share of formal workers in formal sector. It resulted in overall decline in the share of formal workers during this period. Even substantial rise in formal sector workers is no guarantee that the share of formal workers would increase.

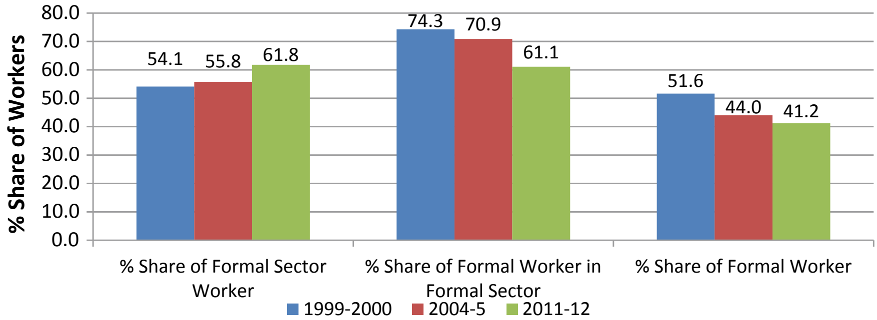

Fig. 12 Formality and informality among regular workers. *Source* Various rounds of NSSO unit level data

If we consider both formal and informal sector together then the share of formal workers among regular workers was only two-fifth in 2011–12 and it showed substantial decline from more than half of its share in 1999–2000 (NCEUS 2007).

In Fig. 13a–c we present Kernel Density Graphs of earnings of regular workers classified into three groups. These are formal sector formal workers, formal sector informal workers and informal sector workers.

As expected the mode of the earning distribution of informal workers lied to the left of formal sector informal workers. Some overlap of earnings between informal sector worker and formal sector informal worker but a section of latter group of workers earned much higher than informal sector workers in 1999–2000 (Fig. 13a). Formal sector formal workers exhibited multiple modes showing bunching of workers at various levels of earnings. Further, the right tail was much longer than other two groups. This group of workers who get social security also include highly paid salaried workers in the private corporate sector as well as in public sector including government.

Compared to 1999–2000, in 2004–5 the earnings of even larger proportion of formal sector informal workers were similar to the earnings of informal workers (Fig. 13b). Even the mode of the earning distribution was almost similar but the mode is far higher for the earnings of informal workers. However, the right side of the distribution was far thicker for the formal sector informal worker compared the informal sector workers indicating presence of some proportion of formal sector informal workers who earned considerably more than the informal workers.

In 2011–12, the earnings of formal sector informal workers were almost similar to the earnings of informal sector workers (Fig. 13c). These two groups of workers were becoming increasingly similar in terms of earnings structure and they have the common characteristic of having no social security. The labour market of these two groups of workers was becoming increasingly integrated. The multiple modes of the distribution of formal sector formal workers over the years had shifted to the right and in 2011–12, the tallest modes were around weekly earnings of Rs 4000 compared to that of Rs. 3,000 in 1999–2000. The gain in the earnings of regular workers during

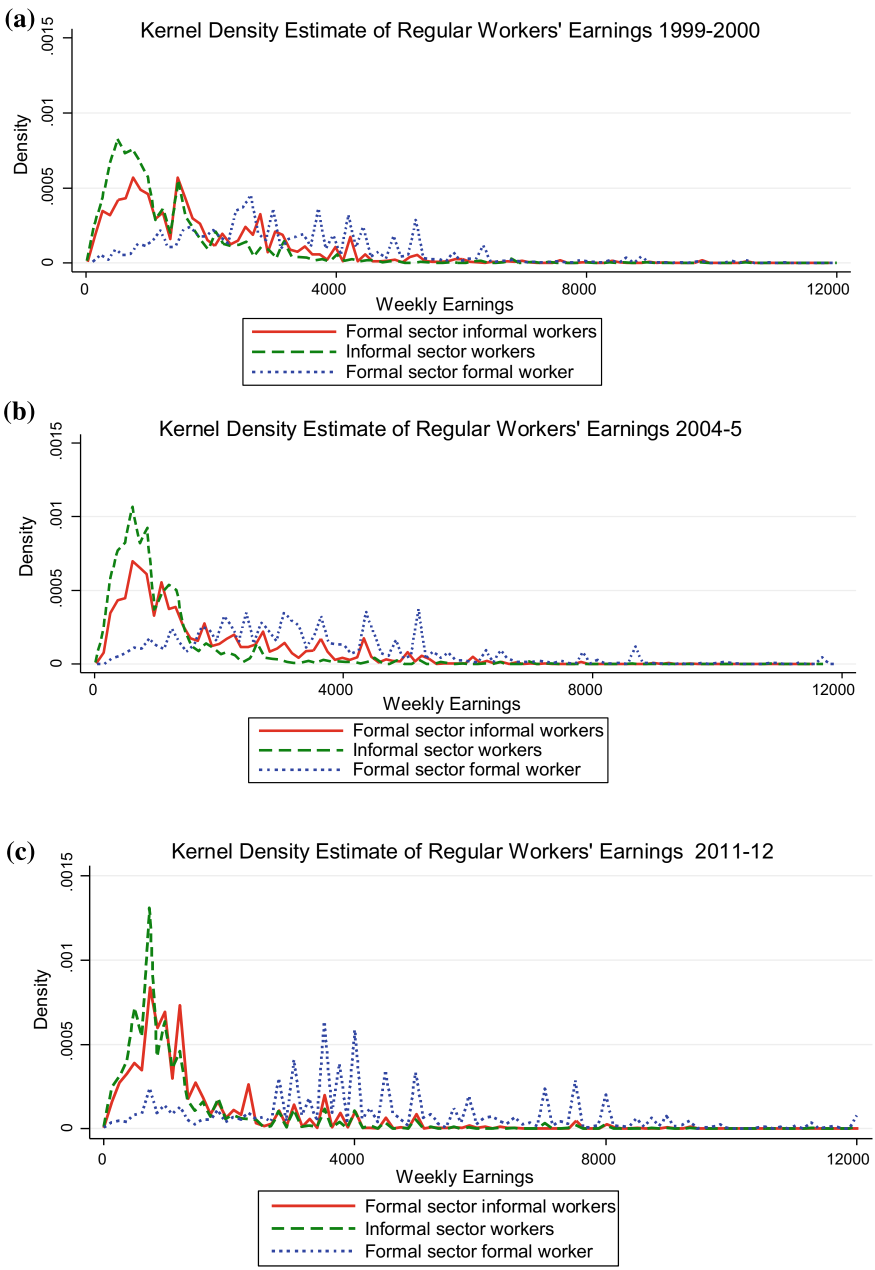

Fig. 13 KDF distributions for formal and informal regular wage earners (weekly earnings in Rs.), various NSS rounds at 2011–12 prices. **a** 1999–2000, **b** 2004–5, **c** 2011–12. *Source* Computed from various rounds of NSSO unit level data

the period 1999–2000 to 2011–12 had been cornered by this group of workers. For informal workers and formal sector informal workers such clear improvement in earnings could not be discerned.

In nutshell, it is observed from Fig. 13a–c:

1. Some overlap of earnings between informal sector worker and formal sector informal worker but a section of latter group of workers earned much higher than informal sector workers in 1999–2000.
2. Compared to 1999–2000, in 2004–5 the earnings of even larger proportion of formal sector informal workers were similar to the earnings of informal workers.
3. In 2011–12, the earnings of formal sector informal workers were almost similar to the earnings of informal sector workers. These two groups of workers are becoming increasing similar in terms of earnings structure and having no social security.

This trend indicates that the dualistic pattern of labour market between formal and informal sectors is getting obliterated. In its place, the dualism is developing in the form of smaller section of formal workers with better salaries and social security benefits and a large pool of informal sector workers and contract workers belonging to formal sector of the economy.

But wage labour market constitutes both regular and casual workers. As we have seen in earlier analysis that one-fourth of wage workers were still casual workers. We examine whether dualistic pattern can be observed when we examine wage levels of all four section of wage workers that include casual wage workers as well.

4 Dualism in the Wage Labour Market

We compared nature of dualism in terms of daily wage rate for four categories of workers identified in earlier section. These are casual wage workers, regular informal workers, regular formal sector informal workers and regular formal sector formal workers. These categories of workers differed distinctly in terms of average wage level in 1999–2000. Wage of regular informal workers was almost double of casual wage workers and that of regular formal sector informal and formal workers' wages were almost three and half times and five and half times of casual wage workers respectively. In the last two decades, the wage of casual workers increased and that of regular informal workers stagnated. Wages of regular formal sector informal workers declined continuously but wages of regular formal sector formal workers shot up substantially in between 2004–5 and 2011–12. It clearly depicts the trend of increasing dualism in Indian labour market (Fig. 14).

However, mean wage rate does not provide ideal summary presentation of wage rate of different categories of workers as wage rates can get affected by extremely large or small values. In Fig. 15, we analyse trend in different segments of wage rate in terms of median wage.

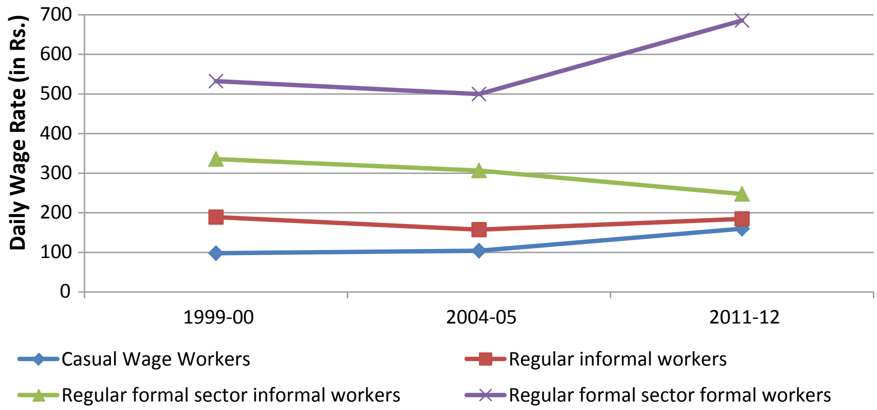

Fig. 14 Mean daily wage rate (in Rs.) at constant 2011–12 prices. *Source* Computed from various rounds of NSSO unit level data

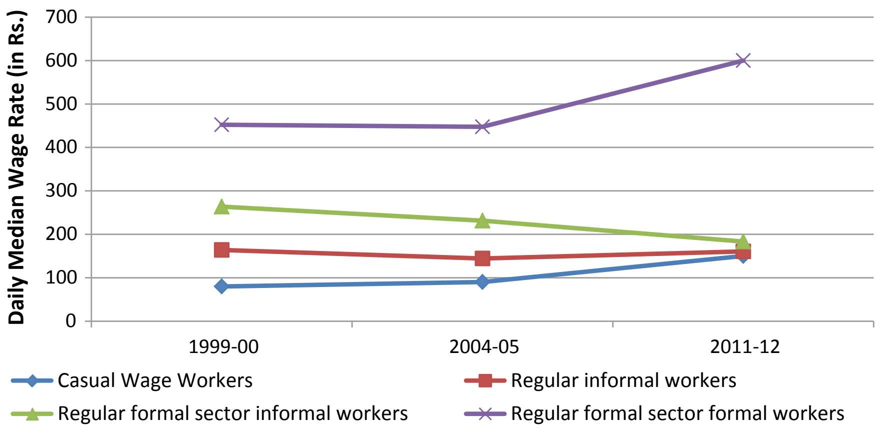

Fig. 15 Median daily wage rate (in Rs.) at constant 2011–12 prices. *Source* Computed from various rounds of NSSO unit level data

Median wage rate captures the dichotomy of Indian wage labour market succinctly. From variegated wage levels in 1999–2000, except for regular formal sector formal workers, other three categories of wage labourers have virtually converged in 2011–12. In the year 2011–12, the regular informal sector median wage rate was only 15% higher than casual wage rate and that of regular formal sector informal workers wage rate was 50% higher.

In terms of wage rate, there is clear trend of development of dual wage labour market with workers with social security benefits and workers without it.

It is important to understand the reason for this increasing dualism in the Indian labour market. The reason lies in substantial increase in the youth labour force. The increase in male labour force went up by 35 millions in between 2004–5 and 2011–12 from 307 million in 2004–5. Ineffective labour market institution in the formal sector and absence of labour market institution in the informal sector has created a situation where unemployed youths with various level of education or skill are willing to work at a low reservation wage.

5 Conclusion

This paper analyses segmentation of labour market originating from various dimensions such as geographical and rural/urban location, status of workers, gender, level of education and skill, caste & religion, industry, institutions of labour regulation, etc.

As a whole, across broad groups, wage differentials did not increase over time across gender, work status, urban-rural residence and social groups except for increasing gap within tertiary educated regular wage workers. As the analysis across various segmentation of labour market did not clearly indicate incidence of increasing dualism in the labour market, we extended our analysis to earning inequality among wage workers in its various characteristics.

It showed that the distribution of earnings of casual workers had also spread out over the years and the earnings of an increasing proportion of the casuals had come nearer the regulars, particularly in the region between the mode and the median. It had been approaching the distribution of regular wage earners over the successive rounds of the NSS surveys, until it more or less coincided with the latter in this particular segment in the year 2011–12.

We observed some overlap of earnings between informal sector worker and formal sector informal worker but a section of latter group of workers earned much higher than informal sector workers in 1999–2000. But, compared to 1999–2000, in 2004–5 the earnings of even larger proportion of formal sector informal workers were similar to the earnings of informal workers. In 2011–12, the earnings of formal sector informal workers were almost similar to the earnings of informal sector workers. These two groups of workers are becoming increasing similar in terms of earnings structure and having no social security.

This trend indicates that the dualistic pattern of labour market between formal and informal sectors is getting obliterated. In its place, the dualism is developing in the form of smaller section of formal workers with better salaries and social security benefits and a large pool of informal sector workers and contract workers belonging to formal sector of the economy.

But wage labour market constitutes both regular and casual workers. We examined whether dualistic pattern can be observed when we examine wage levels of all four section of wage workers that include casual wage workers as well.

In terms of wage rate there is clear trend of development of dual wage labour market with workers with social security benefits (regular formal sector formal workers) and workers without it (constituting casual wage, regular informal sector and regular formal sector informal) workers.

It is important to understand factors leading to the increasing dualism in the Indian labour market. The reason lies in substantial increase in the youth labour force. The increase in male labour force went up by 35 millions in between 2004–5 and 2011–12 from 307 million in 2004–5. Ineffective labour market institution in the formal sector and absence of labour market institution in the informal sector has created a situation where unemployed youths with various level of education or skill are having similar reservation wage.

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Technology, Jobs and Inequality: Evidence from India's Manufacturing Sector

Radhicka Kapoor

1 Introduction

India's post-reform economic development has seen a sustained increase in the capital intensity of production in the manufacturing sector. The rising capital intensity of production is indeed a well-established fact in the literature (Das et al. 2009; Goldar 2000). The adoption of labour saving and capital intensive techniques of production in an economy that has a comparative advantage in unskilled labour is particularly puzzling and has attracted much attention. In fact, Hasan et al. (2013) have shown that India uses more capital intensive techniques of production in manufacturing than countries at a similar level of development and similar factor endowments.

There exists a vast literature examining the factors that determine the capital intensity of production across industries in the Indian manufacturing sector. Several of these studies have highlighted the significance of factor market imperfections in explaining the rising capital intensity of production (Hasan et al. 2013; Sen and Das 2014). India's labour market regulations, in particular, have attracted much attention in this context. It is believed that the stringencies and rigidities in labour laws have imposed costs on labour use, thereby pushing firms towards greater capital intensity. This, in turn, has reduced labour demand and curtailed gains from trade based on factor-abundance driven comparative advantage. However, it has been argued in the literature that labour regulations cannot alone explain the rising capital intensity of production over time. Sen and Das (2014) attribute the increases in capital intensity to an increase in the ratio of real wage to rental price of capital which was mostly due to a fall in the relative price of capital goods. The decrease was driven by trade reforms in capital goods and falling import tariffs on them in the post-reform period. While these factors are pivotal, it is important to remember that rising capital intensity is also reflective of technological transformation. Technological progress has

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been capital-augmenting rather than labour augmenting during the globalization era. Consequently, Indian firms faced with easier access to foreign technology adopted more capital intensive techniques of production.

While the factors explaining the increasing capital intensity of production in India are well documented in the literature, the implications of this phenomenon for the labour market have attracted relatively less attention. The most immediate concern is the impact of labour saving techniques of production on job creation. Since the followers of Ned Ludd smashed mechanized looms in 1811, workers have worried about automation destroying jobs. In both the industrialized and developing world, there is growing anxiety regarding job prospects for large groups of middle-skilled workers on account of automation, computerization, and new technologies. In India, too, given the intensifying demographic pressures, the adoption of capital intensive methods of production in the manufacturing sector poses a significant challenge to productive job creation. While economists have often reassured that new jobs would be created even as old ones were eliminated, the adoption of capital intensive techniques will not affect all types of workers (unskilled versus skilled workers) uniformly. It has been shown in the literature that capital-augmenting technological change has favoured more skilled workers, replacing tasks performed by unskilled, and increasing the demand for skills. This has increased wage inequality between skilled and unskilled workers. For instance, in the case of the US economy, many commentators see a direct causal relationship between technological changes and the radical shifts in the distribution of wages between 1979 and 1995. The college premium (the wages of college graduates relative to wages of high school graduates) increased by over 25% during this period. Overall earnings inequality also soared: in 1971, a worker at the 90th percentile of the wage distribution earned 266% more than a worker at the 10th percentile. By 1995, this number had risen to 366% (Acemoglu 2002). Moreover, capital-augmenting technological progress has boosted capital's return and its share in the distribution of income. Guscina (2006) has shown that the decline in labour's share in national income over the past two decades in OECD countries has largely been an equilibrium, rather than a cyclical phenomenon, as the distribution of national income between labour and capital adjusted to capital-augmenting technological progress and a more globalized world economy.

In the Indian context, the literature on impact of the adoption of increasing capital intensive techniques of production on distribution of wages and income is limited. This paper attempts to fill this gap by examining the implications of rising capital intensity on wage and income structure in India's manufacturing sector. Using data from a sample of manufacturing firms from the Annual Survey of Industries, this paper presents new empirical evidence on the impact of adoption of capital intensive techniques of production on inequality at the firm level. It is important to mention here that India's manufacturing sector is characterized by dualism, i.e. the prevalence of a formal/organized sector which coexists with a large "unorganized sector". The latter accounts for a disproportionately large share of employment (90%), but a very small share of value added in manufacturing. The formal sector accounts for over 65% of total output and it is this sector which is the focus of analysis in our study. This is because it firmed in this sector which resorted to increasing mechanization and automation, while firms in the unorganized sector continued to employ relatively more labour intensive techniques of production. Moreover, India's labour regulations to which much of the high capital intensity of production is attributable cover only the organized sector. Though it would be useful to study both formal and informal sector firms, given the absence of comparable annual data on the unorganized sector, it is difficult to study both together.[1]

This paper organized as follows. We begin by examining some key trends in the organized manufacturing sector in Sect. 2. Is it the case that the capital intensity of production has increased in industries across the manufacturing sector, or is it just the more capital intensive industries that have resorted to increasing automation leading to greater disparities in the capital-labour ratio across the manufacturing sector? Is it the case that share of value added going to owners of capital have increased as compared to income going to labour? Has the wage differential between skilled and unskilled workers increased? In Sect. 3, we discuss an independent, though important change in India's labour market during this time i.e. the contractualization of India's workforce. This may well have driven some of the stylized facts we present in Sect. 2. In Sect. 4, we outline our empirical strategy to study the impact of rising capital intensity on inequality. We also describe the data used in the empirical analysis and present the main results. Section 5 puts forward some concluding remarks.

2 Key Stylized Facts

2.1 *Capital Intensity of Production Increased Across Industries*

The increase in the average capital intensity of production in the manufacturing sector is evident in Fig. 1. What is particularly important is that this increase in capital intensity was witnessed across all industries in the manufacturing sector. The trend growth in capital intensity of production across industries at the three-digit level over the last decade shows that the capital-labour ratio[2] has risen for all but eight industries (Fig. 2). Classifying industries on the basis of their capital intensity,[3] we find that this

[1]The National Sample Survey Organization's survey of unorganized manufacturing enterprises covers firms in the unorganized sector but data on this is available only quinquennially.

[2]Capital intensity is defined as the ratio of real fixed capital to total persons engaged. Capital is measured by fixed capital as reported in ASI. This represents the depreciated value of fixed assets owned by the factory on the closing day of the accounting year. It is deflated using WPI for machinery and equipment. Total persons engaged include workers (both directly employed and employed through contractors), employees other than workers (supervisory, managerial and other employees) and unpaid family members/proprietor etc.

[3]In order to classify industries as labour or capital intensive, we calculate the capital intensity for all industries in the organized manufacturing sector for every year from 1999 to 2011. An industry is classified as labour intensive if its capital intensity is below the median value for the manufacturing sector throughout the decade. Similarly, an industry is classified as capital intensive

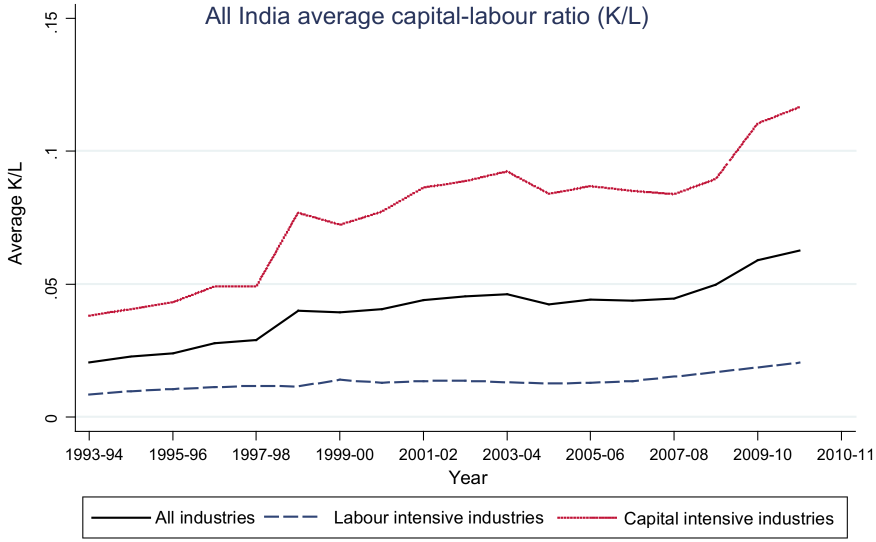

Fig. 1 Capital intensity of production. *Source* Author's calculations based on ASI publishes statistics, MOSPI

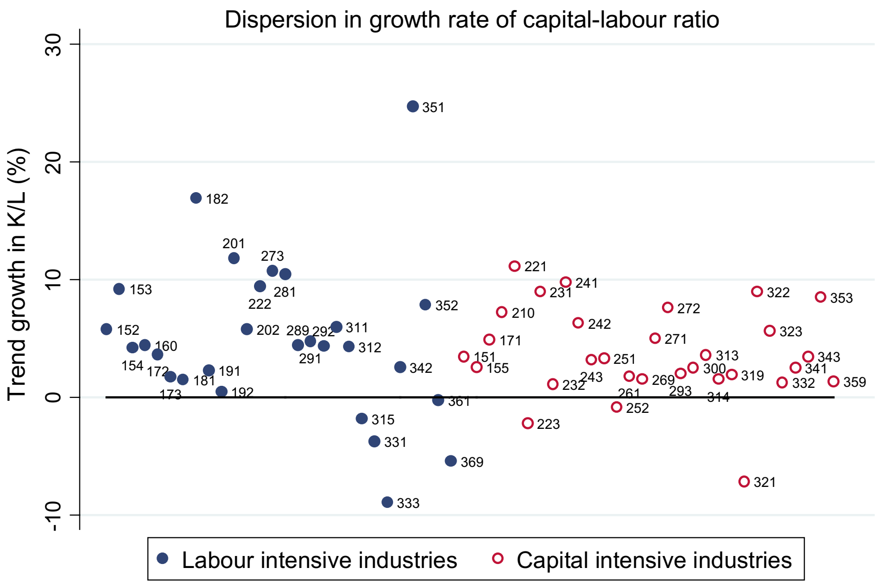

Fig. 2 Trend growth rate in capital intensity of production by industry (NIC-2004). *Source* Author's calculations based on ASI publishes statistics, MOSPI

ratio has increased not just in capital intensive but also labour intensive industries. Rising capital intensity of production, especially in labour intensive industries, is a cause of concern as it raises doubts about the capacity of the manufacturing sector to absorb labour and create jobs.

2.2 Labour Intensive Industries Grew Slower Than Capital Intensive Industries

The rising capital intensity of production in the manufacturing sector has been accompanied by another important phenomenon. Capital intensive industries have also grown significantly faster than labour intensive industries in terms of gross value added (GVA) (Kapoor 2015). This is contrary to what one would expect in an economy where labour is a source of comparative advantage. The rising capital intensity of production, coupled with the fact that labour intensive industries grew slower than capital intensive industries further makes the task of creating productive jobs for India's largely low-skilled and unskilled workforce more challenging (Fig. 3).

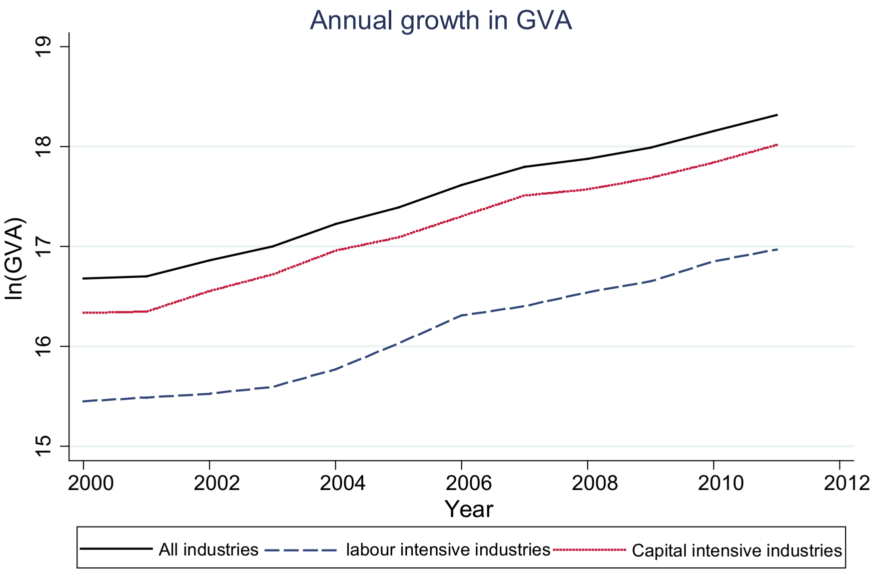

Fig. 3 Growth of value added in the manufacturing sector. *Source* Author's calculations based on ASI publishes statistics, MOSPI

if its capital intensity is above the median value for the manufacturing sector throughout the decade. The remaining industries are classified as ambiguous.

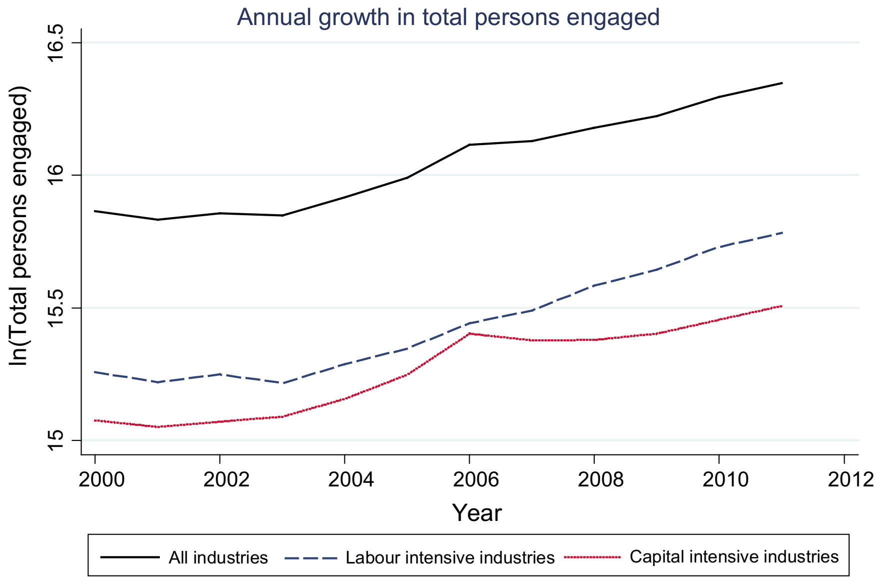

Fig. 4 Growth of employment in the manufacturing sector. *Source* Author's calculations based on ASI publishes statistics, MOSPI

However, when we look at the performance of industries in terms of employment generation, we find that despite having lower employment elasticity of output, capital intensive industries have generated reasonably high rates of employment growth (Fig. 4). Perhaps, this is because output growth in these industries was significantly higher. Table 1 shows that the industry which generated the highest employment growth over the last decade was in fact the most capital intensive industry i.e. manufacture of motor-vehicles, trailers, and semi-trailers. In fact, the trend growth of employment in capital intensive industries appears to be as high as in labour intensive industries. Of course, it is important to mention that the higher growth rates of employment in capital intensive industries could also be partly a result of the base effect i.e. lower initial values of employment. The disconnect between growth of employment and gross value added in the manufacturing sector during this period of rising capital intensity is also worth noting. Results from ASI show that while employment grew at the rate of about 4.6% p.a. between 2000 and 2012, real value added in organized manufacturing grew at almost double the rate (10.2% p.a.).

2.3 Changes in Distribution of Income

With growing capital intensity and the adoption of labour saving techniques of production, the importance of labour relative to capital is likely to decline. Consequently,

Table 1 Trend growth rate of employment across industries

	Industry	Trend growth of employment (%)
Labour intensive	Mf of food products and beverages	2.6
	Mf of tobacco products	−1.8
	Mf of wearing apparels; dressing and dyeing of fur	8.5
	Tanning and dressing of leather; Mf of luggage, handbags, saddlery, harness and footwear	7.6
	Mf of wood and products of wood and cork, except furniture; Mf of articles of straw and plaiting materials	5.1
Capital intensive	Mf of coke and refined petroleum products and nuclear fuel	6.4
	Mf of chemicals and chemical products	0.4
	Mf of rubber and plastic products	7.4
	Mf of basic metals	5.4
	Mf of office, accounting and computing machinery	8.4
	Mf of motor-vehicles, trailers and semi-trailers	10.7

Source Author's calculations based on ASI published data

one would expect the shares of income earned by equipment owners/owners of firms to rise relative to that of labourers. This is exactly what we observe in the Indian manufacturing sector (Fig. 5). The share of total emoluments paid to workers declined from 28.6 to 17.4% of GVA between 2000–2001 and 2011–2012. Significantly, the share of wages to workers in GVA declined steeply from 22.2 to 14.3% over the same period. The interest paid out by firms dwindled from about 29 to 19% of GVA.[4] Importantly, the share of profits in GVA rose from 19.9% in 2000–2001 to 46.2% in 2011–2012. The declining bargaining power of workers vis-à-vis capitalists reflected in these figures raises the issue of equity in the distribution of income. However, it needs to be examined whether these trends were indeed a result of higher capital intensity of production, or there were some other factors at play.

[4]It is beyond the scope of this study to understand the impact of interest rate policy on these estimates.

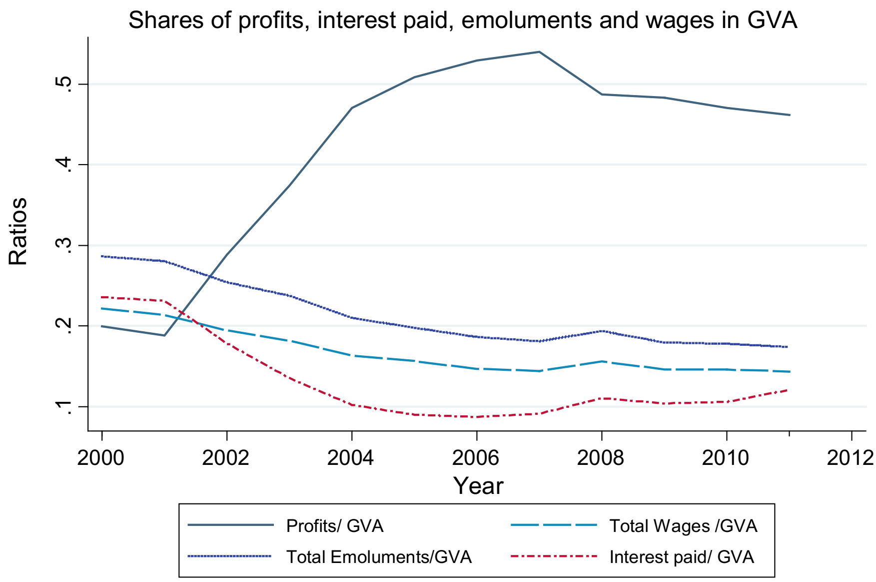

Fig. 5 Changes in key distribution of value added. *Source* Author's calculations based on ASI publishes statistics, MOSPI

2.4 Skilled Versus Unskilled Workers

While the adoption of capital intensive techniques of production may have diluted the importance of labour, the impact of mechanization has been differential across various categories of workers. Capital-augmenting technological progress is not just about introduction of machines but also about the workers who have developed a set of machine-specific skills. While machines are generally substitutes for unskilled labour, they are also complements to skilled labour. Across the world, mechanization has resulted in rising importance of a new portfolio of occupations i.e. engineers, machine builders, toolmakers and a wide range of skilled machine operators who maintain and manage these machines. The increasing role of this portfolio of occupations vis-à-vis production workers has led to the former enjoying a larger share of the total wage pie. The share of wages to production workers has fallen from 57.6% of the total wage bill to 48.8%, while that of supervisory and managerial staff[5] increased from 26.1 to 35.8% between 2000 and 2012. The rising disparity in the wages of supervisory and managerial staff, and production workers is also reflected in the fact that the wages of the latter type of workers remained roughly flat over the last decade, while those of the former category rose sharply (Fig. 6). The ratio of the average wages of supervisory and managerial staff to production workers increased from 3.57 to 5.82 over the last decade.

[5]The supervisory and managerial staff reported in the ASI dataset captures the category of skilled workers, while the production workers capture unskilled workers.

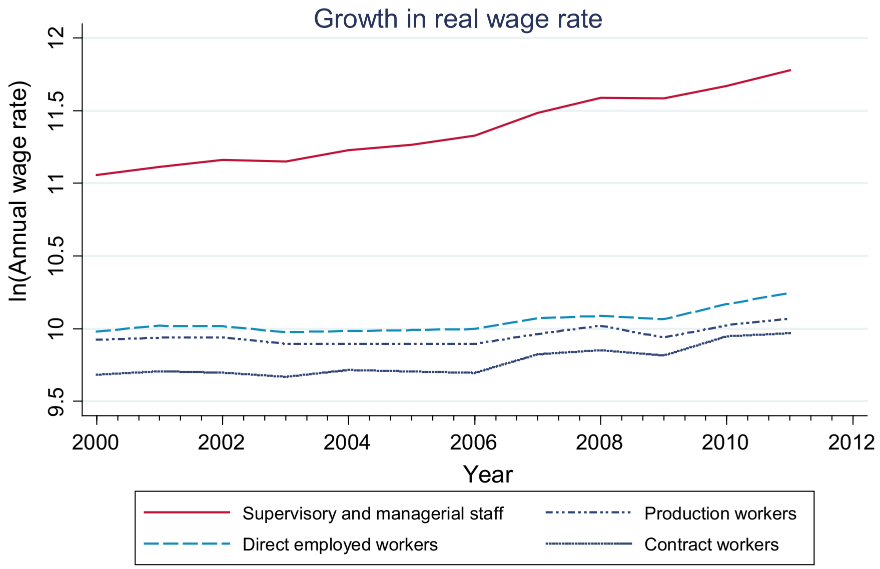

Fig. 6 Growth in real wage rates across various categories of employees. *Source* Author's calculations based on ASI publishes statistics, MOSPI

3 The Contractualization of the Workforce

As mentioned before, this study attempts to identify the implications of rising capital intensity of production on inequality. The preceding section outlines some key stylized facts in India's manufacturing sector pertaining to the distribution of income and wages. However, these changes cannot be attributable to increases in the capital intensity of production alone. There may have been other changes in the labour market during this period which can explain these trends. It is therefore imperative to acknowledge the independent effects of such factors alongside the rising capital intensity. One such critical factor is the increased contractualization of India's workforce.

Production workers in India's manufacturing sector are divided into two categories—permanent and contract workers. The latter are hired via contractors, can be hired and fired at the will of the owners of firms and receive wages which are about half those of permanent workers. The last decade witnessed a sharp increase in the share of contract workers at the expense of regular employment in the organized manufacturing sector (Fig. 7). The share of contract workers in total employment in the organized manufacturing sector rose from 15.7% in 2000–2001 to 26.47% in 2010–2011, while that of directly employed workers fell from 61.12 to 51.53% in the same period. More significantly, the increase in contract workers accounted for about 47% of the total increase in employment in the organized manufacturing sector over

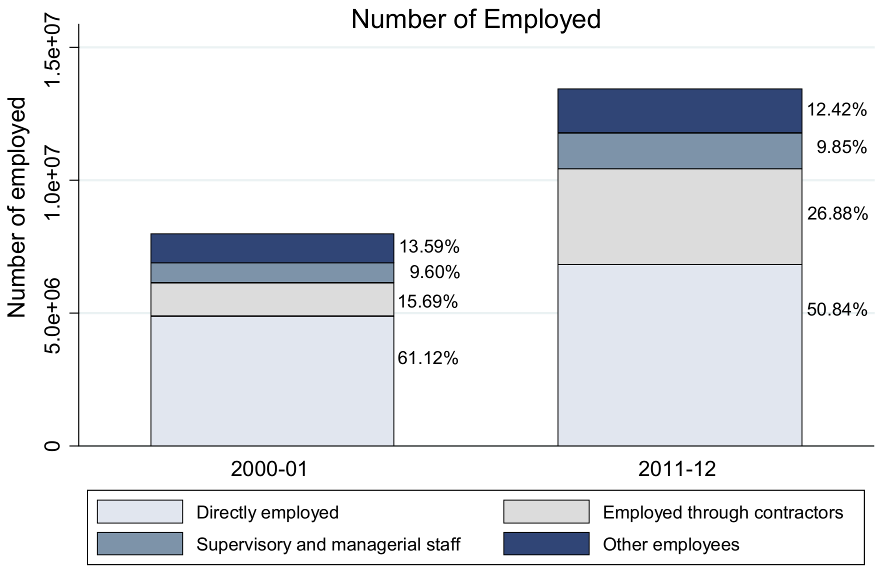

Fig. 7 Composition of employment in organized manufacturing sector. *Source* Author's calculations based on ASI publishes statistics, MOSPI

the last decade.[6] Two reasons have been attributed to this increasing informalization. First, the use of contract workers provides a means of getting around stringent labour regulations, particularly the Industrial Disputes Act, as contract workers do not come under the purview of labour laws that are applicable to directly employed workers in labour markets. Second, increased import competition has led to informalization of industrial labour since the lower wages of informal workers and the savings made on the expenditure of worker benefits helps in reducing costs and thus improving competitiveness (Goldar and Aggarwal 2012).

The contractualization of the workforce though not an implication of the rising capital intensity of production, may well have affected or driven some of the changes we see in the distribution of income and wage inequality in the following manner: contract workers are significantly cheaper, performing the same task as permanent workers. This lowers the average wages paid to production workers. Furthermore, their presence in the workforce helps the firms' management diminish the bargaining power of regular workers and exert downward pressure on their wages. Through these two channels, contract workers help firms lower their wage bill and improve profitability. By putting downward pressure on the average wages of production workers, they may also contribute to rising wage inequality between production workers and the supervisory and managerial staff. Given these effects of contractualization, we

[6]The number of contract workers in the organized manufacturing sector increased from 1.17 million in 2000–2001 to 3.04 million in 2010–2011, while the number of directly employed workers increased from 4.55 to 5.91 million over the same period. The total persons engaged increased from 7.42 to 11.41 million.

need to control for this phenomenon independently, while studying the effect of rising capital intensity on distribution of income and wages.

4 Data and Econometric Analysis

4.1 Data

The stylized facts presented above outline the rising capital intensity of production and the changes observed in the labour market vis-à-vis the distribution of income and wage inequality. However, the question of whether these changes were indeed the effects of the increasing mechanization and automation is best answered through an empirical analysis. We address this issue using plant-level data from the Annual Survey of Industries (ASI). The database covers all factories registered under Sections 2m(i) and 2m(ii) of the Factories Act, 1948 i.e. those factories employing 10 or more workers using power; and those employing 20 or more workers without using power. This database provides a wide array of information on each plant. For each year, firms provide detailed information on aspects such as output, value added, fixed capital, investment, materials, fuel, total persons engaged, workers and wages and salaries to all employees (directly employed workers, contract workers, supervisory and managerial staff and unpaid family workers) It also provides information on the type of ownership, the type of organization, as well as the start year of each plant. The ASI reports the book value of plant and machinery both at the beginning and at the end of the fiscal year (net of depreciation).

Our measure of capital in this study is the net value of plant and machinery at the end of the fiscal year. Employment is measured as the total numbers of persons engaged in a plant. This is divided into two broad categories: production workers(further subdivided into directly employed workers and contract workers) and non-production workers(supervisory and managerial staff). We use these two categories of workers to distinguish between skilled labour (non-production workers) and unskilled labour (production workers). Of course, this categorization is not ideal as skills are best captured by classifications based either on educational characteristics or on a much more detailed classification by working tasks. However, the ASI dataset does not provide us any information on the education or skill level of workers, therefore the only option we have is to rely on this categorization. The classification of workers into 'production' and 'non-production' groups in order to approximate skilled and unskilled labour respectively is not an uncommon one in the literature.[7] International evidence indicates a close relationship between the production/non-manual status of workers and their education level (Goldberg and Pavenik 2007). Therefore, in our analysis we use the wage differential between non-production and

[7]Meschi et al. (2011).

production workers as a measure of skill wage gap. This has been considered a suitable measure for analyzing the impact of globalization on wage inequality in the literature.[8]

The time period under consideration in this study is from 2000–2001 to 2010–2011. There are three different industrial classifications used in the ASI dataset during this time period. For the surveys between 1998–1999 and 2003–2004 the industrial classification used was NIC-1998, between 2004–2005 and 2007–2008 it was NIC-2004, and 2008–2009 onwards it was NIC-2008. In this study, we undertake a concordance exercise across these different classifications to make the dataset comparable as per the NIC-1998 classification.

The data collected from the ASI are at current prices and any analytical work requires deflating these variables. An obvious candidate for this is the wholesale price index (WPI) series. However, we cannot use the WPI as a deflator directly because while ASI follows the NIC classification of industries, WPI is constructed with a view to capturing price movements based on nature of commodities and final demand. Therefore, we create a WPI for each of the industries in the analysis by approximating commodities based on the nature of economic activities and map NIC activities to WPI commodities.[9] To deflate wages, however, we use the Consumer Price Index of Industrial Workers.

The raw data consist of about 384,000 observations over 10 years, with an average of about 38,000 plants surveyed each year. We only study observations corresponding to open plants and plants with positive values of output, plant and machinery and total persons engaged. A problem in the ASI dataset is the presence of a large number of outliers. To reduce their influence in our estimates, we winsorize the data, following Dougherty et al. (2011). This procedure essentially involves top-coding and bottom-coding the 1% tails for each plant-level variable. In other words, for each year and each variable we replace outliers in the top 1% tail (bottom 1% tail) with the value of the 99th (1st) percentile of that variable. This procedure was applied separately to each 2-digit industry.

4.2 Econometric Framework

The proposed empirical specification is as follows:

$$\ln Y_{fist} = \beta_i + \beta_1 (K/L)_{fist} + \beta_2 (CW/TW)_{fist} + \beta_3 (Age)_{fist} + \beta_4 (Size\ Dummy)_{fist} + \mu T + \varepsilon_{fist}$$

The outcome variable, $\boldsymbol{Y_{fist}}$, varies over firm $\boldsymbol{f}$ belonging to industry $\boldsymbol{i}$ in state $\boldsymbol{s}$ at time $\boldsymbol{t}$. The dependent variables, which are of interest are the share of profits in

[8]It may well be the case that this measure is an underestimate of the wage gap since production workers may include some skilled workers.

[9]Capital is deflated using the WPI created for industry, NIC 29.

GVA; share of wages in GVA; ratio of skilled (non-production workers) to unskilled (production workers) and the ratio of their wage rates. We also look at the shares of the wage bill accruing to skilled and unskilled workers separately. As mentioned previously, the former is the share of the wage bill paid to managerial and supervisory staff, while the latter is share of the wage bill paid to production workers. We also control for share of contract workers in total production workers (*CW/TW*) in our specification given the discussion in Sect. 3. T represents the linear time trend, while β_i denotes industry fixed effects. We include industry fixed effects to account for any time invariant industry-specific effects such as industry technology differences, market structure and degree of competition. In addition to the above, we control for the age of the factory and its size. We create a dummy variable for the size of the firm and classify factories into three categories (small, medium and large)[10] on the basis of total persons engaged in them. We also introduce a state-level time variant infrastructure control (log of tele-density[11]) in our specification.

Importantly, this model cannot be estimated using Ordinary Least Squares (OLS). The reason for this is as follows. The firm's decision of the technology it adopts for production or its capital intensity of production is not an exogenous factor. In other words, it is simply not an outside force but an outcome of decisions made by firms, i.e. it is endogenous. Firms may well be responding to profit incentives while making decisions about technology they choose to adopt.[12] That technological change is not an outside force acting on the labour market and wage inequality, but in fact, endogenous has been discussed in the literature (Acemoglu 2003). For instance, the spinning and weaving machines of the nineteenth century were invented because they were profitable. They were profitable because they replaced the scarce and expensive factors—the skilled artisans—by relatively cheap and abundant factors—unskilled manual labour of men, women, and children. Similarly, electrical machinery, air-conditioning, large organizations all were introduced because they presented profit opportunities for entrepreneurs. Similarly, the share of contract workers may well be endogenous, and a result of firms response to profit incentives. Reverse causality may arise as firms with low profits may be incentivized to hire more contract workers to improve profitability. Similarly, firms with a disproportionately large labour share in their wage bill might prefer witching to contract workers to reduce their wage bill.

To address the endogeneity problem, we use Instrumental Variable (IV) estimation in our analysis. We use three instruments in our analysis here—labour market regulations, minimum wages of the state and the level of financial development. The rationale for using these instruments is as follows. Given the argument that it is stringencies in labour legislations that have discouraged firms from hiring workers and instead adopting more capital intensive techniques of production, we use a

[10]Small firms are defined as those having less than 50 employees, medium firms have 50–199 employees and large firms are defined as those having 200 or more workers.

[11]The tele-density variable captures the state-wise telephones statistics per 100 population.

[12]There are also no compelling theoretical reasons to expect technological change always and everywhere to be skill-biased. On the contrary, if replacing skilled workers is more profitable, new technologies may attempt to replace skilled workers, just as interchangeable parts did.

measure of the rigidity of labour market regulations of the state the firm is located in as an instrument. Typically, one would expect the firms which are located in states with inflexible labour regulations to adopt more capital intensive techniques of production. Similarly, it has been argued that it is firms in states with more stringent labour regulation which are incentivized to substitute permanent workers with contract workers (Sen et al. 2010). Quantifying differences in LMR across states is a contentious subject in the existing literature. In our analysis, we use an index of labour market rigidity constructed by Gupta et al. (2008). They create a composite measure of LMR across states by combining information from three key studies.[13] On the basis of this composite index, they categorize states' LMR as flexible, neutral and inflexible assigning scores of 1, 0 and -1.[14]

The choice of the level of financial development as an instrument is driven by the fact that firms located in financially developed states would have increased attractiveness to invest in capital. Data on index of financial development is obtained from Kumar (2002). Finally, we include the minimum wage rate of the state as an instrument in our analysis. As is the requirement of a good instrument, the minimum wage rate[15] in a state is highly correlated with the wages of contract workers. The Contract Labour Act (1970) mandates that wages of contract workers must not be lower than the prescribed minimum wage, therefore states with higher minimum wages observe lower share of contract workers in their workforce (Sen et al. 2010). Data on minimum wages is obtained from the Labour Bureau Statistics (various years).

4.3 Results

As explained in the previous section, the reverse causality between the dependent variables on one hand and capital intensity of production and share of contract workers, on the other hand, taints the OLS results and provides inconsistent estimates. We therefore estimate the above-mentioned equation using Instrumental Variables

[13] They examine state-level indexes of labour regulations developed by Besley et al. (2008), and OECD (2007). The Besley and Burgess measure relies on amendments to the IDA as a whole. Bhattacharjea's measure focuses exclusively on Chapter VB of the IDA—i.e., the section that deals with the requirement for firms to seek government permission for layoffs, retrenchments, and closures. Bhattacharjea considers not only the content of legislative amendments, but also judicial interpretations to Chapter VB in assessing the stance of states vis-à-vis labour regulation. The OECD study is based on a survey of experts and codes progress in introducing changes in recent years to not only regulations dealing with labour issues, but also the relevant administrative processes and enforcement machinery. The regulations covered by the survey go well beyond the IDA and include the Factories Act, the Trade Union Act, and Contract Labour Act among others.

[14] Andhra Pradesh, Rajasthan, Tamil Nadu, UP and Karnataka are classified as having flexible labour regulations. Maharashtra, Orissa and West Bengal are classified as having inflexible labour regulations. Assam, Bihar, Gujarat, Haryana, Kerala, Madhya Pradesh and Punjab are classified as the neutral states.

[15] These wages are determined by respective state governments and vary across states and over time—background as to how minimum wages are determined.

(Table 2). The Wu-Hausman test statistic at the bottom of the table is statistically significant in each of the specifications confirming that the endogenous regressors in the model are in fact endogenous and need to be instrumented.

In the first column, the dependent variable is the share of profits in GVA, i.e. ln(Profits/GVA). The coefficient of the capital intensity of production is negative and statistically significant, suggesting that profitability was in fact lower in firms which witnessed relatively larger increases in the capital-labour ratio. The coefficient on ln(K/L) suggests that if firms increase their capital-labour ratio by 1% their profitability will decline by 0.08%. This may well be a result of the fact that firms require greater financial resources to adopt more capital intensive techniques of production and this lowers their profits in the short-run. The coefficient on the share of contract workers in total workforce is positive and significant. This is not surprising following the discussion on the role of contract workers in improving firm profitability in Sect. 3. This result is noteworthy as it seems to suggest that it is the substitution towards cheaper workers that are driving higher profits and making owners of firms wealthier and not the substitution towards capital (in the short-run). The coefficient on the size dummy is positive and statistically significant suggesting that larger

Table 2 Instrumental variable analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	ln(Profit/GVA)	ln(All wages/GVA)	ln(Wage bill to (NPW)/GVA)	ln(Wage bill to PW/GVA)	ln(NPW/PW)	ln(NPW wage/PW wage)
ln(K/L)	-0.08^{b} (0.04)	-0.25^{c} (0.04)	0.23^{c} (0.04)	-0.30^{c} (0.03)	0.21^{c} (0.06)	0.10^{b} (0.05)
ln(Contract workers/Total workers)	1.01^{c} (0.19)	0.74^{c} (0.19)	0.43^{b} (0.20)	−0.15 (0.17)	0.54^{b} (0.25)	0.74^{c} (0.22)
ln(Age of firm in years)	0.04^{c} (0.02)	0.08^{c} (0.01)	0.24^{c} (0.01)	-0.04^{c} (0.01)	0.19^{c} (0.01)	0.06^{c} (0.01)
Size dummy	0.30^{c} (0.05)	0.26^{c} (0.06)	-0.19^{c} (0.06)	0.12^{b} (0.05)	-0.30^{c} (0.08)	0.26^{c} (0.07)
ln(Tele-density)	−0.03 (0.02)	0.08^{c} (0.01)	0.09^{c} (0.02)	0.03^{b} (0.01)	0.11^{c} (0.02)	−0.02 (0.02)
ln(Real Minimum Wage)		0.18^{c} (0.03)		0.11^{c} (0.03)		-0.09^{c} (0.03)
Time	-0.05^{c} (0.01)	-0.03^{c} (0.01)	-0.02^{c} (0.01)	−0.01 (0.01)	-0.06^{c} (0.01)	0.02^{b} (0.01)
N	63339	71319	64913	71331	68102	68102
RMSE	1.46	1.10	1.26	0.97	0.99	0.87
Wu-Hausman	24.21^{c}	28.15^{c}	147.02^{c}	32.81^{c}	86.41^{c}	165.23^{c}
Cragg-Donald statistic	27.13^{b}	21.99^{b}	15.95^{b}	21.91^{b}	8.55^{b}	8.5^{b}
Sargan chi-square	0.14		0.16		0.21	

Robust *t* statistics are given in brackets. [a]significant at 10%; [b]significant at 5%; [c]significant at 1%

firms are more profitable. Importantly, we need to verify if our estimates suffer from a weak instrument problem, meaning that the explanatory power of the excluded instruments in the first stage regression is too low to provide reliable identification. The Cragg and Donald minimum eigenvalue statistic reported at the bottom of the table is a test of weak instruments and from this, we can reject the null hypothesis that the set of instruments is weak.[16] In addition to the requirement that instrumental variables be correlated with the endogenous regressors, the instruments must also be uncorrelated with the structural error term. Since our model is over-identified, meaning that the number of additional instruments exceeds the number of endogenous regressors, we can test whether the instruments are uncorrelated with the error term. The over-identification test reports Sargan's chi-square tests. The insignificant test statistic suggests that our instruments are not invalid.

In the second column, the dependent variable is the share of wage bill to all employees in GVA i.e. ln(All Wages/GVA). Here, we find that the share of total wage bill in GVA was lower in firms witnessing relatively larger increase in capital-labour ratio. The coefficient on ln K/L indicates that as firms increased their capital-labour ratio by 1%, the share of wages in GVA declined by 0.25%. This suggests that the higher capital intensity of production was squeezing the share of labour in GVA. It is important to mention that we are unable to use the logarithm of real minimum wages as an instrument here. Doing so, misspecifies the equation, as this variable should in fact be included in the structural equation, and not be an excluded exogenous variable.[17] This is because firms in states with a higher minimum wage will typically have to pay higher wages, resulting in the wage bill eating into a larger share of GVA. The coefficient on the log of real minimum wages is positive and statistically significant, confirming this. The other two instruments (index of labour market regulations and level of financial development of the state) are valid. Also, from the Cragg–Donald minimum eigenvalue statistic, we can reject the null hypothesis of weak instruments. The coefficients on the age of the firm and the size dummy are positive and statistically significant suggesting that older and larger firms have a larger share of wage bill in their GVA.

Next, we disaggregate the wage bill into two components, i.e. wage bill accruing to non-production workers/skilled workers (ln(Wage Bill to NPW/GVA)) and that accruing to production workers/unskilled workers (ln(Wage Bill to PW/GVA)). Here, we find that the share of wage bill going to skilled workers is higher in firms witnessing relatively larger increases in the capital-labour ratio (column 3).[18] On the

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[16]The null hypothesis of each Stock and Yogo's tests is that the set of instruments is weak. To perform these tests, we must first choose either the largest relative bias of the 2SLS estimator we are willing to tolerate or the largest rejection rate of a nominal 5% Wald test we are willing to tolerate. Since the test statistic exceeds the critical value in each case, we can conclude that our instruments are not weak.

[17]The Sargan&Basmann's chi-square test reports a statistically significant test statistic when we include real minimum wages as an instrument, suggesting that we either have an invalid instrument or incorrectly specified structural equation.

[18]In this equation, we use the log of real minimum wages as an instrument since the Sargan&Basmann's chi-square test report a statistically insignificant test statistic.

other hand, the share of wage bill going to unskilled workers was lower in such firms (column 4).[19] It is worth noting that the coefficient on the variable age of the firm, is positive and significant in column 3, but negative and significant in column 4. This suggests that the share of the wage bill going to supervisors and managers in older firms is greater than in younger firms. On the other hand, the share of wage bill going to production workers is higher in younger firms. Also, larger firms have a bigger share of their wage bill being paid out to production workers as compared to smaller firms. Not surprisingly, the log of real minimum wage bill is positive and statistically significant in column 4 as higher minimum wages drive up the wages of production (and not non-production workers).

In the fifth column, the dependent variable is the ratio of non-production/skilled to production/unskilled workers (ln(NPW/PW)). Here, we find that firms experiencing relatively larger gains in capital-labour ratio observed relatively larger increases in proportion of skilled to unskilled workers. A 1% increase in the capital intensity of production resulted in a 0.21% increase in the ratio of skilled to unskilled workers. This result underlines the existence of capital-skill complementarity, which means that ceteris paribus, firms with higher capital intensity also employ a higher share of skilled workers. We also find that older firms have a higher ratio of skilled to unskilled workers as compared to younger firms. The coefficient on the size dummy is negative and statistically significant suggesting that larger firms have a lower ratio of skilled to unskilled workers.[20] In this equation, we use all three instruments as they are valid and not weak.

In the last column, we find that the rising capital intensity of production has also exacerbated wage inequality and resulted in growing divergence in wages earned between skilled and unskilled workers. The coefficient on the capital intensity of production is positive and statistically significant suggesting that firms observing relatively larger increases in the capital-labour ratio saw relatively larger increases in wage differential between production and non-production workers (ln NPW wage/PW wage). It needs to be noted here that though statistically significant, the size of the coefficient on the capital-labour ratio (0.10) is smaller than the size of the coefficient on the share of contract workers (0.74). This suggests that hiring of contract workers accentuates wage inequality between the production workers and supervisory and managerial staff. This is a result of the fact that greater presence of contract workers in the firms' workforce helps reducing the average wages of production workers not only because this category of workers receives lower wages, but also because they exert a downward pressure on wages of directly employed workers (Sen et al. 2010 and Saha et al. 2013). Importantly, we find that the wage disparity between skilled and unskilled workers is higher in older and larger firms. Furthermore, in this specification we cannot use the log of real minimum wages as an

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[19]Here, we cannot use the log of real minimum wages as an excluded exogenous variable as the Sargan & Basmann's chi-square test report a statistically significant test statistic. It needs to included in the structural equation.

[20]Firm size is largely driven by the production workers and not non-production workers, as the latter are quite small as a percentage of total persons engaged.

excluded exogenous variable. We therefore include it in the structural equation and find its sign to be negative and significant. This is because a higher minimum wage put upward pressure on the average wages of production workers, thereby reducing inequality between production and non-production workers.

The results of the first stage of the IV are reported in the appendix and they are not surprising. The coefficient on the labour regulation index is negative and statistically significant in both columns suggesting that firms in states with more inflexible labour regulation are incentivized to use more capital intensive techniques of production and have a greater share of contract workers in their workforce. Also, firms in states where the level of the minimum wage rate is higher, employ a greater share of contract workers. However, we do not find the coefficient on the level of the financial development of the state to be statistically significant.

5 Conclusion

That mechanization and automation of production processes threaten employment for India's low-skilled/unskilled workforce is a well-known fact. However, doomsday prediction of the world in which everything is done by machines is also unrealistic. Nevertheless, such prospects are hugely worrying in a country such as India looking to create employment for its rapidly increasingly working age population. Not only has the capital intensity of production been increasing sharply, but recent economic growth has benefited industries which rely more on skilled workers and capital as opposed to unskilled/low-skilled workers. As technology makes it easier to substitute capital for labour, an increase in capital intensity of production over time is inevitable and we can certainly not resist the adoption of new technology only to preserve jobs.

In this paper, we attempt to examine the effects of growing capital intensity (and associated technological change) on inequality of wages and earnings in organized manufacturing in India. The theoretical expectation is that growing capital intensity would not only increase the share of capital in value added, but also skill premium, thus increasing inequality. The increase in the wage gap between the managerial and supervisory staff (high-skilled) and production workers (low-skilled), and the reduction in share of aggregate value added going to labour, in our dataset, is consistent with this expectation. However, the share of managerial and supervisory staff in total employment seems to have remained stagnant, while the share of contract workers in production workers has increased sharply over the last decade. Arguably, had there been no growth of contract workers, the wage gap between the managerial and supervisory staff and the production workers would have increased much less. In other words, it is not just the growth of capital intensity but also the growth of contract workers that explains the growth of inequality. At the same time, it is also possible that the salaries of the managerial and supervisory staff were growing not so much because of growing demand from manufacturing but intensifying competition with the services sector for such staff.

It is important to mention that in India, unlike in the developed world, skill-biased technological change was not accompanied by a large increase in the supply of more educated workers. This may well have exacerbated wage disparity. The serious supply-side constraint is evident from the fact that only 4% of total workers engaged in the manufacturing sector have any technical education and only 27% of workers in manufacturing are vocationally trained, of which 86% are non-formally trained (Mehrotra et al. 2013).

The government's ambitious Skill India program, with a target to skill 40 crore workers over the next five years attempts to address this gap. However, assembly line methods of skill development which produce large numbers of electricians, machine operators, plumbers, carpenters, electricians and other such narrowly skilled and certified persons will not address India's skills challenge. In an uncertain and dynamic world where new technologies will disrupt old forms of production and alter processes of production, it is not possible to predict what the nature of jobs will be in the future and precisely what skills workers will need to perform these jobs. Consequently, workers may end up being imparted skills they may actually not put to any use. For skill development systems to be effective, they need to be able to respond to technological changes in the economy. This requires providing young workers with a broad foundation of basic skills and a minimum level of educational attainment so that they are able to learn the requisite skills in the enterprises where the jobs are being created. Increasing the supply of skilled workers in such a manner will help reduce the growing divergence in wages of skilled and unskilled workers. However, the phenomenon of contractualization poses a serious threat to the skilling challenge. Workers are discouraged from acquiring skills as they feel that even though skilling-up may result in improved productivity, it may not translate into higher wages as firms will prefer to hire them as cheap contract labour.

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Appendix A

First stage regression from IV analysis

	(1) ln(K/L)	(2) ln(CW/TW)
Labour regulations index	−0.36*** (0.01)	−0.06*** (0.00)
Financial development index	0.19*** (0.01)	−0.02*** (0.01)
ln(Real minimum wage)	−0.59*** (0.03)	−0.04*** (0.02)
ln(Age of firm in years)	−0.47*** (0.01)	−0.09*** (0.00)

(continued)

(continued)

	(1) ln(K/L)	(2) ln(CW/TW)
Size dummy	0.59*** (0.01)	−0.14*** (0.00)
ln(Tele-density)	0.27*** (0.01)	−0.01 (0.01)
Time	−0.01 (0.00)	0.03*** (0.00)
N	212851	77545

Robust *t*-statistics are given in brackets. *significant at 10%; **significant at 5%; ***significant at 1%

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Skills, Productivity and Employment: An Empirical Analysis of Selected Countries

Suresh Chand Aggarwal

1 Introduction

Skills development is central to economic performance of the countries in the current milieu when 'disruptive' technology is evolving at a fast pace. Many of the new technology—Internet Of Things (IOT), Artificial Intelligence (AI), achine learning, 3D Printing, etc. is changing the face of how we work, and the skills we need to succeed in our jobs. The new technology may push some workers either temporarily out of employment or into low wage jobs, as the new jobs require higher level of skills (World Development Report 2019). While opening many new windows for investment and increase in productivity and employment, the new technology is simultaneously disturbing the existing technological complementarities and exerting a lot of pressure on the supply of the matching skills. Many jobs which exist today would disappear tomorrow and many new jobs which do not exist today will get created tomorrow. So there is a simultaneous creation and destruction of jobs. The net impact of this process thus depends upon their respective pace. The shortages of 'new' skills put several constraints on growth and development by curtailing the prospects for increases in job creation and income. The mismatch between supply and demand of skills constrains productivity improvements and adds to production costs within firms, which makes it difficult for the domestic firms to compete internationally. As a result, the growth prospects of these firms get adversely affected.

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Internationally the skill mismatches are even more pronounced. In some developing countries, particularly in Africa and South Asia, while tens of millions of young people join the labour market looking for jobs and face uncertain demand due to lack of matching skills; these countries also face the problem of the unavailability of the required skills for the new jobs. Even in advanced economies (OECD 2015) the skill mismatches and shortages are common. According to OECD (2015) "In all, more than 40% of European workers feel their skill levels do not correspond to those required to do their job, with similar findings for Mexico, Japan and Korea. Australia, Finland, Italy and New Zealand experience lower rates of mismatch, but even in these countries more than 30% of workers report mismatch. In parallel, many employers report that they face recruitment problems due to skill shortages." The skill mismatches thus could also lead to underutilization of labour. It does not, however, mean that skill supply is stagnant and is not responding to changing skill needs. It has evolved over the period through better quality of education, expansion of education, increased intensity (hours) of work, etc.

Skill mismatches and skill shake-ups have increased the need for regular skilling, and up-skilling throughout a person's career, because people with low skills are generally the first to lose jobs. But the speed at which jobs are transforming and the workers' capacity to adapt to such changes are not uniform across industries and countries and is also influenced by access to education, availability and cost of Information and Communication Technology (ICT) and the opportunities for lifelong learning[1] inside and outside the workplace. Lifelong learning is needed to resolve both the immediate challenge and to add value through skills in the future. Policy interventions can help in addressing some of the skill mismatches and shortages.[2]

Some of the concerns of the pessimists towards slow or zero employment growth due to new technology have however been dispelled recently by World Development Report (2019) which did not find much empirical support for the same and finds that the share of manufacturing sector jobs has been relatively stable in most developing countries in which the impact of technology on jobs was expected to be more widespread. However, in US and some European countries, the report finds some evidence of shorter job tenures, rise of temporary contracts and increase in part-time employment but the trend need not necessarily be due to only technological change but possibly also due to demographic changes, free trade, and rise in flexible jobs (and time). Greatz and Michaels (2017) also do not find any jobless recovery in developed countries outside US. They explain the jobless recovery in US, based partially on the nature of technology adoption, extension of unemployment benefit extensions and weakening of trade unions. However, the survey by The Economist Intelligence Unit (2018) finds that countries are not yet prepared for the challenges and opportunities of intelligent automation. Only a few countries—Korea, Singapore and Germany

[1] World Development Report (2019, page 47) has suggested "three ways to improve adult learning—more systematic diagnoses of the specific constraints that adults are facing, pedagogies that are customized to the adult brain, and flexible delivery models that fit well with adult lifestyles.".

[2] OECD (2015) identifies mismatch by field of study as the most common form of mismatch, followed by qualification mismatch.

have taken some individual initiatives in this context. The report mentions that the middle income countries may find it even more difficult to adapt to the new skill requirements because of huge policy initiatives required for it.

But to meet the growing challenge of 'new' skills requirement, we have to recognize existing skills, understand skill demands, create right mix of expertise—especially on the job training and learning, and reach out to those firms and people who need it most—the small and medium enterprises (SME), the low skilled workers, and older workers. Since better skills are likely to lead to quick employment and higher income, for them acquiring and updating skills would be the best insurance against job losses. More investment in human capital is thus required at all levels by individuals, firms and government, and public investment alone is not sufficient. Firms have to invest in their employees. Workers, in turn, need to invest in their continuous education. It is all the more necessary as return to different skills[3] is changing fast. While the returns to general cognitive and social-emotional skills are rising, the returns to job-specific skills are uncertain—have increased in some jobs and declined in others.

However, higher economic growth and income also in turn, help a country with the resources to improve the opportunities for acquiring and developing skill base through the expansion of education and training, leading to a virtuous chain of growth in income, skills, productivity and employment. The World Economic Forum Report (WEF 2016a) on The Human Capital Report also finds a clear correlation between the economy's income level and the human capital score (which is a composite score of different parameters and includes enrollment and quality of education; and skills distribution among others (WEF 2016a)), but with overlaps between countries wherein some low income countries have surpassed others on the score and vice versa. There are still quite a few countries, including India which even though have achieved high economic growth, but struggle with low human capital scores; indicating their neglect in expanding education and imparting necessary skills.

The link between skills, productivity and employment has not only been discussed but has also been empirically tested. Fields (1980) had concluding way back in 1980 that education (skills) have a positive impact on the level of income by paving new opportunities for many who acquire the skills. Skills thus help in employment and income. However, a wide gap between skills of the workers may lead to wide disparities in income when workers are paid wages as per their productivity. The survey of adult skills by OECD (2013) also found a positive association between the mean skill level (measured by numeracy score) and the economic performance across countries (measured by PCI (per capita income) in PPP). The significance of skills (talent) in an economy to reap the benefits of the tech revolution and achieve higher productivity and employment has also been pointed out by the WEF (2016b) in its Global Competitiveness Report: 2016–17.

The paper in part I explores this crucial linkage between skills distribution, (labour) productivity and growth in employment both at the national level as well

[3] World Development Report (2019) has identified and defined three types of skills—cognitive skills, job-specific skills, and socio-emotional skills.

as at disaggregate industry level for few selected economies like *BRIC economies, Indonesia, Mexico, South Korea*, *Taiwan, and Turkey* all of which have faced the similar challenges. The exercise is also carried out separately in part II for formal (organized) and informal (unorganized) sectors of the Indian economy, as it is expected that formal sector firms, which are also generally relatively large in size are likely to hire more skilled labour and spend more not only in R&D but also on the job training, resulting in better skills proficiency. So the formal sector firms are expected to experience higher productivity and growth in employment.

The rest of the paper is organized as follows. The next section describes the data used and the research methodology. The discussion about the link between skill, productivity and employment in selected emerging economies is included in part I, in which the pattern in the distribution of employment by skill is discussed in Sect. 3. Section 4 is devoted to the analysis of the structure of the economy with focus on the contribution of high capital intensive industries. Estimates of an econometric model are presented in Sect. 5. In part II on the link for India's organized and unorganized sectors, Sect. 6 describes the distribution of employment by skill in the organized and unorganized sectors in India. Section 7 includes the analyses of skill and employment in the high capital intensive industries in India. Finally, Sect. 8 sums up the main findings and concludes the study.

2 Data and Methodology

As the first part of the study is related to analysis of skill and productivity at the aggregate and disaggregate level of industry for the selected countries, the only data source currently available for skill distribution by industry for international comparison is WIOD database, version 2013 updated in July 2014, which classifies the industries according to ISIC revision 3 and adheres to 1993 version of the SNA. WIOD has revised and published in Feb 2018 the data release of November 2016 where it has classified the industries by ISIC revision 4 and adhered to SNA 2008; but has not updated the data on distribution of employment by skill (education). The 2014 version has data on few variables, e.g. Value added and employment from 1995 to 2011, but the data on distribution of employment (hours worked) by skill is from 1995 to 2009 only. The period for the current study is therefore restricted to only 1995–2009; a period of 15 years.[4] WIOD (2012)[5] has grouped skill into three levels and has defined low skill as education up to primary education, medium-skill as primary to higher secondary education and high skill as higher secondary and above education level. The same grouping has been used in both the sections of the current study. In the first section, the analysis and the data are restricted to a small set of countries which include the BRIC countries along with few other emerging

[4]The short time period is a serious limitation of the study and may not fully capture the impact of recent technological changes. However, the study may show the preliminary results.

[5]WIOD (2012). Socio-Economic Accounts (SEA): Sources and Methods.

economies from different regions—Indonesia, Korea, Mexico, Taiwan and Turkey all of which have faced similar challenges in skilling (up-skilling and re-skilling) their labour force.

The second section of the study relates to the organized and unorganized sectors of the Indian economy and the period of the analysis is 1999–00 to 2011–12. The main data sources for India are National Accounts Statistics for Value added, Wholesale Price Index for price deflators, Employment and Unemployment Survey (EUS) for employment and skill data. The time period of this section is dictated by the fact that data on organized and unorganized employment and on skill are both possible from EUS only since 1999–00 and the latest year for which it is available is only 2011–12.[6] So mainly three rounds of the EUS 1999–00 (55th), 2004–05 (61st) and 2011–12 (68th) are used.

The methodology used in both the sections of the study to map the non-agriculture industries is based on capital intensity of the industry, which is defined as real gross fixed capital formation per person engaged (K/L). It is expected that the industries with high capital labour ratio would generally be the ones using better (may be latest) technology and more skilled labour. One-third of the industries with highest K/L are grouped as high capital intensive industries; the middle one-third are grouped as medium capital intensive industries; and the bottom one-third of the industries are classified as low capital intensive industries.[7] The importance of high capital intensive industries is discussed based on their relative share in the economy's total real value added and total employment. For analyzing the relationship between skill and labour productivity, labour productivity is calculated in section one as real value added per hour worked (OECD 2018) and in section two as double deflated[8] real value added per person employed.

Part I: Skill, productivity and employment in Selected Emerging Economies

3 Pattern in the Distribution of Employment by Skill

Over the years, the labour force in a country becomes more educated as more and more capital investment is made in its population. Investment in human capital has been widely recognized to be the key to increase in labour productivity and to growth of national income (WEF 2016a). The role of education in human capital is but too obvious. The challenges of new technology have made it more imperative to invest

[6] See Appendix for details of methodology to estimate organized and unorganized employment.

[7] Agriculture has been excluded from this exercise.

[8] Double deflated RVA means both output and inputs are deflated by their separate price deflators.

in human capital and develop the 'right' skills.[9] Now there is awareness among countries to invest in education of its population and its labour force for both increases in national income as well as to get ready to embrace the ever-changing technology. However, we observe a wide variation in the skill composition of the labour force of the countries around the world. WEF (2016a) has come out with The Human Capital Report 2016 highlighting differences in the score on the selected human capital indicators. The difference in skill composition in the selected countries is part of the discussion in the next section.

3.1 Distribution and Growth in Employment (Hours Worked) by Skill

The average distribution of total hours worked in the non-agriculture sectors of the economies by skill of the persons engaged during 1995–2009 is shown in Fig. 1. It is seen from it that there are large variations in the average share of hours worked by high-skill persons engaged among the selected nine countries. While the share is around 13–15% in Brazil, India, Mexico, Russia, and Turkey; the share is just 8–9% in China and Indonesia and is moderately high in Taiwan at 27% and significantly high in Korea at 42%. It seems this high-skill advantage to Taiwan and Korea and relative disadvantage to other countries is partially reflected in their production pattern and

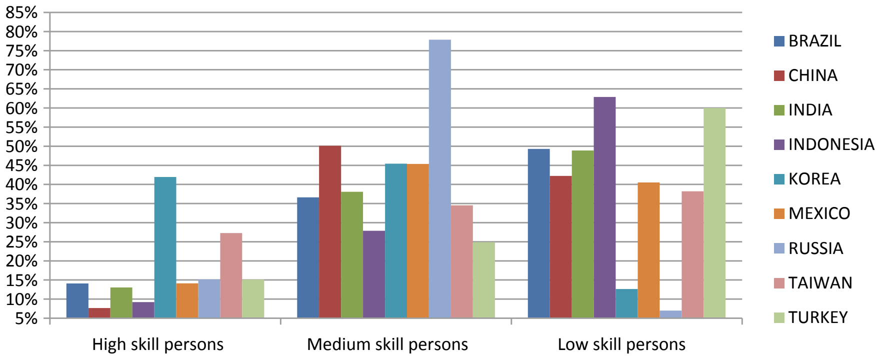

Fig. 1 Average percentage distribution of hours worked by skill of the persons engaged in selected nine countries (1995–2009). *Source* Author's calculations based on data from WIOD database (2014)

[9]However, the development of skills is required not only for better productivity but also for better well being. Education by providing access to more opportunities also facilitates upward income mobility.

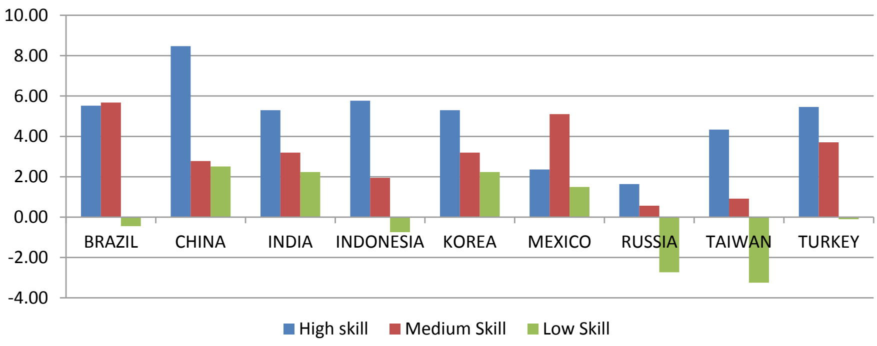

Fig. 2 Average annual growth rate of hours worked by skill of the persons engaged in non-agriculture economy of selected countries (1995–2009). *Source* Author's calculations based on data from WIOD data base (2014)

international trade.[10] The figure also shows that the distribution of hours worked by medium-skill persons also varies among the selected countries. While the share is just 25–28% in Indonesia and Turkey, it ranges between 35 and 40% for Brazil, India and Taiwan; and between 45 and 50% for China, Korea and Mexico. Russia is the only country which has a very high share of hours worked by medium-skill persons engaged (78%) and a very low share of hours worked by low-skill persons engaged (just 7%). The share of hours worked by low-skill persons engaged is around 40–50% for majority of the selected countries—Brazil, China, India, Mexico and Taiwan; a high of 63% in Indonesia and significantly low in Korea (13%) and Russia (7%).

To add more clarity to the pattern of employment by skill, an analysis of growth of employment by skill is undertaken. In Fig. 2, the average annual growth rate of hours worked during 1995–2009 by skill level of the persons engaged for non-agriculture sectors[11] of the economy is shown for all the selected countries. It shows that though the share of high-skill persons engaged as depicted in Fig. 1 is low in majority of the countries, but the growth rate of high-skill persons engaged is higher (or almost same for Brazil) than the growth rate of medium and low-skill persons in all the countries except Mexico. On the contrary, the growth rate of employment of low-skill persons is quite low and is even negative in few of the selected countries, which could be possibly due to the changes in the nature of work where the technology-induced new jobs require significantly higher level of human capital (World Development Report 2019).

[10]While Korea was exporting 47% of its GDP in 2009, the ratio was just 11% for Brazil; around 21–24% for China, India, Indonesia, and Turkey; and 28% for Mexico, Russia and South Africa (World Bank 2018).

[11]Agriculture has been dropped as, in most of the countries it is low-skill intensive with hardly any change in skill composition.

The distribution and growth of skills of persons engaged reflect that while there is a lot of potential for many of these countries to catch up with other countries both within the group as well as with other countries outside the group, the catching up process is on with fast growth in hours worked by high-skill persons engaged. The research question which then arises is how change in skill composition affects labour productivity and growth in employment. The answer to it is being attempted in the next Sect. 3.2.

3.2 Skill Composition, Labour Productivity and Growth in Employment

The relationship between skill composition and labour productivity can be viewed in two perspectives—either at the level of labour productivity or at the growth rate of labour productivity. The paper discusses the relationship at both the 'level' as well as at 'growth'. In Fig. 3, the change in the average annual share of hours worked by high-skilled person engaged in total hours worked; the percentage change in the average level of labour productivity; and the percentage change in the average level of total employment for the two periods of 1996–2002 and 2003–2009 are depicted for the selected countries.

It is clear from the figure that in all the countries, with an increase in the average share of high-skill persons in total hours worked, the average labour productivity has increased (in Mexico, both have reduced) between the two sub-periods. There is thus a positive association between change in the average share of high-skill persons in total hours worked and change in average labour productivity. It is noticed that the average level of employment has also increased in the second sub-period as compared to the first sub-period in all the countries, except Turkey. The empirical evidence thus

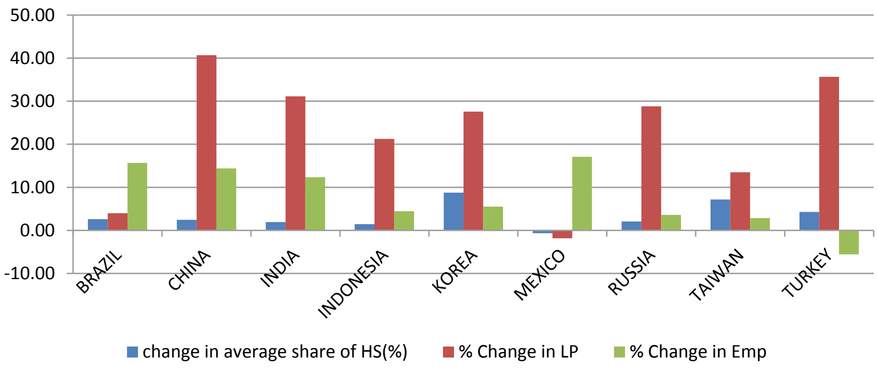

Fig. 3 Change in average share of hours worked by high-skill persons engaged, percentage change in average labour productivity and percentage change in average total employment between 1996–2002 and 2003–2009. *Source* Author's calculations based on data from WIOD data base (2014)

corroborates the argument that increase in skill level may increase labour productivity and employment. However, one may argue that increase in labour productivity (and employment) may be induced by other factors like capital intensity[12] and not necessarily by change in the skill level. An econometric analysis using the panel data has been performed in Sect. 5 to validate the postulated relationship.

The relationship between the change in the share of hours worked by high-skill persons and change in the average growth rates of labour productivity and of employment is presented in Fig. 4; over the two periods of 1996–2002 and 2003–2009 for the selected nine countries. It is evident that the change between share of hours worked by high-skilled persons engaged and the change in average annual growth rate of labour productivity are positive for six out of the nine countries and negative for the two countries; namely Korea, and Taiwan. The positive change supports the contention of increase in the growth of labour productivity with increase in the use of high-skill persons. On further analysis, it is found that the two countries where the relationship is not supported are the ones which had not only the highest average per capita income but also had the highest share of hours worked by high-skill persons engaged during the initial years of 1996–2002 and the maximum change in the share of high-skill persons engaged. It is an indication of their fast adaption of new technology and focus on developing the skills of their labour force. The case of Mexico is an exception where a decrease in both the share of high-skilled persons engaged and the growth in labour productivity between the two periods took place. It reflects that perhaps Mexico could not continue its earlier efforts in increasing the educational level of its labour force, possibly resulting into slow growth in labour productivity and employment in the second sub-period. One of the implications from the pattern observed in these nine selected countries could be that the potential of improvement

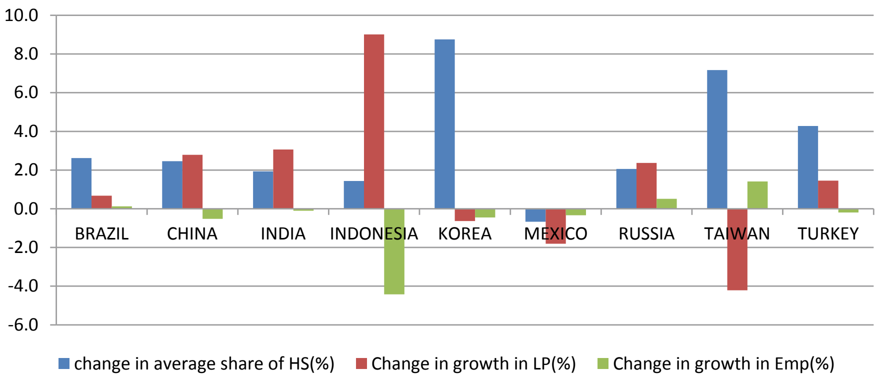

Fig. 4 Change in average share of hours worked by high-skill persons engaged, change in average growth in labour productivity and change in average growth in total employment between 1996–2002 and 2003–2009. *Source* Author's calculations based on data from WIOD data base (2014)

[12]It is observed that in all the selected nine countries, average labour productivity during 1995–2009 is higher in high capital intensive industries than the medium and low-skill intensive industries (Table 2).

in labour productivity by increase in skill levels of persons engaged may be higher for countries with low initial level of income and skills.

On the question of behaviour of growth in employment as a result of increase in the share of hours worked by high-skill persons and growth in labour productivity, the evidence of the selected nine countries in Fig. 4 does show a mixed result. Out of the six countries in which growth rate of labour productivity increased along with increase in the share of hours worked by high-skill persons engaged in the second sub-period, two countries namely Brazil, and Russia experienced a faster growth in employment in the second sub-period than the first sub-period. The experience of the other four countries—China, India, Indonesia and Turkey is, however, opposite and in these countries the growth rate in employment slowed down during the second sub-period as compared to the first sub-period. Of the remaining three countries, while in Taiwan the total employment grew at a faster average annual growth rate during 2003–2009 than during 1996–2002, the rate of growth is slower in the second period in Korea, and Mexico. There is thus no unique pattern between the changes in the three indicators.

4 Structure of the Economy: Contribution of High Capital Intensive Industries

With the evolving of technology at a fast pace since 1990s, it was expected that the firms in all the industries would adopt the new technology to improve their efficiency and to remain competitive. As a result of adoption of the new technology it was expected that two changes would simultaneously happen—first the firms and the industry would become more capital intensive; and second the firms may simultaneously displace some of the labour in the short term, but with improvements in efficiency and increase in demand due to increased incomes and/or lower prices for their products; may increase employment in the long term. As a result of these changes the contribution of capital intensive industries to total value added and employment was likely to increase. Figure 5 shows the contribution of high capital intensive industries in the real value added and in employment (total hours worked) for the selected countries. The figure shows that the share of high capital intensive industries to real value added and employment has increased in 2009 as compared to 1995 in Indonesia, Korea, and Taiwan; while the share increased in value added but decreased in employment in Brazil, and China. On the contrary, the share of high capital intensive industries to both value added and employment fell in India, Mexico, Russia and Turkey. The empirical evidence thus does not fully support the contention that with new technology over time, the high capital intensive industries would necessarily contribute more to value added and to employment. A plausible reason could be that within capital intensive industries the skill level distribution is not uniformly same. Some high capital intensive industries engage more of high-skill

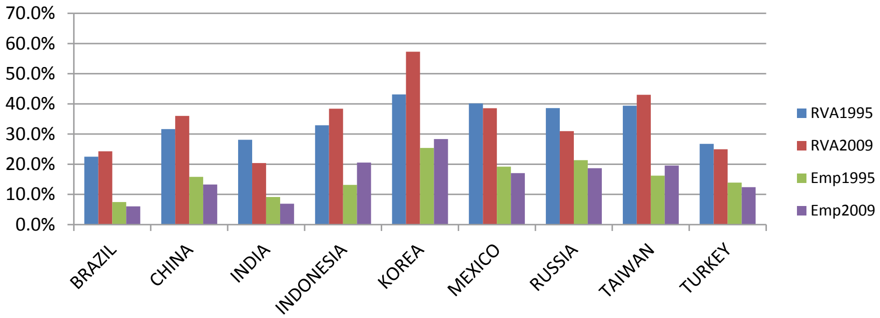

Fig. 5 Contribution of high capital intensive industries in real value added and employment in 1995 and 2009 for selected countries. *Source* Author's calculations based on data from WIOD data base (2014)

persons than others. The detailed analysis of growth in employment by skill level among high capital intensive industries is displayed in Fig. 6.

Figure 6 shows that in all the selected countries except Brazil and Mexico the average annual growth rate in high-skill persons engaged in high capital intensive industries; is different in different countries but is higher than that of medium-skill and low-skill persons engaged. The same trend is visible in Fig. 2 for the total non-agriculture economy. Thus, the trend at the disaggregate level is similar to the trend at the aggregate economy level.

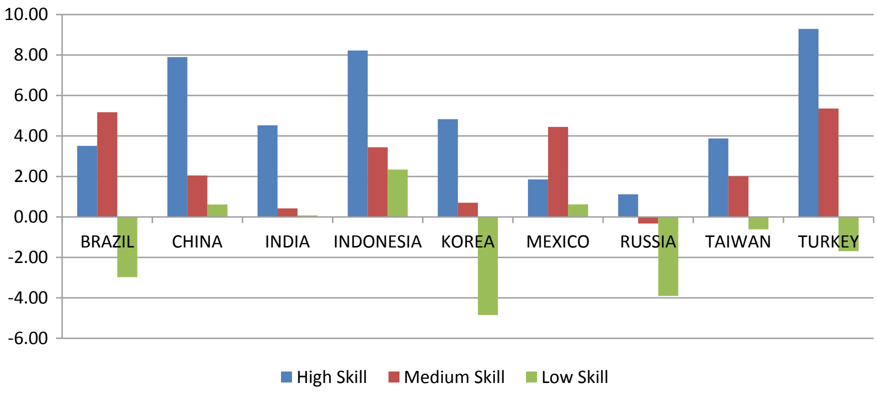

Fig. 6 Average annual growth rate of employment by skill level among high capital intensive industries (1995–2009). *Source* Author's calculations based on data from WIOD data base (2014)

Table 1 Fixed effect panel model estimates-1995–2009. Dependent variable: labour productivity

Explanatory variable	Coefficient	t-ratio
Capital labour ratio	3.53	19.71
Share of high-skill persons engaged	6822.38	6.45
constant	−1066.90	−7.76
No. of observations	135	
No. of groups	9	
F-value	369.77 (0.000)	
R-squared overall	0.946	

Source Author's estimates

5 Estimates of Econometric Model

As mentioned earlier, a simple econometric model has been estimated from the panel data of the selected nine countries for the period 1995–2009 (15 years) in which the relationship between labour productivity, capital labour ratio and the share of high-skill persons engaged in the total hours worked is obtained. For the purpose of this model, capital is defined as real gross fixed capital formation (real GFCF), labour is defined as total hours worked by persons engaged and output is real gross value added (real GVA). Labour productivity thus is defined as real gross value added (real GVA) per hour worked by persons engaged and capital—labour ratio as GFCF per hour worked by persons engaged. The results of the Fixed Effect panel model are presented in Table 1. It shows a significant and positive relationship of labour productivity with share of high-skill persons engaged, which is consistent with the postulated relationship. As expected, capital labour ratio is also found to be a significant determinant of labour productivity.

To confirm the results, the study also tested the relationship between Human capital index score given in The Human Capital Report 2016 (WEF 2016a), labour productivity and growth in employment for the selected eight countries.[13] It found a significant and positive relationship of Human capital score with labour productivity (correlation = 0.703) and GDP per capita (correlation = 0.852) but negative and insignificant correlation with growth in employment (−0.294). Similar results are also obtained from the correlations of score on 'Education and Training' given by Global Competitiveness Report: 2017–18 (WEF 2017) with the three variables of labour productivity, GDP per capita and growth in employment (Table 3).

[13] See Table 3. The score is not available for Taiwan.

Both the exercises in part I thus lead to the same conclusion that higher share of high-skill persons/higher human capital score generally has a positive relationship with higher labour productivity but not necessarily with higher growth in employment.

Part II: Skill, productivity and employment in the Organized and Unorganized Sectors in India (1999–00, 2004–05, and 2011–12)

6 Distribution of Employment by Skill in the Organized and Unorganized Sectors in India

The distribution of employment by skill in the organized and unorganized sector of the Indian economy for the three survey periods of 1999–00, 2004–05 and 2011–12 is presented in Fig. 7. Figure 7 shows that in the organized sector, the share of low-skill employed persons remained almost stagnant between 27 and 30% between 1999–00 and 2011–12. However, the share of medium-skill employed persons fell by 10 percentage points from 47 to 37% and that of high-skill persons employed increased by 8 percentage points from 25 to 33%. The increase in the share of high-skill workers in total employment could be partially due to the change in the nature of work in the organized sector due to fast changing technology requiring better skills. The other reason could be the general increase in the skill (education) level of the population and workers due to increased access and availability of education and training. The distribution of employment by skill in the unorganized sector in India is however very skewed towards low-skill and medium-skill employment. The

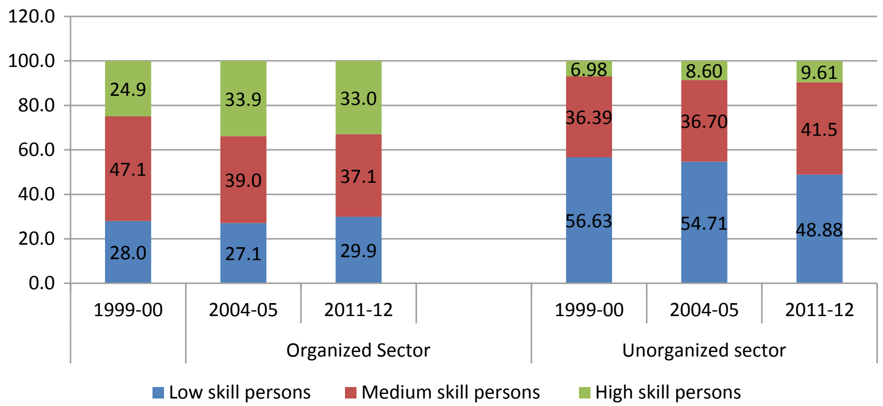

Fig. 7 Share of workers employed by skill in the Indian organized and unorganized sectors. *Source* Author's calculations based on data from different rounds of EUS

share of high-skill employment is very small at 9.6% in 2011–12 and was only 7% in 1999–00. The trend is partly the reflection of the nature of production activity and hence the skills required by the unorganized sector in India.

As a result of the basic difference in the nature of the production and skill requirements, one may also expect differences in the labour productivity between the two sectors. It is clear from Fig. 8 that not only the share of high-skill employment is higher in the organized sector; it is three times of the unorganized sector but the level of labour productivity (Rs. 0000) is also very high; 4–5 times higher in the organized sector as compared to the unorganized sector. However, we notice in Fig. 9

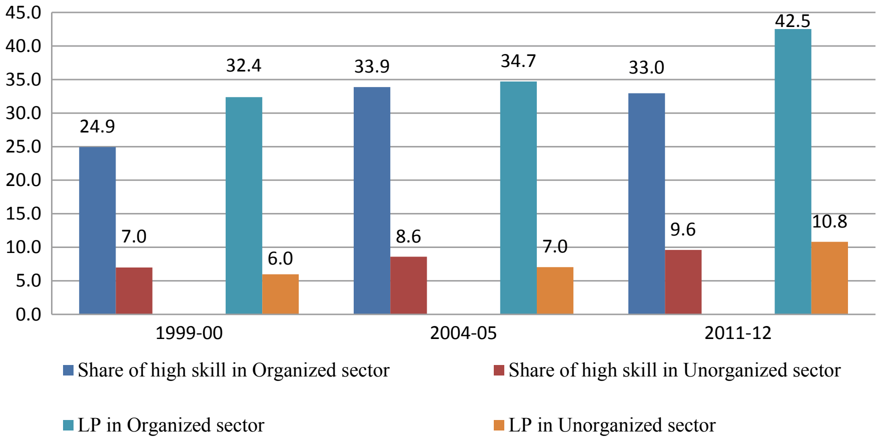

Fig. 8 Share of high-skill employment and labour productivity (LP) (Rs. 0000) in organized and unorganized sectors in India. *Source* Author's calculations

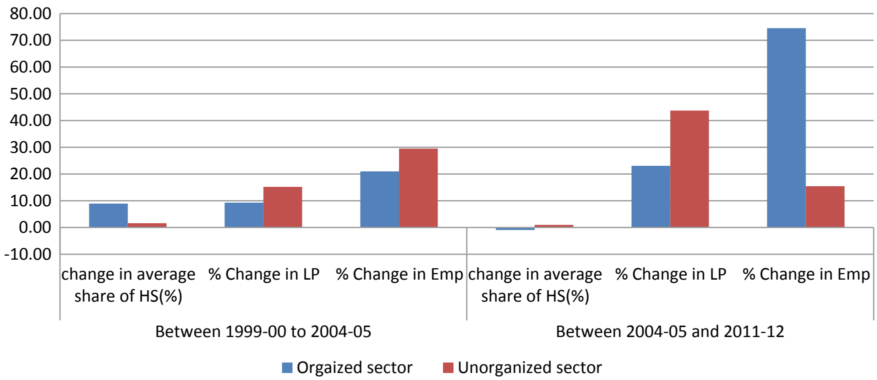

Fig. 9 Change in average share of high-skill persons employed, percentage change in average labour productivity and percentage change in average total employment between 1999–2004 and 2004–11. *Source* Author's calculations

that though the absolute level of labour productivity is higher in the organized sector but the percentage change in labour productivity between the two time periods of 1999–00 to 2004–05 and 2004–05 to 2011–12 is higher in the unorganized sector, thus catching up with the organized sector. However, the percentage change in employment is higher in the unorganized sector in the first period and in the organized sector in the second period. The important policy implication could be that a faster expansion of the organized sector in the Indian economy may help to accelerate the economy's growth.

7 Skill and Employment in the High Capital Intensive Industries in India

As is argued earlier that with capital-augmenting technological progress, the capital intensity of the industries would increase with increase in demand for high-skills and it is the high capital intensive industries that would be critical to the growth of the economy. The adoption of new technology leading to automation and increase in capital intensity of the firms in the organized sector in India is confirmed recently by Kapoor (2016) and was earlier concluded by Das et al. (2015) and Goldar (2000).

The analysis of the high capital intensive industries in Indian organized and unorganized industries begins with a look at their contribution in their respective total real value added and employment. It is noticed in Fig. 10 that high capital intensive industries have a more significant contribution in RVA and employment in the orga-

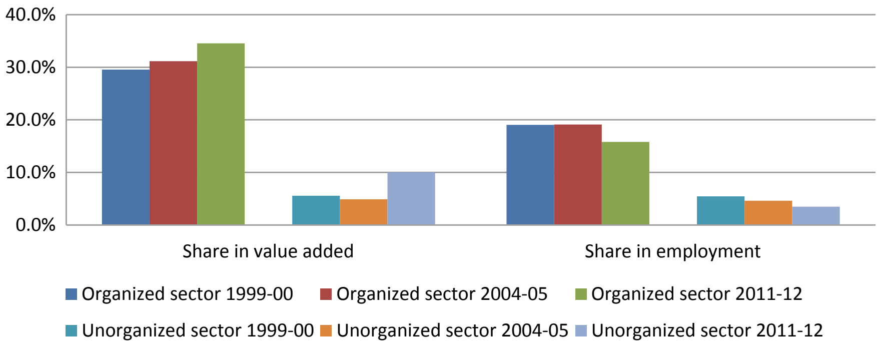

Fig. 10 Share of high capital intensive industry in Indian organized and unorganized sectors. *Source* Author's calculations

nized sector and in unorganized sector their contribution is rather small. However, the contribution in value added has been increasing but in employment it witnessed a declining trend. It is thus obvious that the high capital intensive industries will play a more important role in the growth of the Indian economy. But what kind of skills is used and how these are changing over the recent period in both the organized and unorganized sectors of the Indian economy is displayed in Fig. 11.

Figure 11 shows that among the high capital intensive industries, the growth in employment during 1999–00 and 2011–12 is highest in the low-skill employed persons in both the organized and unorganized sectors and is slower in medium-skill employed persons and moderate in high-skill employed persons. However, the growth of high-skill workers in the organized sector is much higher than the unorganized sector (where in fact it has declined), supporting the contention that it is the organized sector which might have more easily adopted and used the new technology requiring high skills. Kapoor[14] (2016) also finds support for the contention that firms with high capital intensity employed a higher share of skilled workers. The high growth in low-skill employment is partially the result of low access to education and training to the workers; both within the firm and outside the firms and is partly due to the increase in sub-contracting and informalization of the workers (Mehrotra et al. 2013; Goldar and Aggrawal 2012).

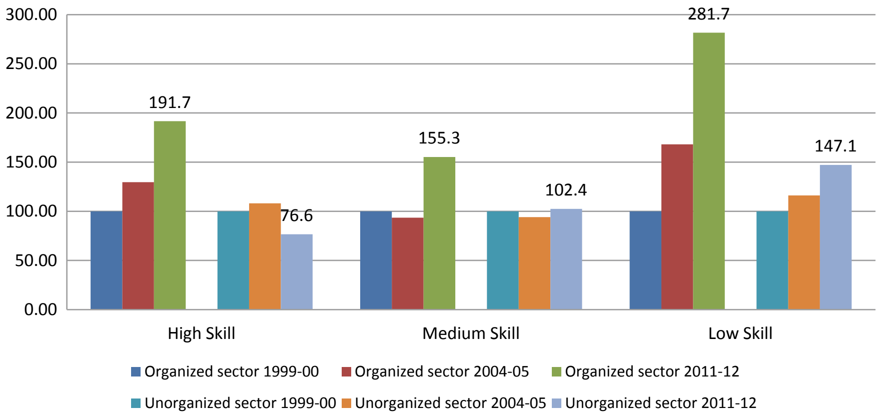

Fig. 11 Index of employment by skill level among high capital intensive industries in the Indian organized and unorganized sector (1999–2011). *Source* Author's calculations

[14]The author believes that it has led to a widening inequality of income between the high-skill and low-skill workers.

8 Summary and Conclusion

In a rapidly changing world with increased globalization, fast technical change, demographic transitions, migration and immigration have put pressure on the structure of skill requirements in most countries in recent decades. There is a growing concern that these changes are making many of the old skills redundant and there is a surge in some of the new skills which are in short supply. The costs of mismatch and shortages of skills are presumed to be substantial through its impact on productivity and income for individuals, employers, as well as society as a whole. However, the exact costs are hard to measure and some efforts are made to find the exact mismatch of the skills.

The current paper has just looked at the supply side of the skills whereby the changes in the supply of three different types of skills-high-skills, medium-skills, and low skills are examined in the first part of the paper for the selected countries and for the organized and unorganized sectors of the Indian economy in the second part. It is observed that generally the share of high–skill employed persons has increased over the period of the study. It is also evident that in the selected countries, the change in the share of high-skill workers is associated with a positive change in labour productivity and total employment with some exceptions. The share of high capital intensive industries in the value added and employment has also witnessed an increase in majority of the countries. The growth in employment of high-skill workers within high capital intensive industries is positive in all the selected countries. The econometric analysis also lends support to the positive association between the share of high-skill persons engaged and labour productivity.

The evidence from the Indian organized and unorganized sector supports the hypothesis that generally the share of high-skill employed persons and the level of labour productivity are higher in the organized sector than the unorganized sector. However, recently there seems to be some catching up of labour productivity by the unorganized sector. An interesting trend observed in the Indian organized and unorganized sector is that, while the share of high capital intensive industries in value added has increased over the period of 1999–2011, its share in employment has declined. The declining share in employment could be possible due to the labour displacing nature of capital intensive industries. One distinct feature observed within high capital intensive industries is that while employment of all the three skill levels increased in the organized sector; it is only the low-skill employment which grew in the unorganized sector. The growth of low-skill employment in the unorganized sector in India does not auger well for the future of economic growth in India because the unorganized sector is not only huge in terms of its contribution to total value added and total employment but the labour productivity in the sector is also very low. Thus, government intervention is required to promote the organized sector in the economy and also to improve the productivity of the unorganized sector. Based on the evidence, it may be argued that there is a close association between skills of the person employed and the labour productivity. The countries have to make serious efforts to improve the share of the (hours worked by) high-skill workers

Table 2 Index of labour productivity by capital intensity in selected countries

Country	Labour productivity in High Capital Intensive Industries	Labour productivity in Medium Capital Intensive Industries	Labour productivity in Low Capital Intensive Industries
Brazil	100	35.3	14.8
China	100	50.9	16.2
India	100	37.9	25.4
Indonesia	100	30.1	27.6
Korea	100	48.0	27.9
Mexico	100	68.3	18.6
Russia	100	56.4	44.6
Taiwan	100	45.4	26.1
Turkey	100	71.2	31.6

Source Author's calculation

to both improve their labour productivity and thus economic growth; as well as to quickly adapt to the 'fourth industrial revolution'. Efforts by individuals, firms and governments are required to minimize the mismatch in the demand and supply of skills by continuously updating the skills through education and training.

Appendix: Methodology of Estimating Organized and Unorganized Employment

Since 1999–00, NSSO surveys on employment and unemployment (EUS) provide information about the type of enterprises, the number of workers and whether the enterprise uses electricity. From these, one can discern the nature of enterprise, whether it belongs to organized or unorganized sector. Organized sector employment is defined as the workers employed in either (a) Government/Public sector enterprises (code 5) or in public/private limited company (code 6) or cooperative societies/trusts/other non-profit institutions (code 7), or (b) in other manufacturing enterprises employing 20 and more workers or using electricity and employing 10 or more than 10 workers (Sundaram 2008).

The methodology used in this study to estimate employment in the organized and unorganized sectors of the Indian economy is based on the above framework given by Sundaram (2008) (Tables 2 and 3).

Table 3 Relationship between Human capital score, labour productivity, GDP per capita and growth of employment

Country	Human Capital score 2016	Score on education and training—2016	Labour productivity per person employed in 2017 US$ (converted to 2017 price level with updated 2011 PPPs)	GDP per capita in 2017 US $ (converted to 2017 price level with updated 2011 PPPs)	Growth of employment (percentage change)
Brazil	64.51	4.2	30,810	15,399.169	1.802
China	67.81	4.8	27,628	15,378.107	−0.318
India	57.73	4.3	18,473	7,434.626	1.376
Indonesia	67.61	4.5	27,970	13,040.361	1.237
Mexico	69.25	4.1	46,235	20,088.396	0.845
Russia	77.86	5.1	58,010	27,966.140	0.688
South Korea	76.89	5.3	77,315	40,064.685	0.840
Taiwan	67.57	4.8	76,789	26,363.858	3.098
Correlation of Human Capital score	–		0.703	0.852	−0.294
p-value	–		0.0518	0.007	0.480
Correlation of Score on education and training	–	–	0.665	0.776	−0.184
p-value			0.0718	0.0236	0.6634

Source Author's calculation
Sources of data 1. Table 1: The Human Capital Index (WEF 2016a) for Human capital score which is not available for Taiwan. 2. The Global Competitiveness Report: 2017–18 (WEF 2017) for the score on education and training. 3. Total economy database (The Conference Board 2019) for other three variables

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