India Studies in Business and Economics

Tanmoyee Banerjee Chatterjee
Arpita Ghose
Poulomi Roy *Editors*

Risks and Resilience of Emerging Economies

Essays in Honour of Professor Ajitava Raychaudhuri

Springer

India Studies in Business and Economics

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Preface

The present volume is a tribute to Prof. Ajitava Raychaudhuri an outstanding and brilliant teacher, a renowned scholar and a person with an open mind and great candor of judgement. Professor Raychaudhuri, an alumnus of the Department of Economics, Jadavpur University, received his Ph.D. from American University, Washington, D.C., USA, in 1988. He was a Fulbright Fellow of Economic Growth Center, of Yale University, New Haven, USA, during 1996–1997. He also received several awards and medals for his outstanding academic achievements. He joined his *alma mater* as a lecturer in Economics in 1981 and remained there, till his retirement as a professor in Economics in June 2022. He was a visiting faculty in institutes like Economic Research Unit, Indian Statistical Institute (ISI), Calcutta, Indian Institute of Foreign Trade, Kolkata Campus. His primary research interest lies in the fields of trade and development, macroeconomics and public economics. His special interest was issues specifically related to developing countries. He actively took part in policy-centric empirical research works and conducted many research projects sponsored by well-known national and international organizations like the Ministry of Finance, Government of India, SANEI-III, Global Development Network (GDN), World Bank, PEP Network, UNESCAP and WTO, Asian Development Bank, Planning Commission of India, Finance Commission of India to name a few. He has published extensively in nationally and internationally acclaimed journals as well as in edited volumes. He has also authored and edited several volumes, which were well received among the academia. Professor Raychaudhuri was also a very capable academic administrator. He was Dean of the Faculty of Arts, Jadavpur University, Joint Coordinator of Social Science programme under UGC funded by the UPE-II programme (2013–2019).

During his career as a teacher in the Jadavpur University spanning over four decades, Prof. Raychaudhuri has taught scores of students. For the students attending 'ARC Sir's' classes marked with his insights and excellent clarity of exposition on macroeconomics, international trade and econometrics was a memorable experience. His way of teaching would attract even the most irregular of students. The students who flourished under his tutelage are now employed in academia, in government administration and in industry in India and abroad enjoying very successful careers.

To his colleagues, Prof. Raychaudhuri was always accessible and available for advice and guidance. He encouraged his younger colleagues to get involved in research and never to compromise with the academic standard of Jadavpur University.

The volume is a small token of gratitude and appreciation to our revered teacher and former collogue better known to many of us as ‘ARC Sir’ or ‘Ajitava Da’. The book brings together contributions from his students, colleagues and research associates, who will always admire his intellect. We thank all the contributors who have joined us to complete this project. We sincerely thank Prof. Sushil K. Haldar, Prof. Malabika Roy and Prof. Saikat Sinha Roy of the Department of Economics, Jadavpur University, for their constant support, encouragement and valuable counsel. We are extremely thankful to Ms. Paulomi Basu and our team of reviewers for their relentless effort. We also appreciate the help extended by Ms. Nupoor Singh and Naresh Kumar Mani of Springer to fulfil this entire project.

Kolkata, India

Tanmoyee Banerjee Chatterjee
Poulomi Roy
Arpita Ghose

Editors' Note

The world economy that was striding with leaps and bounds with digital revolution and growing interconnectedness faced a serious challenge due to the outbreak of the COVID-19 pandemic. This global exogenous health distress compelled the academicians, policy practitioners to reinvestigate the policies related to growth, trade, development, finance and social sector in the light of threat posed by the COVID-19 pandemic. The present edited volume seeks to explore the recent advances and frontiers of research in development economics including international trade, international finance and social sector; also, the volume will re-examine certain old issues from a new perspective. The book covers a wide range of topics like recent developments in macro-economic theory in the light of pandemic, economic growth and efficiency, fiscal policies, issues related to global value chain, exchange rates, export performance, functioning of banking sector and microfinance institutions, in the context of India and other emerging economies. Most importantly, the book will discuss the concerns in education policies and occupational segregation through a gender lens.

The present volume contains 15 papers divided into two broad parts: The first part will include contributions to macroeconomic theory, international trade, finance and fiscal policies. The second part will include papers on demography and social sector.

In the 'COVID-19: A Means of Exploitation' chapter of Part one, Ambar Ghosh and Durba Ahmed develop a macro-theoretic framework suitable for India to examine the macroeconomic impact of the pandemic on India. It shows that the downsizing of the workforce of the organized sector that the pandemic-related restrictions and lockdowns had induced and the switch from offline to online services and greater use of digital technology led to a cumulative shrinkage of the unorganized sector enabling the capitalists to grab the market of the unorganized sector and also a larger part of the output of the organized sector for their own consumption and investment. The pandemic-induced restrictions and lockdown also produce similar effects. This is a matter of grave concern since about 99% of Indians derive their livelihood from the unorganized sector.

In the 'An Analysis of the Impact of GST on States' Indirect Tax Revenue and on Economic Formalization with Special Focus on West Bengal' chapter, Hari

Krishna Dwivedi, Achin Chakraborty and Sudip Kumar Sinha discuss one of the most important fiscal reform that has been carried out in India in the form of introduction of Goods and Services Tax (GST) which was rolled out in India on July 1, 2017, with an ideology of 'one nation one tax'. The authors have carried out an inter-state comparison of the impact of GST on the indirect tax revenue of the General Category States (GCS) in India with special reference to West Bengal. Indicators such as Tax-to-GSDP ratio and Tax Buoyancy have been used to measure tax revenue performance in the pre-GST and post-GST era for each GCS. The chapter observes a steady decline in tax revenue for most of the states including the consumption-states in the post-GST era, even if GST is designed to be a consumption-based tax as against production-based tax. The study also observes the adverse effect of the COVID-19 pandemic and subsequent nationwide lockdown measures on tax collection.

Sangita Dutta Gupta and Madhumita Guha Majumder in the 'Digital Transformation, Digital Entrepreneurship, and Economy: A Cross-Country Analysis Using Moderated Mediation Modeling Technique' chapter will shed light on the role of entrepreneurship in the economic growth of emerging economies. This study identifies the determinants of digital adoption required for digital or technological entrepreneurship. Using data related to the digital platform economy index of 116 countries and GNI (Gross National Income) per capita data is collected from World Bank the study confirms that digital access, digital literacy and financial facilitation contribute to the digital technology entrepreneurship of a country. The study concludes that countries need to embrace technology that can enhance technology entrepreneurship leading to economic well-being.

The problem of the Indian agricultural sector and its volatility has been discussed in the 'Bi-Directional Causality Between Volatility in Output Growth and Price Growth: Evidence from Rice Production in India Using ARCH/GARCH and Panel VECM Approach' chapter by Dipyaman Pal and Chadrima Chakraborty. The paper estimates the volatility of growth in output (VGRP) and volatility of growth in price (VGPRP) of rice for four major rice-producing states of India as India is the major producer and exporter of rice in the world. The study observes that both in the long run and short run the volatility in price growth is significantly affected by the volatility in output growth. Further, in the long run, the effect of volatility in price growth on the volatility in output growth is higher than the effect of the volatility in output growth on the volatility in price growth.

In the 'Unlocking the GVC Potentials in India: Role of Trade Facilitation' chapter, Prabir De writes about Global Value Chains (GVCs) and trade facilitation in the context of the Indian economy. An open international trade and investment policy plays a critical role for any economy aspiring for global economic integration through GVCs. The COVID-19 pandemic has a major impact on labour-intensive value chains and also has an impact on demand as well as supply factors. The chapter discusses the challenges faced by India in trade facilitation while promoting the GVCs and the opportunities.

In the 'Exchange Rate Pass-Through in South Asian Countries' chapter will present the study by Darpajit Sengupta and Saikat Sinha Roy on the Exchange Rate Pass-Through (ERPT) to import prices for a sample of five South Asian Countries

(Bangladesh, India, Iran, Pakistan and Srilanka). The results show that in the short run pass-through of import prices are incomplete. The long-run ERPT is marginally higher than in the short run, but still incomplete. Their results bring about an empirical verification of the traditional theoretical wisdom that depreciation of currency leads to an increase in import prices thereby making these products less attractive in the domestic market. The findings on exchange rate pass-through have implications for exchange rate being used as a price-based policy instrument for import control, thereby reducing the current account deficit.

In the 'Export Decision and Export Performance of Manufacturing Firms An Experience from Indian Organized Sector' chapter Paramita Roy Biswas and Simontini Das explore the determinants of the export performance of Indian organized manufacturing firms using ASI unit-level cross-sectional data. This cross-sectional study analyses the impact of firm-level heterogeneity in explaining inter-firm variation in their export decision and export performances at firm level. The technical efficiency, spatial location, ownership pattern, technological advancement, quality standard and skill intensity explain the firm-level heterogeneity. Firm-level technical efficiency is estimated using Stochastic Frontier Analysis. Ownership pattern has diverging impacts on export decision and export performances across the manufacturing units. Technical efficiency, standardization of quality, transfer of sophisticated technology in terms of usage of imported input and urban location improve the export performance of the manufacturing unit.

The next two chapters of Part 1 of the book will concentrate on problems related to banking and finance. In the 'The Impact of Global Financial Crisis on the Efficiency of Indian Banks: Evaluation with Data Envelopment Analysis' chapter of the book, Karan Singh Khati, Shivam Kushwaha and Deep Mukherjee delve into a study on non-radial Data Envelopment Analysis (DEA) in order to evaluate productive efficiency of banks in Indian context. Results of DEA indicate a lot of scope for improvement in resource utilization if non-radial efficiency measure is employed. The disaggregation of efficiency reveals that physical capital, labour and other incomes are the main contributors to inefficiency. This insight into the components leading to inefficiency will assist managerial decision-making for performance improvement. The study reveals that the non-radial efficiency has a U-shaped relationship with size of bank. Further, the study reveals that the global financial crisis (GFC) of 2007 and 2008 had a positive impact on the efficiency of public sector banks but has an adverse effect on the same for private banks.

In the 'Does Government Effectiveness and Regulatory Framework of a Country Influence the Performance of MFIs? an Empirical Study on Selected Asian Countries' chapter, Chandralekha Ghosh examines whether the impact of different governance-related factors on both financial and social performance vary from country to country. This set of countries, namely Afghanistan, Pakistan, Bangladesh, India, Indonesia, Vietnam and Thailand, have different backgrounds in the evolution of Micro Finance Institutions (MFIs) and have differences in their regulatory frameworks and government effectiveness and other governance-related factors. Using a multi-level model chapter shows that country-specific variables, namely regulatory quality estimate, have a differential impact on return on assets (ROA) and government effectiveness on profit margin has a differential impact on different countries.

The first part, of the book brings about some recent ideas on various branches of development economics. It touched upon the possible impact of the COVID-19 pandemic from a macroeconomic perspective of a developing nation. The papers also shed light on some deep-rooted problems of the Indian economy and other emerging economies relating to international trade and finance. The second part of the book will explore the concerns related to the social sector of an economy.

The first paper of part two, as presented in the 'Subaltern Urbanization: The Birth of Census Towns in West Bengal' chapter of the book by Saumyabrata Chakrabarti and Vivekananda Mukherjee discusses one important demographic problem in India. The chapter is about the growth of census town in India where a village becomes a census town when it has a population of 5000 or more; its population density is at least 400 per square kilometre; and 75% of its male main workforce working in non-farm sector. Using a principal component analysis present study observes that in all the districts of West Bengal, the presence of highways within 5 km radius of a village played an important role in the formation of census town. In the districts bordering Kolkata, the capital city of the state, the population density at the nearest city had been important.

In the 'Gendered Occupational Segregation and Its Cost in India: Evidence from NSSO Data' chapter, Suchetana Das, Riya Basu, Utsav Biswas, Anuska Das and Mousumi Dutta address the issue of gender-based occupational segregation, which is one of the most persistent aspects of gender inequality in the labour market of India, creating a barrier to a country's welfare. Using the two rounds of NSSO data (61st and 68th rounds), the results show an increase in occupational segregation across gender at the all-India level and for most states.

Saibal Kar and Archita Pramanik discuss the issue of labour market participation and school enrolment for women in South Asia in the 'Does Job Prospect Influence School Enrolment for Women in South Asia?' chapter. The region is characterized by wide dispersion in the level of school enrolment for females across countries. In particular, the study shows that job prospects in industries, and not services, generate a strong positive impact on secondary school enrolment in south Asian countries.

In the 'Regional Patterns and Dynamics of Learning Outcomes in India' chapter, Muneer Kalliyil, Srividya Aluru and Soham Sahoo use convergence models from the growth literature to see whether the learning outcomes are converging among the districts over the years. Using the measures of beta and sigma convergence to understand the dynamics of average learning across the Indian districts over time, the study shows that there is beta convergence across the districts in India. The convergence rate increases other relevant variables capturing the initial conditions of the districts that are controlled.

The issue of gender inequality in learning outcome is discussed by Antara Bhattacharyya and Sushil Kr. Haldar in the 'Gender Differential of Educational Outcomes in India: How Does Space Matter?' chapter. The study measures learning outcome by literacy rate and enrolment ratio. The paper examines the spatial influence of gender differential in educational outcomes along with conventional socio-economic variables in a panel data framework. The results show that gender disparity of net enrolment is found to be negative which means females are better off compared to males but disparity prevails in respect of literacy rate though over time it is found to be declining in all the states; we find that net enrolment is space-neutral but the literacy rate is space-dependent.

Finally, in the 'Inheritance of Educational Attainment: Instance of Caste Certificate in India' chapter, Rilina Basu, Poulomi Roy and Sishir Roy discuss the efficacy of caste-based reservation policy through the acquisition of caste certificate among the educational attainment of three generations. Using the Indian Human Development Survey (IHDS) 2010–2011, the study has identified two pairs of 'lower caste' father–son to trace intergenerational mobility in higher education. Analysis shows that third-generation son is more mobile than second-generation son. So over time, intergenerational higher educational mobility of backward castes is increasing.

Thus, the present edited volume will considerably add to the existing literature pertaining to various important topics of development economics and social sector. The volume will present different studies that use cutting-edge techniques to discuss emerging aspects of development fundamentals and also will focus on sectors that are affected by the COVID-19 pandemic.

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Editors and Contributors

About the Editors

Tanmoyee Banerjee Chatterjee is Professor in Department of Economics, Jadavpur University, Kolkata. She did her Ph.D. from Jadavpur University in industrial organization. Presently, her area of research encompasses industrial organization, microeconomic theory, microeconometrics, microfinance, financial inclusion, gender analysis, and economic growth. She has undertaken various empirical research projects funded by national agencies of India like ICSSR and UGC. She has published extensively in reputed international journals.

Arpita Ghose is currently Professor-Economics, Chair Professor (Honorary), Planning and Development Unit, Jadavpur University(JU) (NITI Aayog) and presently Dean Faculty of Arts, JU. She did her Ph.D. from Indian Statistical Institute, Kolkata, and works in the area of disequilibrium economics. She has published her research in reputed national and international journals. At present, she is working on computable general equilibrium models, productivity and efficiency analysis using data envelopment approach and stochastic frontier models, and also on applied time series econometrics. She has completed projects funded by DFID-UNCTAD, Government of India, for Jadavpur University's Trade Research Capacity Building Program; Shastri Indo-Canadian Institute, Calgary, Canada; UGC and ICSSR.

Poulomi Roy is Associate Professor in Department of Economics, Jadavpur University, Kolkata. She did her Ph.D. from Jadavpur University on fiscal policy. Presently, her area of research covers public policy, economic growth, development economics, and gender analysis. She has undertaken various empirical research projects funded by national and international agencies like UGC and UNDP. She has published extensively in reputed national and international journals.

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Development Fundamentals: Macroeconomic Parameters

COVID-19: A Means of Exploitation

Ambar Ghosh and Durba Ahamed

1 Introduction

Professor Ajitava Roychoudhury has always been a progressive person. At one time in his life, as we have heard from his friends, he was associated with a movement which sought to change this world into a just and equal one. In this Festschrift that is being brought out in his honour, we, therefore, consider it appropriate to pay our tribute to him by contributing this write-up, which seeks to bring out the injustice, violence and exploitation that are ingrained in our capitalist societies.

The outbreak of COVID-19 and the imposition of the lockdown robbed a large section of the common people all across the capitalist world of their livelihood. Their misery and suffering knew no bound and the government's assistance was either non-existent or too inadequate. This became most visible in India through the plight of the migrant workers who took to the streets in millions and started a long and arduous walk back towards their homes. Many of them died on the way. The second wave of COVID-19 in India took precious lives of millions of ordinary Indians because of the shortage of adequate healthcare facilities for them. The government did not even arrange for proper cremation of the people who died. It threw their dead bodies in the rivers or just covered them with sand on river banks much to the horror of the whole world. Government's apathy towards the misery, starvation and death of the common people not only in India but also all across the capitalist world is extremely puzzling in view of the political system the capitalist world has. Ghosh and Ghosh (2019) has resolved this puzzle in Chap. 7. We briefly present it here for the convenience of the readers. (The same argument has also been presented in Bhattacharya & Ghosh, 2021.)

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On the top of the capitalist world are the capitalist countries. Examples of the capitalist countries are the Western European countries and the US. The most important feature of a capitalist country is that in such a country just a few giant firms carry out the entire production of almost all the goods and services and just a few giant businessmen, referred to as the capitalists, manage them. Thus, the capitalists have in their control almost all the capital and natural resources of the country. They produce goods and services by hiring workers with wages and salaries. The rest of the people, therefore, derive their livelihood by being workers of the capitalists. In a capitalist country, therefore, the capitalists are pitted against more than ninety-nine per cent of the people. The survival of the capitalists, therefore, depends crucially on how effectively they are able to subjugate the masses. If they fail to do so, the masses will simply overpower them and take over their wealth and business empire. The most important way in which they subjugate the masses is by being united and usurping the State Power. Clearly, if they are divided and fight against one another, they will become weak and lose their business empire and wealth to the masses. Thus, the capitalists in a capitalist country are united. How do they usurp State Power? We recount it below.

Every capitalist country in the capitalist world has democracy, where people choose their ruler. No ruler is thrust on them. In a democracy, two or more political parties compete for State Power. A general election is held every four or five years. People express their choices as regards which political party would rule them until the next general election is held by casting votes. Every adult citizen has one vote irrespective of his economic condition. The political party that gets the highest number of votes becomes the ruler until the next general election is held. As democracy makes all the individuals politically equal by empowering each of them to cast just one vote irrespective of his economic status, every political party should work for the masses who constitute more than ninety-nine per cent of the voters. In a capitalist country, the fate of more than ninety-nine per cent of the people hangs on the decisions of just a few capitalists. They decide which of the workers will get employment and what the wage rate and the working conditions would be. This makes the scenario very precarious for the masses. Obviously, a political party in power working for the masses cannot let this situation continue. It should take away all the wealth of the capitalists and distribute them among the masses. It should nationalize all the enterprises of the capitalists and run them in the interest of the masses so that every worker gets a job, a decent working condition and a decent living. Thus, democracy should destroy the capitalists and capitalism and establish the rule of the masses almost overnight. However, no political party works against the capitalists. They, in fact, work for the capitalists and against the masses. They, for example, forcibly take away whatever little land the poor masses possess and give it to the capitalists free of cost. Democracy does not scare the capitalists in any manner. They love democracy so much that they call their countries not capitalist countries but democracies as opposed to autocracies which, they think, the socialist countries are. How do the capitalists survive and thrive in a democracy? This is indeed a big puzzle. Obviously, one has to solve this puzzle to know how a capitalist country works. We seek to resolve it below.

Clearly, ordinary people cannot set up a country-wide business enterprise or a political party. The latter requires millions of dedicated workers of varied skills—from muscle men to highly talented strategists and speakers—in every nook and corner of the country. It should have almost limitless access to all kinds of media. The richest party hires the best brains and the strongest muscles and, thereby, outcompetes the other parties. Hence, only the wealthiest of the people of a country can set up and run political parties. In a capitalist country, the capitalists are the wealthiest of all people. They also need the State Power to protect their enormous wealth and business empire from the masses. Hence, it is the capitalists who set up and run the political parties in a capitalist country and, thereby, usurp the State Power through them. The capitalists subjugate the workers not only by exercising State Power but also by creating large-scale unemployment. The presence of large-scale unemployment makes the employed workers so much scared of losing their jobs that they surrender completely to the capitalists. The unemployed masses are kept in check through the deployment of the whole of the administrative apparatus of the government including the police and the military. The capitalists relentlessly innovate technologies that make the production process more automatic in order to generate large-scale unemployment. The massive investments that are being made at the present in artificial intelligence and robotics may in not so distant a future make the production process fully automatic. When that happens, all the workers, except for a few highly talented ones, will become redundant in production. They will become jobless and their lives will be in jeopardy. From the above it follows that a capitalist country is fully under the control of the capitalists, who are just a few in numbers and who are a united lot.

What kind of a country is India? To understand that, we have to refer briefly to history. Western European countries were the birth place of capitalism. Capitalism started in these countries when the capitalists became so wealthy that they could raise a military that was many times larger than what the kings of those countries could (see in this context Hunt & Lautzenheiser, 2014). Accordingly, the kings of those countries became puppets in the hands of the capitalists. Capitalists right from their very birth started conquering other countries to expand their business empire. The conquest enabled the conqueror to own all the natural resources of the conquered country, and establish himself as the sole producer and distributor of all the produced goods and services by obliterating the indigenous bases of production and distribution. This made it possible for the conqueror to secure labour from the conquered country at the lowest possible price and sell his produced goods and services at the highest possible price. Thus, a company, the East India Company, conquered India and made it its colony. India gained independence in 1947 after the Second World War was over. What is its state at the present? We will discuss that below.

India, as pointed out in Ghosh and Ghosh (2019) is virtually still a colony of the capitalists of the Western European countries and the US, who are now a united lot and whom we will henceforth refer to as the Western capitalists (for a detailed discussion on this point, go through Ghosh & Ghosh, 2019, Chap. 7). India is bereft of any independent base of knowledge and technology. It sources all its knowledge and technology from the US and the Western European countries. We can illustrate this point by taking the example of teaching and learning any subject in India. All the text books and all the journals teachers refer to are of US and Western European origin; the computers the students, teachers and researchers use come from these countries; and all the software also comes from these countries. Online teaching and research during the pandemic were made possible by the computers and software supplied by these countries. In fact, to set up any modern facility such as a modern educational institute or a modern hospital in India, all the knowledge inputs and high-tech machines have to be bought from these countries. The kind of imported technology and knowledge India uses to produce its goods and services has made India heavily dependent on imported intermediate inputs such as petroleum and petroleum products, chemicals and components. Therefore, India requires imports on a massive scale to sustain even moderate levels of production and investment. However, to make these imports, India requires currencies of the US and the Western European countries by selling its products to these countries. India's ability to sell its products to these countries by competing with other countries is virtually nil, since imported technology and knowledge are always dated and, therefore, do not give India any competitive edge over other countries. India, therefore, cannot keep itself going. How does it survive then? The only plausible hypothesis is the following. The Western capitalists control all the firms and the governments in those countries. They buy Indian products and Indian bonds and stocks on a large scale and, thereby, provide India with the necessary amount of foreign currency. Indian capitalists also have no access to any independent base of original knowledge and technology. Hence, they have no competitive strength vis-a-vis the Western capitalists. The Indian capitalists cannot, therefore, sustain themselves on their own. Nor can they compete in any manner with the Western capitalists. How can one, then, explain their survival? The only plausible hypothesis is that they are just employees of the Western capitalists and managing the Western capitalists' businesses in India. Hence, the Western capitalists own and run all the political parties in India. It, therefore, follows that India at the present is still a colony of the Western capitalists. In the colonial days, they used to rule India and run their businesses in India directly. Now, they do so not directly but through their Indian employees.

The above discussion suggests that the governments in capitalist countries and their satellites such as India did not give much assistance to the ordinary people who became victims of COVID-19 and the lockdown that was imposed to contain it because the capitalists asked them to do so (1). The question is why. The answer that seems most plausible is the following. At the present, the capitalists have in their command digital technology by dint of which they can run the capitalist world keeping a large section of the people at home. If the capitalists are able to do this, their control over the masses will increase enormously. If people cannot study and work together, if they cannot mix with one another, they cannot become united against the capitalists. At the same time, the capitalists at the present have at their disposal a huge arsenal of tremendous biological weapons using which they can create a pandemic at will. In our view, the capitalists have created the pandemic so that they can use the digital technology at their command to keep most of the people studying and working from home so that their control over the masses increases manifold (2). The pandemic and the digital technology also enable them to take away the land of the small producers who still own eighty-five per cent of the agricultural land in India (see NABARD, 2021). The objective of this paper is to show how the pandemic brings about a transfer of land from the small producers to the capitalists using a theoretical framework suitable for India. The model we have developed here for our purpose is similar to the one used in Bhattacharya and Ghosh (2021). Both are based on a specific view as regards how the capitalist countries and their satellites like India work. This view, partly summarized above and espoused first in Ghosh and Ghosh (2019), states that the capitalist world consisting of the countries mentioned above, is ruled, run and managed by the Western capitalists. They determine not only the supply but also the demand and set all the prices. For evidential support of this view, one may go through Chaps. 5 and 7 of Ghosh and Ghosh (2019).

1.1 The Model

To show how the pandemic enables the capitalists to grab the land of the small producers, we divide India into two sectors: the organized sector and the unorganized sector. The government sector, the private corporate sector and the large unincorporated private enterprises constitute the organized sector. The small producers including the farmers and the village and the cottage industries are the constituents of the unorganized sector. We describe the two sectors in greater detail below.

The Organized Sector

Unlike mainstream macroeconomics, which is of the view that the capitalist world is governed by impersonal market forces, we postulate that the Western capitalists have full control over the organized sector of India. The output of the organized sector is used for purposes of consumption by both the capitalists and the workers. It is also required for purposes of investment. It is also demanded as an intermediate input in the production of the unorganized sector. The Western capitalists maximize profit not in terms of money but in terms of their command over the output of the organized sector. They require as much of the output of the organized sector as they can manage to secure for purposes of investment. The reason is that through investment they want to incorporate as much automation as possible in the production process. They also want to set up facilities for the production of new types of luxury goods, better varieties of existing luxury goods and more powerful weapons of control and destruction. Hence, they set aggregate planned investment at such a level in every given short period that the output of the organized sector is always at its capacity level. The prices and wages in the organized sector are set by the capitalists. We will not try to decipher the price setting principle of the capitalists and simply assume them to be given. We will denote the output of the organized sector by O and its price by P_O. The output of the organized sector is produced with labour and capital. The labour is the variable input and the labour requirement per unit of O is l. The stock of capital is fixed in the given short period under consideration. The equilibrium condition of the organized sector may be written as follows:

$$\overline{O} = C_c \cdot \left(\overline{O} - \frac{W}{P_O} l\overline{O} - \frac{\omega i_o}{P_O}\right) + C_w \cdot \mu\left(\frac{P_U}{P_O}\right) \cdot \left(\frac{W}{P_O} l\overline{O} + \frac{\omega i_o}{P_O}\right) + I + \theta U \tag{1}$$

In (1), $\overline{O}$ is the capacity output of the organized sector in the given short period under consideration. c_c denotes the fixed average and marginal propensity to consume of the capitalists. W is the fixed money wage rate of the workers of the organized sector. Workers of the organized sector hold all their savings in the form of bank deposits and ω denotes the stock of bank deposits of the workers at the beginning of the given period and i_0 is the average interest rate applicable to ω. Since i_0 is the average of the interest rates that prevailed in the past, it is given in the given period and so is ω. The first term of the expression on the RHS of (1), therefore, gives the aggregate planned consumption demand of the capitalists. The organized sector and the unorganized sector produce close substitutes in quite a large number of sectors such as food, clothing, shelter, education, healthcare, finance, hotels and restaurants, entertainment, servicing and repairing, retail trade, etc. Workers consume a fixed c_w fraction of their income on consumption and allocate μ fraction of it to the output of the organized sector. It is reasonable to make μ an increasing function of $\left(\frac{P_U}{P_O}\right)$, where P_U is the price of the output of the unorganized sector. I denotes aggregate planned investment. The capitalists set it at such a level that the productive capacity of the organized sector is fully utilized. Finally, θ is the fixed amount of O required as intermediate input per unit of U, where U denotes the output of the unorganized sector.

The Unorganized Sector

We assume that the output of the unorganized sector is determined by the amount of the intermediate inputs the producers of the unorganized sector are able to buy from the organized sector. Note that agriculture is by far the largest segment of the unorganized sector. It requires seeds, fertilizer, pesticides, power, fuel, transportation, etc. from the organized sector. The other segments of the unorganized sector also require intermediate inputs from the organized sector. For simplicity, we assume that the small producers do not have any money of their own to buy the intermediate inputs. They buy them with loans. The amount of loan the small producers are able to secure from their lenders, denoted D, is too small to enable them to fully utilize the land and capital they have at their disposal. Therefore, the supply of U is given by the following equation:

$$U = \frac{D}{\theta P_{OU}} \tag{2}$$

In (2), P_{OU} denotes the price of the intermediate inputs bought from the organized sector. The small producers keep a fixed fraction γ of their output for self-consumption and investment and supply the rest to the market. Denoting the market supply of U by US, we get

$$US = (1-\gamma)\left[\frac{D}{P_{OU}}\frac{1}{\theta}\right] \tag{3}$$

Only workers of the organized sector demand U in the market. Their demand for U, denoted UD, is given by

$$UD = C_w \cdot \left(1 - \mu\left(\frac{P_U}{P_O}\right)\right) \cdot \left[\frac{W \cdot lO + \omega i_o}{P_{OU}}\right] \tag{4}$$

From the above it follows that the unorganized sector is in equilibrium when

$$C_w \cdot \left(1 - \mu\left(\frac{P_U}{P_O}\right)\right) \cdot \left[\frac{W \cdot l \cdot \overline{O} + \omega i_o}{P_U}\right] = (1-\gamma)\left[\frac{D}{P_{OU}}\frac{1}{\theta}\right] \tag{5}$$

The small producers use the sales revenue to pay off their loans along with interest. Usually, some of them default, while others are able to save a part of it after meeting the debt service charges. Normally, this saving is quite small and we ignore it for simplicity and without any loss of generality.

The small producers' investment comes from their own products that they set aside for self-use. For example, the animals and implements that constitute a part of the capital stock of agriculture, village and cottage industries are produced in the unorganized sector. The government invests in infrastructure such as roads, power distribution facilities, irrigation, flood control facilities, drainage, transportation, etc. to provide the small producers with these services. Some of these services are free, while others are supplied at a price. These prices are included in P_{OU}.

We have described above both the organized and the unorganized sectors. We will now turn to the financial sector.

The Financial Sector

To identify the determinants of D, we have to focus on the financial sector. The Reserve Bank of India (RBI) and the commercial banks by assumption constitute the financial sector. We do not bring in any other financial institution for simplicity. Clearly, it is a part of the organized sector and its output includes the value added of the financial sector. We assume that both the workers and the capitalists hold their savings with the commercial banks as deposits. The planned supply of new loans of the commercial banks denoted DS is given by the following equation:

$$DS = \left(1 - \vartheta\left(\bar{i}\right)\right) \cdot \left[(1 - C_c) \cdot (P_o O - WlO - \omega i_0) + (1 - C_w) \cdot (WlO + \omega i_0)\right] \tag{6}$$

Let us now explain (6). Here, ϑ denotes the cash-reserve ratio of the commercial banks. We make it a decreasing function of i. However, the central banks all across the capitalist world including India seek to keep i at a target level through their monetary policies. Hence, i is a policy variable of the RBI and it seeks to keep it at the target level $\bar{i}$. We assume for simplicity that the capitalists finance their entire investment with loans taken from the commercial banks. Even if they had used their saving to finance a part of their investment, our results would have remained unaffected. The commercial banks also give D amount of loans to the small producers. Therefore, the equilibrium condition of the financial sector may be written as follows:

$$\left(1-\vartheta\left(\bar{i}\right)\right).\left[(1-c_c).\left(P_O\overline{O}-Wl\overline{O}-\omega i_0\right)+(1-c_w).\left(Wl\overline{O}+\omega i_0\right)\right]-D+\epsilon=I \tag{7}$$

In (7), ϵ denotes central bank's new lending to the commercial banks. If there emerges an excess demand for new bank loans at $\bar{i}$, the central bank lends to the commercial banks so that the latter meets this excess demand. ϵ assumes a positive value in this case. In case there emerges an excess supply of new loans at $\bar{i}$, the commercial banks lend their surplus supply to the RBI at $\bar{i}$. The RBI keeps i at $\bar{i}$ in this manner.

Determination of D

The Government of India is pursuing the New Economic Policy (NEP) at the present. Under the NEP, the financial institutions have become autonomous profit-driven commercial organizations. The RBI has imposed on them prudential lending norms (such as Basel norms), which have made banks extremely wary about lending to the financially weak borrowers. Accordingly, they lend to the small producers small amounts of loan only against collateral. The small producers only have their land to offer as collateral. Given the prudential norms, D is determined by the amount of land in the possession of the small producers, which we denote by φ. Therefore,

$$D=D(\varphi);\ \frac{dD}{d\varphi}\equiv D^{/}>0 \tag{8}$$

The small producers at the time of taking the loans do not know how much revenue they will be able to earn from their market supply. Both the price that will prevail at the time of the sale of their market supply and the natural factors that affect the productivity of the intermediate inputs measured by $(1/\theta)$ are uncertain, among others. Therefore, the small producers may default on their loans if their expectations regarding the factors mentioned above go wrong. Since the small producers service their debt using the revenue they earn, we consider it reasonable to assume that the small producers' default rate on loans is a decreasing function of the revenue they earn, denoted R. Denoting the default rate of the small producers by B, we get

$$B=B(R);\ B^{/}<0 \tag{9}$$

Let us now focus on the determinants of R. For that purpose, we rewrite (5) as follows:

$$c_w.\left(1-\mu\left(\frac{P_U}{P_O}\right)\right).\left(W.l.\overline{O}+\omega i_0\right)=P_U.(1-\gamma)\left[\frac{D}{P_{OU}}\frac{1}{\theta}\right] \tag{10}$$

In (10), all variables other than P_U and D are given by assumption. We can solve (10) for P_U as a function of D and $\overline{O}$, among others. The solution is shown in Fig. 1, where P_U is measured on the vertical axis and the LHS of (10), which is R, and the RHS of (10), which is the value of the market supply of U, denoted F, are measured on the horizontal axis. A ceteris paribus increase in P_U leads to an increase in μ and, thereby, brings about a decline in R. Therefore, the RR schedule giving the values of R corresponding to different values of P_U is downward sloping. The FF schedule, on the other hand, gives the values of F corresponding to different values of P_U. It is clearly a ray through the origin. The equilibrium values of P_U and R correspond to the point of intersection of RR and FF. We, therefore, get R and P_U as functions of D and $\overline{O}$, among others. Thus,

$$R=R\left(D,\overline{O}\right);\ R_D>0,\ R_{\overline{O}}>0 \tag{11}$$

and

$$P_U=P\left(D,\overline{O}\right);\ P_D<0,\ P_{\overline{O}}>0 \tag{12}$$

Let us explain the signs of the partial derivatives of (11) and (12) using Fig. 1. Following a given increase in D, the value of F corresponding to any given $P_U>0$ increases. Hence, FF rotates rightward. However, the value of R corresponding to any given P_U remains unaffected. Therefore, R increases and P_U falls. Again, following a given increase in $\overline{O}$, the value of R corresponding to any given P_U increases, while that of F remains unchanged. Therefore, the RR schedule shifts to the right, but the FF schedule remains the same. This brings about an increase in both R and P_U. One can also derive the signs of the partial derivatives of (11) and (12) mathematically quite easily.

Substituting (11) into (9), we rewrite it as follows:

$$B=B\left(R\left(D,\overline{O}\right)\right)\equiv b\left(D,\overline{O}\right);\ b_D<0,\ b_{\overline{O}}<0 \tag{13}$$

The sign of b_D requires explanation. We give it here. The small producers are poor. Quite a large section of them produce basic necessities of life such as food, clothing, etc. Most of them require some minimum amount of loan to produce the amount of output or generate the amount of revenue they require for their subsistence. They have to secure more than this minimum amount of loan to generate surplus revenue for debt servicing. The assumption here is that the more loan they get and, therefore, the more they produce, they are able to secure larger amount of revenue and the increase

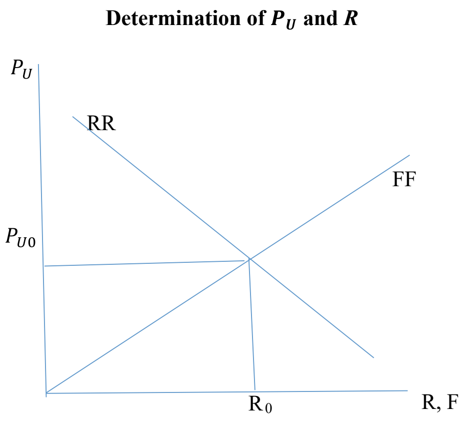

Fig. 1 Determination of P_U and R

in the revenue exceeds the rise in the debt service charges due to the increase in the amount of the loan. This is the boundary condition of the model. This condition is necessary for the survival of the small producers.

As the small producers default on their loans, they lose their collateral to the capitalists. We denote the amount of land that the small producers had at the beginning of the period by $\overline{\varphi}$. Therefore, the amount of land they end the period with is given by

$$\varphi = \overline{\varphi} - k.b\left(D, \overline{O}\right); k > 0 \tag{14}$$

In (14), k is a parameter. Substituting (14) into (8), we rewrite it as follows:

$$D = D\left(\overline{\varphi} - k.b\left(D, \overline{O}\right)\right) \tag{15}$$

We have delineated above our model. The key equations it contains are (1), (2), (7), (10), (14) and (15). They contain 6 endogenous variables: I, U, ϵ, P_U, D and φ. We solve these equations in the following manner. Solving (15), we get the equilibrium value of D. Putting it in (2) and (14), we get the equilibrium values of U and φ, respectively. Putting the equilibrium value of D in (10), we get the equilibrium value of P_U. Substituting the equilibrium values of U and P_U in (1), we get the equilibrium value of I. Finally, substituting the equilibrium values of I and D in (7), we get the equilibrium value of ϵ.

From the above it is clear that the derivation of the equilibrium value of D is the key to finding out the equilibrium values of the rest of the endogenous variables. We, therefore, explain now how we derive the equilibrium value of D. We can solve (15) for D provided $D\left(\overline{\varphi} - k.b\left(0, \overline{O}\right)\right) > 0$ and $0 < D_{\varphi}(-kb_D) \equiv \tau < 1$. Solving (15), we get D as a function of $\overline{O}$, among others. Thus, we have

$$D = g\left(\overline{O}\right); g^{/} > 0 \tag{16}$$

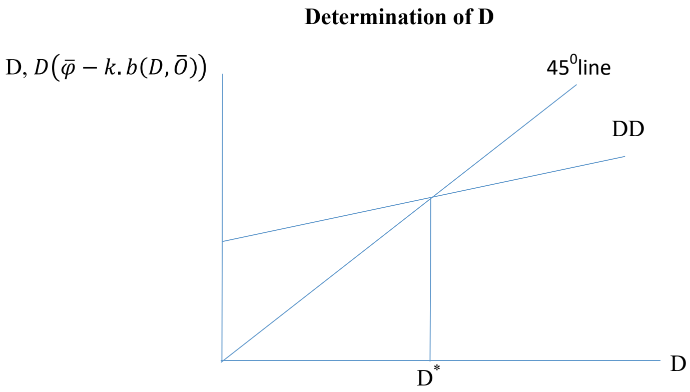

Fig. 2 Determination of *D*

Using Fig. 2, we will show the solution of (15) and explain the sign of the derivative of (16). In Fig. 2, we measure D on the horizontal axis and the LHS and the RHS of (15) on the vertical axis. Plotting the values of D (the LHS of (15)) against D, we get a 45° line. Plotting the values of the RHS against D, we get the line DD. It has a positive vertical intercept and its slope lies between 0 and 1. The equilibrium D corresponds to the point of intersection of the 45° line and the DD schedule.

Following a given increase in $\overline{O}$, b falls and φ goes up corresponding to any given D. Therefore, the value of D corresponding to any given D increases bringing about an upward shift in the DD schedule. Hence, the equilibrium value of D increases. This explains the sign of the derivative of (16). We will explain it further shortly.

We are now in a position to explain how the outbreak of COVID-19 is likely to impact the capitalists and the small producers. This is what we do below.

1.2 COVID-19-Related Restrictions and Lockdown and the Land Holding of the Small Producers

Following the outbreak of COVID-19 in India, large segments of the organized sector such as passenger transport, entertainment, large parts of the organized offline retail stores etc. were shutdown. A part of the unorganized sector was shutdown as well putting the lives of many small producers in jeopardy. However, we focus here not on the impact of government restriction induced shutdown of the unorganized sector but on the impact that the shutdown of the large segments of the organized sector produced on the unorganized sector. We will principally focus here on the issue of land loss of the small producers. The shutdown of a large segment of the unorganized sector implies a large fall in $\overline{O}$. We will first derive its impact on D, φ and U mathematically and, then, explain them.

Taking total differential of (15) treating all variables other than D and $\overline{O}$ as fixed and, then, solving for dD, we get

$$dD = \frac{-D_\varphi k b_{\overline{O}} d\overline{O}}{1-\tau} < 0 \tag{17}$$

Again, taking total differential of (14) treating all variables other than φ, D and $\overline{O}$ as fixed, and, then, solving for $d\varphi$, we get

$$d\varphi = k(-b_D)dD + k\left(-b_{\overline{O}}\right)d\overline{O} < 0 \,\text{since}\, dD < 0 \,\text{and}\, d\overline{O} < 0 \tag{18}$$

Finally, taking total differential of (2) treating all variables other than U and D as fixed and, then, solving for dU, we get

$$\mathrm{dU} = \frac{dD}{\theta P_{OU}} \tag{19}$$

Let us now explain (17), (18) and (19). Focus on the U-market equilibrium condition (10). Following a given decline in $\overline{O}$ by d$\overline{O}$, R falls at the initial equilibrium P_U, while F remains unaffected giving rise to an excess supply at the initial equilibrium P_U. Hence, P_U begins to fall. The fall in P_U lowers F and raises R and, thereby, restores equilibrium at a lower R and a lower F. As R falls at the initial equilibrium D, default rate increases by $(b_{\overline{O}}\ d\overline{O})$ making the small producers lose $d\varphi_1 = k\left(-b_{\overline{O}}\right)d\overline{O}$ amount of land—see (13) and (14). This is the end of Round 1. At the beginning of Round 2, the small producers have a smaller amount of land to offer as collateral. Hence, the lenders lower D by $dD_1 = D_\varphi k(-b_{\overline{O}})d\overline{O}$. This lowers U by $dU_1 = \frac{dD_1}{\theta P_{OU}}$. Consider now (10). The fall in U lowers F at the P_U that equilibrated the U-market in Round 1 creating an excess demand for U. Hence, P_U increases raising F and lowering R and, thereby, equilibrating the U-market at a lower R. By the boundary condition of the model, the fall in R will exceed the decline in debt service charges due to the decrease in D by dD_1. Therefore, the small producers' default rate will go up by $(b_D)dD_1$ making them lose dφ_2 = k$(-b_D)dD_1$ amount of land—see (14). This is the end of Round 2. This loss in land in Round 2 induces the lenders to lower D at the beginning of Round 3 by $dD_2 = D_\varphi k(-b_D)dD_1 = \tau dD_1$. This will, as happened in Round 2, lower U and φ by $dU_2 = \frac{dD_2}{\theta P_{OU}}$ and dφ_3 = k$(-b_D)dD_2$, respectively. This is the end of Round 3. In Round 4, D, U and φ will go down by $dD_3 = D_\varphi k(-b_D)dD_2 = \tau dD_2 = \tau^2 dD_1$, $dU_3 = \frac{dD_3}{\theta P_{OU}}$ and dφ_4 = k$(-b_D)dD_3$, respectively. This process of land loss will continue until amount of land loss that takes at the end of each successive round eventually falls to zero. Thus the total fall in D, U and φ are given respectively by

$$dD = dD_1 + \tau dD_1 + \tau^2 dD_1 + \ldots\ldots.. = \frac{dD_1}{1-\tau} = \frac{D_\varphi k(-b_{\overline{O}})d\overline{O}}{1-\tau} \tag{20}$$

$$dU = \frac{dD_1}{\theta P_{OU}} + \frac{dD_2}{\theta P_{OU}} + \frac{dD_3}{\theta P_{OU}} + \ldots\ldots\ldots = \frac{dD}{\theta P_{OU}} \tag{21}$$

And

$$d\varphi_1 = k\left(-b_{\overline{O}}\right)d\overline{O} + \mathrm{k}(-b_D)dD_1 + \mathrm{k}(-b_D)dD_2 + \ldots\ldots = k\left(-b_{\overline{O}}\right)d\overline{O} + \mathrm{k}(-b_D)dD \tag{22}$$

The above discussion explains (17), (18) and (19).

The intuition of the result reported above may be explained as follows. The COVID-19-related restrictions lead to a large shrinkage in the output of the organized sector. This lowers organized sector workers' income and, consequently, their spending on the output of the unorganized sector. There, thus emerges, an excess supply in the market of the output of the unorganized sector. This lowers the price. The small producers accordingly earn less revenue from the sale of the market supply out of their output produced with a given amount of loan. This makes some of them default on their loans. Let us explain this point in greater detail. As we pointed out earlier, the small producers are poor. Quite a large section of them produce basic necessities of life such as food, clothing, etc. Most of them require some minimum amount of loan to produce the amount of output or generate the amount of revenue they require for their subsistence. They have to secure more than this minimum amount of loan to generate surplus revenue for debt servicing. The assumption here is that the more loan they get and, therefore, the more they produce, they are able to secure larger amount of revenue and the increase in the revenue exceeds the rise in the debt service charges due to the increase in the amount of the loan. This is the boundary condition of the model. This condition is necessary for the survival of the small producers. Note that the minimum amount of loan that a small producer requires for subsistence varies from one small producer to another. This is because the skill level, access to public infrastructure facilities and services, natural and other factors impinging on production vary across small producers and, therefore, so does the productivity of the inputs used by them. The larger the minimum amount of loan that a small producer requires for subsistence, the more is the amount of the loan that he requires for servicing his debt. Thus, if the loan secured by the small producers is not sufficiently large, some of them will default. Moreover, the more adverse the circumstances, that is, the less the revenue a given amount of loan generates, the larger is the amount of loan the small producers require to service their debt. In the present case, therefore, as the COVID-19-related restrictions make the output of the organized sector shrink lowering the amount of revenue the small producers earn from the given amount of loan they were able to secure, some of the small producers default on their loans and lose their land. In the next round, therefore, the small producers are able to secure a smaller amount of loan. As a result, some more small producers default. Thus, there takes place a cumulative fall in the amount of land in the possession of the small producers. Note that COVID-19-related restrictions are temporary, but the loss of land of the small producers is permanent. Thus, COVID-19 enables the capitalists to take over the land of the small producers permanently in return for a short period loss. This yields the following proposition:

Proposition 1
The shutdown of a part of the organized sector due to COVID-19-related restrictions makes the small producers lose a large amount of land to the lenders who are under the control of the capitalists. Thus, COVID-19 enables the capitalists make permanent gains in return for a transient loss.

1.3 COVID-19-Induced Shutdown of the Unorganized Sector and Distress Sale of Land

COVID-19 led to shutdown of a large segment of the unorganized sector as well such as small non-essential production establishments, small retail outlets, road side eating joints, small transporters, street entertainers, etc. Small producers and the members of their families also contracted COVID-19. The small producers are so poor that to tide over even short periods of income loss or to meet the expenses of illness, they may have to sell off land to the agents of the capitalists. When normalcy returns and work resumes, the small producers, therefore, can offer only a smaller amount of land as collateral. This induces the lenders to reduce their lending to the small producers. As a result, for reasons explained in the previous section, some of the small producers default and lose their land to the capitalists. This, as before, starts a cumulative process of land loss. We can capture this process mathematically as follows.

The shutdown of a part of the unorganized sector or contraction of COVID-19 brings about a fall in $\overline{\varphi}$ in (14) and (15). Taking total differential of (15) treating all variables other than $\overline{\varphi}$ and D as fixed and, then, solving for dD, we get

$$\mathrm{dD} = \frac{\mathrm{D}_{\varphi}\mathrm{d}_{\overline{\varphi}}}{1-\tau}\,\text{since}\,\mathrm{d}\overline{\varphi} < 0 \tag{23}$$

Again, taking total differential of (14) treating all variables other than φ, $\overline{\varphi}$ and D as fixed and, then solving for dφ, we get

$$\mathrm{d}\varphi = \mathrm{d}\overline{\varphi} + \mathrm{k}(-\mathrm{b_D})\mathrm{dD} < 0\,\text{since}\,\mathrm{d}\overline{\varphi} < 0\,\text{and}\,\mathrm{dD} < 0 \tag{24}$$

Equations (23) and (24) can easily be explained following lines described in the previous section. The above discussion yields the following proposition.

Proposition 2
COVID-19-induced shutdown of a segment of the unorganized sector or contraction of COVID-19 by the small producers and the members of their families may lead to a permanent, large and cumulative transfer of land from the small producers to the capitalists.

1.4 COVID-19, the Spread of Digital Technology and the Loss of Land of the Small Producers

The fear of COVID-19 and the imposition of lockdown and other restrictions lead to online delivery of many services such as education, health care, entertainment, etc. People in educational institutes and many other workplaces work/study from home. The campuses close down. People also switch from offline to online purchases of their requirements due to the fear of contracting the disease and/or compulsion. They also switch from offline to online services such as online education, online entertainment, online consultation of doctors, etc. The small producers do not have the resources to offer online services, which the organized sector offers with ease. All the factors mentioned above have led to a large loss of the market of the unorganized sector and its loss accrues as gain to the organized sector. Therefore, μ in Eqs. (1) and (10) should be an increasing function of not only $(\frac{P_U}{P_O})$ but also V, where V denotes the degree of spread of COVID-19. Therefore, we rewrite (10), which is the relevant equation for our purpose, as follows:

$$c_w.\left(1-\mu\left(\frac{P_U}{P_O},V\right)\right).\left(W.l.\overline{O}+Bi_0\right)=P_U.(1-\gamma)\left[\frac{D}{P_{OU}}\frac{1}{\theta}\right] \tag{25}$$

From (25) it is clear how an increase in V will affect the small producers. Following an increase in V, some of the workers of the organized sector switch from the output of the unorganized sector to that of the organized sector. This creates an excess supply in the market of the unorganized sector at the prevailing price of the output of the unorganized sector. Therefore, the price of the output of the unorganized sector falls. This lowers the revenue earned by the small producers from their market supply produced using a given amount of loan. This makes some of the small producers default on their loans. They, therefore, lose land to their lenders who are agents of the capitalists. Let us illustrate the point with an example. Think of a small-time vegetable vendor or a small-time grocer in a city. They take loans from the money lenders to pay rent as well as to buy the goods they sell. As the fear of the pandemic makes the people switch from offline to online purchase of the basic necessities of life, the sale of the vegetable vendor and the grocer fall. They cannot service their debt after meeting their subsistence requirements. Interest charges begin to accumulate. The money lenders start harassing them. Suppose they have land in the countryside, which other members of their families cultivate. They are also too poor to have any saving. Moreover, they are also under considerable stress because of the pandemic-induced lockdown and restrictions, which substantially reduce their sales. Under these circumstances, the vegetable vendor or the grocer may be forced to sell a part of their land to pay their dues to the money lenders. As the land in the possession of the small producers fall, they are able to secure less loan from the lenders in the next round. This forces, for reasons explained in the previous sections, some more small producers to default on their loans and, thereby, lose their land. Thus, the small producers will suffer a permanent, large and cumulative loss of land to the capitalists. We can easily derive these results mathematically. We do this below.

Focus on (25). Following a given increase in V, the LHS, which is R, falls at the initial equilibrium P_U, while the RHS, which is F, remains unaffected. Thus, at the initial equilibrium P_U, there emerges an excess supply. Hence, P_U falls raising R and lowering F and, thereby, restoring equilibrium at a lower R. Therefore, R in (11) becomes a decreasing function of V as well. Incorporating V in (11), we rewrite it as follows:

$$R = R\left(D, \overline{O}, V\right); R_D > 0, R_{\overline{O}} > 0, R_V < 0 \tag{26}$$

Again, putting (26) into (13), we rewrite it as follows:

$$B = B\left(R\left(D, \overline{O}, V\right)\right) \equiv b\left(D, \overline{O}, V\right); b_D < 0, b_{\overline{O}} < 0, b_V > 0 \tag{27}$$

Since a ceteris paribus increase in V lowers R, it raises the default rate of the small producers, given the values of D and other variables. This explains the sign of b_V.

Finally, substituting (27) into (14) and (15), we rewrite them as follows:

$$\varphi = \overline{\varphi} - k.b\left(D, \overline{O}, V\right); k > 0 \tag{28}$$

$$D = D\left(\overline{\varphi} - k.b\left(D, \overline{O}, V\right)\right) \tag{29}$$

To derive the impact of an increase in V on D, we take total differential of (29) treating all variables other than D and V as fixed and, then, solving for dD, we get

$$\mathrm{dD} = \frac{-\mathrm{D}_{\varphi}\mathrm{kb_v dV}}{1-\tau} < 0\left(\text{since}\ \mathrm{D}_{\varphi} > 0,\ \mathrm{k} > 0,\ \mathrm{b_v} > 0\ \text{and}\ \mathrm{dV} > 0\ \text{- see (27) and (29)}\right) \tag{30}$$

Taking total differential of (2) treating all variables other than U and D as fixed and, then, solving for dU, we get

$$dU = \frac{dD}{\theta P_{OU}} < 0\ \text{since}\ \mathrm{dD} < 0 \tag{31}$$

Again, taking total differential of (28) treating all variables other than φ, D and V as fixed and, then, solving for $d\varphi$, we get

$$d\varphi = k(-b_D)dD - kb_v dV < 0 \text{ since dD <0 and } (-b_D) > 0 - \text{see (27)} \qquad (32)$$

From (30), (31) and (32) it is clear that there will take place a cumulative decrease in D, U and φ following a given increase in V.

Equations (30), (31) and (32) can be easily explained following the line suggested in the previous sections. From the above discussion, we get the following proposition.

Proposition 3
If the fear of contracting COVID-19 and the COVID-19-related restrictions and lockdown induce and/or force people to switch from offline purchase of goods and services to online purchase of goods and services, there will take place a large and cumulative decline in the output of the unorganized sector and a permanent, large and cumulative fall in the land holding of the small producers.

1.5 Conclusion

This paper shows how the outbreak of COVID-19 in India enables the capitalists to acquire the land of the small producers. This strengthens our suspicion that the capitalists deliberately created the pandemic. It is a part of their exploitative machinery. Of course, how much land the small producers have lost on account of COVID-19 is an empirical issue. We want to estimate this land loss in our future research. The framework used here also considers a closed economy. It should be extended to allow for foreign trade in goods and assets. This is likely to open up new avenues of grabbing the land of the small producers by the capitalists. Unearthing them is also a part of our future research agenda.

Notes

1. Making an assessment of the lockdown and its management as a policy of containing the pandemic in India is beyond the scope of this paper. We have done it in Ahamed and Ghosh (2021).
2. The purpose of this paper is to develop theoretical arguments that yield the hypothesis that the capitalists have created the pandemic. It also shows theoretically how in several ways the pandemic benefits the capitalists at the expense of the common man. However, establishing this hypothesis empirically is beyond the scope of this paper. To the best of the authors' knowledge, there does not exist any study that proposes this hypothesis or seeks to establish it empirically.

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An Analysis of the Impact of GST on States' Indirect Tax Revenue and on Economic Formalization with Special Focus on West Bengal

Hari Krishna Dwivedi, Achin Chakraborty, and Sudip Kumar Sinha

Abbreviations

CGST	Central Goods and Services Tax
Covid-19	Coronavirus Disease 2019
FY	Financial Year
GCS	General Category States
GoI	Government of India
GSDP	Gross State Domestic Product
GST	Goods and Services Tax
GSTR	GST Return
INR	Indian Rupees
IGST	Integrated Goods and Services Tax
ITC	Input Tax Credit
MOSPI	Ministry of Statistics and Programme Implementation
MSMEs	Micro, Small and Medium Enterprises
N/A	Not Applicable
PIB	Press Information Bureau
RBI	Reserve Bank of India
RNR	Revenue Neutral Rate

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SGST	State Goods and Services Tax
UTGST	Union Territory Goods and Services Tax
VAT	Value Added Tax

1 Introduction

GST is an indirect tax which was implemented in India on 1st July 2017 with the idea of 'One Nation, One Tax'. It was introduced in India with the objective of eliminating the distortions arising out of cascading effects of taxes, curbing tax evasion, increasing the taxpayers base and harmonizing the indirect tax rates between the Centre and States and among the States inter se. Cascading effect happens when there is a tax levied on value of product at every step of distribution. In pre-GST regime, the manufacturer could not use the credit of central excise duty paid on the commodity for payment of VAT, as the two levies were levied by Central and State governments, respectively, with no statutory linkage between the two. Hence, the manufacturer was required to pay VAT on the entire value of the commodity. This would increase the tax burden of the manufacturer. GST has mitigated such cascading of taxes as most of the indirect taxes levied by Central and the State Governments on supply of goods or services or both, has been combined together under a single levy. GST is levied on the supply of goods and services on every value addition. It is known as a destination-based tax which means tax revenue is received by the state in which goods are consumed but not by the state in which such goods are manufactured.

Under GST, there are four components—Central GST (CGST), State GST (SGST), Integrated GST (IGST) and Union Territory GST (UTGST). The Central Government collects CGST while the State governments collect SGST. For intra-state transactions i.e. when the supply of goods or services occurs within a state then both CGST and SGST are collected whereas for inter-state transactions i.e. when the supply of goods or services occurs between the states, IGST is collected, and the SGST is paid back to the consumption state through a clearing mechanism. Similarly, UTGST is levied by the Union Territory Governments on the intra-union territory supply of goods and services.

After the implementation of GST, a large part of states' revenues from indirect taxes got subsumed under GST. The share of revenue subsumed under GST is about 50% for states and about 37% for the Centre (RBI, 2019). The state's indirect taxes subsumed within GST includes VAT (except for levies on alcoholic liquor and fuel), entertainment tax (except those levied by the local bodies), octroi and entry tax, purchase tax, luxury tax, central sales tax, taxes on lotteries, betting and gambling, taxes on advertisements, taxes on vehicles, taxes on goods and passengers and state cess and surcharges (for supply of goods) (RBI, 2019). Since subsumed taxes constitute a major portion of revenues of the state governments, the states were entitled to get compensation as per "The Goods and Services Tax (Compensation to States) Act, 2017" for the loss of revenue arising on account of implementation of GST in pursuance of the provisions of the Constitution (One Hundred and First Amendment) Act, 2016. According to this Act, compensation fund will be provided to a state for a period of five years from the date on which the state enacts the State GST Act.

Implementation of such a large tax reform has motivated us to examine the impact of GST on the tax revenues of the states. In this paper, we have scrutinized the impact of GST on the states' indirect tax revenue with special reference to West Bengal.

Also, since GST covers a much larger base of enterprises with lower exemption thresholds than the earlier indirect tax regime, it is also seen as a mechanism to formalize the economy by trying to bring the informal enterprises under the tax net. This aspect has motivated us to perform the inter-state comparison to examine the impact of GST on formalization of the economy among the GCS.

The rest of the paper is organized as follows: Sect. 2 discusses the findings and insights from the relevant literature. Section 3 defines data and methodology of this study. Section 4 examines the impact of GST on the states' tax revenue for General Category States (GCS). Section 5 assesses the impact of COVID-19 on the states' tax collections with special reference to West Bengal. Section 6 examines the impact of GST on formalization of the economy of GCS. Finally, Sect. 7 concludes the paper.

2 Literature Review

Extensive literature on the impact of GST on tax revenue in India suggests that the GST collections are not very promising due to the design, structural nature, compliance requirements, tax administration and other related factors of GST (Mukherjee, 2019).

Paliwal et al. (2019) found that after introduction of GST, in India, the revenue generated from taxes has become less responsive to the changes in GDP. They also opined that in the current slowdown of GDP, as the tax revenue has become less responsive, the economy may not be able to mobilize sufficient revenue through taxation.

Mukherjee (2020) estimated the GST efficiency of a state as a function of its per capita income using the time variant truncated panel Stochastic Frontier Approach using data for the period 2012–2013 to 2019–2020. He has found that except for Arunachal Pradesh and Mizoram, GST efficiencies of all states have gone down post FY 2017–2018. He has also found that GST capacity of a state depends on the size and structural composition of the economy and introduction of GST has reduced states' own tax capacity.

Nayaka and Panduranga (2020) concluded that as GST is a destination-based tax, the inter-state trade would necessarily mean tax revenue loss to origin states (manufacturing states) that will have a significant impact on states' spending on various welfare activities. Thus, implementation of this tax structure benefits the consumption states at the cost of the manufacturing states.

Rao (2020) suggests that there is a lot of scope for improvements of GST system such as reducing the number of tax rates to simplify the system, revisiting the rate structure to minimize anomalies, reducing the number of exemptions, firming up the technology platform, making the tax base more comprehensive by including the excluded items such as petroleum products, real estate and electricity.

Ghosh (2020) mentioned that GST led to coercive formalization of economy by putting small businesses to risk as these firms seemed to be stuck between two sources of competition. On one hand, if small firms did not register under GST, they could stand to lose market share as registered clients would not buy from them due to the perception of Reverse Charge Mechanism (RCM) and non-availability of Input Tax Credit (ITC). On the other hand, if small firms choose to join GSTN, they will face higher compliance costs and the burden of excessive paperwork.

Economic Survey 2017–2018 claims that the introduction of GST has brought more firms into the tax net. The number of enterprises paying indirect taxes has gone up by 3.4 million, an increase of 50% as compared to the previous year. Moreover, the Indian workforce is getting more formalized than most people believed. Nearly a third of the non-farm Indian workforce of 240 million has some social security coverage and more than half of the non-farm workforce is employed in firms that now pay taxes.

As per the economic survey of 2021–2022, the quarterly Periodic Labour Force Survey (PLFS) data shows that up to March 2021, employment in urban sector affected by the pandemic has recovered almost to the pre-pandemic levels. Employees Provident Fund Organisation (EPFO) data suggests that not only formalization of jobs continued during second-COVID-19 wave, but its adverse impact by far on formalization of jobs was also much lower than during the first-COVID wave.

In this paper, apart from estimating the impact of GST on states' tax collections, we have tried to estimate the impact of COVID-19 on states' tax collections. We have also put the additional focus on West Bengal by utilizing the quarterly GST collection data for the state of West Bengal in order to draw additional insights. Additionally, we have utilized the year-wise number of MSME registrations data from FY 2015–16 to FY 2019–2020 as well as data on total number of registered persons on payroll as per EPFO to assess the extent of formalization in economy.

3 Data and Methodology

3.1 Data

The study is analytical in nature and is based on secondary data. We have considered GCS for our analysis purpose. Out of 29 states, 18 states are categorized as GCS.[1] In Sect. 4 of this paper, we have undertaken an inter-state comparison of the impact of GST on states' revenue for which, the data for eight financial years starting from 1st April 2012 to 31st March 2020 has been taken as per the data availability. We have labeled the period from 1st April 2012 to 31st March 2017 as pre-GST era and the period from 1st April 2017 to 31st March 2020 as post-GST era. Although GST was implemented on 1st July 2017, still we have considered the whole FY 2017–2018 as post-GST period because 9 out of 12 months of this FY belong to GST regime i.e. 75% of the data belong to GST regime. Therefore, we have extrapolated this data to 12 months.[2] It is to be noted that to assess the impact of GST on states' revenue we have not considered the data for FY 2020–2021 for inter-state comparison because of the steep decline in state revenue collections on account of nation-wide lockdown imposed due to Covid-19 pandemic outbreak. Hence, considering FY 2020–2021 data for analysis could have led to biased results. Alternatively, we have performed a separate analysis of the impact of COVID-19 on states' tax collections using the state-wise GST collection data for June, July and August for FY 2019–2020 and FY 2020–2021 as obtained from the official website of Department of Revenue, Ministry of Finance.

For pre-GST era, we have taken the year-wise tax revenue data of all the indirect taxes that were subsumed under GST, i.e. Sales Tax/VAT; Central Sales Tax; Works Contract; Lottery, Betting and Gambling Tax; Luxury Tax; Entry Tax; Advertisement Tax; Entertainment Tax; Cesses and Surcharges; Purchase Tax from the official website of Goods and Service Tax as per the data availability. We have labelled these taxes as "Subsumed Taxes". Also, data on Subsumed Taxes collection for FY 2012–2013, 2013–2014, 2014–2015 and 2016–2017 were not provided by Gujarat and Haryana to the Department of Revenue, Government of India and therefore, estimates for the same have been taken from Mukherjee (2020).

For post-GST era, we have taken the data of GST Compensation and SGST collection[3] for each GCS from RBI—State Finances: A Study of Budgets various years.

[1] Andhra Pradesh, Bihar, Chhattisgarh, Goa, Gujarat, Haryana, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, Telangana, Uttar Pradesh and West Bengal.

[2] This extrapolation has been done by dividing the SGST collection of 9 months by 9 in order to arrive at average monthly SGST collection. Then, we have multiplied it by 12 to arrive at yearly SGST collection for FY 2017–2018.

[3] The SGST collection includes IGST settlement for each GCS.

The data on GSDP at current prices for each GCS from 2012–2013 to 2019–2020 has been taken from the official website of Ministry of Statistics and Programme Implementation (MOSPI). Apart from this, we have collected data on monthly SGST and IGST collection of West Bengal from June 2019 to July 2021 for additional analysis and insights for West Bengal. This data has been collected from the Directorate of Commercial Taxes, West Bengal.

In order to assess the extent of formalization of the economy, we have considered indicators such as the change in the number of MSME registrations and the number of persons registered on payroll. Data on the number of MSME registrations has utilized from Udyog Aadhaar Memorandum for FY 2020–2021 whereas data on number of registered persons on payroll has been taken from EPFO records for FY 2017–2018 to FY 2020–2021.

3.2 Methodology

With the objective of performing an inter-state comparison of the impact of GST on states' indirect tax revenue, first, we need to examine the impact of GST on indirect tax revenue for each GCS. An inter-state comparison of the impact of GST on indirect tax revenue for each GCS can be assessed by comparing the tax performance of a state before the implementation of GST vis-à-vis after the implementation of GST.

To measure tax revenue performance, we have used two indicators. First, Tax to GSDP ratio has been used for each GCS. Second, we have considered tax buoyancy as our indicator to measure revenue performance. Tax buoyancy measures the efficiency and responsiveness of tax collection in response to growth in the GSDP. We have estimated the tax buoyancy using two techniques. First, percentage change in tax collection in relation to percentage change in GSDP i.e. for the pre-GST era, we have calculated,

$$\frac{\frac{(\text{Tax Collection}_{2016-2017} - \text{Tax Collection}_{2012-2013})}{\text{Tax Collection}_{2012-2013}}}{\frac{(GSDP_{2016-2017} - GSDP_{2012-2013})}{GSDP_{2012-2013}}}$$

where *Tax Collection*$_{2016–2017}$ shows the tax collection of a state for the FY 2016–2017 and *GSDP*$_{2016–2017}$ shows the GSDP of that state for FY 2016–2017. This is similar for other FYs as well. Similarly, for post-GST era, we have calculated,

$$\frac{\frac{(\text{Tax Collection}_{2019-2020} - \text{Tax Collection}_{2017-2018})}{\text{Tax Collection}_{2017-2018}}}{\frac{(GSDP_{2019-2020} - GSDP_{2017-2018})}{GSDP_{2017-2018}}}$$

It is also important to determine the extent of dependency of states on GST compensation because the Central Government will end the GST compensation fund to the states from June 2022 onwards.[4] In order to do so, we have analysed the amount of GST compensation as a percentage of total GST revenue (including GST compensation).[5] A large share of GST compensation will signify greater dependency and therefore raises the need to continue with GST compensation fund beyond June 2022. We have also undertaken an inter-state comparative analysis to study the extent of dependency of states on GST compensation.

For testing the hypothesis that GST would increase the tax collection of consumption states we have examined whether consumption states such as West Bengal have benefitted from the implementation of GST or not. For this analysis, we have undertaken an inter-state comparison of SGST collection to GSDP ratio for consumption states vis-à-vis manufacturing states.

The sharp economic slowdown induced by the COVID-19 pandemic has significantly dented state revenues. Therefore, we have estimated the impact of COVID-19 on states' GST collections by comparing the total GST collection by all states for June, July and August for FY 2019–2020 as against the total GST collection for June, July and August for FY 2020–2021.

In this paper, we have also analysed the impact on revenue performance for the state of West Bengal after the implementation of GST. We have carried out trend analysis of quarterly GST collection of West Bengal from June 2019 to July 2021 to estimate the impact of implementation of GST and COVID-19 pandemic on the state's GST collections.

4 Assessment of Impact of GST on the States' Indirect Tax Revenue

In this section, we have carried out an inter-state comparison of the impact of GST on states' indirect tax revenue using two tax revenue performance indicators, first, tax collection to GSDP and second, tax buoyancy.

4.1 Tax Collection to GSDP

Tax Collection to GSDP of a state represents share of tax collection as a percentage of GSDP for that state. This ratio is a measure of the government's ability to finance its expenditure. Higher ratio increases the ability of the government to spend more on infrastructure, health, education, etc. and also reduces the debt obligations of the government.

[4] https://www.newindianexpress.com/business/2021/sep/17/no-gst-compensation-to-states-beyond-july-2022-2,360,243.html.

[5] In our paper, total GST revenue denotes the sum of SGST collection 5 & GST compensation.

Table 1 shows the average of tax collection to GSDP ratio for Pre-GST era as well as Post-GST era for each GCS. In this table, we have also compared the percentage change in average of tax collection to GSDP ratio from Pre-GST era to Post-GST era in order to find that whether on an average, tax collection has increased post-GST implementation or not. For the Pre-GST era, we have considered the Subsumed Taxes collection as percentage of GSDP and for Post-GST era, we have considered SGST collection (after IGST Settlement) as a percentage of GSDP. Now, in order to compare the average of tax collection to GSDP ratio among the GCS, we have ranked the GCS from Rank 1 to Rank 18 according to their percentage change in ratio of tax collection to GSDP from Pre-GST era to Post-GST era. As the percentage change for a state increases as compared to other GCS, the rank of that state moves up. Besides, as the state of Telangana was officially formed on 2nd June 2014, statistical data for Telangana for FY 2012–2013 and FY 2013–2014 were not available. Also, the data on Subsumed Taxes collection for FY 2014–2015 was not provided by Telangana to Department of Revenue, Government of India.

From Table 1, it can be observed that except for Bihar, Rajasthan and Uttar Pradesh, average tax collection to GSDP ratio has fallen for all other GCS in Post-GST era as compared to the Pre-GST era. The largest decline in the average of tax collection to GSDP ratio is for the state of Punjab (decline of 2.06% points) followed by Gujarat (0.82), Goa (0.81) and Karnataka (0.78). Besides, average of tax collection to GSDP ratio for the state of Rajasthan has increased by 0.01% points after the implementation of GST whereas for Bihar, average of tax collection to GSDP ratio has increased by 0.12% points and for Uttar Pradesh, it has increased by 0.10% points. For West Bengal, the ratio has declined marginally by 0.10% points in post-GST era.

4.2 Tax Buoyancy

Tax buoyancy is one of the standard tools for assessment of the effectiveness of any tax system. It is an indicator to measure efficiency in revenue mobilization in response to growth in GDP. If tax buoyancy is high, it indicates built-in flexibility in the tax structure. Further, if it is greater than one, it indicates more than proportionate response of the tax revenue to rise in GDP, and if it is less than one, it indicates less than proportionate response of the tax revenue to rise in GDP (Paliwal et al., 2019). In Table 2, we have calculated the tax buoyancy as percentage change in tax collection in a response to percentage change in GSDP for Pre-GST era and Post-GST era for each GCS and undertaken the comparison to determine the impact of change in tax structure on tax buoyancy of a particular state. We have also carried out an inter-state comparison of tax buoyancy by ranking the states on the basis of calculated tax buoyancy.

Table 1 Average of tax collection to GSDP ratio

States	(A) 2012–2017[a] (Pre-GST)	(B) 2017–2020[b] (Post-GST) Percentage (%)	(C) Change (From A to B) Percentage points		Ranking on the basis of (C)
Andhra Pradesh (Divided)	2.31[c]	2.29	−0.03	↓	4
Bihar	**3.09**	**3.21**	**0.12**	↑	**1**
Chhattisgarh	3.19	2.69	−0.50	↓	11
Goa	4.17	3.36	−0.81	↓	16
Gujarat	3.09	2.27	−0.82	↓	17
Haryana	3.09	2.49	−0.60	↓	13
Jharkhand	3.06	2.80	−0.26	↓	7
Karnataka	3.50	2.73	−0.78	↓	15
Kerala	3.06	2.57	−0.49	↓	10
Madhya Pradesh	2.93	2.38	−0.55	↓	12
Maharashtra	3.34	3.07	−0.28	↓	8
Odisha	3.39	2.63	−0.75	↓	14
Punjab	4.58	2.51	−2.06	↓	18
Rajasthan	**2.43**	**2.44**	**0.01**	↑	**3**
Tamil Nadu	2.63	2.34	−0.28	↓	9
Telangana	2.86[d]	2.63	−0.23	↓	6
Uttar Pradesh	**3.04**	**3.14**	**0.10**	↑	**2**
West Bengal	2.62	2.51	−0.10	↓	5

Source Calculated from Appendix Tables 6,7 and 8
[a]Taxes Subsumed in GST
[b]SGST (after IGST settlement)
[c]Since on 2 June 2014, Telangana was separated from Andhra Pradesh as newly formed state, we have considered the data of FY 2015–16 and 2016–17 for the Pre-GST era for Andhra Pradesh
[d]The state of Telangana was formed on 2 June 2014 and as per data availability, we have taken the data of FY 2015–16 and 2016–17 for Pre-GST era

From Table 2, it can be seen that in the Post-GST era tax buoyancy has increased for Gujarat, Haryana and Maharashtra. Except for Gujarat, Haryana and Maharashtra, tax buoyancy has decreased in Post-GST period for all other GCS. Since, for these states tax revenue has become less responsive to GSDP, it implies that these states will not be able to mobilize sufficient revenue through taxation to the same extent as the increase in public expenditure. It can have adverse implications on the fiscal sustainability in the long run (Paliwal et al., 2019).

As observed from Tables 1 and 2, average tax to GSDP ratio (Table 1) has declined for all states except Bihar, Rajasthan and Uttar Pradesh whereas tax buoyancy has

Table 2 Tax buoyancy

States	Pre-GST era (2012–2013 to 2016–2017)		Post-GST era (2017–2018 to 2019–2020)		
	Tax buoyancy	Rank	Tax buoyancy		Rank
Andhra Pradesh (Divided)	1.12[a]	4	0.44	↓	8
Bihar	1.83	1	−0.41	↓	18
Chhattisgarh	0.72	12	−0.39	↓	17
Goa	0.84	8	0.80	↓	2
Gujarat	**0.26**	**18**	**0.42**	↑	**9**
Haryana	**0.86**	**7**	**1.06**	↑	**1**
Jharkhand	1.62	2	0.05	↓	15
Karnataka	0.75	10	0.71	↓	5
Kerala	0.76	9	0.54	↓	6
Madhya Pradesh	0.59	14	0.38	↓	10
Maharashtra	**0.44**	**17**	**0.76**	↑	**3**
Odisha	0.75	11	0.06	↓	14
Punjab	0.61	13	0.45	↓	7
Rajasthan	0.91	6	0.18	↓	12
Tamil Nadu	0.48	16	0.24	↓	11
Telangana	1.44[b]	3	0.71	↓	4
Uttar Pradesh	0.54	15	−0.30	↓	16
West Bengal	**1.01**	**5**	**0.11**	↓	**13**

Source Calculated from the Appendix Tables 6, 7 and 8
[a]Since on 2 June 2014, Telangana was separated from Andhra Pradesh as newly formed state, we have considered the data of FY 2015–16 to 2016–2017 for the Pre-GST era for Andhra Pradesh
[b]Since on 2 June 2014, Telangana was separated from Andhra Pradesh as newly formed state, we have considered the data from FY 2015–16 to 2016–2017 for the Pre-GST era for Andhra Pradesh

declined for all states but Gujarat, Haryana and Maharashtra (Table 2). The decline in tax to GSDP ratio post GST is due to slower growth in tax collections. The CAGR of tax collection for all GCS except for Gujarat and Maharashtra has decreased from Pre-GST era to Post-GST era. The most affected states in the terms of fall in CAGR of tax collection are shown in Fig. 1.

Now, the change in tax collection can be defined as the product of change in tax base and change in tax rate, i.e.

$$\text{Change in Tax Collection} = \text{Change in Tax Base} \times \text{Change in Tax Rate}$$

Hence, the fall in CAGR of tax collection post-GST period can be due to overpowering effect of decline in tax base over rise in tax rate, overpowering effect of decline in tax rate over rise in tax base or a decline of both tax rate and tax base.

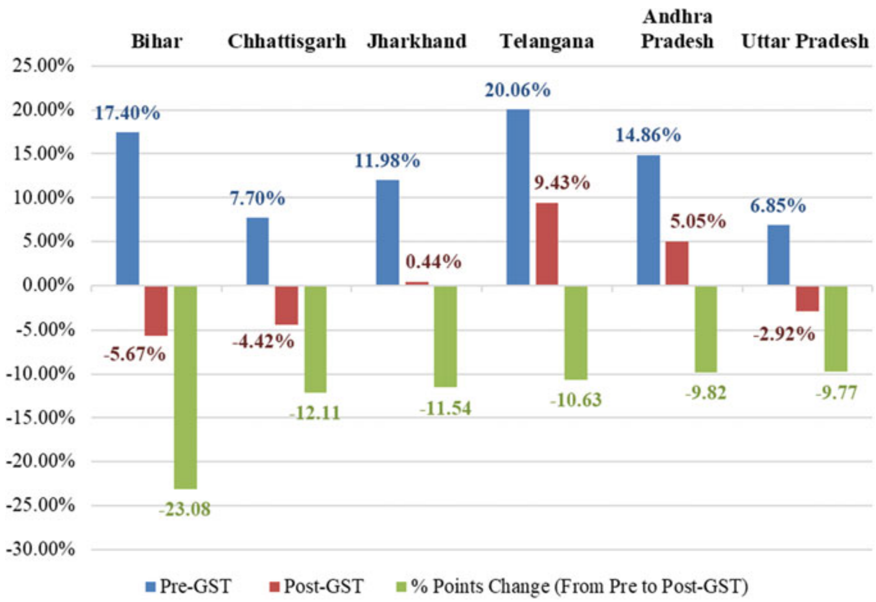

Fig. 1 CAGR of GST collection

In order to find the reason for slow growth in tax collections post GST, we have first examined the change in tax base post introduction of GST. To assess the change in tax base we have used taxpayers base as an indicator. As per the GSTN data, the number of registered GST payers has increased significantly since April 2018. With the addition of over 27 lakh new registrations since April 2018, total registrations (new plus migrated) increased to 1.35 crore, as on 28 February 2021 (Fig. 2). This growth indicates an increase in tax base and a change in taxpayers' compliance behaviour.

If the number of new taxpayers has increased, then the decline in growth in tax collections post-GST period compared to pre-GST period may be on account of reduction in tax rates of commodities. Reduction in rates of commodities may have pulled down the overall growth rate in tax collections. In order to study this, we have analysed the change in tax rates of commodities across various tax slabs during last three years. It is observed that the GST tax rates for many goods falling under 28% slab has been reduced to a lower rate.[6] The number of entries in the 28% slab has been reduced from 228 to 37 over a period of three years (Fig. 3).

Also, as per RBI state finances report of 2019–2020, the continuous reduction in tax rates of commodities by the GST council has led to a fall in the effective weighted GST rate from 14.4% at the time of introduction of GST to 11.6% in 2019 (Refer Fig. 4).

[6] Only GST rates change that have been notified up to 25 June 2020 have been considered.

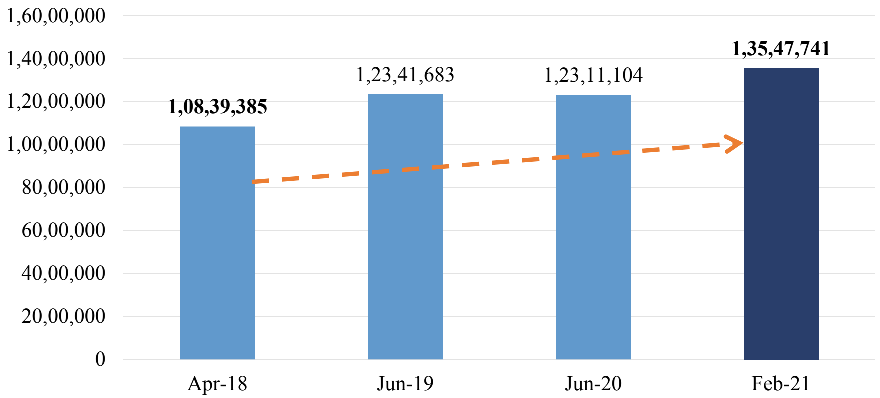

Fig. 2 Number of GST taxpayers (active taxpayers net of cancellations). *Source* A Statistical Report on Completion of 3 years of GST; Goods and Services Network Official website of GST—www.gst.gov.in

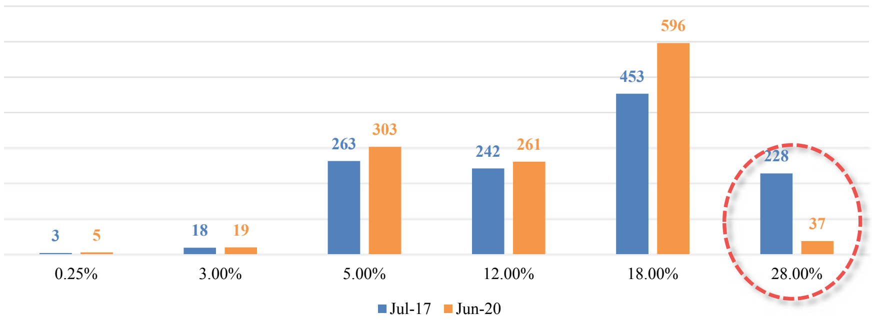

Fig. 3 Change in number of commodities falling under different GST slabs (Figure above each bar represents number of commodities under each GST slab). *Source* https://www.cbic.gov.in/

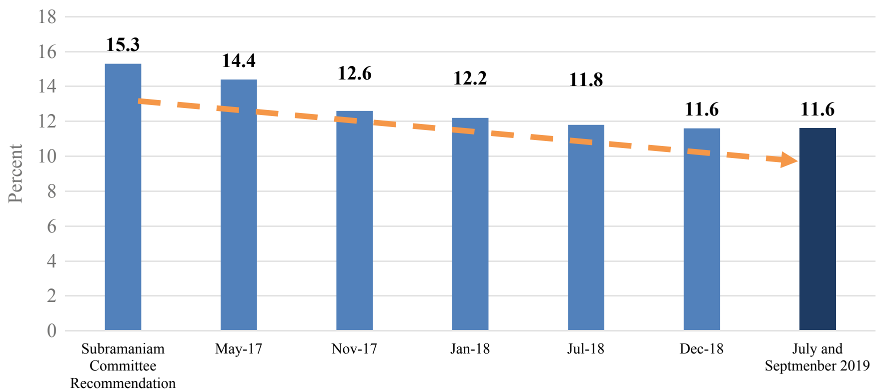

Fig. 4 Weighted average effective GST rate. *Source* State Finances: A Study of Budgets of 2019–2020

Thus, the overpowering effect on reduction in GST rate as compared to increase in tax base may have led to a reduction in growth in tax collections for most of the states in post-GST period.

4.3 Dependency of States on GST Compensation Cess

The Central government committed to compensate states for any shortfall in their revenue from their actual revenues from the merged taxes as on 2015–2016 increased by 14% every year for a period of five years, in order to get the States to agree. The compensation was to be financed by a separate cess on the demerit and luxury items over and above CGST and SGST levied at rates varying from 15 to 96% of the tax rate applicable (Rao, 2020).

The regime of paying compensation fund to states for revenue shortfall resulting from GST implementation is going to end in June 2022 but the compensation cess levied on luxury and demerit goods[7] will continue to be collected till March 2026. This extension of GST cess till 2026 is to generate revenue to reimburse the states for the loans which will be taken by state governments either from the market or from the central government to make up for the shortfall in the GST compensation disbursements. Therefore, it is important to examine the extent of dependency of states on GST compensation. In order to determine the extent of dependency on GST compensation, we have calculated the share of GST compensation fund in the total GST revenue[8] for GCS as per the data availability and performed inter-state comparison. Greater the share of GST compensation of a state in its total GST revenue signifies the greater dependency of that state on GST compensation. Through this analysis, we have cross-examined possible impact of the policy decision of not extending the compensation fund beyond June 2022.

In Table 3, we have presented the share of GST compensation in total GST revenue for GCS for FY 2017–2018, 2018–2019 and 2019–2020. Additionally, we have calculated the change in the share of GST compensation from FY 2017–2018 to FY 2019–2020 for these states.

[7] A Demerit good is a good or service whose consumption is considered unhealthy, degrading, or otherwise socially undesirable due to the perceived negative effects on the consumers themselves, for example tobacco products.

[8] Remember, total GST revenue has been the sum of SGST collection (including revenues from IGST) and GST compensation.

Table 3 GST compensation analysis

States	Percentage of GST Compensation in Total State GST Revenue			Change - GST Compensation
	(A) 2017-18	2018-19	(B) 2019-20	(B) - (A)
	Percent (%)			Percentage Points
Punjab	31.03	34.54	40.85 **Rank ①**	9.82
Chhattisgarh	18.62	20.69	28.07 **Rank ②**	9.45
Karnataka	18.57	20.13	25.59 **Rank ③**	7.02
Goa	-	-	25.14	-
Gujarat	13.64	15.37	23.79	10.15
Odisha	17.56	21.15	22.93	5.37
Haryana	9.39	13.06	22.42	13.03
Kerala	11.45	8.94	21.42	9.98
Tamil Nadu	2.44	7.45	18.86	16.43
Bihar	18.59	13.32	18.24	-0.35
Madhya Pradesh	-	12.67	18.14	18.14
Rajasthan	14.32	8.39	16.82	2.50
Jharkhand	19.75	11.76	15.40	-4.34
Maharashtra	-	9.10	15.38	15.38
West Bengal	**7.46**	**6.56**	**13.76**	**6.30**
Uttar Pradesh	5.35	0.63	9.88	4.53

Source Calculated from Appendix Tables 7 and 9

From Table 3, it can be observed that between FY 2017–2018 and FY 2019–2020 all GCS are dependent on GST compensation from the central government for the loss arising due to GST implementation. Punjab, Chhattisgarh and Karnataka are top three states which have the highest dependency on GST compensation in FY 2019–2020 as well as Punjab has consistently highest dependency on GST compensation from FY 2017–2018 to FY 2019–2020. Also, it can be seen that for Punjab, Chhattisgarh, Karnataka, Gujarat, Odisha, Haryana, Tamil Nadu, Madhya Pradesh and Maharashtra, the dependency has been strictly increasing over a period of time at an increasing rate. For such states, decision of not continuing with the policy of GST compensation fund has been a serious concern and therefore GST council is required to look into this matter once again.

The increasing dependency on GST compensation does not simply imply that GST collection has been decreasing over a period of time. Instead, it implies that the growth in GST collection is less than the estimated growth of 14% year-on-year as decided for giving GST compensation to states. Also, for most of the states, before the implementation of GST, the annual growth rate of subsumed taxes was much lesser than 14% growth rate.

As seen from Table 3, West Bengal has relatively lower dependency on GST compensation as compared to other states. This is because even before the implementation of GST, the state had low tax to GSDP ratio due to several factors such as high presence of informal sector, low consumption of taxable commodities, etc. Low tax collections prior to GST implementation resulted in lower protected revenues (14% y–o–y applied on 2015–2016 subsumed taxes figure) post implementation of GST. Additionally, GST to GSDP ratio of the state remained more or less similar to pre-GST levels. Hence, the GST compensation to the state has remained low as compared to other states.

4.4 GST Collection (Manufacturing Versus Consumption States)

GST has brought up the concern among manufacturing states that the shift towards consumption-based and destination-based tax would increase the tax collections of consumption states at the expense of manufacturing states. In this section, we have analysed this hypothesis and examined whether consumption states in particular, West Bengal has benefitted from the implementation of GST or not. In Table 4, we have examined the state's share of manufacturing sector in its GSDP and state's SGST[9] to GSDP ratio for each GCS for FY 2016–2017 & FY 2019–2020, respectively. From this, we have carried out an inter-state comparison of the SGST to GSDP ratios among the consumption states and manufacturing states.

From Table 4, out of 18 GCS, top 5 ranked states on the basis of manufacturing share in GSDP are considered as manufacturing states. These states include Goa, Gujarat, Tamil Nadu, Jharkhand and Haryana. Goa held 1st position in SGST to GSDP ratio (3.26%) while its rank on the basis of manufacturing share was also 1st. This implies that although Goa is top manufacturing state, its SGST to GSDP ratio is better than top consumption states like West Bengal. Similarly, Jharkhand held 5th position in SGST to GSDP ratio (2.62%) while its rank on the basis of manufacturing share was 4th. West Bengal stands at 12th position in manufacturing share and hence can be termed as consumption state as compared to other top 11 states. However, the ratio of SGST to GSDP for West Bengal has not increased in post-GST era. Also, WB's rank on the basis of SGST to GSDP ratio is less as compared to Jharkhand which held 4th rank on the basis of share of manufacturing in GSDP for FY 2019–2020. Similarly, there are other consumption states including Bihar, Kerala and Madhya Pradesh that were supposed to get benefitted from GST as it is a destination-based and consumption-based tax but it is not the case. The results on whether GST has benefitted the consumption states are therefore mixed and further state-wise research is required to analyse the issue in detail.

[9] Inclusive of IGST settlement.

Table 4 Effect of GST on manufacturing versus consumption state

State	Manufacturing share in GSDP	Rank	(A) Subsumed taxes to GSDP ratio	Rank	(B) (SGST[a])to GSDP ratio	Rank	% Δ from (A) to (B)
	FY 2019–2020		FY 2016–2017		FY 2019–2020		(%)
Andhra Pradesh	8.89	15	2.33	17	2.08	18	−10.55
Bihar	5.27	18	3.46	3	2.66	4	−23.15
Chhattisgarh	12.30	9	3.07	7	2.29	12	−25.47
Goa	39.62	1	3.81	2	3.26	1	−14.42
Gujarat	31.32	2	2.58	15	2.09	17	−18.81
Haryana	16.24	5	3.04	9	2.42	8	−20.49
Jharkhand	18.01	4	3.41	4	2.62	5	−23.18
Karnataka	12.52	8	3.27	5	2.59	6	−20.91
Kerala	8.67	16	2.92	11	2.39	10	−18.11
Madhya Pradesh	7.96	17	2.67	13	2.18	15	−18.41
Maharashtra	15.38	7	3.07	8	2.93	2	−4.50
Odisha	15.88	6	3.23	6	2.41	9	−25.37
Punjab	12.06	10	4.32	1	2.36	11	−45.30
Rajasthan	9.00	14	2.33	18	2.20	14	−5.48
Tamil Nadu	19.41	3	2.40	16	2.14	16	−11.15
Telangana	9.37	13	2.94	10	2.46	7	−16.37
Uttar Pradesh	11.10	11	2.83	12	2.80	3	−1.11
West Bengal	**11.01**	**12**	**2.60**	**14**	**2.26**	**13**	**−12.93**

Source MOSPI and Appendix Tables 7 and 9
[a]SGST collection including IGST settlement
[b]Δ indicates Change

5 Impact of COVID-19 on States' Tax Collection

COVID-19 pandemic has created a concern among states as their tax collections have fallen due to decrease in the consumption induced by lockdown across states in India. In this section, we have examined the impact of COVID-19 on states' GST collections. Figure 5a shows the monthly GST collections for FY 2020–2021 on aggregate basis and Fig. 5b shows the yearly GST collection for FY 2019–2020 and FY 2020–2021 on aggregate basis.

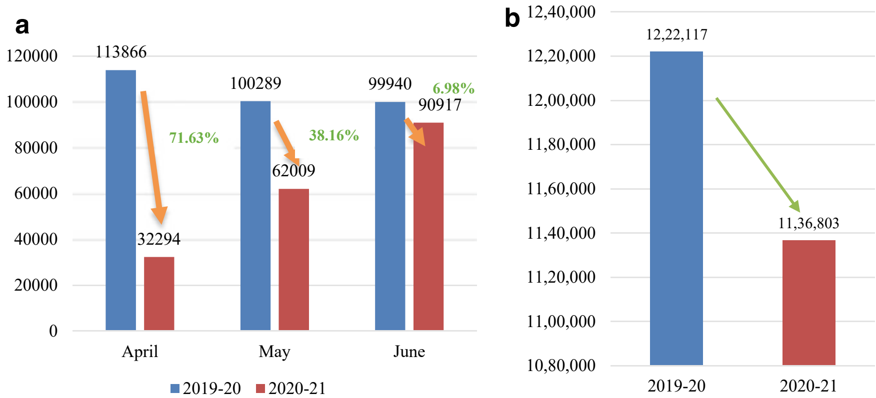

Fig. 5 All states monthly GST collection (INR crores). b All states annual GST collection (INR crores). *Source* Department of Revenue, Ministry of Finance

From Figure 5a, we can see that monthly GST collection for FY 2020–2021 had fallen by a significant proportion as compared to FY 2019–2020. For the month of April, GST collection of all states taken together had fallen by 71.63% which can be attributed to the nation-wide lockdown induced by the global COVID-19 outbreak. This nation-wide lockdown in the month of April also followed in May and hence fall in GST collection for the month of May can be seen of about 38.16%. The decline in GST collection in May is less as compared to April. This is due to relaxation of lockdown restrictions induced by classification of the districts into green, red and orange zones based on the spread of virus. In the month of June, nation was witnessing gradual unlocking of states and easing out of the restrictions. Therefore, the fall in GST collection was to the tune of 9%. If we compare the GST collection of FY 2019–2020 as against FY 2020–2021, GST collection has fallen by 6.98%.

5.1 *Impact of COVID-19 on West Bengal GST Collection*

Figure 6 shows the trend analysis of the percentage change in quarterly[10] GST collection for the state of West Bengal. We have taken the data from June 2019 to July 2021 to examine the seasonal variation in the quarterly growth rate of GST collection.

If we look at Fig. 6, there is a dip in GST collection in the first quarter of FY 2020–2021 and this dip is about 54.8% as compared to quarter 4 of FY 2019–2020. This can be attributed to the nation-wide lockdown announced in April 2020 but after the month of April 2020, the state has witnessed the increase in GST collection in May 2020. This increase in GST collection has occurred due to ease in lockdown

[10] First quarter of any financial year constitutes the months of April, May and June, second quarter constitutes the month of July, August and September, third quarter constitutes October, November and December and fourth quarter constitutes January, February and March.

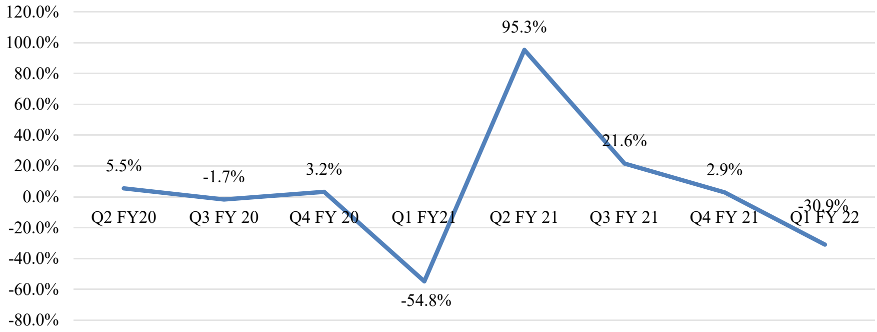

Fig. 6 Trend analysis—percentage change in quarterly GST collection. *Source* Directorate of Commercial Taxes, Government of West Bengal

restrictions induced by the classification of districts in the country into Red, Orange and Green Zones. Also, in second quarter of FY 2021, GST collection has arisen on the account of relaxation of the restrictions of lockdown on the basis of guidelines issued by Ministry of Home Affairs.

Also, the second wave of COVID-19 in April and May 2021 has led to fall in GST collections and therefore fall in quarterly growth rate of GST collection for quarter 1 of FY 2021–2022. It may be argued that the Central Government needs to take into account the adverse impact of COVID-19 on states arising on account of the low tax revenue and may consider continuation of GST compensation fund beyond June 2022.

6 Impact of GST on Formalization of Economy

In this section, we have analysed the impact of GST on the formalization of the economy. In order to do so, we have used the following indicators to assess the extent of formalization of the economy. These are as follows:

- Change in the Number of MSME registrations from Pre-GST era to Post-GST era
- Number of registered persons on payroll as per EPFO records from FY 2017–2018 to FY 2020–2021.

6.1 Change in Number of MSME Registrations

As we know that the increase in the formalization of economy is backed by increase in total number of registered businesses but due to unavailability of year-wise number of business registrations data for GCS, we referred to yearly MSME registrations data for GCS. In Table 5, we have calculated the state- wise annual change in the number of MSME registrations from FY 2015–2016 to 2019–2020.

After enactment of GST, for Andhra Pradesh, Bihar, Jharkhand, Odisha, Uttar Pradesh and West Bengal, average number of MSME registrations from Pre-GST era to Post-GST era has decreased whereas for Chhattisgarh, Goa, Gujarat, Haryana, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Punjab, Rajasthan, Tamil Nadu and Telangana, average number of MSME registrations from Pre-GST era to Post-GST era has increased.

From the data set available we cannot therefore conclude that GST has encouraged more MSMEs to register under GST to reap benefits.

Table 5 (State-wise) change in average number of MSME registrations from pre-GST to post-GST era

State	Pre-GST average (From FY 2015–2016 to FY 2016–2017)	Post-GST average (From FY 2017–2018 to FY 2019–2020)	% Change (From Pre-GST to Post-GST Era)	
Andhra Pradesh	90,509	55,449	−39%	↓
Bihar	371,234	81,476	−78%	↓
Chhattisgarh	8,015	17,820	122%	↑
Goa	1,351	2,106	56%	↑
Gujarat	149,353	183,013	23%	↑
Haryana	16,352	48,870	199%	↑
Jharkhand	45,669	26,432	−42%	↓
Karnataka	37,979	85,021	124%	↑
Kerala	22,919	28,180	23%	↑
Madhya Pradesh	82,508	266,326	223%	↑
Maharashtra	158,717	487,536	207%	↑
Odisha	28,675	20,230	−29%	↓
Punjab	15,183	58,337	284%	↑
Rajasthan	84,824	140,542	66%	↑
Tamil Nadu	175,339	235,548	34%	↑
Telangana	49,440	69,782	41%	↑
Uttar Pradesh	245,289	136,421	−44%	↓
West Bengal	**57,150**	**37,223**	**−35%**	↓

Source Udyog Aadhaar Memorandum, Registration of Micro, Small and Medium Enterprises (MSMEs) in India, 2020–2021

6.2 Total Number Registered Persons on Payroll

An organization with 20 or more employees is required to register an individual under Employees Provident Fund (EPF) scheme of EPFO governed by Ministry of Labour and Employment, Government of India. So, another measure we have considered to analyse the impact the GST on the formalization of the economy is to examine the impact of GST on formal employment. In order to do so, we have visualized the year-wise number of registered persons on payroll from FY 2017–2018 to FY 2020–2021.

The number of persons registered for payroll has continuously increased in post-GST era except FY 2020–2021. We can see that the formal employment has increased by about 129.6% from FY 2017–2018 to FY 2018–2019 whereas it was just about 28.6% of increase in FY 2019–2020 as compared to FY 2018–2019. Also, the fall in the number of registered persons can be attributed to the demand constrained induced by COVID-19 pandemic which had forced the small businesses to shut down the production and to layoff the employees.

There are several policy options that can be implemented in GST in order to boost formalization of economy in an enhanced manner such as further simplifying GST returns filing, simplifying the system of Outward and Inward supplies matching, removal of taxation on stock transfers and deemed supplies, extending the time limit of returning the goods, removal of GST on advances, etc.

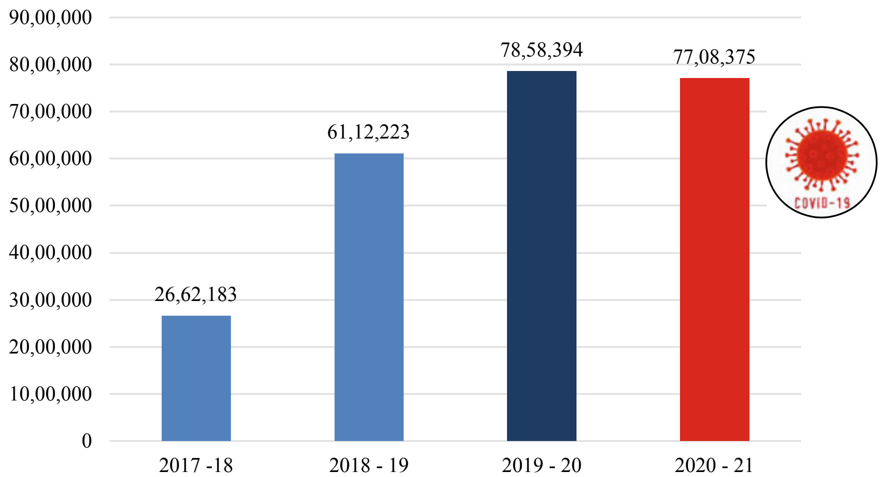

Fig. 7 Year wise number of persons on payroll as per EPFO. *Source* Ministry of Labour & Employment, Government of India

7 Conclusion

GST was introduced with the objective of implementation of a transparent and efficient tax system to decrease the cascading of tax, increase the tax base and revenue in the long run. Since the inception of GST, many changes and modifications have been incorporated to bring more transparency and efficiency in this system. But most of the states have witnessed a decrease in their tax collections and increase in their dependency on GST compensation. This may be because of inherent limitations in the design structure of GST which might have ignored state-specific issues in generation of revenue. We have seen that for several states including Chhattisgarh, Haryana, Karnataka, Odisha, Punjab and Tamil Nadu, the dependency on GST compensation has been increasing considerably over a period of time.

Inadequate growth of tax revenue during post-GST period has raised concern among the states as GST compensation fund will be discontinued after June 2022 coupled with the already declined revenues due to COVID-19 outbreak. The discontinuation of compensation fund to states may lead to massive shock to state finances. Moreover, the postulate that GST benefits consumption states appears to be inconclusive since states like West Bengal, Kerala and Bihar have not shown significant increase in revenue in the Post-GST era. Moreover, almost all the states have witnessed low tax collection due to nation-wide lockdown measures implemented since March 2020 consequent to COVID-19 pandemic which led to limited economic activities, extension of GST return filings timelines without payment of interest, late fee or penalty, etc. Centre and States may examine the issues in detail and take appropriate actions such as frequent changes in GST rates, reducing waiver of interest rates and penalties over unpaid tax returns, improving efficiency of revenue collection by bringing stringent measures that will curb tax evasion and increase efficiency, encouraging the use of the tax technology and bringing more exempted goods under the GST ambit, thereby broadening the tax base.

Appendix

See Tables 6, 7, 8 and 9.

Table 6 State-wise revenue from taxes subsumed in GST

(INR Crores)

States	2012–2013	2013–2014	2014–2015	2015–2016	2016–2017	2017–2018 (Till 30th June)
Andhra Pradesh	26,828.60	28,338.52	28,034.39	13,873.30	15,935.33	4,456.20
Bihar	7,670.67	9,496.19	9,874.81	12,620.56	14,573.71	2,314.91
Chhattisgarh	5,999.19	6,510.24	6,840.18	7,357.00	8,070.14	2,769.45
Goa	1,546.39	1,809.08	1,915.02	2,181.38	2,398.09	566.13
Gujarat	25,935.95[a]	27,083.21[a]	28,939.23[a]	28,856.39	30,075.15[a]	18,495.35[a]
Haryana	11,135.46[a]	11,975.58[a]	13,752.97[a]	15,230.59	17,071.30[a]	13,578.36[a]
Jharkhand	5,127.10	5,598.36	6,262.41	6,410.51	8,060.55	1,849.21
Karnataka	25,397.85	28,899.09	32,919.25	36,144.15	39,505.39	11,013.32
Kerala	13,166.93	14,456.85	15,786.15	16,821.37	18,546.89	6,506.00
Madhya Pradesh	12,282.92	12,996.79	14,160.30	15,329.20	17,373.72	3,982.98
Maharashtra	55,269.06	56,652.27	59,694.10	60,504.60	67,458.64	20,673.19
Odisha	9,233.71	10,036.71	10,756.29	11,049.34	12,682.28	2,966.73
Punjab	14,587.40	16,505.52	17,681.81	14,471.77	18,441.60	4,690.91
Rajasthan	11,860.86	13,054.51	15,748.72	17,158.62	17,684.30	4,528.66
Tamil Nadu	25,041.26	25,875.36	27,783.45	29,786.36	31,304.25	7,359.69
Telangana	#	#	+	16,108.73	19,339.59	5,397.78
Uttar Pradesh	27,976.47	28,277.21	30,822.03	33,387.85	36,468.43	12,470.72
West Bengal	15,313.09	18,031.34	19,552.90	20,097.72	22,657.08	5,650.78

Source Department of Revenue, Government of India

[a]Data has not been provided by the concerned State for the said period. Estimated data for the same has been taken from Mukherjee (2020)

[+]Data has not been provided by Telangana for the said period

[#]The state of Telangana was officially formed on 2 June 2014, therefore, statistical data for Telangana for FY 2012–2013 & FY 2013–2014 is not available

Table 7 SGST collection[a]

States	July 2017–March 2018	2017–2018 (Adjusted for 12 Months)	2018–2019	2019–2020	Total
INR Crores					
Andhra Pradesh	13,747.99	18,330.65	21,257.1	20,227.0	59,814.76
Bihar	13,318.96	17,758.62	16,737.9	15,800.5	52,308.48
Chhattisgarh	6480.92	8641.23	8665.4	7894.8	26,847.64
Goa	1720.77	2294.36	2529.1	2438.5	7405.37
Gujarat	23,347.89	31,130.52	35,351.3	34,106.7	115,216.83
Haryana	11,570.51	15,427.35	18,775.3	18,873.0	53,926.53
Jharkhand	6258.32	8344.43	8200.8	8417.7	26,395.27
Karnataka	27,386.90	36,515.87	42,663.0	42,147.2	121,926.90
Kerala	13,707.65	18,276.87	21,389.7	20,447.0	63,456.20
Madhya Pradesh	13,828.60	18,438.13	19,750.9	20,447.8	57,512.22
Maharashtra	53,817.52	71,756.70	83,180.5	82,601.6	241,407.12
Odisha	9765.75	13,021.00	12,638.9	13,203.5	39,359.89
Punjab	8973.46	11,964.61	13,509.8	12,751.2	38,917.59
Rajasthan	15,873.50	21,164.67	23,762.6	21,954.2	70,532.53
Tamil Nadu	27,324.87	36,433.16	39,136.6	38,376.2	119,788.13
Telangana	14,730.03	19,640.04	24,205.8	23,516.7	69,662.81
Uttar Pradesh	37,585.72	50,114.29	48,801.9	47,232.4	155,026.60
West Bengal	19,943.90	26,591.87	28,165.8	27,307.5	85,105.67

Source RBI State Finances: A Study of Budgets
[a]This SGST collection is after IGST settlement

Table 8 Gross state domestic product at current prices

State\UT	2013–2014	2014–2015	2015–2016	2016–2017	2017–2018	2018–2019	2019–2020
INR Crores							
Andhra Pradesh	464,272	524,976	604,229	684,416	786,135	870,849	971,224
Bihar	317,101	342,951	371,602	421,051	468,746	527,976	594,016
Chhattisgarh	206,833	221,118	225,163	262,802	282,283	318,101	344,955
Goa	35,921	47,814	55,054	62,976	69,352	71,853	74,828
Gujarat	807,623	921,773	1,029,010	1,167,156	1,329,095	1,492,156	1,630,240
Haryana	399,268	437,145	495,504	561,424	644,963	704,957	780,612
Jharkhand	188,567	218,525	206,613	236,250	269,816	305,695	321,157
Karnataka	816,666	913,923	1,045,168	1,207,608	1,336,914	1,490,624	1,628,928
Kerala	465,041	512,564	561,994	634,886	701,588	790,302	854,689
Madhya Pradesh	439,483	479,939	541,068	649,823	726,338	813,820	937,405
Maharashtra	1,649,647	1,779,138	1,966,225	2,198,185	2,352,782	2,579,628	2,818,555
Odisha	296,475	314,250	328,550	392,804	440,804	498,286	547,959
Punjab	332,147	355,102	390,087	426,988	471,014	512,511	539,687
Rajasthan	551,031	615,642	681,482	760,587	828,661	921,789	998,999
Tamil Nadu	968,530	1,072,678	1,176,500	1,302,639	1,465,051	1,630,209	1,797,229
Telangana	451,580	505,849	577,902	658,325	750,050	860,078	957,207
Uttar Pradesh	940,356	1,011,790	1,137,808	1,288,700	1,416,006	1,584,764	1,687,818
West Bengal	676,848	718,082	797,300	872,527	974,700	1,102,283	1,207,823

Source MOSPI

Table 9 GST compensation data

States	2017–2018 (9 Months)	2017–2018 (Adjusted for 12 Months)	2018–2019	2019–2020
INR Crores				
Bihar	3,041.00	4,054.67	2,571.00	3,524.78
Chhattisgarh	1,483.00	1,977.33	2,261.00	3,081.44
Goa	–	–	–	818.70
Gujarat	3,687.00	4,916.00	6,419.00	10,646.52
Haryana	1,199.00	1,598.67	2,820.00	5,453.43
Jharkhand	1,539.90	2,053.20	1,092.71	1,532.72
Karnataka	6,246.00	8,328.00	10,754.00	14,496.90
Kerala	1,772.00	2,362.67	2,100.00	5,575.04
Madhya Pradesh	–	–	2,866.00	4,530.78
Maharashtra	–	–	8,330.00	15,018.13
Odisha	2,079.76	2,773.01	3,390.00	3,928.78
Punjab	4,037.00	5,382.67	7,129.00	8,804.54
Rajasthan	2,653.14	3,537.52	2,176.00	4,439.53
Tamil Nadu	682.00	909.33	3,151.00	8,922.03
Uttar Pradesh	2,124.00	2,832.00	308.00	5,179.52
West Bengal	1,608.00	2,144.00	1,977.00	4,358.74

Source RBI State Finances: A Study of Budgets

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Digital Transformation, Digital Entrepreneurship, and Economy: A Cross-Country Analysis Using Moderated Mediation Modeling Technique

Sangita Dutta Gupta and Madhumita Guha Majumder

1 Introduction

Entrepreneurship is considered to be a driver of growth (Schumpeter, 1936). Eradication of poverty remains the biggest challenge for many countries. Entrepreneurship can be considered providing impetus to economic growth (Gries & Naudé, 2010; Valliere & Peterson, 2009; Wong et al., 2005) and help in employment generation, eradication of poverty, and socio-economic development (Audretsch, 2001; Baumol & Strom, 2007).

However, many economists believe that the relationship between economic growth and entrepreneurship is ambiguous (Van Praag & Versloot, 2007). Solow (1957) mentioned convergence and the possibility of developing economies catching up with the developed and advanced economies. Entrepreneurship can play an important role in this convergence.

Entrepreneurial activities have undergone considerable changes due to the advent of digital transformation (Hess et al., 2016). The diffusion of digital technology can drive entrepreneurial growth and enhance competitiveness (Matt et al., 2015). The use of digitalization can bring rapid changes in industry and business (Giotopoulos et al., 2017) and is also considered to be important for enhancing productivity (Jorgenson et al., 2008), prosperity of business activity (Levendis & Lee, 2013, Quereshi, 2013). The need for digitalization has become more pronounced post-Covid-19 pandemic. The restrictions like social distancing and lockdowns made the companies reshape

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their strategies and move towards digital transformation (Gavrila Gavrila & de Lucas Ancillo, 2022).

Access and use of digital means like the internet play an important role in accelerating economic growth (Kelly et al., 2010). Access to digital means can help in economic inclusion (UNDAW, 2003). Industry 4.0 and the adoption of digitalization have added significant dividends to many economies of the world. Industrial development especially for emerging economies can help in a country's economic development (Hess et al., 2016; Matt et al., 2015). Entrepreneurship can be considered a driver of growth and generating employment (Chakraborty & Biswas, 2019). It plays an important role in improving a nation's economic state (Adla et al., 2019). This is mainly applicable to emerging economies as entrepreneurship creates opportunities for people at the bottom of the pyramid. London and Hart (2011) pointed out about BoP 2.0 is all about creating opportunities for people at the bottom of the pyramid. Thus, it can be seen that entrepreneurship plays an important role in economic development. Entrepreneurship has transformed due to the advent of digitalization. However, digital adoption is required for digital entrepreneurship or technology entrepreneurship.

Our study identifies the determinants of digital adoption required for digital technology entrepreneurship. It also establishes the relationship between digital entrepreneurship and the economic well-being of economies measured through GNI (Gross National Income) per capita and checks the moderating influence of the types of economies. Countries have been categorized into four types—high income, upper middle income, lower middle income, and low income based on GNI data. Data on digital adoption is collected from the Digital platform economy index by The Global Entrepreneurship and Development Institute. Data analysis is done in three phases. The first phase is descriptive analysis followed by Pearson correlation analysis. The final phase is path analysis using smartPLS3.0.

The article is structured as follows. The second section contains a review of the existing literature. Section 3 discusses the theoretical background leading to the development of hypotheses. The methodology is discussed in Sect. 4. The section after that deals with the findings. The penultimate section discusses the results. The last section summarizes the findings of this study and concludes while highlighting the possible limitations and the future scope for research.

2 Review of Literature

Extensive literature can be found about the adoption intention of digital means although the outcome of ICT intention can be contradictory. Many factors have an impact on the adoption of digital means. Factors such as age, gender, and lifestyle (Fitzallen and Brown 2006) are important determinants of digital adoption.

Digital adoption can foster entrepreneurship (Dosi, 1982). Digital adoption can reduce information asymmetry and help in increasing market efficiency (Donner & Escobari, 2010). Chao et al. (2015) pointed out that the return on digital investment is more than physical investment if we consider the impact of digitalization on the productivity of the firm. Manufacturing firms can lower costs and improve productivity by adopting e-business technology (Jardim–Goncalves et al., 2012). Yunis et al. (2018) pointed out digital transformation is a key element of entrepreneurship. Firms with better IT capability tend to have higher profit ratios (Bharadwaj, 2000). So, digital transformation generates many opportunities for the firms (Stam & Gamsey, 2007).

Covid-19 pandemic is not only a health emergency but has impacted the society and economy by putting pressure on the business (Carlsson-Szlezak et al., 2020; Wren & Lewis, 2020). Many countries declared lockdown during the Covid-19 pandemic. During the lockdown, there has been an increase in the number of internet domain registrations. This was because social distancing norms made the organizations explore various survival strategies which included shifting from traditional channels to digital channels to face the new market realities (Gavrila Gavrila & de Lucas Ancillo, 2022). Before the pandemic, online presence or presence on the social network was not considered the core priority of the business (Gavrila Gavrila & de Lucas Ancillo, 2022). However, following the lockdown and social distancing norms, organizations have been increasing their digital presence through websites, e-commerce activity, or social networking sites (Bellaiche, 2020; Bhatti et al., 2020; UNCTAD, 2020). So, Covid-19 has been fostering digital entrepreneurship (Gavrila Gavrila & de Lucas Ancillo, 2022). Lockdown and temporary shutdown have adversely impacted the business, but it has also provided an opportunity to reshape and re-think their strategy and embrace digital transformation. **Digital transformation is the adoption of digital technology in all areas of business. Entrepreneurs who have adopted digital technology, address various activities of entrepreneurship through utilization of digital infrastructure.** Startups due to their lean and agile business models could adopt digital transformation quickly compared to traditional organizations (HBR, 2020). New technologies like Blockchain, Artificial Intelligence, Internet of Things, and social media have changed the way traditional businesses function (Kraus et al., 2019). Digital transformation has become a driver of growth for enterprises (Berman, 2012; Nambisan, 2017). There have been studies that highlighted that digital transformation not only helps in the development of enterprises but also gives a boost to the nation's economy (Ferreira & Franco, 2019; Festa et al., 2019). This is particularly true for developing economies, digital transformation has improved the economic health of many countries (Abedi et al., 2019).

Based on a review of literature, we find there are some studies about digital transformation and digital technology entrepreneurship and some studies about the impact of digital transformation on the economic health of any country. We combine both the aspects and look at the determinants of digital adoption required for digital technology entrepreneurship and how digital entrepreneurship can impact the economic health of any country measured through GNI per capita. So, the objectives of the studies are as followed:

a. To identify the factors contributing to digital technology entrepreneurship.

b. To study the impact of digital entrepreneurship on economic health moderated by the country type.

3 Theoretical Background

Enterprises are responding to digital transformation by changing their business strategies (Chatterjee & Kar, 2020; Shemi & Procter, 2018). So the adoption of digital transformation is important. Adoption of digital transformation can lead to technology entrepreneurship. Technology adoption can be at the level of organization (Leonard-Barton & Deschamps, 1988) or at the individual level where the adoption intention is the dependent variable (Compeau & Higgins, 1995; Davis et al., 1989). There are theories at the firm level and individual level. Diffusion of Innovation (DOI) by Rogers (1995) and Technology, Organization and Environment (TOE) by Tornatzky and Fleischer (1990) are important models at the organizational level. TOE model as the name suggests, points out that different contexts like technological, organizational, and environmental factors decide the adoption of technology. Most cited and extensively used models at individual levels include the Technology Acceptance Model (TAM), Theory of Planned Behaviour (TPB), or United Theory of Acceptance and Use of Technology (UTAUT) model. Individuals in the target organizations adopt the technology. So, the individual-level viewpoint is also important. Observed usefulness and ease of use are important constructs of the TAM model (Davis, 1986, 1989; Davis et al., 1989). Facilitating conditions, social influence, and expectations from the performance are important determinants of technology adoption in the case of the UTAUT model (Venkatesh et al., 2003). Facilitating conditions mean the resources and knowledge required for the adoption of technology. So, digital literacy and financial facilitation along with digital access which means access to the device have been considered the determinants of adoption of technological adoption leading to digital entrepreneurship. Enterprises are adopting digital transformation to respond to the rapidly changing market conditions (Chatterjee & Kar, 2020), particularly in the pandemic-hit world economy. So, the following hypotheses have been considered for the study.

H_1: High digital access contributes positively to digital technology entrepreneurship.

H_2: Digital literacy has a positive relationship with digital technology entrepreneurship.

H_3: Financial facilitation encourages digital technology entrepreneurship initiatives.

H_4: High digital access contributes positively to the GNI per capita of a nation mediating through digital technology entrepreneurship.

H_5: Digital literacy enhances GNI per capita of a nation mediating through digital technology entrepreneurship.

H_6: Financial facilitation contributes positively to GNI per capita through digital technology entrepreneurship initiatives.

Digital transformation has given a considerable boost to the economic health of many countries (Abedi et al., 2019). Entrepreneurship is important for removing poverty and enhancing the standard of living of the people of the country. So, we have considered the following hypothesis.

H_7: Digital technology entrepreneurship has a positive impact on the GNI of a nation.

There have been studies that showed that digital transformation and entrepreneurship are important mainly from the perspective of developing countries (Abedi et al., 2019; Matt et al., 2015). So, our study will look into whether the impact of digital technology entrepreneurship depends on the country type or not. As per World Bank data, countries have been categorized into high income, upper middle income, lower middle income, and low income based on GNI. We have combined lower middle-income and low-income countries into one group. The impact will be dependent on the categorization of countries. So, the following hypotheses have been considered.

H_8: The effect of digital access on digital technology entrepreneurship is stronger for lower middle-income group countries compared to those of upper middle-income and high-income group countries.

H_9: The effect of digital literacy on digital technology entrepreneurship is stronger for lower middle-income group countries compared to those of upper middle-income and high-income group countries.

H_{10}: The impact of financial facilitation on digital technology entrepreneurship is different across the country groups.

H_{11}: The impact of digital technology entrepreneurship on GNI is least for the high-income group among all categories of countries.

H_{12}: The mediation effect of digital technology entrepreneurship in the relationship between digital access and GNI is moderated by country type.

H_{13}: The mediation effect of digital technology entrepreneurship in the relationship between digital literacy and GNI is moderated by country type.

H_{14}: The mediation effect of digital technology entrepreneurship in the relationship between financial facilitation and GNI is moderated by country type.

Based on the above discussion, the study conceptualizes the research model, presented in Fig. 1, to test all the eight hypotheses.

4 Research Methodology

4.1 Data and Sample Description

We have collected data from the Digital Platform Economy (DPE) Index 2020 of the Global Entrepreneurship and Development Institute (GEDI, 2020) and World Bank (2022). The study has gathered five key variables including digital access, digital literacy, financial facilitation, digital technology entrepreneurship and GNI per capita, and one moderator, namely, country type, for 116 countries to test the

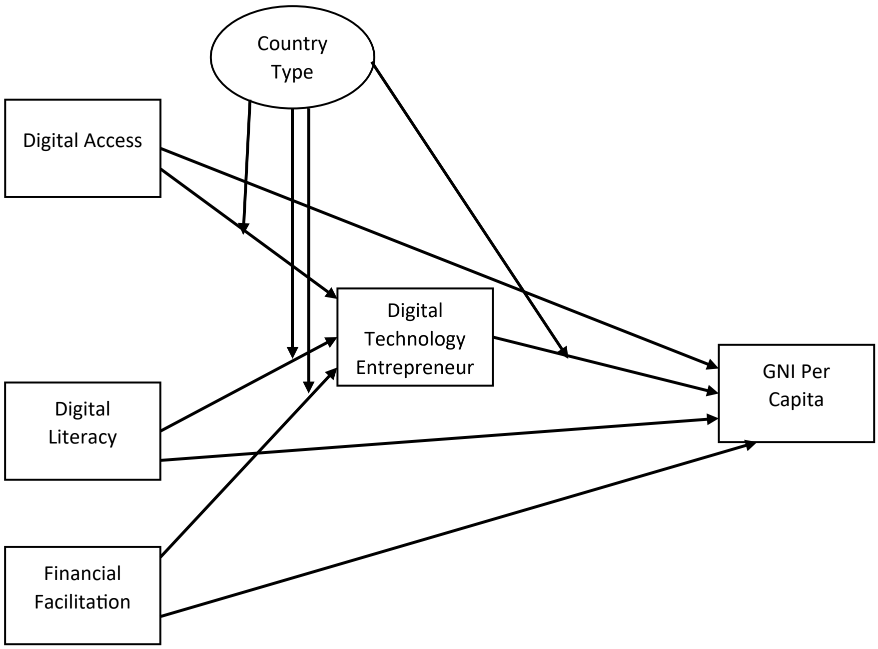


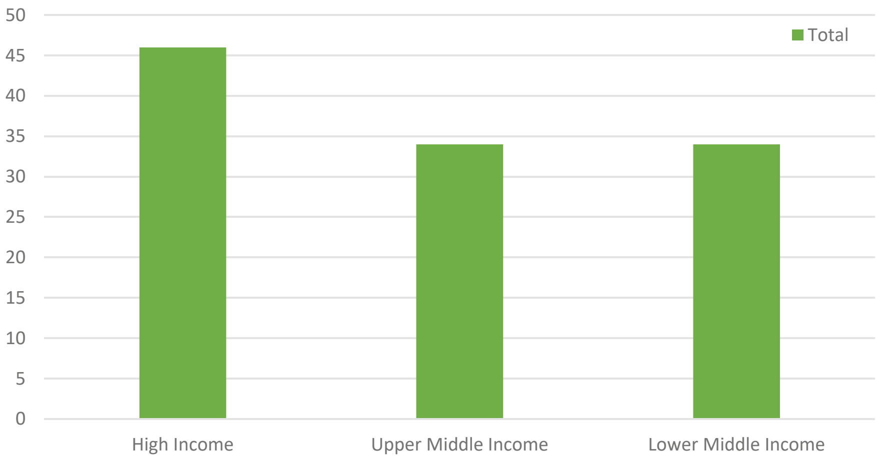
Fig. 1 Research conceptual model

hypotheses. As per the GNI per capita of these nations, the World Bank has classified them into four categories, namely, *High Income*, *Upper Middle Income*, *Lower Middle Income,* and *Low Income*, the distribution of which is presented in Fig. 2. As there are only 7 countries under a low-income group, we have taken them under the lower middle-income group. The study, therefore, has considered three groups of countries.

4.2 Analytical Approach

The analysis of the present study has been carried out in two phases. Firstly, we explored the pattern in data using descriptive analysis. We examined the concentration using the mean value of the distributions. Skewness and kurtosis coefficients have been used to observe the normality in the distribution. We have also adopted an exploratory data analysis tool to observe the five-point data summary of the distributions. Box plots are used to represent the result of exploratory data analysis. To have the statistical evidence of the observed variations in GNI per capita, we analyzed variance (ANOVA) with respect to country types.

Finally, we have performed path analysis using SmartPLS 3.0 (Ringle, 2015) to test all the research hypotheses. Streiner (2005) defines path analysis as an extension of multiple regression analysis and a special form of structural equation modeling



Source: World Bank Data (GNI, Atlas method (current US$) - Peru | Data (worldbank.org)

Fig. 2 Country type distribution. *Source* World Bank Data (GNI, Atlas method (current US$)—Peru | Data (worldbank.org)

technique, which uses both measured and latent variables. Further, to test the moderation effect of country type, Partial Least Squares-Multi Group Analysis (PLS-MGA) has been carried out using again SmartPLS 3.0 (Hair et al., 2017; Henseler et al., 2009). The first step of MGA divides the data into three subsamples according to the 'country type' (High Income, Upper Middle Income, and Lower Middle Income) as moderator and then estimate the same path model for each subsample. Then we have adopted the bootstrap method of Henseler (2007), to test whether the differences are statistically significant. As this approach is distribution free, it examines the significance using the confidence interval method (Henseler et al., 2009). Further, we have examined the hypotheses using a one-tailed test as the study examines all the directional hypotheses.

We have examined three sets of relationships to test the hypotheses of the study. Firstly, we have estimated the contributions of digital access, digital literacy, and financial facilitation to digital technology entrepreneurship. Secondly, we have examined the impact of these three independent variables on GNI per capita mediating through digital technology entrepreneurship; lastly, we have measured the effect of digital technology entrepreneurship on GNI per capita of nations. We have also scrutinized whether these relationships are different for different country groups using multigroup analysis.

Table 1 Operationalization of the variables

Variables	Role	Variable type
Digital access	Exogenous variable	Quantitative
Digital literacy	Exogenous variable	Quantitative
Financial facilitation	Mediator variable	Quantitative
Digital technology entrepreneurship	Mediator variable	Quantitative
GNI per capita	Endogenous variable	Quantitative
Country type	Moderator	Categorical

4.3 Measures

The key measures of the study including digital access, digital literacy, financial facilitation, digital technology entrepreneurship and GNI per capita represent quantitative variables, and one moderator, namely, country type is a categorical variable. The operationalization of these variables in the study has been given in Table 1.

Digital access is access to digital means. Digital access depends on factors like fixed broadband subscription/100 population; percentage of the population with personal computers, percentage of individuals using a computer, internet bandwidth kb/s per user, global cyber security index technical sub-index, and global cyber security index organization. Digital literacy is the skill set required for digital access. It depends on factors like digital skills among the population, quality of the education system, internet access in schools, and the number of searches by users in a country. Financial facilitation includes ownership of debit and credit cards, and the use of digital means to make payments among others. Digital technology entrepreneurship is the utilization of digital means for entrepreneurship (GEDI Report, 2020).

5 Results and Findings Data Processing and Analysis

5.1 Descriptive Analysis

To gauge the patterns of variables, we present the descriptive measures of the variables in Table 2.

Further, we were curious to know whether the variations in distributions for two primary endogenous variables, namely, digital technology entrepreneurship and GNI per capita, are subjected to country type or not. We have performed exploratory data analysis on these two variables and have found that variations in GNI per capita and technology entrepreneurship are highly affected by the country type. The variations in both digital entrepreneurial activities and GNI per capita are highest among the high-income countries.

Table 2 Descriptive measures

Measures	Digital access	Digital literacy	Financial facilitation	Digital technology entrepreneurship	GNI per capita
Mean	35.76	36.28	36.17	34.5	18,313
Median	31.25	31.55	29.35	30	8595
Mode	4.9	36.5	20.5	28.1	1160
Standard deviation	28.78	19.56	25.11	19.5	20,803
Kurtosis	-0.88	0.95	-0.63	0.03	0.9057
Skewness	0.52	1.09	0.73	0.9	1.3597
Range	99.8	97.1	97.9	83	82,390
Minimum	0.2	2.9	2.1	9.3	230
Maximum	100	100	100	92.3	82,620

The results in Figs. 3 and 4 prompted the authors to check the statistical significance of such variations using ANOVA. The test statistic, $F_{(2,\ 111;\ 0.05)} = 99.65$ ($p < 0.001$) of the first ANOVA model taking digital technology entrepreneurship as a dependent variable and country type as an independent variable, is highly significant, indicating that average entrepreneurial activities are truly different across the various country groups. The result of the second ANOVA model, taking GNI per capita as the dependent variable and country type as the independent variable, also becomes highly significant [$F_{(2,\ 111;\ 0.05)} = 104.65$ ($p < 0.001$)], establishing the fact that the average GNI per capita is truly different across the country groups. These inspire the authors to take country type as moderator while testing all the hypotheses under study.

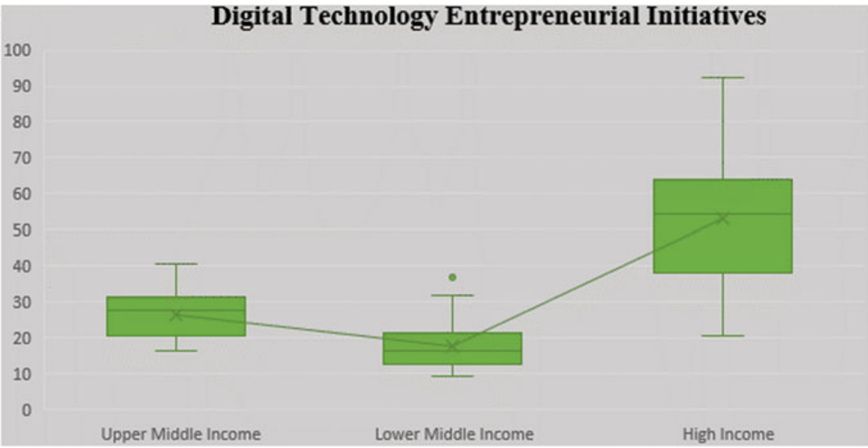


Fig. 3 Digital technology entrepreneurial initiatives

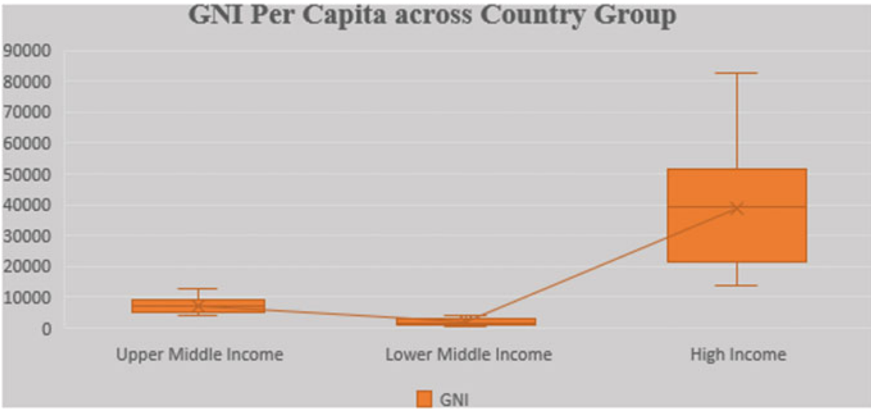


Fig. 4 GNI per capita across country group

As digital technology entrepreneurship is the key predictor for GNI per capita, we wanted to examine the correlation between the two variables with respect to various country types. In order to examine the pattern of relationship between the two variables, we pulled a scatter matrix in SPSS environment and the graph is exhibited in Fig. 5.

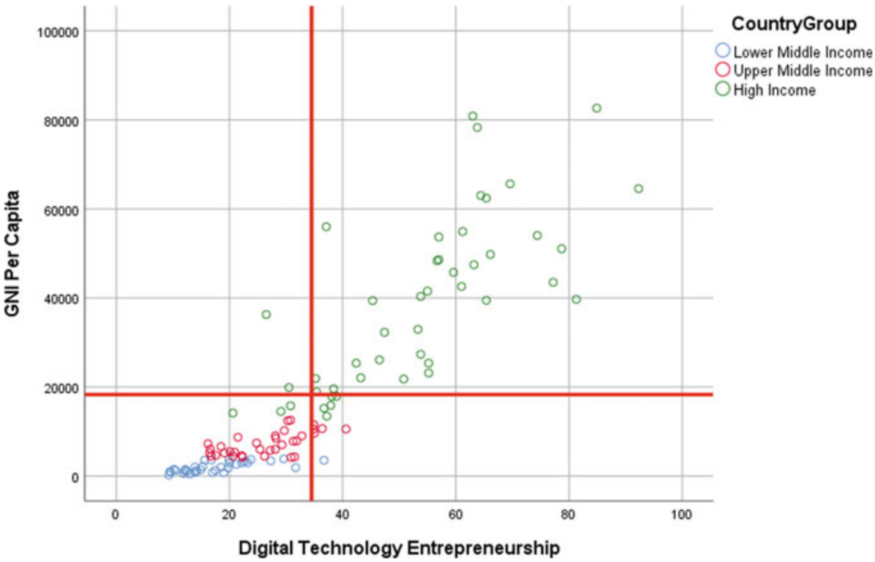


Fig. 5 Relationship between digital entrepreneurship and GNI per capita by country type

5.2 *Path Model*

To simultaneously analyze the effects of digital access, digital literacy, and financial facilitation on GNI per capita mediating through digital technology entrepreneurship, path analysis has been adopted. The study has used SmartPLS 3.0 environment to estimate the path model.

Table 3 shows several measures of model fit. Golob (2003) suggests that if the value of chi-square divided by its degrees of freedom is close to 1, the model is a good fit. Alwin and Hauser (1975) express that Standardized Root Mean Squared Error, an absolute fit measure, should be less than 0.08 for a good fit. A more conservative measure, suggested by Hooper et al. (2008), states that the value should preferably be lower than 0.05. The present model reveals a 0.025 (<0.05) indicating a good fit. As increment fit index with a 0.9 or higher value indicates a good fit (Alwin & Hauser, 1975; Coffman & MacCallum, 2005), the model NFI with a 0.947 score suggests that the model fit is good.

In Table 4, the R^2 values of two endogenous variables reveal that the explanatory power of independent variables is quite strong; 89.1% of variations in digital entrepreneurship has been explained while 83.3% variations in GNI per capita have been explained by the model.

The model has also been checked for multicollinearity. Chin (2010) suggests that the variance inflation factor (VIF) should be lesser than 10 to establish the absence of multicollinearity. We confirm that there is no multicollinearity in the model (Table 5) as all the VIF values are less than 10.

5.2.1 Testing the Hypotheses

After ensuring the fitness of the model, we estimate a path model in which digital access, digital literacy, and financial facilitation are the independent variables, digital technology entrepreneurship is the mediator, and GNI per capita is taken as the

Table 3 Model fit measures

Model fit index	Value	Desired value
Standardized root mean squared error	0.025	<0.08
NFI	0.947	>0.9
Chi-Square/degrees of freedom	0.76	<1

Table 4 Explained variations

Variable	R^2 value
GNI per capita	0.833
Digital technology entrepreneurship	0.891

Table 5 Examining multicollinearity using variance inflation factor

Country type	Variables	DTE	GNI
High income group	Digital access	3.288	3.45
	Digital literacy	2.585	3.653
	Financial facilitation	3.217	3.389
	Digital technology entrepreneurship		3.931
Upper middle-income group	Digital access	1.597	1.781
	Digital literacy	1.41	1.613
	Financial facilitation	1.664	1.926
	Digital technology entrepreneurship		2.307
Lower middle-income group	Digital access	1.608	2.445
	Digital literacy	1.237	2.978
	Financial facilitation	1.875	1.875
	Digital technology entrepreneurship		4.164

dependent variable (see Fig. 1). The country type is taken as a moderator in the PLS-Multigroup Analysis (PLS-MGA). The path analysis has been performed using the bootstrapping method (Byrne, 1998).

To test the hypotheses, first, we used the entire sample of 114 countries. We confirm the significance of a hypothesis as the lower limit and upper limit of bootstrapping result do not include zero. To test the moderating effects, we conducted Multi-Group Analysis (MGA) for Country Type with the subsamples of the High-Income group ($n = 46$), Upper Middle-Income group ($n = 34$), and Lower Middle-Income group ($n = 34$). In this case, a significant difference in path coefficients confirms the hypothesis.

Main Effects

The result of path analysis, displayed in Table 6, shows that the effects of digital access ($\beta = 0.333$, [0.223, 0.436]), effects of digital literacy ($\beta = 0.374$, [0.267, 0.493]), and effects of financial facilitation ($\beta = 0.292$, [0.130, 0.438]) on DTE are significant and positive. Hence, we support H_1, H_2, and H_3. Further, digital technology entrepreneurship also has a significant and positive ($\beta = 0.571$, [0.260, 0.845]) impact on GNI per capita, supporting hypothesis H_7.

Mediating Effects

The mediating effects of digital technology entrepreneurship on estimating the relationship of digital access, digital literacy, and financial facilitation on GNI are presented in Table 7. The direct effect ($\beta = -0.046$, [-0.21, 0.13]) of digital access

Table 6 Testing main effects for complete sample

Complete sample	Effects	5%	95%
Digital Access -> Digital Technology Entrepreneurship	0.333	0.223	0.436
Digital Literacy -> Digital Technology Entrepreneurship	0.374	0.267	0.493
Financial Facilitation -> Digital Technology Entrepreneurship	0.292	0.13	0.438
Digital Technology Entrepreneurship -> GNI	0.571	0.26	0.845

Table 7 Testing mediating effects for complete sample

Path	Direct effect	5%	95%	Indirect effect	5%	95%	Mediation effect
Digital Access -> Digital Technology Entrepreneurship -> GNI	−0.046	−0.21	0.13	0.188	0.09	0.31	Full
Digital Literacy -> Digital Technology Entrepreneurship -> GNI	−0.058	−0.23	0.08	0.216	0.09	0.37	Full
Financial Facilitation -> Digital Technology Entrepreneurship -> GNI	0.461	0.25	0.72	0.166	0.07	0.31	Partial

on GNI is insignificant; however, the indirect effect ($\beta = 0.188$, [0.09, 0.31]) is significant. This establishes the fact that DTE fully mediates the relationship, supporting hypothesis H_4. The direct effect ($\beta = -0.058$, [−0.23, 0.08]) of digital literacy on GNI is also insignificant while the indirect effect ($\beta = 0.216$, [0.09, 0.37]) is significant. Thus, digital technology entrepreneurship fully mediates the relationship between digital literacy and GNI, supporting hypothesis H_5. Lastly, as the direct effect ($\beta = -0.0461$, [0.25, 0.72]) of financial facilitation on GNI is significant and the indirect effect ($\beta = -0.166$, [0.07, 0.31]) is also significant, digital technology entrepreneurship plays a partial mediator role in the relationship of financial facilitation and GNI. Hence, we support hypothesis H_6.

Moderating Effects

We then examined the variations in estimating the impact of digital access, digital literacy, and financial facilitation on digital technology entrepreneurship for various country types. Table 8 displays the moderation effects of country type on the regression coefficients of all three relationships. The effect of digital access on digital technology entrepreneurship for lower middle income ($\beta = 0.46$, [0.206, 0.605]) is

Table 8 Testing moderating effects of country type on all the relationships

Path	Country type	Coefficient	5%	95%	HIG-LMI	UMI-LMI
Digital Access -> Digital Technology Entrepreneurship	HI	0.203	0.017	0.372	−0.257[b]	−0.177
	UMI	0.283	0.05	0.548		
	LMI	0.46	0.206	0.605		
Digital Literacy -> Digital Technology Entrepreneurship	HI	0.518	0.305	0.727	−0.094	−0.319[b]
	UMI	0.293	−0.004	0.549		
	LMI	0.612	0.432	0.789		
Financial Facilitation -> Digital Technology Entrepreneurship	HI	0.212	−0.051	0.456	0.185	0.319[b]
	UMI	0.346	0.092	0.541		
	LMI	0.027	−0.183	0.25		
Digital Technology Entrepreneurship -> GNI	HI	0.493	0.104	0.814	0.004	0.053
	UMI	0.542	0.145	0.98		
	LMI	0.489	0.118	0.996		

Note [a]Significant at 10% level; [b]Significant at 5% level

greater than that of upper middle income ($\beta = 0.283$, [0.05, 0.548]) and high income ($\beta = 0.203$, [0.017, 0.372]) groups. As the difference (−0.257) between high income and lower middle income is significant ($p < 0.05$), the stronger impact of the lower-middle-income group gets established and thus H_8 is supported. A similar scenario is observed in the path coefficient of digital literacy and DTE. The effects ($\beta = 0.612$, [0.432, 0.789]) of the lower middle-income group are significantly higher (−0.319, $p < 0.05$) than that of upper middle-income countries, supporting hypothesis H_9. Further, the result reveals that the impact of financial facilitation on digital technology entrepreneurship is not the same across country groups, as the impact of upper middle income is significantly higher (0.319, $p < 0.05$) than in lower middle-income countries. We, therefore, support H_{10}. These moderation effects have further been demonstrated in Figs. 6, 7, and 8. As the moderation effects on the regression path of digital technology entrepreneurship and GNI are not significantly different, we do not support hypothesis H_{11}.

Moderated Mediation Effects

Finally, we examine the moderation effects of country type on the mediation role of digital technology entrepreneurship between the three predictors and GNI, the dependent variable. Table 9 exhibits that digital technology entrepreneurship acts as a full mediator in examining the contributions of digital access and digital literacy on GNI per capita for all three country groups. As the role of a mediator is the same across various country types, we do not support hypotheses H_{12} and H_{13}. However, we observe a different scenario while examining the impact of financial facilitation

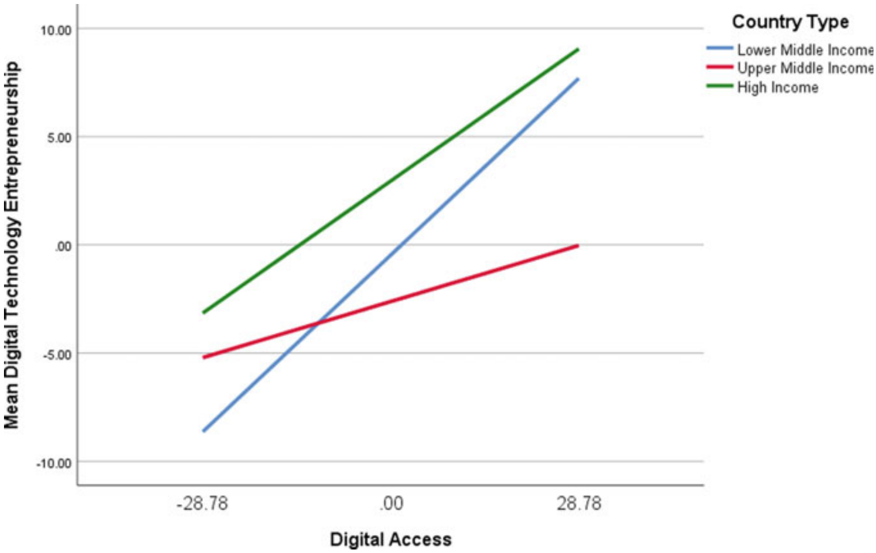


Fig. 6 Moderating effects of country type: digital access on DTE

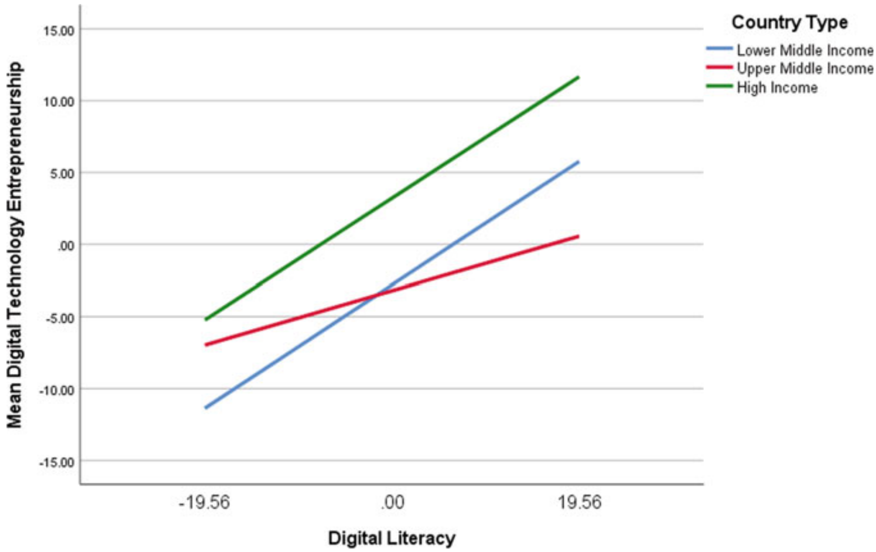


Fig. 7 Moderating effects of country type: digital literacy on DTE

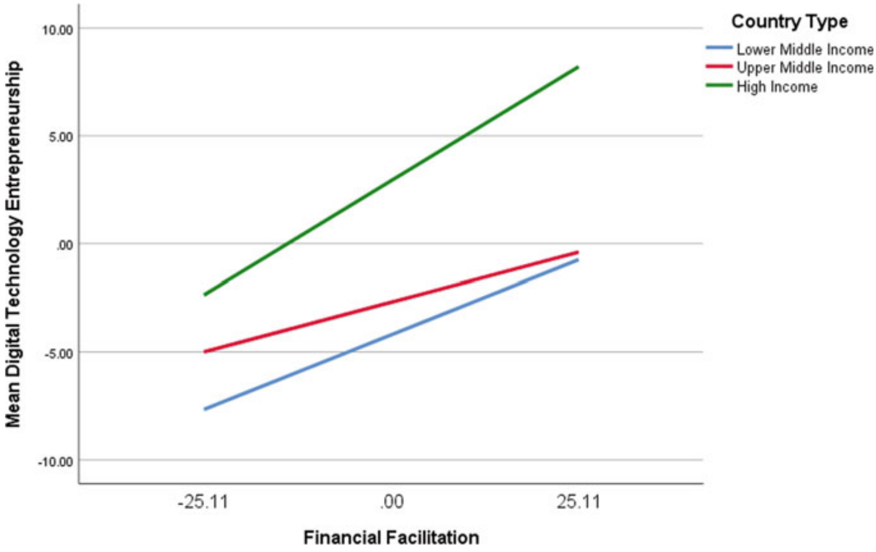


Fig. 8 Moderating effects of country type: financial facilitation on DTE

on GNI through DTE. Digital technology entrepreneurship acts as a full mediator in the case of upper middle-income countries, while it has got no mediation role to play in the case of lower middle-income and high-income countries. Hence, the hypothesis, H_{14}, does not get supported.

6 Discussion of Findings

6.1 Descriptive Analysis

The descriptive analysis in Table 2 shows that the average GNI per capita which is taken as a measure of the economic health of a nation is \$18,313 (Mean = 18,313, SD = 20,803). The average digital technology initiative is recorded as 34.5 with a standard deviation score of 23.02. As the skewness (digital access = 0.52, digital literacy = 1.09, financial facilitation = 0.73, digital technology entrepreneurship = 0.9 and GNI per capita = 1.36) and kurtosis (digital access = −0.88, digital literacy = 0.95, financial facilitation = −0.63, digital technology entrepreneurship = 0.03 and GNI per capita = 0.9) coefficients for all the variables are close to +1 and −1, normal distributions are implied for all the five variables. A relatively high standard deviation is observed across all the variables, which is suggestive of high volatility in the distribution. An exploratory data analysis in Fig. 3 reveals that the average level of digital entrepreneurship is much higher among high-income countries compared to the rest of the world and the variations of such initiatives are also very high. The

Table 9 Testing moderating effects of country type on mediation role of DTE

Path	Country type	Direct effect	5%	95%	Sig?	Indirect effect	5%	95%	Sig?	Mediation effect
Digital Access -> Digital Technology Entrepreneurship -> GNI	HI	−0.15	−0.48	0.14	No	0.093	0.02	0.24	Yes	Full
	UMI	0.09	−0.30	0.51	No	0.154	0.03	0.50	Yes	Full
	LMI	0.31	−0.13	0.64	No	0.23	0.05	0.52	Yes	Full
Digital Literacy -> Digital Technology Entrepreneurship -> GNI	HI	−0.05	−0.35	0.25	No	0.263	0.05	0.52	Yes	Full
	UMI	0.01	−0.22	0.27	No	0.161	0.01	0.44	Yes	Full
	LMI	−0.09	−0.55	0.26	No	0.316	0.08	0.78	Yes	Full
Financial Facilitation -> Digital Technology Entrepreneurship -> GNI	HI	0.55	0.26	0.90	Yes	0.101	-0.01	0.31	No	No
	UMI	0.05	−0.29	0.47	No	0.185	0.04	0.44	Yes	Full
	LMI	0.12	−0.23	0.43	No	0.006	-0.1	0.11	No	No

curiosity to observe the variation in the economic growth of such countries led us to pull yet another box plot which is shown in Fig. 4. As expected, the average GNI per capita turns out to be highest among the high-income group, along with high variations. Thus, Figs. 2 and 3 reinforce the inclusion of country type as a moderator in the study.

The scatter in Fig. 5 reveals two key aspects of the relationship between GNI per capita and digital technology entrepreneurship. Firstly, the average GNI per capita of lower middle-income and upper middle-income countries is lesser than the global average of GNI (<18,313), implying that their general economic health must be improved a lot to match with the rest of the world. The average entrepreneurial initiative for these two groups is also lower than the global average ($< = 34.5$), barring a few. Secondly, the strength of correlation between digital entrepreneurship and GNI per capita is much stronger for the lower middle-income and upper middle-income countries compared to those of the high-income group. The correlation results, thus, justify the selection of digital technology entrepreneurship as a mediator and 'country type' as a moderator.

6.2 Mediation Analysis

The results discussed in Sect. 5.2.1.1 reveal that digital access, digital literacy, and financial facilitation are the true predictors of digital technology entrepreneurship, which in turn contribute to the GNI of a nation. As the direct path between all the three predictors, including digital access, digital literacy, and financial facilitation, and the dependent variable, namely, digital technology entrepreneurship exhibit positive and significant effects, it indicates that accessibility, technological knowledge, and financial facility help to initiate the digital entrepreneurial activities. This is in line with the UTAUT model by Venkatesh et al. (2003). While analyzing the role of mediators using an indirect path, we have found that digital technology entrepreneurship acts as a full mediator in estimating the effects of digital access and digital literacy on GNI (Table 7); however, it acts as a partial mediator between financial facilitation and GNI per capita. Knowledge in technology, along with high digital access, can contribute to the growth of a nation, only if entrepreneurial activities are adopted. However, good financial facilities can directly contribute to the growth of a nation, and this impact may further be amplified through entrepreneurial activities.

6.3 Moderation Analysis

A comparison of group means with respect to digital entrepreneurial activities and GNI per capita across the globe reveals that the effect of entrepreneurial activities is positive and significant across all the country types, however, they are not distinctly different from one another. It indicates that if entrepreneurial activities are taken, that would enhance the growth of a nation. However, while examining the impact of digital access, literacy, and financial facilitation on entrepreneurial activities, we observe that the impact depends on the type of nation. For example, if digital accessibility is provided to a lower middle-income country, it results in higher entrepreneurial activities compared to the high-income group. This is evident in Fig. 6 which depicts that the positive slope of the lower middle-income group is the steepest among all groups. A similar pattern is observed in case of digital literacy (Fig. 7, Table 8). This is probably because the lower-income countries are yet to get exposed to enough digital access and they are yet to receive sufficient knowledge in digital literacy. Therefore, a little push in these two areas probably results in more entrepreneurial activities. Upper middle-income groups have the knowledge to initiate the entrepreneurial initiatives, however, they do not have sufficient funds. It results in the fact that if they are financially facilitated, then more entrepreneurial initiatives may be churned out. As lower-income groups need to create the knowledge base first and the high-income group probably has reached the saturation level with respect to the supply of finance, upper middle-income countries exhibit the highest impact (Table 8) of financial facilitation on DTE.

6.4 Moderated Mediation Effects

Finally, Table 9 depicts the fact that only accessibility to digital access and technological knowledge does not result in the economic growth of a nation unless proper entrepreneurial initiatives are adopted. This does not depend on the economic condition of a nation. This is true for any country type. However, the contribution of financial facilities towards economic growth through entrepreneurial activities of a nation is truly moderated by economic conditions. High-income and low-income countries may not need entrepreneurial activities to turn the financial facilities into economic growth. Financial facilitations are well developed in high-income countries. So, entrepreneurial interventions are not required. In the case of low-income countries, financial facilities are weak. In the case of middle-income countries, financial facilities can help in entrepreneurial growth which can result in economic growth.

7 Conclusions, Implications, and Scope for Future Research

Based on our analysis, we conclude that digital access, digital literacy, and financial facilitation are the predictors of digital entrepreneurial activities. This is in line with the technology adoption theories like TAM and UTAUT. The study also establishes that digital entrepreneurship has a positive impact on GNI per capita. Based on this evidence, we conclude that the economic growth is fuelled by ~~the~~ entrepreneurial initiatives. This finding is in line with the findings from existing literature about the positive impact of digital transformation and digital entrepreneurship on the economic health of a country. The study establishes that although digital access, digital literacy, and financial facilitation impact the GNI per capita of a country through digital entrepreneurship activities, these effects depend on the country type.

The conclusion with regard to the research hypothesis is presented in Table 10.

The proposed model in the study has practical implications. Developing countries need to embrace technology and support technology entrepreneurship for the better

Table 10 Summary of hypotheses

No	Hypothesis	Status
H_1	High digital access contributes positively to digital technology entrepreneurship	Supported
H_2	Digital literacy has a positive relationship with digital technology entrepreneurship	Supported
H_3	Financial facilitation encourages digital technology entrepreneurship initiatives	Supported
H_4	High digital access contributes positively to the GNI per capita of a nation mediating through digital technology entrepreneurship	Supported
H_5	Digital literacy enhances GNI per capita mediating through digital technology entrepreneurship	Supported
H_6	Financial facilitation contributes positively to GNI per capita through digital technology entrepreneurship initiatives	Supported
H_7	Digital technology entrepreneurship has a positive impact on the GNI of a nation	Supported
H_8	The effect of digital access on digital technology entrepreneurship is stronger for lower-middle-income group countries compared to those of upper-middle-income and high-income group countries	Supported
H_9	The effect of digital literacy on digital technology entrepreneurship is stronger for lower middle-income group countries compared to those of upper middle-income and high-income group countries	Supported
H_{10}	The impact of financial facilitation on digital technology entrepreneurship is different across the country groups	Supported
H_{11}	The impact of digital technology entrepreneurship on GNI is least for the high-income group among all categories of countries	Not Supported
H_{12}	The mediation effect of digital technology entrepreneurship in the relationship between digital access and GNI is moderated by country type	Not Supported
H_{13}	The mediation effect of digital technology entrepreneurship in the relationship between digital literacy and GNI is moderated by country type	Not Supported
H_{14}	The mediation effect of digital technology entrepreneurship in the relationship between financial facilitation and GNI is moderated by country type	Supported

economic health of the country. Facilitating conditions need to be provided for digital adoption.

The study is based on 2020 data. This is the limitation of the paper. This also gives the opportunity to further extend the paper. It can be extended to study the impact of the pandemic on digital transformation. Future research can also compare pre-pandemic and post-pandemic periods.

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Bi-directional Causality Between Volatility in Output Growth and Price Growth: Evidence from Rice Production in India Using ARCH/GARCH and Panel VECM Approach

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1 Introduction

Agriculture is an essential sector in India. In rural India, nearly 70% of the population depends on income from agriculture (Government of India, Planning Commission, "Risk Management in Agriculture" for 11th Five Year Plan (2007–2012)). Seventy-five percent of the rural poor are engaged in agriculture in diverse ways (Government of India, Planning Commission, "Risk Management in Agriculture" for 11th Five Year Plan (2007–2012)). Twenty-eight percent of all rural households are self-employed in agriculture while 47% of all rural poor are primarily dependent on agriculture as labour (Government of India, Planning Commission, "Risk Management in Agriculture" for 11th Five Year Plan (2007–2012)).

There is variability in crop production, which is mainly due to the volatility and uncertainty involved in the production process. The volatility in case of the agricultural sector can either come from agricultural output or price or both. Such type of volatility can be associated with a multiplicity of factors, starting from variability in climate, numerous natural disasters, indecisions in yields, feeble rural infrastructure, imperfect markets and deficiency of financial services, including partial span and plan of risk control mechanisms such as credit and insurance. There is a positive association between output volatility and negative outcomes that comes from imperfectly predictable biological, climatic (rainfall) and price variables, which undermine

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the viability of the agriculture sector. This kind of variability is a potential threat of poverty to the farmers and the labour force engaged in the agricultural sector and has negative effects on the farmers' livelihood and incomes. Apart from these, some other variables like natural adversities (for example, pests and diseases) and climatic factors namely flood, drought, etc., not within the control of the farmers, lead to adverse changes in both input and output prices.

Volatility indicates variability, which can help to estimate the fluctuations empirically (see Sect. 2.1 for details). Agricultural sector is affected by two sources of volatility; Production volatility and Price or Market volatility.

Production volatility is the high variability in production outcomes and is one of the basic characteristics of Indian agriculture. This exists as the farmers cannot forecast correctly the amount of output from the production process and the production losses (if any) are due to adverse effects like volatility in the rainfall, input uses, etc., which the farmers are to face at the harvesting time. Price or market volatility is the output price variability in the agricultural market. Agricultural commodity price is extremely unstable due to both internal and external market shocks. The segmented agricultural markets affect mainly the local supply and demand conditions, whereas the globally integrated market is affected by the international production dynamics. For local markets, "natural hedge" effect may alleviate price volatility signifying that an increase (or decrease) in annual production is likely to fall (or rise) output price. In case of integrated markets, a price decline is usually not linked with local supply conditions and so price shocks may affect producers in a noteworthy manner (Government of India, Planning Commission, 11th Five-year plan). Consequently, finding out the relation between production volatility (i.e. volatility in the growth of output) and price volatility (i.e. volatility in the growth of price) in Indian agriculture becomes imperative. In other words, it is needful to have knowledge about the extent of causality between these two series.

In the agricultural sector, the decision of a farmer at a single point of time is based on the expectation of an uncertain future. As uncertainty is subjective, the probability distribution cannot be determined empirically (Heady, 1961). Sankar (1997) points out to some theoretical problems related to risk and uncertainty in Indian agricultural sector. For empirical purposes, absolute risk or volatility and relative risk or volatility are measured by standard deviation of profit and the coefficient of variation (CV), respectively (Dandekar, 1976; Heady, 1952). Bliss and Stern (1982), by assuming a linear production function and using the expected utility maximization framework, analysed the risk in wheat cultivation in Palanpur district, India. They established the risk premium to be 3.5 for land, 3.8 for fertilizer at the time of sowing and 3.2 for ploughing. Rangaswamy (1982), employing experimental data during 1971–72 to 1973–74 estimates fertilizer response functions, calculates the nitrogen return at different levels per ha for each year and measures risk by the standard deviation of net returns. Singh and Nautiyal (1986) estimated the probability distribution of the profitability of fertilizer application in high-yielding variety seeds (HYVs) of wheat and paddy crops considering four different agro-climatic regions of Uttar Pradesh. The risk of achieving a minimum desiring return/losing money is determined from the profitability distribution. Sankar and Mythili (1987) recognized the causes of annual variations in the proportion of net sown area to cultivated area and cropping intensity.

Although the above studies are grounded on alternative model specifications and various estimation methods, there is a dearth in the volatility measurement using modern time series technique. The above earlier studies have considered the concept but have not estimated volatility. In time series econometrics, there may exist correlation between the variance of the random term in any particular year with that of the previous year. Thus, points towards a heteroskedastic stochastic process, which is called volatility clustering. The literature lacks in estimation procedure of volatility as well as the use of modern time series techniques for estimating the long-run and short-run causalities among the price volatility and output volatility.

The present paper contributes to the existing literature in this direction and attempts to measure the volatility of output growth (GVRP) and price growth (GVPR) in case of rice for four major rice-producing states in India like Andhra Pradesh (AP), Punjab (PU), Uttar Pradesh (UP) and West Bengal (WB) for the period 1963–64 to 2018–19 by using ARCH/GARCH method. After estimating volatility, this paper tries to find out the two-way, long-run and short-run causalities between the volatility of output growth and price growth by using the Panel Vector Error Correction Model (VECM). Now, before estimating long-run and short-run association between the GVRP and GVPR, this paper also tested the unit root and co-integrating relationship between the above two series by using Panel unit root and Panel co-integration approach. Rice crop is chosen because India is the major producer and exporter of rice in the world.[1] Those states whose share is more than 10% in all India production are taken. Apart from this, the total share of rice production in all India of these four states is almost 60%.

The present paper is organized as follows: Sect. 2 presents the methodology and data sources. Section 3 discusses the results of estimation. Some concluding remarks are made in Sect. 4.

2 Methodology and Data Source

For estimating the causalities between long-run and short-run GVPR and GVRP, this paper follows five steps procedure constituting: (I) estimation of volatility in the growth of output and price is obtained by using ARCH/GARCH method of volatility approach as explained in Sects. 2.1 and 2.2, respectively; (II) after estimating the volatility by ARCH/GARCH method for each state, this paper constructs panel for GVPR and GVRP, then this paper uses panel unit root test for checking stationarity of these two series. The methodology of this is explained in Sect. 2.3; (III) Sect. 2.4 describes the methodology of testing the co-integrating relationship by using panel co-integration approach if the variables are not stationary at level. This paper tests panel co-integrating relation in both ways, i.e. in the first case, one can take GVPR as

[1] (https://www.statista.com/statistics/255947/top-rice-exporting-countries-worldwide-2011/).

the dependent variable and GVRP as the explanatory variable and in the second case, one can take GVRP as the dependent variable and GVPR as the independent variable; (IV) in case of co-integration holds, estimating panel co-integration model using FMOLS method, to evolve the long-run equilibrium relationship between GVRP and GVPR, which is described in Sect. 2.5 and (V) finally, Sects. 2.6 and 2.7 explain the methodology of panel VECM and Wald test for estimating the bi-directional long-run and joint effect in the short-run relationship between these two series.

The growth rate is calculated by using the formula:

$$1 - \frac{y_{t-1}}{y_t}$$

2.1 *The Estimation of Volatility: The Autoregressive Conditional Heteroskedasticity Model (ARCH)*

One of the basic hypotheses of the classical regression model is *homoscedasticity*, i.e. the hypothesis of constant error variance: $\text{var}(e_t) = \sigma^2(e_t)$, where $e_t \sim N\ (0, \sigma^2)$. In modern time series literature, it is assumed that the error variance may not be constant over time. Thus, a better specification would be to choose a model without constant variance. As per the literature of time series econometrics, the variance of the random term of any particular year is expected to be correlated with the variance of the random term of the previous year, so one can get heteroskedastic variance in case of the stochastic process. This nature of the time series data is called *volatility clustering* or *volatility pooling*. This characteristic indicates that there is a positive association between the present level of volatility with its immediate previous periods. Using the ARCH model of Engle (1982), one can estimate this phenomenon. For explaining the model definition of the conditional variance (CVar) of a random variable, e_t is required. According to Engle (1982), the CVar of $e_t(\sigma^2)$ is designated as:

$$\sigma^2 = \text{var}(e_t|e_{t-1}, e_{t-2}, \ldots) = E\{[e_t - E(e_t)]^2|e_{t-1}, e_{t-2}, \ldots\} \tag{1}$$

Since $E(e_t) = 0$, Eq. (1) becomes:

$$\sigma^2 = \text{var}(e_t|e_{t-1}, e_{t-2}, \ldots) = E\left[e_t^2|e_{t-1}, e_{t-2}, \ldots\right] \tag{2}$$

Equation (2) indicates that the CVar of a random variable e_t is equivalent to the conditional expected value of the square of e_t. Thus, the autocorrelation in volatility in case of the ARCH model is demonstrated as:

$$\sigma^2 = \delta_0 + \delta_1 e_{t-1}^2 \tag{3}$$

This kind of model is famous as ARCH(1), where the CVar of the error term σ^2 depends on the immediately preceding value of the squared error.

Now, one can consider the following relationship of ARCH(1) model, where y_t is the dependent variable and x_t is the independent variable:

$$y_t = a_1 + a_2x_{2t} + a_3x_{3t} + e_t \tag{4}$$

$$\sigma^2 = \delta_0 + \delta_1 e^2_{t-1} \tag{5}$$

where $e_t \sim N(0, \sigma^2)$.

So, the more general case of ARCH(q), where the variance of the error term depends on q lags of squared errors.

$$y_t = a_1 + a_2x_{2t} + a_3x_{3t} + e_t \tag{6}$$

$$\sigma^2 = \delta_0 + \delta_1 e^2_{t-1} + \delta_2 e^2_{t-2} + \cdots + \delta_q e^2_{t-q} \tag{7}$$

where $e_t \sim N(0, \sigma^2)$.

Since σ^2 represents the CVar, its value must be strictly positive. So, all the coefficients in the CVar equation should be positive: $\sigma_i \geq 0$, for all $i = 0, 1, 2, \ldots, q$.

2.2 The Estimation of Volatility: The Generalized Autoregressive Conditional Heteroskedastic Model (GARCH)

The limitation of the ARCH approach towards the measurement of risk is that it does not consider the total volatility. The ARCH model denotes only a part of the total variance because the other part, which describes how the σ^2 varies over time, is not captured by the ARCH model.

Bollerslev (1986) and Taylor (1987) independently developed the GARCH model, which indicates that the CVar of any variable may depend upon its own previous lags and the lag of the random term. The CVar of GARCH (1,1) model is specified as:

$$\sigma^2 = \delta_0 + \delta_1 e^2_{t-1} + \mu_1 \sigma^2_{t-1} \tag{8}$$

The CVar may be represented as a sum of a long-term average value (dependent on δ_0), the volatility-related information during the previous period ($\delta_1 \cdot {e^2}_{t-1}$) and the variance of the previous period ($\mu_1 \cdot {\sigma^2}_{t-1}$).

The common form of the GARCH (q, p) model, where the CVar depends on q lags of the squared error and p lags of the CVar can be specified as:

$$\sigma^2 = \delta_0 + \delta_1 e_{t-1}^2 + \delta_2 e_{t-2}^2 + \cdots + \delta_q e_{t-q}^2 + \mu_1 \sigma_{t-1}^2 + \mu_2 \sigma_{t-2}^2 + \cdots + \mu_p \sigma_{t-p}^2 \tag{9}$$

In empirical analysis, a GARCH (1,1) model is enough in capturing the development of the volatility.

The unconditional error variance in case of GARCH (1,1) model is constant and measured by the following equation:

$$\mathrm{var}(e_t) = \frac{\delta 0}{1 - (\delta_1 + \mu_1)} \tag{10}$$

If $\delta_1 + \mu_1 < 1$ then $\mathrm{var}(e_t) > 0$.

The present paper measures the volatility of both output growth and price growth of series by estimating the GARCH (1,1) model. The estimated value of the CVar is taken as a measure of volatility. Before estimating the model, one needs to test for the presence of ARCH effects. Therefore, the present paper is resorted to the Engle (1982) test for detecting the ARCH effect, which needs estimation of optimum lag. For the optimum lag, this paper uses the figures of the correlogram which shows that the second partial correlation coefficient is significant, in all cases, suggesting an optimum lag of two for each. Thus ARMA(2,2) series is used to run the heteroskedasticity test.

2.3 Panel Unit Root Tests

In case of the panel data unit root test, co-integration test can increase the power of the test rather than testing for single time series (Levin & Lin, 1992, 1993; Maddala & Wu, 1999; Quah, 1994).

For the panel unit root test, Levin, Lin and Chu (LLC), Breitung or Hadri tests deal with common or homogeneous unit root process. On the other hand, Im, Pesaran and Shin (IPS), Fisher-ADF or Fisher-PP tests deal with individual or heterogeneous unit root process. In this chapter, we have used LLC and IPS tests.

LLC considers the following ADF specification:

$$\Delta Y_{i,t} = \alpha_i + \rho Y_{i,t-1} + \sum_{k=1}^{n} \varphi_k \Delta Y_{i,t-k} + \delta_i t + \theta_t + u_{it} \tag{11}$$

δ_i is the unit-specific time trends and α_i is the $(i-1)$ state dummies and θ_t is the $(t - 1)$ time dummies. The coefficient of lagged Y_i is restricted to be homogeneous for all panel units.

Null hypothesis, $H_0 : \rho = 0$ and

Alternative hypothesis, $H_1 : \rho < 0$.

Now, suppose that $Y_{i,t-1}$ is heterogeneous, then one can use IPS (1997, 2003) test based on the average of the individual unit root test statistics as below:

$$\Delta Y_{i,t} = \alpha_i + \rho_i Y_{i,t-1} + \sum_{k=1}^{n} \varphi_k \Delta Y_{i,t-k} + \delta_i t + \theta_t + u_{it} \tag{12}$$

The null hypothesis, $H_0 : \rho_i = 0$ for all, i is tested against the alternative, $H_1 : \rho_i < 0$ for at least one i. The corresponding $\bar{t}$ statistic is defined as $\bar{t} = \frac{1}{N}\sum_{i=1}^{N} t_{\rho i}$, where $t_{\rho i}$ is individual ADF t-statistic for testing $H_0 : \rho_i = 0$ for all i. Schwarz (1978) method is used for selecting the lag differences and Newey-West 1994 and Bartlett Karnel are used for the bandwidth selection.

2.4 *Panel Co-integration Test*

In this chapter, we have used Pedroni (1999, 2004) and Kao (1999) for co-integration test. Pedroni suggests the consequent panel regression model:

$$Y_{it} = \alpha_i + \delta_i t + \sum_{m=1}^{M} \beta_{mi} X_{mi,t} + e_{i,t} \tag{13}$$

Y and X are assumed to be I (1). This is a two-step method. First, residuals are obtained from the.

Equation (13) and then, in the next step, it is tested that whether residuals are I (1) or not by considering the following auxiliary regression for each cross-section.

$$e_{it} = \rho_i e_{it-1} + u_{it} \tag{14}$$

Or

$$e_{it} = \rho_i e_{it-1} + \sum_{j=1}^{p_i} \psi_{ij} \Delta e_{it-j} + v_{it} \tag{14'}$$

One can have categorized Pedronico-integration statistics into two parts; the first set of statistics are Panel v-Statistic, Panel rho-Statistic, Panel PP-Statistic, Panel ADF-Statistic, which are uniting along the "within" dimension whereas the other set of statistics are Group rho-Statistic, Group PP-Statistic, Group ADF-Statistic reflecting the "between" dimension cases. The co-integration test based on Kao-residual reflects the analogous approach as the Pedroni tests, but it considers cross-section-specific intercepts and homogeneous coefficients on the panel regressors. Ghosh and Das (2013) also used this kind of methodology in their paper.

2.5 Estimation and Inference of Panel Co-integrating Model

For estimating the co-integration vector using panel data, there are various methods and Full Modified Ordinary Least Square (FMOLS) is one such method. It deals with corrections for serial correlation. Hence, the probable association between the error term and the first differences of the regressors as well as the existence of a constant term is taken into account (Maeso-Fernandez et al., 2006: 507). The FMOLS long-term coefficient estimator is as under:

$$\widehat{\beta_i} = (\sum_{t-1}^{T} x_{it}^{'} x_{it})^{-1} \sum\nolimits_{i=1}^{T} (x_{it}^{'} y_{it}^{*} - T\widehat{\lambda_i}) \tag{15}$$

Here y_{it}^{*} are the regress ands adjusted for covariance between the error term and the first differences of the regressors (Δx_t); and $T\ \widehat{\lambda_i}$= adjustment for a constant term.

The mean group FMOLS long-term coefficient is the average of the group estimate over n, namely $\widehat{\beta}_{\mathrm{MG}}^{\mathrm{FMOLS}} = n^{-1} \sum_{i=1}^{N} \widehat{\beta}_i$ and the corresponding t-statistic converges to a standard normal distribution (Maeso-Fernandez et al., 2004).

The paper uses monthly data on wholesale price and after finding out the monthly volatility, their average is taken to get the yearly volatility.

2.6 Panel Vector Error Correction Model (VECM)

Next, one can apply the GMM (Arellano & Bond, 1991) to estimate the panel vector error correction model. For estimating the Panel error correction model, this paper has considered the following error correction model:

$$\Delta y_{i,t} = \left[\sum_j \propto_l \Delta y_{i,t-j} + \gamma_l \Delta(x)_{i,t-j}^{/} \right] + \gamma \left(y_{i,t-1} - \widehat{\delta_i} - \widehat{\theta_1}(x)_{i,t-1}^{/} \right) + \varepsilon_{i,t} \tag{16}$$

where $y_{i,t}$ and $x_{i,t}$ are the two series. Now, $\left(y_{i,t-1} - \widehat{\delta_i} - \widehat{\theta_1}(x)_{i,t-1}^{/} \right)$ is the residual term in one period lag estimating from the FMOLS method in co-integrating relationship and γ is the speed of long-run association. If γ is negative and statistically significant, then one can conclude that there exists a long-run association between the two series and $\left(y_{i,t-1} - \widehat{\delta_i} - \widehat{\theta_1}(x)_{i,t-1}^{/} \right)$ is the error correction term.

2.7 Wald-Test for Estimating the Short-Run Fluctuations

To check the joint effect of previous year's GVRP on GVPR and vice-versa in the short-run, the Wald test is performed as below:

The required test statistic is $\lambda_w = \frac{(\text{RRSS}-\text{URSS})}{\sigma^2}$, which follows χ^2 distribution with a degree of freedom equal to the number of restrictions in the model under H_0, where, RRSS = Residual sum of squares under the restricted model, i.e. the model under H_0, URSS = Residual sum of squares under the unrestricted model, i.e. the model under H_1

$$\sigma^2 = \frac{\text{URSS}}{N - K}$$

N = Number of observations, K = Number of parameters in the unrestricted model, i.e. the model under H_1. The null hypothesis is H_0:$\gamma_l = 0$ in the Eq. (16).

2.8 Data Sources

The data on rice production has been taken from the different issues of the Statistical abstract, Agriculture at a Glance, Agriculture in Brief, Handbook of Statistics of Indian Economics, Cost of Cultivation data and the data on the price of rice has been collected from different issues of Agricultural prices in India published by the Government of India for the year 1963–64 to 2018–19.

3 Results of Analysis

3.1 Output Volatility

The results of the Engle (1982) test using output series are presented in Table 1. The estimated values of F statistics are significant in all the four states implying that there are ARCH effects in the growth of rice production.

Table 1 Heteroskedasticity test for detection of ARCH effect in case of growth of rice production

States	F statistic	Prob
Andhra Pradesh	52.58498*	0.000
Punjab	2854.025*	0.000
Uttar Pradesh	5.245804**	0.0271
West Bengal	49.72933*	0.000

*Implies significant at 1% level; **Implies significant at 5% level

Table 2 Results of ARCH/GARCH estimation in case of growth of rice production

States	Constant	RESID(−1)^2	GARCH(−1)^2
Andhra Pradesh	0.006457 (0.758444)	0.297878* (3.313715)	0.6102754* (3.645488)
Punjab	0.001316* (2.312656)	0.112081* (2.471399)	0.873917* (14.70634)
Uttar Pradesh	0.002879* (2.594286)	0.703085* (2.995748)	0.115744 (1.031708)
West Bengal	0.000702 (1.865901)	0.976874* (3.158443)	0.075873 (1.158666)

*Significant at 1% level; Z values are given in the parenthesis

Table 3 Heteroskedasticity test after the estimation of ARCH/GARCH in case of growth of rice production

States	F statistic	Prob
Andhra Pradesh	0.667778	0.4186
Punjab	0.189891	0.6653
Uttar Pradesh	0.253484	0.6173
West Bengal	0.540380	0.4665

The results of estimation of the GARCH (1,1) model are presented in Table 2. The coefficient of the squared error is significant at 1% level for all states. The coefficient of the CVar is statistically significant at 1% level in case of Andhra Pradesh and Punjab. This implies that there exists a persistent shock to the CVar. The value of the coefficient of the CVar in case of Andhra Pradesh and Punjab is large. These results imply that a large (small) change in the conditional variance of volatility of Andhra Pradesh and Punjab is due to the large (small) change in its own value of the variance of the previous year and also due to the lag value of the variance of the random term of the previous period (i.e. other variable). From these results, one can determine that the series of growth of rice production is highly volatile in nature for all four states.

Now, before going a step further, we have to verify whether the squared error of the GARCH (1,1) model presents the ARCH effects. For this purpose, the heteroskedasticity test is used again and the results are presented in Table 3. The results indicate that there exists no additional ARCH effect in the squared errors series for all the states and hence the use of GARCH (1,1) is justified.

3.2 *Price Volatility*

Table 4 represents the results of the Engle (1982) test for the detection of ARCH effect in case of growth of price for all the four states. The estimated values of F statistics are highly significant in all cases suggesting the existence of the ARCH effect for all four.

Table 4 Heteroskedasticity test for detection of ARCH effect in case of growth of the price of rice

States	*F* statistic	Prob
Andhra Pradesh	6499.090*	0.000
Punjab	10062.09*	0.000
Uttar Pradesh	5.216694**	0.0228
West Bengal	10812.57*	0.000

*Implies significant at 1% level; **Implies significant at 5% level

Table 5 represents the results of estimation of the GARCH (1,1) model. The coefficient of the squared error is significant at 1% level for all states. In case of Punjab, the coefficient of squared error is high, which implies that the variance of the current year is highly correlated with its lag. The coefficient of the CVar is statistically significant at 1% level for all states, thus implying that the shocks to the CVar are persistent. The value of the coefficient of the CVar in case of Andhra Pradesh, Uttar Pradesh and West Bengal are large, which implies that the large (small) changes in current year's volatility is due to large (small) changes in its own value of the variance of the previous year and also due to the lag value of the variance of the random term of the previous period (i.e. other variables).

Thus, from the results, one can conclude that the growth of the price series of rice production is highly volatile in nature for all four states.

Now, one has to verify whether the squared error of the GARCH (1,1) model presents the ARCH effects or not. This is done by using the heteroskedasticity test and the results are presented in Table 6. According to the results, there are no additional ARCH effects in the squared errors series in case of all the four states, as the *F* statistics are insignificant for each.

Table 5 Results of ARCH/GARCH estimation in case of growth of the price of rice

States	Constant	RESID(−1)^2	GARCH(−1)^2
Andhra Pradesh	0.001940 (1.799178)	0.000736* (5.198889)	0.963600* (43.40847)
Punjab	0.003991* (34.82813)	0.874662* (20.73044)	0.007985* (16.04039)
Uttar Pradesh	0.144637* (55.01335)	0.222283* (4.474522)	0.600210* (4.197395)
West Bengal	0.001152* (6.748331)	0.248640* (6.979118)	0.559626* (9.984588)

*Significant at 1% level**;** *Z* values are given in the parenthesis

Table 6 Heteroskedasticity test after the estimation of ARCH/GARCH in case of growth of price of rice

States	*F* statistic	Prob
Andhra Pradesh	0.860383	0.3540
Punjab	0.050835	0.8217
Uttar Pradesh	0.001451	0.9696
West Bengal	1.502438	0.2208

Table 7 Panel unit root test results

Variable	Method		
		Levin, Lin and Chu t	Im, Pesaran and Shin W-stat
		Exogenous variables: individual effects	
GVPR	Level	−0.08092 (0.4957)	0.6241 (0.731)
	1st difference	−16.5162* (0.000)	−14.4984* (0.000)
GVRP	Level	0.27911 (0.6996)	2.9525 (0.9854)
	1st difference	−19.0571* (0.000)	−41.24758* (0.000)

*Implies significant at 1% level. *P*-values are given in the parenthesis
Null hypothesis is no unit root (stationary)
GVPR: volatility of growth of price of rice. GVRP: volatility of growth of rice production

3.3 Panel Unit Root Tests Results

LLC and IPS tests are conducted separately and the results are presented in Table 7, considering the models with individual effects. Probabilities for both LLC and IPS tests assume asymptotic normality. The null hypothesis of unit root is not rejected in case of both GVRP and GVPR at their level-value but is rejected for these variables at their first differences for both of the tests. Thus, it is concluded that both GVRP and GVPR are I (1) series, i.e. stationary at their first difference.

3.4 Panel Co-integration Tests Results

The results of panel co-integration are presented in Tables 8 and 9.

In order to find out the bi-directional co-integrating relationship in the first step, one can run the panel co-integration test by taking GVPR as the dependent variable and GVRP as the explanatory variable. Equation (17) represents the panel co-integrating relationship as follows:

Table 8 Panel co-integration test results of the model. Dependent: volatility of growth of price of rice (GVPR); explanatory: volatility of growth of rice production (GVRP)

	Trend assumption: no deterministic trend		Trend assumption: deterministic intercept and trend		Trend assumption: no deterministic intercept or trend	
1. Pedroni residual co-integration test						
	Statistic	*P*-value	Statistic	*P*-value	Statistic	*P*-value
Panel v-statistic	−1.34007	0.9099	−2.62286	0.9956	−0.99301	0.8396
Panel rho-statistic	−11.757*	0	−9.21495*	0	−11.1784*	0
Panel PP-statistic	−9.92125*	0	−10.5864*	0	−5.69992*	0
Panel ADF-statistic	−6.16678*	0	−6.13043*	0	−2.96573*	0.0015
Group rho-statistic	−6.14011*	0	−4.56953*	0	−4.08469*	0
Group PP-statistic	−6.48561*	0	−6.43372*	0	−3.73237*	0.0001
Group ADF-statistic	−4.97192*	0	−5.0197*	0	−2.194**	0.0141
2. Kao residual co-integration test						
	Statistic				*P*-value	
ADF-*t* statistic	−3.81884*				0.0003	

*Implies significant at 1% level; **Implies significant at 5% level; ***Implies significant at 10% level. Null hypothesis: no co-integration

Table 9 Panel co-integration test results of the model. Dependent: volatility of growth of rice production (GVRP); explanatory: volatility of growth of price of rice (GVPR)

	Trend assumption: no deterministic trend		Trend assumption: deterministic intercept and trend		Trend assumption: no deterministic intercept or trend	
1. Pedroni residual co-integration test						
	Statistic	*P*-value	Statistic	*P*-value	Statistic	*P*-value
Panel v-statistic	−1.03022	0.8485	−2.31333	0.5896	−4.5436*	0
Panel rho-statistic	−4.50195*	0	−4.43536*	0	−6.25081*	0
Panel PP-statistic	−3.85631*	0.0001	−4.43167*	0	−3.98785*	0
Panel ADF-statistic	−5.40691*	0	−4.72139*	0	−5.09779*	0
Group rho-statistic	−4.22975*	0	−3.2163*	0.0006	−5.04539*	0
Group PP-statistic	−4.27268*	0	−4.23334*	0	−4.81424*	0
Group ADF-statistic	−12.8304*	0	−7.51223*	0	−11.0457*	0
2. Kao residual co-integration test						
	Statistic				*P*-value	
ADF-*t* statistic	−8.9326*				0	

*Implies significant at 1% level; **Implies significant at 5% level; ***Implies significant at 10% level. Null hypothesis: no co-integration

$$\mathrm{GVPR}_{it} = \alpha + \delta_t + \beta_i \mathrm{GVRP}_{it} + e_{it} \tag{17}$$

Table 8 presents only the results of various panel co-integration tests applied to Eq. (17). The test statistic values are reported along with their probabilities within the brackets and lead to the following results:

Now, in the second step, to find out the bi-directional relationship, one can run against the panel co-integration by taking GVRP as the dependent variable and GVPR as the exogenous variable to test the co-integrating relationship between GVRP and GVPR. This panel co-integrating relationship is represented by Eq. (18).

$$\mathrm{GVRP}_{it} = \alpha + \delta_t + \beta_i \mathrm{GVPR}_{it} + e_{it} \tag{18}$$

Table 9 presents the result of various panel co-integration tests applied to Eq. (18).

Now, by analysing the results of Tables 8 and 9, the results of Pedroni Residual Co-Integration test can be summarized as follows:

(a) In case of no deterministic trend, Panel rho statistic, Panel PP statistic, Panel ADF statistic, Group rho statistic, Group PP statistic and Group ADF statistic indicate that there exists a co-integrating relationship in both cases. That means, there exists a two-way co-integration between GVPR and GVRP.
(b) In case of deterministic intercept and trend, Panel rho statistic, Panel PP statistic, Panel ADF statistic, Group rho statistic, Group PP statistic and Group ADF statistic indicate a two-way co-integration between GVPR and GVRP as in the case of no deterministic trend.
(c) In case of no deterministic intercept and trend, all variables are co-integrated in both cases as per Panel rho statistic, Panel PP statistic, Panel ADF statistic, Group rho statistic, Group PP statistic and Group ADF statistic.

Among the seven alternative statistics used for Pedroni test, a 5% level of significance is obtained only for Group ADF test for the model with no deterministic intercept and trend in case of GVPR as the dependent variable and GVRP as the explanatory variable. The rest of the statistics are significant at a 1% level of significance. These results imply that there exists a bi-directional relationship between GVPR and GVRP.

By analysing the results of Kao Residual Co-integration test from Tables 8 and 9, it can be concluded that, as per Kao ADF t statistic, there is a two-way co-integration between both the series at a 1% level.

3.5 Estimation and Inference of Panel Co-integrating Model

Tables 10 and 11 report the FMOLS estimation of β's, i.e. the long-run marginal effect of GVPR and GVRP using panel co-integrating Eqs. 17 and 18. The following results are obtained:

Table 10 Estimation and inference using FMOLS method model: GVPR = *f* (GVRP)

Dependent variable: GVPR				
Method: fully modified least squares (FMOLS)				
Variable	Coefficient	Std. error	*t*-statistic	Prob
GVRP	0.00093*	0.000091	10.1901	0
C	0.012162*	0.002625	4.633371	0

*Implies significant at 1% level, **Implies significant at 5% level

Table 11 Estimation and inference using FMOLS method. Model: GVRP = *f* (GVPR)

Dependent variable: GVRP				
Method: fully modified least squares (FMOLS)				
Variable	Coefficient	Std. error	*t*-statistic	Prob
GVPR	0.1297*	0.0197	6.5704	0.0000
C	0.0754**	0.0351	2.1491	0.0330

*Implies significant at 1% level, **Implies significant at 5% level

From the results of Table 10, it can be concluded that the panel co-integrating Eq. 17 suggests that GVPR is significantly and positively influenced by GVRP in long run. From Table 10, one can conclude that a 1% increase in GVRP may increase the GVPR by 0.093%.

The results of the estimation of the Eq. 18 by FMLOS method are presented in Table 11. From the results of Table 11, it can be concluded that 1% increase in the GVPR may positively and significantly increase the GVRP by 12.97%.

Thus, in the long run, the marginal effect of GVPR on the GVRP is higher than the long-run marginal effect of GVRP on the GVPR.

3.6 *Estimation and Inference of Panel VECM Model*

The results of the Panel VECM model are presented in Tables 12, 13, 14, and 15.

From Table 12, one can conclude that GVPR is significantly influenced by GVRP, both in the long run and in the short run, with an error correction speed equal to 60.69%. Furthermore, from Table 13, it can be concluded that the joint effect of previous years' GVRP on the GVPR is positive and statistically significant.

On the other hand, from Table 14, it can be established that GVRP is significantly influenced by GVPR, both in the long run and in the short run, with an error correction speed equal to 68.29%, and from Table 15, one can conclude that the joint effect of previous years' GVPR on the GVRP is positively significant.

Table 12 Panel VECM estimation results. Volatility of growth of rice production (GVRP) to volatility of growth of the price of rice (GVPR)

Variable	Coefficient	t-statistic
C	0.00017	0.043496
DGVPR(−1)	−0.27148	−0.5585
DGVPR(−2)	−0.13416	−0.58208
DGVRP(−1)	0.002163**	1.990158
DGVRP(−2)	0.006373*	2.666962
Error correction term	−0.60694*	−6.70459

*Implies significant at 1% level; **Implies significant at 5% level

Table 13 Results of the Wald test

Test statistic	Value	df	Probability
F-statistic	3.812389**	(2, 162)	0.0241
Chi-square	7.624777**	2	0.0221
Null hypothesis: $C(4) = C(5) = 0$			

*Implies significant at 1% level; **Implies significant at 5% level

Table 14 Panel VECM estimation results. Volatility of growth of price of rice (GVPR) to volatility of growth of rice production (GVRP)

Variable	Coefficient	t-statistic
C	−0.00226	−0.10644
DGVRP(−1)	−0.32986	−0.86175
DGVRP(−2)	−0.28311	−0.97556
DGVPR(−1)	0.042523**	1.754299
DGVPR(−2)	0.014186	0.60208
Error correction term	−0.68294*	−4.004

*Implies significant at 1% level; **Implies significant at 5% level

Table 15 Results of the Wald test

Test statistic	Value	df	Probability
F-statistic	19.88782*	(2, 162)	0
Chi-square	39.77565*	2	0
Null hypothesis: $C(4) = C(5) = 0$			

*Implies significant at 1% level; **Implies significant at 5% level

4 Conclusion

This paper[2] estimates the extent of growth of price volatility, the growth of output volatility and also analyses the long-run and short-run relationships between these two in case of rice for the four major rice-producing states in India, namely Andhra Pradesh, Punjab, Uttar Pradesh and West Bengal, by using modern time series approach, for the period 1963–64 to 2018–19. While the existing studies relating to Indian agriculture used the conventional method of taking variance or coefficient of variation as the measure of variability, the present study is based on the technique of measurement of volatility by using the ARCH/GARCH method of modern time series analysis. Furthermore, this paper estimates the long-run and short-run relationship between the above-said series by using the Panel VECM model.

The main findings of the paper are that, for Andhra Pradesh and Punjab, volatility of both the GVRP and GVPR, the coefficient of the CVar are significantly large. But, in case of Uttar Pradesh and West Bengal, only for GVPR, the coefficient of the CVar is statistically significant and large. These results imply that large (small) changes in the CVar of volatility of the series are due to the large (small) changes in its own variance of the previous year and also due to the lag value of the variance of the random term of the previous period (i.e. other variables) for both GVRP and GVPR for Andhra Pradesh and Punjab but only in case of GVPR for Uttar Pradesh and West Bengal. From the results of the Panel VECM, it is clear that the GVPR is significantly influenced by the GVRP both in the long run and short run, and vice-versa. Further, it is evident that in the long run the marginal effect of GVPR on GVRP is higher than the marginal effect of GVRP on GVPR, implying that the effect of GVPR on GVRP is stronger.

Thus, one can suggest that in India, in order to control the GVRP, the government should take steps to reduce the GVPR, both in the long run and short run. The government can reduce the GVPR by applying the minimum support price policy more effectively or by monitoring the market price by the task force efficiently, i.e. by reducing the effect of middlemen's intervention in the market.

Another finding of the paper is that, there exists a two-way relationship between the GVPR and the GVRP. So, in order to reduce the GVPR, the government may take some steps to reduce GVRP by increasing the irrigation facilities, use of modern inputs such as tractors, electricity in agriculture, use of HYV seeds, etc.

One of the main limitations of this study is that, in this paper, we are considering only two variables: (i) GVPR and (ii) GVRP. But, GVPR also depends upon some other variables like the availability of institutional loan, rural infrastructure, market intervention by the middlemen, storage facilities of crops, etc. Similarly, GVRP also depends on some other socio-economic variables like volatility in rainfall, use of modern inputs, education level of the farmers, government expenditure on agricultural research and extension, etc. These variables are not taken into consideration in

[2] Abstract of the earlier version of this paper has been published in Abstract of Contributed Papers of 38th Annual Conference of Bangiya Arthaniti Parishad.

the present study. Thus, there is further scope of study of this analysis by considering all of these socio-economic variables.

Appendix 1: Correlogram (Partial Correlation Plot) Results of GVRP and GVPR for All Four States

Andhra Pradesh		Punjab	
GVRP	GVPR	GVRP	GVPR
Partial correlation	Partial correlation	Partial correlation	Partial correlation
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Uttar Pradesh		West Bengal	
GVRP	GVPR	GVRP	GVPR
Partial correlation	Partial correlation	Partial correlation	Partial correlation
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Unlocking the GVC Potentials in India: Role of Trade Facilitation

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1 Introduction

Global value chains (GVCs) popularly refer to international production sharing, a phenomenon where production is broken into activities and tasks carried out in different countries (OECD, 2013a, 2013b, 2021). An open international trade and investment policy is critical for any economy-aspiring global economic integration through GVCs. Over the years, trade openness has proved to be an important determinant of Foreign Direct Investment (FDI) inflow in many developing economies. Countries like South Korea, China, Thailand, Malaysia, Mexico, Chile, and now Vietnam have successfully leveraged their open trade and investment policy to integrate into the global production networks. India, which has potential and has shown promise to emerge as a major manufacturing and export hub, has the scope to improve its response through necessary, timely trade policy reforms and ease of doing business.[1]

India's GVC participation is in a nascent stage and it is imperative for India to enhance its participation in GVCs.[2] Presently, a comparison of India with other countries reveals that GVC participation on its own is inadequate to make India a major location for GVCs, such as China. Compared with Vietnam, it is clear that while an increase in FDI has played a critical role for both India and Vietnam, the orientation of FDI is different among these two economies. In Vietnam, FDI is export-oriented, while in India, it is primarily oriented towards the vast domestic market with a consumer base of about 500 million people.

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[1] Results of the study by Mitra et al. (2020) indicate increasing GVC participation can positively impact the economy and contribute to raising per capita income, labor productivity, investment, and exports.

[2] Refer, for example, Mitra et al. (2020), Niti Aayog (2020), etc.

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Why is joining GVCs so important for India? First, GVCs make companies increasingly reliant on imports of intermediate goods, that is, goods that are sourced for the purpose of serving as inputs for the production of other goods. Second, via this mechanism, GVCs have been depicted as facilitating trade liberalization,[3] reducing industries' demand for the use of trade remedies,[4] and helping countries to achieve deep economic integration.[5]

For increased integration into GVCs, a combination of initiatives linked with domestic and international policies are important. These include improvement in trade facilitation, open FDI regime, developing domestic capacities to build ecosystems in specific sectors, and good governance principles including timely policy response.[6] Interestingly, a focus on GVCs becomes an important frame of reference for all the components of such a policy response. The five important essentials to facilitate GVCs are: trade policy, investment policy, market size, connectivity, and technology.[7]

The recent pandemic has had a major impact on labour-intensive value chains and has an impact on demand and supply factors. Supply chain disruptions during the first leg of pandemic have exposed our GVCs to a new set of challenges. Exposure levels vary considerably, depending on the nature of the sectors that are engaged in a value chain. For example, domestic production of automobiles, electronics, and pharmaceuticals industries was delayed due to supply chain disruptions and shortages of imported raw materials.[8] On the other, sectors such as agriculture, textiles, apparel, and food and beverages are labour intensive that are engaged in value chains are highly exposed to heat stress, pandemic, flood, a.o., thereby generating job loss and social disruptions. In such a challenging scenario, trade facilitation has an important role not only in protecting the GVC from further decline, but also strengthening the trade relations. This article makes an attempt to analyse the role that trade facilitation can play in strengthening India's GVC participation.

What is trade facilitation? Trade facilitation is the simplification, modernization, and harmonization of export and import processes by providing provisions for expediting the movement, release, and clearance of goods, including goods in transit.[9] According to the WTO, "Bureaucratic delays and 'red tape' pose a burden for moving goods across borders for traders. Trade facilitation—the simplification, modernization, and harmonization of export and import processes—has therefore emerged as

[3] Refer, Chase (2005); Manger (2009); Blanchard and Matschke (2015); Gawande, Hoekman, and Cui (2015); Baccini, Pinto, and Weymouth (2017).

[4] Refer, for example, Jensen, Quinn, and Weymouth (2015).

[5] Refer, for example, Antràs and Staiger (2012); Chase (2005); Manger (2009); Johns and Wellhausen (2016); Kim (2015).

[6] There are plenty of literatures on benefits of GVCs. Refer, World Bank (2020a, 2020b) for a comprehensive overview.

[7] Based on author's own literature on GVCs and more particularly Authukorala (2014, 2017).

[8] Production of automobiles, telecom items, electronics, engineering goods, etc., have been delayed due mainly to non-availability of imported chips in India. This has picked up headlines in all major media in India in recent months.

[9] Several literature on definition of the trade facilitation Refer for example, WTO (2015).

an important issue for the world trading system".[10] Trade facilitation is an essential condition for the rise in GVCs. Importance of trade costs for the participation of developing countries in Global and Regional Value Chains is well documented.[11] For example, faster handling of goods and services facilitate trade and promote GVCs. Other enabling factors are digital technology, paperless trade, etc. Trade facilitation is also the key to supply chain resilience. In the soft side of trade facilitation—paperless trade, harmonization of standards, whereas in the hard side—port connectivity, economic corridor, digital networks, etc., are keys to strengthen the supply chain networks and building resilience. Today's shortage of containers and semiconductors worldwide, which has disrupted production, trade, and value chains, both within and across borders, reminds us of the urgent need for improved trade facilitation.[12] Therefore, faster and on-time delivery of goods and services in a cross-border production network is essential for the sustainability of the GVCs.

The rest of the chapter is arranged as follows: Sect. 2 analyses the trends in India's participation in GVCs and major constraints faced by India. Section 3 then discusses the challenges faced by India in trade facilitation while promoting the GVCs. Section 4 then concludes with some recommendations towards improved trade facilitation.

2 India and GVCs: Emerging Trends

The GVC is known as cross-border production chains comprising more than two countries. A GVC product (or services) may have two major components—domestic value added and foreign value added. If the country A produces raw materials, countries B and C make the further value additions, and country D consumes the final product, the entire chain illustrates the quantity of domestic and foreign value added and also the double counting.[13] Nonetheless, the GVC production chains indicate several important policy insights in terms of trade, connectivity (supply chain), foreign investment, technology, jobs, and genders, among others.

Today, over 70 per cent of contemporary international trade involves GVCs.[14] The world seems to have three interconnected production hubs for the extensive trade in parts and components: one centered in the United States, one in Asia (China, Japan, and Korea), and the third one in Europe (especially Germany). While the United States, China, and European Union (EU) are India's major trading partners, India

[10] Refer, https://www.wto.org/english/tratop_e/tradfa_e/tradfa_e.htm.

[11] Refer, OECD (2013b).

[12] Refer, for example, UNCTAD (2021).

[13] For example, a typical 100-unit gross export is embedded with 72 units of domestic value added in exports and 28 units of foreign value added. However, the entire process also has significant amount of double counting if we look at the value-added statistics (UNCTAD, 2013).

[14] Refer, WTO (2019).

has been trying to integrate with the East Asia value chain network through the free trade agreement (FTA) route.

A country's participation in GVCs is a good indicator of the strength of integration.[15] Illustrated in Table 1, a set of countries depend more on backward linkages (e.g. Korea, Thailand) in their GVC participation, whereas forward linkages drive the GVC participation of another group of countries (e.g. China, Singapore, India, etc.). Variations of backward and forward linkages notwithstanding, the share of GVC in a country's exports clearly suggests higher value chains. Table 1 also tells us that the higher the country's global competitiveness (represented by GCI score), higher the country's GVC.[16]

Several economies with high GVC participation rates are known for their orientation towards international trade, especially exports. China, Vietnam, and Korea are good examples. In sharp contrast, India's GVC participation remains weak.[17] Illustrated in Table 2, India's GVC participation has declined from 45% in 2010 to about 41% in 2018. Both forward and backward participations have witnessed decelerations. However, product-level GVC participation in country's gross exports presents an interesting trend.

India, at present, has limited number of products, where it owns GVCs. Appendix 1 presents trends in GVC participation. India has witnessed a rise in GVCs participation in three products between 2000 and 2017: (i) Coke, refined petroleum, and nuclear fuel; (ii) Sale, maintenance, and repair of motor vehicles and motorcycles; retail sale of fuel; and (iii) Agriculture, hunting, forestry, and fishing. GVC participation in the rest of the products has witnessed decline or constant share between 2000 and 2017. It also indicates a scope to scale up the GVC participation in the country's exports.

Which region offers high GVC potentials for India? India has witnessed a rising trend in trade in parts and components in automobiles, electronics, machineries, transport equipment, etc., with Southeast and East Asia countries.[18] China appears as India's top trading partner in the trade of parts of components. In 2020, India's import of parts and components from China was US$ 16 billion, which was about US$ 7 billion in 2010 (Table 3). Gradually, India's value chain dependence on China, Japan, Korea, Vietnam, Thailand, Malaysia, and Singapore has sharply increased in the last decade, thereby suggesting the need for stronger supply chain resilience with Southeast and East Asia. Undoubtedly, if GVCs need to be strengthened, supply chains resilience and connectivity have to be improved.[19] Besides, FTAs have an important catalytic role in promoting GVCs.

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[15] In a popular way, GVC participation is defined by forward and backward linkages, where forward linkages refer to domestic value-added exports of a country which goes into exports of other countries and backward linkages mean foreign value added in gross exports of a country.

[16] Both GCI rank and rank in share of GVC in gross exports show high correlations.

[17] This was also the finding of the Mitra et al. (2020).

[18] Refer, for example, Mitra et al. (2020).

[19] The difference between value chains and supply chains is simple. The value chain is a process in which a company adds value to its raw materials to produce products eventually sold to consumers, nationally or internationally, whereas the supply chain represents all the steps required to get the product from factory to the customer.

Table 1 Developing country-wise GVCs participation, 2018

Country	Backward linkage^ (%)	Forward linkage^ (%)	Strength of GVC* (%)	Ratio of forward linkages to backward linkages	GCI Rank +
Afghanistan	7.42	23.86	31.28	3.22	
Bangladesh	9.02	21.70	30.72	2.41	103
Bhutan	30.68	24.48	55.16	0.80	
Brunei	10.59	39.14	49.73	3.70	62
Cambodia	18.19	12.84	31.04	0.71	110
China	12.87	31.70	44.57	2.46	28
India	14.10	27.27	41.37	1.93	58
Indonesia	11.13	38.92	50.05	3.50	45
Lao PDR	6.65	25.33	31.99	3.81	112
Malaysia	35.40	28.56	63.96	0.81	25
Maldives	25.29	18.20	43.49	0.72	
Namibia	27.09	14.51	41.60	0.54	100
Nepal	15.68	21.06	36.74	1.34	109
Pakistan	5.76	34.39	40.14	5.97	107
Philippines	28.27	29.23	57.50	1.03	56
South Korea	36.68	21.01	57.69	0.57	15
Russia	9.08	49.98	59.06	5.51	43
Singapore	61.87	13.61	75.48	0.22	2
Sri Lanka	11.48	26.29	37.78	2.29	85
Thailand	30.68	21.15	51.83	0.69	38
Viet Nam	32.08	17.23	49.31	0.54	77
World	28.26	28.26	56.52	1.00	

[*] In terms of share of GVC in country's gross exports (%) ^share in country's gross exports (%) + GCI stands for Global Competitiveness Index of the World Economic Forum (WEF). *Source* Author's own calculation based on WITS

Kumar commented: "The Foreign Trade Policy (2015–2020) has been aimed at raising India's participation in world trade as well as increasing domestic value-added content in India's exports along with promoting brand 'India'. One of the ways in which these objectives can be simultaneously achieved is, if India initiates its own GVCs in a manner that it not only increases its share in world trade but also increases its trade competitiveness. Make in India and FTAs could be leveraged to attract more FDI and in turn use this to connect Indian SMEs to large firms".[20]

Recent FTAs focus on GVCs, which are an important part of the growth in international trade. FTAs focus on creating conditions to promote GVCs, particularly among the nations which are part of FTAs. They cover many policy areas in this

[20] Refer, Kumar (2016).

Table 2 India's production linkages

	Backward linkage^ (%)	Forward linkage^ (%)	Strength of GVC* (%)
2010	14.43	30.55	44.98
2011	16.54	30.49	47.03
2012	16.28	29.88	46.16
2013	15.96	29.73	45.69
2014	15.70	29.46	45.16
2015	15.06	28.10	43.16
2016	13.93	29.70	43.63
2017	14.10	28.34	42.44
2018	14.10	27.27	41.37

* In terms of share of GVC in country's gross exports (%) ^share in country's gross exports (%)
Source Calculated based on OECD-WTO database

Table 3 India's value chain linkages with select economies

	India's export of parts and components				India's export of parts and components			
	2010		2020		2010		2020	
	Value (US$ Million)	Share in total exports, %	Value (US$ Million)	Share in total exports, %	Value (US$ Million)	Share in total imports, %	Value (US$ Million)	Share in total imports, %
Australia	224.3	13.6	243.1	7.0	64.8	0.5	42.3	0.6
Japan	132.4	2.8	352.2	8.7	2193.6	27.4	2041.0	20.3
China	366.7	2.1	799.0	4.2	6457.6	17.0	15,652.9	26.8
Korea	118.1	3.3	280.5	6.2	2460.9	26.0	3454.0	28.5
Indonesia	186.4	4.1	278.9	6.4	187.4	1.9	180.6	1.5
Malaysia	186.5	5.3	285.2	4.6	751.3	12.6	486.8	6.6
Philippines	114.8	14.4	167.7	11.8	194.8	49.8	82.4	16.3
Singapore	577.0	6.9	852.3	10.3	1144.7	15.9	2565.3	20.9
Thailand	272.0	12.7	579.4	15.3	763.9	19.5	811.5	15.5
Vietnam	98.7	4.0	455.4	10.1	96.6	9.7	1379.3	24.8
ASEAN	**1465.0**	**6.6**	**2710.1**	**9.2**	**3139.4**	**10.6**	**5516.3**	**12.5**
World	13,816.5	6.4	25,361.5	9.2	27,336.3	8.0	45,414.1	12.4

Source WITS Database

context and have deeper levels of liberalization as well as coherence and collaboration, with a major focus on tariff elimination/reduction, reducing the trade-related costs of non-tariff measures, and trade facilitation. India's Comprehensive Economic Partnership Agreement (CEPA) with Japan and Korea and the one which is being negotiated with the EU are aimed to facilitate its integration into the GVCs.

On the other, trade facilitation and connectivity help facilitate the GVCs. With production processes and tasks in production facilitate increasingly fragmented across national borders, time-sensitive logistics services and ICT are the key to facilitating GVCs (Kimura and Kobayashi, 2009). In a study, the World Bank (2020a, 2020b) has identified that GVC participation is determined by economic endowments, market size, geography and institutional quality. Mitra et al. (2020) have identified that trade facilitation, logistics and infrastructure are some of the key determinants of the GVCs. Here, we look at the progress in trade facilitation and identify the gaps in policy measures next.

3 Trade Facilitation: Achievements So Far

3.1 Why Trade Facilitation?

Trade facilitation supports modern and effective customs administrations, streamlined and transparent trade processes/procedures, and improved services and information for private sector traders and investors. It often refers to measures reducing/removing non-tariff institutional, administrative, and technical barriers to trade. In some studies, trade facilitation has been described not just as tariffs and international transport, but also as an instrument to deal with geography, social and cultural costs (language), logistics performance, etc. "Narrow" trade facilitation often refers to customs and border procedures. Product standards (SPS and TBT), regulatory differences across countries, etc., are also discussed as part of trade facilitation. Grainger (2011) identifies four interdependent elements that constitute trade facilitation: (i) simplification and harmonization of applicable rules and procedures; (ii) modernization of trade compliance systems; (iii) administration and standards; and (iv) institutional mechanisms and tools.

Trade facilitation fosters logistics performance, and better logistics spurs growth, competitiveness, and investment. Customs and border management or the improvement of transit regimes are a few areas where trade facilitation can help improve logistics (World Bank 2019). Cutting additional costs through improved trade facilitation have helped countries in raising trade flows and/or diversifying the exports to newer markets—regionally or otherwise (WTO 2020). Behind-the-border measures have been comprehensively used throughout the ongoing crisis such as streamlining procedures, contactless trade, digitization, etc. (ADB-ESCAP, 2014; UNESCAP 2021). These have continued to be important trade policy tools in the post-crisis economic recovery phase. Simplification of trade processes and procedures along with harmonization of trade transaction data and documents are envisaged as key to improving the competitiveness of exports across most of the countries across the world.[21]

[21] Several studies conducted on it. Refer, for example, UNESCAP (2020, 2021), OECD (2021), WTO (2021).

Trade facilitation at WTO also refers to GATT Articles V, VIII, and X, which relate to the freedom of transit, fees and formalities, and the publication and administration of trade regulations. WTO's Trade Facilitation Agreement (TFA) which was signed at the WTO's 9th Ministerial Meeting, held at Bali, Indonesia on 3–7 December 2013, has added a new dimension to trade facilitation. Trade facilitation research priorities are changing very fast, more particularly after the WTO Trade Facilitation Agreement (TFA). Out of 164 member countries of WTO, 145 countries have already ratified the WTO TFA.[22] The TFA has already entered into force on 22 February 2017.

3.2 Trade Facilitation Achievements

India being a geographically dispersed country is susceptible to high and volatile trade costs. India has made substantial progress in documentary and border compliances, both in terms of time and cost. Access to digital technology and its application to trade facilitation helped India raise its performance globally. According to the World Bank's *Trading Across Border* indicators,[23] documentary compliance captures the time and cost associated with compliance with the documentary requirements of all government agencies of the origin economy, the destination economy, and any transit economies. On the other hand, border compliance captures the time and cost associated with compliance with the economy's customs regulations and with regulations relating to other inspections that are mandatory in order for the shipment to cross the economy's border, as well as the time and cost for handling at its port or border.

India has been able to reduce the documentary and border compliance costs of export consignment, both in terms of costs and time between 2015 and 2020 (Table 4). In 2020, India's border compliance and documentary compliance costs of exports were less than that of China. Compared to export, the absolute cost of border compliance of import consignment is more expensive in India. However, India has remarkably halved the border compliance cost of import between 2015 and 2020, thereby narrowing the gap with China in trade facilitation. On the contrary, China offers faster clearance of goods, both in case of border and documentary compliance. Although India still takes higher time towards border clearance for an import consignment, India's achievement has been phenomenal in reducing border compliance time. The progress is mainly due to application of digital technology along with procedural reforms. Border compliance time and turn-around time at ports have also been improved from a peak of 5 days to less than 2 days (De and Kumarasamy 2020). Documentary compliance time for export cargo has also reduced from over almost two days to just 15 h in India during 2015 and 2020. By making e-filling of documents mandatory, India has witnessed substantial progress in reducing documentary burden on exporters and importers. Due to trade facilitation reforms, documentary

[22] As on 1 August 2019, available at https://www.tfadatabase.org/.

[23] Methodology was developed based on Djankov et al. (2008) and was revised in 2015.

Table 4 Trading across borders: 2015 and 2020

(a) Time

		Time to export: Documentary compliance (hours)	Time to import: Documentary compliance (hours)	Time to export: Border compliance (hours)	Time to import: Border compliance (hours)
Afghanistan	2020	228.00	324.00	48.00	96.00
Afghanistan	2015	242.67	336.00	48.00	96.00
Bangladesh	2020	147.00	144.00	168.00	216.00
Bangladesh	2015	147.00	144.00	168.00	216.00
Bhutan	2020	9.00	8.00	5.00	5.00
Bhutan	2015	9.00	8.00	5.00	5.00
China	2020	8.63	12.80	20.70	35.65
China	2015	21.20	65.70	25.93	92.31
India	**2020**	**11.64**	**19.88**	**52.12**	**65.30**
India	**2015**	**41.47**	**63.32**	**109.26**	**287.38**
Maldives	2020	48.00	61.33	42.00	100.00
Maldives	2015	48.00	61.33	42.00	100.00
Nepal	2020	43.00	48.00	11.00	11.00
Nepal	2015	18.64	48.00	37.50	62.70
Pakistan	2020	55.00	96.00	58.00	120.00
Pakistan	2015	61.71	105.57	78.86	131.29
Sri Lanka	2020	48.00	48.00	43.00	72.00
Sri Lanka	2015	76.00	58.00	43.00	72.00

compliance time for export and import cargoes has been reduced to just a few hours in India. In a landmark initiative to reduce documentary compliance, India has rationalized the documentation requirement for exports and imports to just 3 from 7 and 10, respectively.[24]

(b)					
		Cost to export: Documentary compliance (USD)	Cost to import: Documentary compliance (USD)	Cost to export: Border compliance	Cost to import: Border compliance
Afghanistan	2020	344.44	900.00	452.78	750.00
Afghanistan	2015	344.44	900.00	511.11	850.00
Bangladesh	2020	225.00	370.00	408.17	900.00
Bangladesh	2015	225.00	370.00	408.17	900.00

(continued)

[24] Refer, CBIC, http://www.cbic.gov.in/htdocs-cbec/home_links/trade_agreement.

(continued)

(b)					
		Cost to export: Documentary compliance (USD)	Cost to import: Documentary compliance (USD)	Cost to export: Border compliance	Cost to import: Border compliance
Bhutan	2020	50.00	50.00	59.17	110.11
Bhutan	2015	50.00	50.00	59.17	110.11
China	2020	73.57	77.25	256.20	241.25
China	2015	84.57	125.89	484.14	745.00
India	**2020**	**57.95**	**100.00**	**211.92**	**266.11**
India	**2015**	**101.68**	**144.71**	**413.10**	**574.04**
Maldives	2020	300.00	180.44	595.75	980.50
Maldives	2015	300.00	180.44	595.75	980.50
Nepal	2020	110.00	80.00	102.86	190.00
Nepal	2015	85.00	80.00	202.86	155.56
Pakistan	2020	118.00	130.00	288.00	287.00
Pakistan	2015	168.14	180.71	308.43	307.57
Sri Lanka	2020	57.58	282.78	366.11	299.67
Sri Lanka	2015	57.58	282.78	366.11	299.67

Source The World Bank

However, India still takes over 3 days to complete the border compliance for import cargo, an improvement from 12 days needed in 2015. While India's performance in border compliance time of import cargo is laudable, India must improve it further to ease the burden of mandatory border regulations and inspections. It is encouraging to note that costs and time have declined rapidly between 2015 and 2020. One of the critical factors for the rise in costs and time in India could be inefficient logistics and border infrastructure, reducing its trade competitiveness.

To step up the trade facilitation as a priority, India has ratified the WTO's Trade Facilitation Agreement (TFA) in April 2016, which came into force in February 2017. The TFA aims to expedite the movement, release, and clearance of goods in trading across borders. India has already ratified over 70% of the provisions under Category A of the TFA, and has also implemented certain provisions of Category B such as SWIFT, RMS for which India had opted for a five years time.

What follows is that India has succeeded in reducing documents required to export and import, but India still takes considerable time for export and import, particularly at the land border. Although India's performance in trade facilitation has been impressive, there is ample scope to improve it further, particularly the performance in border and documentary compliance. The CII noted "In particular, there is scope for further simplification of documentary requirements and bridging alignment with international standards with application of digital technology".[25] India has recognized the application of digital technology as an important component of national trade facilitation. India has achieved phenomenal progress in the automation of trade documentation. For example, almost 100% of trade documents are now submitted electronically in India through customs' single window.[26]

India has set up the National Committee on Trade Facilitation (NCTF) in 2016 and has introduced the National Trade Facilitation Action Plan (2020–2023). Besides, India has also set up Customs Clearance Facilitation Committees (CCFC), which are directly feeding information to the NCTF, that aims to transform cross-border clearance ecosystem through efficient, transparent, risk-based, coordinated, digital, seamless, and technology-driven procedures, which are supported by state-of-the-art sea ports, airports, land border crossings, rail, road, and other logistics infrastructure.[27] According to the CBIC: "NCTF has a mission to bring down the overall cargo release time within 2 to 3 days. For instance, NCTF has a target to release sea cargo within 2 days and on the same day for Air Cargo, Inland Container Depots & Land Customs Stations for exports. In case of import, it aims to release cargo within 2 to 3 days for Sea Cargo, Air Cargo & Inland Container Depots and on the same day for Land Customs Stations respectively".[28]

India has attempted to enhance trade process efficiency by implementing several modernized procedures such as SWIFT, Pre-Arrival processing, Direct Port Deliveries (Imports), Direct Port Exit (Exports), Integrated Risk Management, Revamped AEO scheme, Deferred Payment, Reduce paper and rely on digital signatures. India has renewed its focus on Digital Customs through new investment in IT infrastructure and applications such as Project Saksham. India has also taken initiatives for better coordination among various stakeholders in the border clearance. India's initiative on several digital reform measures has effectively smoothened the trade facilitation process and helped reduce trade time and costs considerably.[29]

To expedite the cargo release time and mitigate risks, India has introduced an integrated Risk Management System (RMS) to enable low-risk consignments to be cleared without examination. Besides, SWIFT and E-Sanchit eliminate physical interfaces with authorities and smoothen the trade procedures.[30] E-Sanchit is an online application, which is mandatory for traders to submit all supporting documents

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[25] Refer, for example, CII (2018). Also read, CBIC's presentation on WTP TFA, available at http://www.cbic.gov.in/resources//htdocs-cbec/implmntin-trade-facilitation/tfa-presentation.pdf;jsessionid=4307CF3FCC8A6F0FE94D4BD524634D0A.

[26] It also handles all e-filing, e-payments, drawback disbursal and message exchange with stake holders almost 100 per cent India's international trade.

[27] Refer, CBIC (2017), available at http://www.cbic.gov.in/htdocs-cbec/home_links/trade_agreement.

[28] Ibid.

[29] Based on author's own discussions with the CBIC and LPAI.

[30] Customs Single Window in India allows importers and exporters to lodge their clearance documents online at a single point only. CBIC has already executed major projects to automate customs clearance processes and provide electronic data interchange (EDI) within all agencies. This system integrates nine separate forms required by the six Partner Government Agencies (PGAs) and has

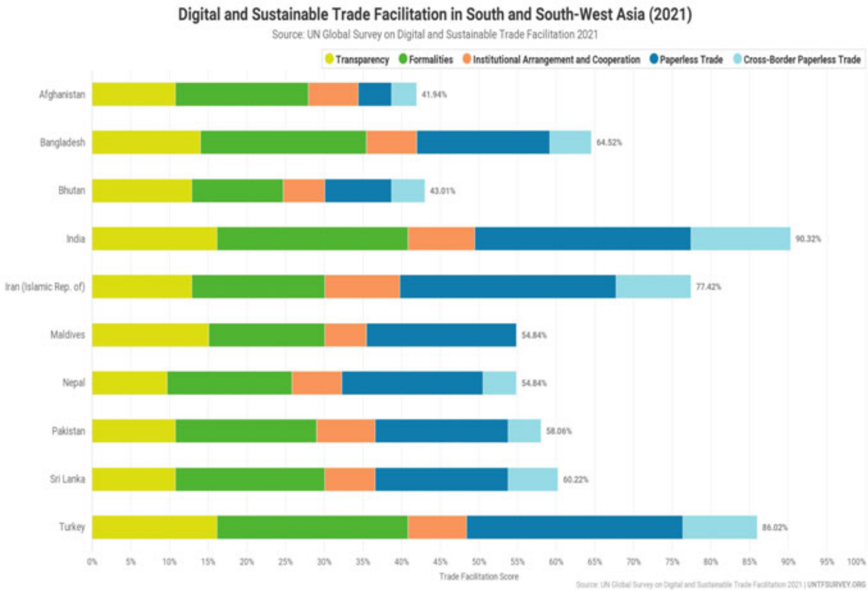
for clearance of consignments electronically with digital signatures. On top, the use of e-Delivery Orders, e-Payments, and e-Invoice have been made mandatory since April 2018 for all stakeholders in the maritime trade to reduce the documentary compliance time. Schemes like Direct Port Delivery (DPD) for imports and Direct Port Entry (DPE) for exports were introduced, which have offered large savings in terms of time as well as costs.

India has implemented the Port Community System (PCS) to provide electronic connectivity to the maritime community. The PCS aims to integrate the electronic flow of trade-related documents. All the major ports and several non-major ports have aligned with the PCS.

India has also revamped the Authorised Economic Operator (AEO) programme. The AEO programme provides benefits of Mutual Recognition Agreements (MRAs), paperless declarations with no supporting documents, deferred duty payments, among others. This programme reduces the release time of consignments and congestion at ports (Fig. 1).

With the objective of complying with international safety standards, ports across the country are being encouraged to install Radiological Detection Equipment (RDE) for screening containers. Jawaharlal Nehru Port has introduced the RDE to promote

Box 1: India leads in digital and sustainable trade facilitation



Source: UNESCAP (2021)

Fig. 1 India leads in digital and sustainable trade facilitation

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done away with the requirement of importers seeking approvals from multiple government agencies for their consignments (CII, 2018).

hassle-free inspection and cargo evacuation. Radio Frequency Identification (RFID) has also been adopted across all major ports to reduce the overall time taken for container movement. RFID application has helped in eliminating the need for manual verification and facilitated the reduction in transaction time from the earlier 5 min to less than a minute at India's largest container port—Jawaharlal Nehru Port.[31]

The e-sealing procedure has been introduced to replace the erstwhile practice of supervised sealing by departmental officers. It provides for the use of RFID tamper-proof e-seals in place of bottle seals by those who were earlier availing the benefit of self-sealing facility. This has helped in the reduction of time and cost associated with the clearance of export containers.

Indian government has shifted to paperless clearance methods and the requirement of routine printouts of documents have stopped. Some major documents which are no more handled manually include GAR 7 Forms/TAR 6 Challans, TP Copy, Export Promotion Copy of Shipping Bill.[32]

The CBIC has extended the 24×7 customs clearances facility to non-facilitated Bills of Entry at 19 seaports and 17 Air Cargo Complexes. Further, the requirement of payment of Merchant Overtime (MOT) charges in respect of the services provided by the Customs officers at 24×7 Customs Ports and Airports has been eliminated.

In a joint collaboration with RBI, Import Data Processing and Management System (IDPMS) has been launched in order to facilitate efficient data processing for payment of imports and effective monitoring. Recently, JP Morgan jointly with major Indian banks have initiated live blockchain platform to address the complex cross-border payments, which helps to reduce cost and mitigate risk in cross-border financial transaction.

4 Challenges, Priorities, and Policy Interventions

India faces several challenges in its trade facilitation efforts. First, limited role played by the national trade facilitation committee till date. Second, National Single Window/Customs EDI has played a striking role, but interoperability in the South Asia region or between regions has not happened yet. Third, cross-country e-commerce is yet to be fully unlocked. Fourth, slow or nil inter-country coordination and many measures are ad-hoc or temporary. Sixth, rising gap in information sharing, delay in reporting of measures to WTO/WCO, etc.

To boost India's participation in GVCs, trade facilitation has a catalytic role. The trade facilitation factors, which need to be addressed for creating a good enabling environment for India's integration into the GVCs are as follows:

[31] Refer, the CBIC appraisal through the time release study.

[32] Also refer, Table 2.

4.1 Placing Trade Facilitation as a National Priority

The primary goal of trade facilitation is to help make trade across borders faster, cheaper, and more predictable, while ensuring its safety and security.[33] Priorities should be based on the trade facilitation need. Air or pipeline are better suits for faster delivery whereas highways carry the bulk of the goods. In terms of soft aspect of connectivity, trade facilitation is about simplifying and harmonizing formalities, procedures, and the related exchange of information and documents between the various partners in the supply chain. Improved trade facilitation between countries paves the way for GVCs.

Future improvement in GVCs will come from addressing non-tariff measures (NTMs) to trade, including through digital trade facilitation. With the application of digital technologies, trade facilitation priorities have also undergone a drastic transformation in the last few years.

With the unveiling of GatiShakti Master Plan, the need of multimodal transport connectivity is well received. However, the implementation of the national trade facilitation action plan is yet to gain the required momentum. At the same time, NTFC in India is not yet fully active in driving the WTO TFA mandates. The agencies will operate in full scale once the political leadership provides the required direction, while the country makes a case of trade facilitation a national priority.

4.2 Strengthening Trade Logistics

Call for strengthening trade logistics refers the OECD's benchmark: "As goods now cross borders many times, first as inputs and then as final products, fast and efficient customs and port procedures are essential to the smooth operation of supply chains. To compete globally, firms need to maintain lean inventories and still respond quickly to demand, which is not possible when their intermediate inputs suffer unpredictable delays at the border. A country where inputs can be imported and exported within a quick and reliable time frame is a more attractive location for foreign firms seeking to outsource production stages**.** As such, trade facilitation measures are crucial to foster integration into global production networks and global markets".[34]

India's performance has improved a great deal in the last few years. Its preference in *Trading Across Borders*, as per the Doing Business report of the World Bank, has improved from the level of 146 in 2018 to 68th position in 2020. The government remains focussed on sustaining the improvement, which is critical for reducing the transaction cost in exports and imports. According to the OECD, developing countries like India can reduce the transaction cost by 13–15% by adopting the best practices in trade facilitation.

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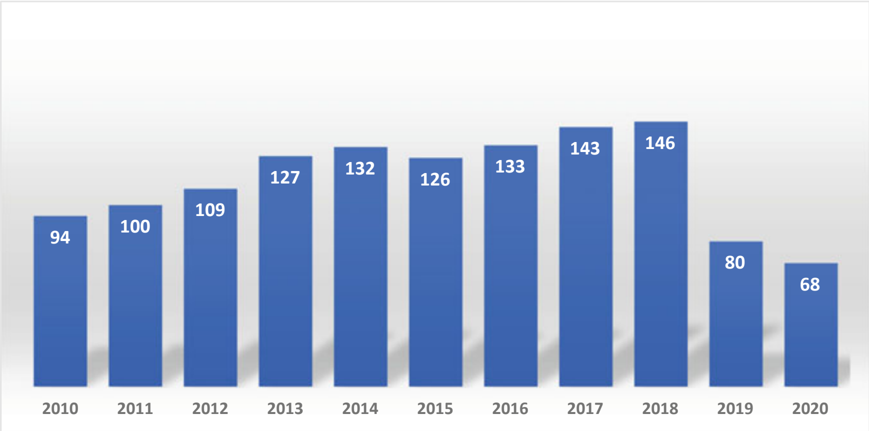
[33] This is a common definition of trade facilitation, drawn upon UN's trade facilitation implementation guide, available at http://tfig.unece.org/details.html.

[34] Refer, OECD (2013a)



Source: Doing Business Report, World Bank

Fig. 2 Trend in trading across borders ranking in India

Impressive improvement in India's trade facilitation performance is attributable to a series of reforms implemented by the government over the last several years. Notable among them are the introduction of rationalized documentation requirement, an integrated Risk Management System (RMS), the Single Window Interface for Facilitating Trade (SWIFT), E-Sanchit, Faceless customs clearances, Authorized Economic Operator (AEO) programme, Director Port Delivery (DPD) for importers, and Direct Port Entry (DPE) for exporters.

World Bank's Doing Business (DB) Report presents quantitative indicators of the business environment for 190 economies, assessing and ranking countries across 10 broad areas, including trading across borders. As per the DB report (2020), India stands at 68th position out of 190 economies, witnessing sharp improvement in its performance in the last 2 years, as seen in Fig. 2 and Table 5.

There is a scope for further improvement in the country's performance of trading across borders, which is evident from the fact that it takes 52 h and US$ 212 to meet border compliances, much higher than South Korea with 13 h and US$ 185 (Table 5). India is, of course, doing better than many neighboring countries but it should be competing with the best in the world. With regard to meeting border compliances for imports, it takes 65 h and US$ 266 in India as compared to 33 h and US$ 220 in Singapore. Here also, India performs better than many neighboring countries. Similar is the case regarding documentary compliances for exports and imports, which result in high dwelling cost and time for trading across borders.

Besides procedural and operational barriers, infrastructural barriers are still causing challenges in the seamless movement of goods and services. There is a high degree of congestion at the ports for certain types of cargoes. According to the CII: "The process of road to rail conversion is sluggish at several ports including, Jawaharlal Nehru Port Trust (JNPT) in Mumbai. Rush of containers and tractor trailers at the entry gates of the various parking plazas for document processing leads to

Table 5 Compliance cost in trading across borders: India vis-a-vis other countries

Border Compliance	India (68)	United Kingdom (33)	United States (39)	South Korea (36)	Singapore (47)	Malaysia (49)	Sri Lanka (96)	Vietnam (104)	Bangladesh (176)
Exports									
Time (hrs)	52	24	2	13	10	28	43	55	168
Cost (USD)	212	280	175	185	335	213	366	290	408
Imports									
Time (hrs)	65	3	2	6	33	36	72	56	216
Cost (USD)	266	0	175	315	220	213	300	373	900
Documentary Compliance	India (68)	United Kingdom (33)	United States (39)	South Korea (36)	Singapore (47)	Malaysia (49)	Sri Lanka (96)	Vietnam (104)	Bangladesh (176)
Exports									
Time (hrs)	12	4	2	1	2	10	48	50	147
Cost (USD)	58	25	60	11	37	35	58	139	225
Imports									
Time (hrs)	20	2	8	1	3	7	48	76	144
Cost (USD)	100	0	100	27	40	60	283	183	370

Source World Bank

delay in procedure and congestion. Empty trucks arriving to pick up DPD (Direct Port Delivery) containers have to wait in long queues to get in and out of the terminals. There is inadequate warehousing facility at several ports, which increases the transaction cost and dwell time. The road connectivity from the port to the various container freight stations (CFSs) and the highways is also in poor condition in some portions. This often poses the risk of goods getting damaged, besides resulting in slow movement of trailers and trucks, causing congestion and delays. At some ports, due to time restriction on movement of vehicles on some roads, the containers fail to report at the port on time, leading to an increase in the turnaround time and a high parking cost".[35]

4.3 Compliance with Trade-Related Standards

In the modern trading system, standards and technical regulations determine the export potential and overall competitiveness of an economy. India's standards regime is still at the nascent stage of development, and awareness and adoption of standards are very low. The lead companies in GVCs follow the strict standard compliance for sourcing intermediates. More often, they insist on adoption of private standards, which are expensive to comply with.

The OECD says: "The rising number of quality and safety standards is in part driven by concerns about information, coordination and traceability which are more acute in a world dominated by GVCs. While the need to protect final consumers through appropriate quality standards should not be understated, their complexity and above all their heterogeneity has become one of the main barriers to insertion into GVCs, in particular for small and medium-sized enterprises (SMEs)".[36] Stronger compliance procedures sometimes add additional time, which the SMEs are unable to manage. Heterogeneity in standards often has differential impacts, both for trade and industrial productions. Thus, mutual recognition of standards between countries encourages the GVCs.[37]

Noted in the OECD "Upstream firms supplying intermediate inputs to several destinations may have to duplicate production processes to comply with conflicting standards, or to incur burdensome certification procedures multiple times for the same product. In agro and consumer appliances value chains, meeting public and private standards has been identified as the main obstacle to participation in GVCs. Increasing international regulatory cooperation, including via the convergence of standards and certification requirements and mutual recognition agreements, can go a long way to alleviate the burden of compliance and enhance the competitiveness of small-scale exporters".[38]

[35] Refer, CII (2018), Kumar (2016).

[36] Refer, OECD (2013a).

[37] Refer, for example, Kaplinsky (2010).

[38] Refer, OCED (2013a).

A study by the Asian Development Bank Institute (ADBI) found that quality certification was a statistically significant indicator of GVC participation.[39] This implies that proof of quality is necessary to create GVC linkages and attract FDI, as large MNCs, which are drivers of GVCs will be attracted to markets where they are assured quality products where they can do further value addition at a lower cost.

Globally, the standards ecosystem is complex. It requires a fair amount of navigation and negotiation between countries to ensure ease of exports when it comes to standards compliance. The best examples of regional harmonization are found in the EU in the west, and ASEAN in the east. Noted in the MoCI "It has to be recognized that the days of differential standards—low for domestic market and high for exports—are over and if the Indian industry has to survive and thrive, it has to adopt global standards. The Ministries/regulators/state governments have to realize that their initiatives and schemes have to be built around global standards if they have to succeed in their objectives. Moreover, by measuring up to standards and conformity assessment procedures, exports can also be increased both in volume as well as in value terms".[40]

It has been noted that upgrading to international standards, making standards mandatory, requisite infrastructural facilities like testing, certification, trace-back, packaging and labelling, and schemes for promoting adhering to international standards can go a long way in meeting the challenges of a large number of SPS and TBT measures.[41]

India needs a more comprehensive coverage of goods under mandatory technical regulations. For this, there is a need for easier conformity assessment procedures, which are less burdensome to apply and administer. This is also required for ease of doing business. Internationally, there are varieties of options for conformity assessment available depending upon the level of risk involved. For low-risk items, Suppliers Declaration of Conformity (SDoC) is used, which is a costsaving approach and less onerous approach to conformity assessment.

However, in India, under BIS Act, only two types of conformity assessment options were available: licensing (all products except electronics) and registration (electronics). The new BIS Act 2016 will make available other options of conformity assessment. The new Act also allows multiple types of simplified conformity assessment schemes including self-declaration of conformity against a standard which will give simplified options to manufacturers to adhere to the standards and get certificate of conformity. The Act enables the Central Government to appoint any authority/agency, in addition to the BIS, to verify the conformity of products and services to a standard and issue certificate of conformity.[42]

Further, there is one more requirement of enabling law for less onerous conformity assessment schemes, i.e. SDoC as it works well only in combination with a strong

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[39] Refer, Urata (2020).

[40] Refer, MoCI (2016).

[41] Ibid.

[42] Bureau of Indian standards (BIS) Act 2016 brought into force with effect from 12th October, 2017, Press Information Bureau, Government of India.

product liability law and market surveillance, both of which are weak in India. Most developed countries have enacted product liability laws. Product liability is the area of law in which manufacturers, distributors, suppliers, and retailers are held responsible for any injuries that products cause during their life cycle. The solution that came out of CII-Ministry of Commerce National Standards Conclave deliberations was that we should have a legal regime for product liability. Subsequently, Consumer Protect Act was amended in 2019 to include the provisions of product liability, which assigns the responsibility on product manufacturer or product seller, of any product or service, to compensate for any harm caused to a consumer by such defective product manufactured or sold or by deficiency in services relating thereto.[43]

5 Conclusions

In the rise of the COVID-19 pandemic, the global supply chain has witnessed certain structural changes, and may gain further momentum in the near future. The pandemic has exposed the vulnerabilities in global supply chain as the businesses were over-relying on limited manufacturing hubs. Due to this structural change in the global supply chains, disruptions in the demand and supply are expected. Thus, the minimization of its impact on business depends upon how well the multinationals respond to it.

To address the challenges caused due to this disruption, companies need to reform their business models as per the necessity and opportunity. For example, consumer goods companies, which have seen their offline stores close around the world, have moved to target potential customers with online activities in an effort to increase sales.

There exists considerable scope for India to leverage its strengths in these products and services or supply chains which could then translate into action for attracting international companies in India in those areas/sectors. India's trade policy ecosystem should enable domestic manufacturing to slot into GVCs. This will require an integrated approach to manufacturing, investments and trade including both exports and imports. We believe that an open trade environment with low tariffs can significantly drive India's GVC integration in the region.

A conducive manufacturing ecosystem is being created through the Production Linked Incentive (PLI) scheme for certain globally traded items such as electronics and textiles and garments. The technical and financial support consistent with the WTO rules will encourage more firms to foray into the GVCs through risk sharing and market access incentives. This would help in India's participation in GVC to a great extent.

Despite India's steady efforts to open up its economy, its trade and investment regime remains restrictive relative to other countries at similar levels of development. While India's vibrant export-oriented services market is relatively open in several

[43] FAQs on Consumer Protection Act 2019, Ministry of Consumer Affairs, Government of India.

sectors (computer, audio-visual and engineering), there is scope for improvement other sectors such as basic infrastructure, legal and air transport services. India's full implementation of measures in the WTO Trade Facilitation Agreement could reduce trading costs, and facilitate wider participation in GVCs.

India has made significant improvements in digital trade facilitation measures and the analysis indicates that significant improvement in trade facilitation measures in the reporting country would facilitate the export to the partner countries. India should continue to instill new dimensions in digital trade facilitation through reforms and new technologies. Further, the analysis shows that the implementation of electronic trade facilitation does promote exports.

Harmonization of documentary requirements across the world is needed to facilitate India's GVC participation. Although its implementation rate varies, the WTO TFA is a good beginning towards this direction.

India has achieved substantial economic gains by reducing policy-related non-tariff trade costs, which is a crucial catalyst for promoting GVCs. There are many areas where India can do better in trade facilitation, particularly in the neighbourhood. For example, India can introduce a coordinated border management with the neighboring countries based on approaches such as collocation of facilities, close cooperation between agencies, delegation of administrative authority, cross-designation of officials, and effective information sharing. Interoperability of single windows with partner countries is another line of activities that India may initiate. In a futuristic sense, India may think of Joint Border Post (JBP) in the neighborhood, particularly with friendly countries, which allows bordering countries to coordinate import, export, and transit processes to ensure that traders are not required to duplicate regulatory formalities on both sides of the same border. Signing of the UN's paperless trade agreement may add further momentum in the digital trade facilitation programs.

India may consider conducting national trade facilitation performance monitoring mechanisms. Along with it, the WCO TRS and ESCAP BPA may be undertaken regularly. The monitoring of the performance and application of the digital technology and adaptation will help achieve paperless trade targets. We may also explore international examples of instruments for simplification of trade procedures.

The development of trade infrastructure has to commensurate the progress made in the soft side of trade facilitation. India could unleash its full potentials in GVCs, provided it improves the infrastructure facilities, which are at present not sufficient to meet the growing demand of the country.

Countries have to strengthen the resilience through trade promotion and facilitation cell, mechanisms to address trade and investment barriers, etc., as discussed in this article. Promote digitization of trade documentation, activities for promotion of trade and investment and identification of sectors for cooperation, among others. Besides, scaling up FTAs, harmonization of standards, streamlining ROOs, etc., would pave the way for India's active participation in GVCs.

To conclude, better trade facilitation leads to reduced trade costs, thereby driving GVCs/RVCs. India has achieved substantial economic gains by reducing policy-related non-tariff trade cost. India is quite successful in introducing a digital customs arrangement in the country. India should continue to instil new dimensions in digital trade facilitation through reforms and new technologies. The trade facilitation agenda should be harmonization of documentary requirements across the world. Although India is yet to become world's major hub for GVCs, the country can easily scale up the production chains across borders through the improved trade facilitation. This article highlights some of the opportunities that India should attempt to utilize while unlocking the GVC potential.

Appendix –Trends in India's Sectoral GVCs (%)

Sr. no	Sector	2000	2010	2017
1	Coke, refined petroleum, and nuclear fuel		48.96	50.25
2	Leather, leather products, and footwear	61.31	42.96	43.76
3	Chemicals and chemical products	44.37	42.50	42.22
4	Sale, maintenance, and repair of motor vehicles and motorcycles; retail sale of fuel	27.65	20.36	42.17
5	Pulp, paper, paper products, printing, and publishing	44.12	41.55	41.19
6	Basic metals and fabricated metal	45.20	42.72	40.45
7	Rubber and plastics	44.10	41.78	40.15
8	Mining and quarrying	41.21	37.34	35.90
9	Electrical and optical equipment	34.89	34.24	32.97
10	Water transport	30.91	32.37	30.88
11	Wood and products of wood and cork	32.77	28.19	30.28
12	Air transport	30.76	34.26	28.27
13	Inland transport	31.91	30.32	27.71
14	Textiles and textile products	32.81	33.91	27.37
15	Machinery, nec	30.86	34.26	27.14
16	Other nonmetallic minerals	45.24	27.48	26.97
17	Manufacturing, nec; recycling	30.46	36.43	24.22
18	Transport equipment	38.68	31.51	24.01
19	Construction	26.42	25.95	22.96
20	Financial intermediation	24.08	23.84	22.50
21	Other supporting and auxiliary transport activities; activities of travel agencies	23.97	21.67	21.27
22	Wholesale trade and commission trade, except motor vehicles and motorcycles	30.50	33.00	21.06
23	Retail trade, except motor vehicles and motorcycles; repair of household goods	26.71	22.15	20.02
24	Electricity, gas, and water supply		17.11	18.18

(continued)

(continued)

Sr. no	Sector	2000	2010	2017
25	Agriculture, hunting, forestry, and fishing	3.66	14.97	17.33
26	Renting of M&Eq and other business activities	34.50	28.16	15.18
27	Food, beverages, and tobacco	12.45	13.35	9.78
28	Post and telecommunications	23.05	17.53	9.39
29	Health and social work			9.19
30	Hotels and restaurants			7.17
31	Other community, social, and personal services	6.95	5.96	2.98
32	Education			1.33
33	Public administration and defense; compulsory social security	0.00	0.04	0.00
34	Real estate activities	0.67	1.21	

*GVC = ((DVA + FVA)/Gross Exports)*100. *Source* Calculated based on ADB-MRIO database

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Exchange Rate Pass-Through in South Asian Countries

Darpajit Sengupta and Saikat Sinha Roy

1 Introduction

This paper aims to measure exchange rate pass-through to import prices for major South Asian countries (Bangladesh, India, Iran, Pakistan, and Sri Lanka). The reaction of prices in general, and prices of traded goods in particular, to changes in exchange rates is known as exchange rate pass-through (ERPT). The exchange rate pass through is a two-step process. In the first stage, fluctuations in nominal exchange rates lead to changes in export and import prices, and in the second stage, these changes in the prices of traded goods also affect domestic prices. The ERPT therefore has significant connotation for shock propagation and design of monetary policy in an open economy. Friedman (1953) states that such exchange rate flexibility allows for relative price adjustments when countries are hit by specific real shocks. The relative price adjustments to exchange rate changes help in diversion of expenditures between domestic and foreign commodities, partially offsetting the inceptive effects of the disturbance. This results in imperfect transmission of exchange rates as not all exchange rate fluctuations are reflected in prices. Complete or perfect pass through means that there is a one-to-one relationship between exchange rate and prices, and transmission is incomplete if the change in prices are less than the exchange rate. In a perfectly competitive market, theory predicts a perfect pass-through to prices of importable goods (Dornbusch, 1987). Imperfect pass through occurs under possible strategic interaction between competitors in an imperfectly competitive market structure. Exchange rate movements are either passed on to prices or absorbed by firms and affect inflationary trends. In the two-country model, production costs are assumed to be separable and convex, so monopolistic competitors resort to price discrimination

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between home and foreign markets (Yang, 1997; Clark & Faruqee, 1997; Atkeson & Burstein, 2008). In addition, the extent of pass-through is related to accounting of balance of payments. This is because a relatively small price response (low pass-through) to a currency appreciation or depreciation produces a similar response to total imports . A high rate of import price pass-through improves the trade balance by depreciating the currency. This is because higher import prices can lead to increased demand for domestic goods. With this perspective in the background, it is crucial to understand the issues in the emerging literature on the subject.

1.1 Review of Literature

The inception of ERPT literature was during the period when US import prices were reacting slowly to the sharp appreciation and subsequent depreciation of the dollar from 1980 to 1985. For European economies, Dornbusch (1987) and Dornbusch and Krugman (1976) showed that countries with high inflation experienced relative devaluation of their currencies. In general, most early analyses of pass-through, such as Gordon (1981) and Dornbusch and Fischer (1986), correlated a rising dollar with falling inflation. In a perfectly competitive environment, the price of the goods in the host country is the same as the exporter's price measured in the host country's currency under the law of one price. Thus, according to Dornbusch (1987), imperfect competition allows imperfect propagation of shocks for firms with variable markup. Exchange rate movements are either passed on to the price or absorbed by the markups. Atkeson and Burstein (2008) developed a model that relates markups, prices, and market share. Yang (1997) presents his modified Dixit-Stiglitz model showing that pass-through can result from increased marginal cost and variable elasticity of demand. The paper also shows a negative relationship between import share and exchange rate pass-through. As a theoretical explanation, Krugman (1987) presents evidence of market pricing for low pass-through. This behaviour varies by importer, exporter, type of goods, and country-specific influences (such as demand and competition). In particular, Krugman (1987) also shows that export prices of German machineries to the United States remained stable in the face of a stronger dollar. However, exchange rate movements are greatly reflected in the prices of the same category of goods exported to other countries. Clark and Faruqee (1997) argue that market price movements guarantee greater stability with respect to export market currencies when export prices for the same goods differ from domestic prices because markets are fragmented. Marston (1990) and Giovannini (1988), using Japanese data, found that there is little pass-through to price when the price contract is invoiced in foreign currency. However, Athukorala and Menon (1994) rejected the proposition that Japanese exporters depended on pricing-to-market strategies to maintain market share during periods of yen appreciation. Gagnon and Knetter (1995) also show low transmission for local currency pricing (as in the United States), again suggesting that market pricing is a component of imperfect transmission. In subsequent work, Betts and Devereaux (2000) developed a theoretical model showing that higher prices have lower pass-through to the market and exchange rate fluctuations reduce spending.

The macroeconomic literature on open economies is replete with various studies that explain low exchange rates pass through. The role of production functions explains the low level of contagion and the variability of contagion across industries. Olivei (2002) discusses the possibility that production effects can offset exchange rate movements, creating a negative or even more than proportionate complete pass-through. Marazzi and Sheets (2007) distinguish between industries and commodities by examining the role of changes in import baskets. Gopinath et al. (2010) found that pass-through to US imports is almost four times greater for goods priced in the exporting country's currency than for goods paid in dollars. Bergin and Feenstra (2001), Gopinath and Itskhoki (2010), and Antoniades and Zaniboni (2016) show that firms that adjust prices often have higher commodity pass-through coefficients. In a similar study, Engel (2002) also showed that when exchange rates were more volatile, exporters with fixed prices (e.g., due to contract or menu costs) were more likely to set prices in local currencies. Froot and Klemperer (1989) uses a theoretical model to show that exporters react differently to exchange rate fluctuations based on their market share and potential competition with other players in the market. Knetter (1993) provides a comparitive analysis of the pricing-to-market behaviour of exports from Japan, Germany, the United Kingdom, and the United States, focussing on reducing margins in depreciated markets. He found that prices became more stable when exporters faced more competition in the commodity's destination market. Feenstra et al. (1996) showed a non-linear and increasing relationship between market shares and variables with pass-through coefficients approaching 1, indicating that exporters respond differently depending on market structure. Bachata and Wincoop (2002) also found that when domestic firms compete with other sectors (eg, Non-traded goods) to produce domestic final goods, the pass-through to import prices is almost perfect, but the pass-through to consumer prices is almost zero. Auer and Schoenle (2012) also used US import data across a wide range of product groups from many exporting countries and found pass-through rates are maximized at the extreme ends of the market share distribution. Using cross-country evidences, Yang (1997), Campa and Minguez (2006), Garetto (2009) and Hong and Li (2013) also highlight the relative importance of market structure in causing low ERPT.

According to Pyne and Sinha Roy (2019), pass-through is more than proportionate for food & food products, and transport equipment but incomplete for chemicals and manufacturing. The pass-through coefficient is low and insignificant for crude materials other than fuel. However, in contrast, Mallick and Marques (2005) argue that evidence of first stage of exchange rate pass-through to import prices in India is observed only after 1991, and that pass-through coefficient was more in subsequent periods. Mallick and Marques (2008), in a disaggregated study of import prices in India, found that the extent of pass-through varied according to sectors and was explained using the ratio of import penetration and effective protection rates. Dholakia and Saradhi (2000), Dash and Narasimham (2011), and Yanamandra (2015) found perfect pass-through in the short term and even higher pass-through in the long term. Patra and Pattanaik (1994), using the annual data from 1970–1971 to 1992–1993, tried to show trade balance in India is likely to improve under the floating exchange rate regime through its effect on export and import prices. It estimated ERPT to export price at 0.93, supporting almost a complete pass-through.

Contrary to this, Ranjan (1995), taking almost the same analysis period, finds that export price elasticity to exchange rate change needs to be higher to improve the export quantity and the earning substantially. He estimated the ERPT to export prices and found high coefficients for leather chemicals and low coefficients for gems, jewellery, and textiles. Sinha Roy and Pyne (2014) observe the transmission of high but imperfect exchange rates to Indian export prices at the aggregate and disaggregate levels. However, the extent of transmission varies by product group, with export prices of chemicals, animal fats and vegetable oils being almost fully affected, and export prices of technical products, leather and leather products being incompletely and lowly transmitted. Takhtamanova (2010), Choudhri et al. (2005), and Frankel et al. (2011) compared pass-through in different inflationary environments and raised questions on the endogeneity between low pass-through and inflation. Zorzi et al. (2007) also found that the degree of exchange rate pass-through to prices for many emerging markets of Asia, Latin America, and Central and Eastern Europe depends on inflation and import openness. The CPI includes non-tradable goods and is influenced by other factors such as distribution channels and retail chain market structure, so it has a smaller pass-through to CPI. Therefore, the impact of exchange rate changes on CPI is more indirect than on import prices (Ghosh & Rajan, 2009). McCarthy (2007), Mendali and Das (2017) also considers the relationship between inflation, exchange rates, and import price movements. Using data from nine developed countries and a VAR model, McCarthy (2007) finds that while the pass-through to import prices is declining, the link between import prices, CPI, and PPI inflation rate remains stable.

Bailliu and Fujii (2004), Gagnon and Ihrig (2004) also postulate that low inflation was primarily caused by changes in monetary policy and not by external influences. An important extension of Taylor's (2000) work is to compare transmission with other macroeconomic indicators, as shown by Choudhri and Hakura (2006). They find that the inflation effect dominates, indicating that the inflationary environment of importers is the most important indicator of low pass-through. However, Campa and Goldberg (2002), Campa et al. (2005) examine differences in pass through rates across countries and how these rates have changed over time. The results indicate that changes in trade composition, rather than changes in the inflationary environment, were one of the main reasons for the low pass-through rate. Interestingly, pass-through rates in the food and manufacturing industries are lower than in the raw materials and energy sectors. However, most of these studies focus on the relationship between ERPT and price (inflation), emphasized in market pricing theory models in which foreign exporters change prices in importing countries asymmetrically according to the volume and direction of trade in goods. Recent studies have therefore considered the role of non-linearity and asymmetry in studies of the relationship between exchange rates and domestic prices in advanced economies (Nogueira et al., 2008; Choudhri & Hakura, 2015; Anne & Villavicencio, 2012; Brun-Aguerre et al., 2012, 2017; Yanamandra, 2015; Baharumshah et al., 2017; Kassi et al., 2019).

As observed from the literature only a small number of research have examined the phenomenon of ERPT in South Asia. Moreover, no prior studies have looked into cross-country variations in pass-through elasticity and its causes. This article examines some of these concerns because the exchange rate is a crucial tool for increasing exports and preserving the current account balance.

The structure of this study is as follows. The theoretical model that supports the additional econometric requirements is described in Sect. 2. A thorough explanation of the procedures and information used is provided in the section that follows. The estimation findings and their associated interpretations are presented in Sect. 4. The main conclusions and the consequences for policy are summed up in the final section.

1.2 Theoretical Background

The theoretical model that serves as the foundation for the econometric specification for calculating the coefficients of exchange rate pass through of exporting firms is presented in this section. Consider the classic static profit maximization problem that export firms confront, which is frequently found in the literature (Bailliu & Fujii, 2004). Let us consider a foreign firm that sells goods in that destination country. The following profit maximization problem is optimized by an export firm:

$$\text{Max}\,\pi = e^{-1}px - C(x) \tag{1}$$

where p is the good's price (in home currency), $C(.)$ is the cost function (in foreign currency units), and x is the quantity demanded for the good. Here, π stands for profits (expressed in the foreign currency). e is the exchange rate measured in units of the domestic currency per unit of the foreign currency.

The first-order condition is obtained from Eq. 1 is as follows:

$$p = e\text{MC}_x\mathcal{M} \tag{2}$$

where, $\mathcal{M}$ is the price markup over marginal cost and MC_x is the marginal cost. The markup is additionally described using Lerner's Index as

$$\mathcal{M} = \frac{\eta'}{\eta' - 1} \tag{3}$$

where, η' is the elasticity of demand. Equation (2) illustrates that the variations in exchange rates, changes in enterprises' marginal costs, and/or adjustments in firms' markup rates are responsible for fluctuations in the price of a good in domestic currency. The firm's markup and marginal cost, however, are subject to modify regardless of currency movements. For instance, a rise in the cost of locally sourced raw materials can raise the marginal cost. Demand shocks in importing nations can also alter the margins of exporters. In order to differentiate between the effects of exchange rate fluctuations on import prices, we must account for the changes in these parameters when assessing pass-through. As a result, the straightforward log-linear equation can be reduced to the following equation:

$$p_t = \alpha + \lambda e_t + \tau \mathrm{MC}_t + \eta Y_t + \varepsilon_t \tag{4}$$

where, MC_t and Y_t are the marginal cost of the exporter and the demand conditions of the importing country, respectively. Here, the coefficient λ measures ERPT. The exchange rate pass-through literature frequently uses various formulations of Eq. (4) as empirical specifications, as stated in Goldberg and Knetter (1997).

2 Empirical Methodology and Data Description

2.1 Econometric Modelling

Depending on the kind of cross-sectional heterogeneity, multiple panel data analysis models exist. When cross-sectional heterogeneity is associated with other explanatory factors, fixed-effects models offer reliable estimates. Provided that the unobserved cross-sectional heterogeneity is uncorrelated with the other explanatory variables in the model, the random effects model provides an effective estimate of the parameters. The Hausmann specification test aids in differentiating between models with fixed-effects and those with random effects. The fixed-effects model is preferred over the random-effects model when the Hausman test's null hypothesis is rejected. This is because other explanatory variables and cross-sectional heterogeneity have been shown to correlate. However, the impact of exchange rate fluctuations on import prices may not be entirely apparent right once, particularly if domestic (foreign) businesses require some time to adjust pricing. Consequently, it is crucial to take into account the potential inertial behaviour of traded commodities prices by estimating dynamic models, as various empirical investigations have shown (e.g. Bussière, 2013; Olivei, 2002; Yang, 2007). This is typically accomplished by accounting for the potential for delayed adjustments in export or import prices by introducing lagged import prices as explanatory variables. So, to create a dynamic panel model, we insert a lagged dependent variable in Eq. (4)

$$\mathrm{p}_{it} = \alpha_i + \mu_t + \beta_1 \Delta \mathrm{e}_{it} + \beta_2 \mathrm{Z}_{it} + \beta_3 \mathrm{p}_{it-1} + \varepsilon_{it} \tag{5}$$

where α_i is the country-specific effect, μ_t is the time dummy, p represents the import price of ith commodity over t time periods, e represents the nominal exchange rate, z represents the set of control variables, and p_{it-1} is the lagged term to account for export inertia. Equation (5) assumes that the disturbance term will behave according to accepted assumptions regarding import price dynamics (5). The direct effect of exchange rates on import prices can be calculated. Short-term ERPT calculated using factor β_1. Moreover, it is possible to calculate the long-run ERPT as $\frac{\beta_1}{1-\beta_3}$.

The presence of the lagged dependent variable P_{it-1} can lead to autocorrelation, which can lead to conflicting results when using conventional OLS approaches to estimate panel data models. Fixed effects instrumental variable (IV) estimation can be utilized to overcome these problems. However, Arellano and Bover (1995) discovered that numerous instruments are often weak in the first-stage statistics of 2SLS regression, and that for such weak measurements the fixed-effect IV estimator is biased. As a result, Arellano and Bover's System Generalized Method of Moments Estimator (SYS-GMM) is used in the analysis (1995). This combines level regression and difference regression. We also run a specification test to make sure the SYS-GMM estimator is consistent. We use tests for over identification such as the Sargan-Hansen test, which assesses the overall effectiveness of the instrument by comparing moment conditions to sample analogues. Moreover, we conduct a second-generation panel unit root test (as in Pesaran (2007)) while accounting for cross-country dependencies. Lastly, we use the Westerlund (2007) error-correction-based panel cointegration test to implement cointegration analysis. Compared to the widely used residual-based panel cointegration test, it has superior small-sample characteristics and high power (Pedroni, 2004). By determining whether the error correction term in the conditional error correction model is equal to zero, the approach is intended to test the null hypothesis that there is no cointegration. When the null hypothesis of "no error correction" is shown false, the null hypothesis of "no cointegration"" is likewise proven false. Consistent datasets improve the performance of econometric estimation methods, which are discussed in the following subsection.

2.2 Data

We consider annual data from 1991 to 2017 for five South Asian countries: Bangladesh, India, Iran, Pakistan, and Sri Lanka. The data used for each country are taken from the United Nations World Integrated Trade System (WITS) time series database, except for the nominal effective exchange rate series. Using import price data for US manufacturing goods, Pollard and Coughlin (2004) asserted on the use of appropriate index of the exchange rate as results may vary depending on the choice of the exchange rate index. So, the data on nominal effective exchange rates are important for this study. The exchange rate data used in this study are Nominal Effective Exchange Rates (NEER). It is a weighted measure of bilateral trade shares of 36 countries, collected from the Handbook of Statistics on Indian Economy published by the Reserve Bank of India (RBI). The base year used for computing NEER is 1993–94

= 100. Concerning the dependent variable, i.e. the domestic import prices, we use import unit values indices of goods and services. The unit values of import prices of core goods are calculated by excluding the primary raw commodities because of their volatile nature. We use data on World Growth (%), as a proxy for foreign demand and is obtained from World Integrated Trade System (WITS) database. A measure of trade openness is calculated by taking the difference in value of export and value of import and GDP and expressed as a percentage of GDP. Being unobservable and difficult to measure, marginal costs of foreign producers is calculated using a proxy variable. The standard practice in the literature is to compute a weighted average of costs of the trading partners of an economy (Campa & Goldberg, 2005; Bailliu & Fujii, 2004). Hence, we use the data on nominal and real effective exchange rate to capture implicitly the foreign costs of each country's major trade partners:

$$\mathrm{MC} = \frac{\mathrm{WPI} * \mathrm{REER}}{\mathrm{NEER}}$$

where, WPI is the wholesale price Index. As the nominal and real effective exchange rate (REER) series are functions of bilateral trade shares of an economy, MC will be a suitable proxy to provide a measure of costs of the trading partner.

3 Econometric Results

Before estimating the coefficient of ERPT for import prices in the five South Asian countries, we used a second-generation panel unit root test (taking into account inter-country dependencies), as in Pesaran (2007), to estimate the behaviour of major macro variables. The results suggest that all series are non-stationary at level, as shown in Table 1, but stationary when first differenced.[1] The only exception is trade openness, which is by construction a stationary variable. To observe the long-term trend, we use cointegration analysis by Westerlund (2007), which is an error-correction-based panel cointegration test. This test is suitable with small samples and have high power compared to the other residual-based panel cointegration test (Pedroni, 2004). By determining whether the error correction term in the conditional error correction model is equal to zero, this technique is used to test the null hypothesis that there is no cointegration. Rejection of this null hypothesis also leads to the rejection of the null hypothesis of "no cointegration". The results in Table 2 show that the null hypothesis is rejected when considering the Kao or Pedroni tests. However, considering the Westerlund test, the null hypothesis cannot be rejected and therefore no cointegration exists. Citing the strength of the Westerlund test and its superiority over other conventional tests, we have the following model specifications:

[1] Pesaran (2007) developed panel unit root tests to examine the possibility that a unit root exists over the entire panel. Hence, a failure to reject their null can be clearly understood as proof that non-stationarity exists across the entire panel.

Table 1 Levin-Lin-Chu unit-root test

Variable	Intercept (panel means)	Intercept and trend
${p_{it}}^{m}$	−0.35	0.05
$\boldsymbol{\Delta} {p_{it}}^{m}$	−4.77***	−3.20***
e_{it}	−2.42	−2.11
$\boldsymbol{\Delta} e_{it}$	−3.78***	−2.78***
gdp	3.95	−0.94
Δgdp	−2.71***	−2.70***
mc	−6.20	−5.31
Δmc	−5.20***	−3.32***
to	−2.40**	0.20

Source Author's Calculation
Note [*** indicates *p*-value <1% ** indicates *p*-value <5% * indicates *p*-value <10%]
Individual lag lengths are based on Akaike Information Criteria (AIC)

Table 2 Panel co-integration for ERPT to import prices

Hypothesis	Kao test (modified dickey-fuller *t*)	Pedroni test (Phillips-Perron *t*)	Westerlund test
Ho: no cointegration versus Ha: all panels are cointegrated	−9.87***	−8.54***	−1.20

Note [*** indicates *p*-value <1% ** indicates *p*-value <5% * indicates *p*-value <10%]
Optimal lag and lead lengths are determined by Akaike Information Criterion (AIC)

$$\Delta p_{it}^{m} = \alpha_i + \mu_t + \beta_1 \Delta e_{it} + \beta_2 \Delta mc_{it} + \beta_3 \Delta p_{it-1} + \beta_4 \Delta gdp_{it} + \beta_5 to_{it} + \varepsilon_{it} \tag{6}$$

In order to provide some insight into the ERPT to aggregate import prices in South Asia, we estimate our dynamic panel data benchmark specification as in Eq. (6).

As previously mentioned, we employ two SYS-GMM estimator variants, SYS-GMM1 and SYS-GMM2, which we use, respectively, to compress two (or three) period delays from all variables included in each estimation as the instrument sets. Table 3 displays the results. Before discussing these findings, it is important to note that both of our two SYS-GMM model pass the standard diagnostic tests, the results of which are listed in Table 3. Using the M2 test in particular, we do not find any evidence of second-order autocorrelation,[2] and Sargan–Hansen test has been used to check for the validity of the instruments.

The coefficients for the variables of interest have expected signs and are statistically significant. A positive sign associated with Δe_i indicates that devaluation of the domestic currency leads to higher import prices and limits import demand. For example, a factor of 0.4 means that a 1% depreciation of the domestic currency will

[2] Arellano and Bover (1995) and Blundell and Bond (1998) assumes that at first-differenced errors, there is no presence of second order autocorrelation.

Table 3 Dynamic panel estimation for ERPT to import prices

Variables	Model 1(SYS-GMM1)	Model 2(SYS-GMM2)
$\Delta p_{it-1}{}^{m}$	−0.04 (−0.49)	−0.06 (−1.05)
Δe_{it}	0.25** (4.89)	0.27*** (3.56)
Δgdp_{it}	1.45*** (2.79)	1.43*** (3.43)
Δmc_{it}	0.40*** (2.77)	0.54*** (4.56)
to_{it}	0.61*** (4.89)	0.70*** (6.61)
LR ERPT	0.27** (4.44)	0.29*** (5.21)
No of observations M2 test for autocorrelation	125 0.370	125 0.420
Sargan-Hansen test	141.263	128.26

Source Author's Calculations
Note Figures in brackets are Z values
Short-run ERPT is measured by $\boldsymbol{\beta_1}$ and long-run ERPT by $\boldsymbol{\beta_1/(1-\beta_3)}$.
[*** indicates p-value <1% ** indicates p-value <5% * indicates p-value <10%]

increase foreign currency spreads by 0.4%. That is, the pass-through to import prices is imperfect in the short run. This indicates that the rate of absorption into foreign currencies after exchange rate fluctuations is high and the pass-through to domestic currencies is very low. This result is consistent with results from the incomplete pass-through literature. Long-term ERPT is slightly higher than short-term, but still incomplete. Overall, our results confirm conventional wisdom that the degree of ERPT is imperfect in the short term. However, in the long term, we find no evidence of complete pass through. The next step is to test the impact of several macroeconomic factors (as faced by South Asian countries) on the magnitude of pass-throughs such as local currency depreciation and appreciation. To see if these events affected import price responsiveness, we create the dummy variable D: This variable takes the value 1 during periods of currency depreciation and 0 otherwise. We use the Wald test for structural breaks to identify periods of abrupt exchange rate movements for a given country. Then, once one or more breaks have been identified, combined with visual inspection of the NEER series, periods of high and low exchange rates can be distinguished, respectively (see Table 4).

We then re-formulate Eq. (6) by including interactive dummy variable separately for each country "*i*" of interest as follows (see Table 5):

Table 4 Structural-break test

Countries	India	Iran	Pakistan	Srilanka	Bangladesh
S Wald statistics	55.7837 (0.000)	173.3604 (0.000)	53.8733 (0.000)	223.8500 (0.000)	37.5530 (0.000)
Estimated break year	1997	1996	1999	2004	2004

Source Author's calculations
Note Figures in parenthesis are *p*-values

$$\Delta p_{it}^{m} = \alpha_i + \mu_t + \beta_1 + \beta_2 \Delta mc_{it} + \beta_3 \Delta gdp_{it} + \beta_4 to_{it} + \beta_5 D + \beta_6 (D * \Delta e_{it}) + \varepsilon_{it} \quad (7)$$

To see if the interactive term affects the extent of propagation, we compute the short-term ERPT as $(\beta_1 + \beta_6)$. The use of dummy interactive variables to capture the effects of some specific event is a typical approach in the empirical literature. For example, Bailliu and Fujii (2004) used two dummy policy variables to represent fluctuations in prices(inflation) in the 1980s and 1990s to test the impact of a transition to a low-inflation regime on his ERPT. The results show that short-term pass-through is significant in all countries and generally higher than the panel's estimates. Pass-through is relatively high in all counties except Pakistan. The pass-through elasticity derived from the estimated coefficients depends on the depreciation or appreciation of each country's domestic currency. This is particularly evident for countries such as Bangladesh and Sri Lanka from the significant coefficients of both the appreciation and depreciation dummy, and the interaction term between the dummy variables and the exchange rate. The results point to the fact that during the depreciation period, the absorption of foreign currency markup is generally higher, the foreign currency price of imported goods rises, and the demand for imports in the importing country shrinks. This result is, therefore, consistent with the predictions of the classical open macroeconomic literature.

Table 5 Effect of macroeconomic events on ERPT

Countries	India	Iran	Pakistan	Srilanka	Bangladesh
Δe_t	3.44* (1.88)	0.14* (1.69)	0.27* (1.19)	1.24** (2.15)	0.89** (4.20)
D	−0.10 (−0.87)	0.76 (0.53)	0.06 (0.60)	0.11*** (2.62)	−0.0009 (−0.02)
$(D^* \Delta e_t)$	−2.57 (−1.36)	0.26 (0.71)	−0.09 (−0.06)	1.77** (2.22)	0.46 (0.48)
SR ERPT	0.87*	0.40*	0.18*	3.01**	0.42**

Source Author's Calculations
Note Figures in brackets are Z values
[*** indicates *p*-value <1% ** indicates *p*-value <5% * indicates *p*-value <10%]

4 Conclusions

This paper evaluates the first stage pass-through, the reaction of import prices to changes in exchange rates, for a sample of five South Asian countries. The results show imperfect pass-through to import prices in the short term. This indicates that the rate of absorption into foreign currencies after exchange rate fluctuations is high and the pass-through to domestic currencies is almost zero. This result is consistent with results from the incomplete pass-through literature. Long-term ERPT is marginally more than short term, but remains incomplete. Overall, our results are in alignment with the previous literature that shows the degree of ERPT is imperfect in the short term. Nonetheless, we find no evidence of complete of transmission exchange rate fluctuations to import prices in the long term. Furthermore, the study shows that short-term pass-through is significant in all countries and generally higher than the panel's individual estimates. Of the five South Asian countries analyzed in this study, Pakistan has the lowest pass-through elasticity. Consistent with our expectations, the pass-through elasticity revealed by the estimated coefficients depends on the depreciation or appreciation of each country's local currency. This is manifested by the significant coefficients of both the dummy variable indicating an increase or decrease and the interaction term with the dummy variable and the exchange rate, especially in countries like Bangladesh and Sri Lanka. This result leads to an empirical reassessment of traditional theory that devaluing the exchange rate leads to higher import prices, making products less attractive in the domestic market and reducing import volumes. The results obtained from this study suggest that exchange rate is an important macroeconomic policy tool that helps in reducing imports and driving economic growth on the one hand and contain the current account deficit on the other.

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Export Decision and Export Performance of Manufacturing Firms an Experience from Indian Organized Sector

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1 Introduction

In the era of globalization, export performance is considered to be one of the important factors in determining the long-run growth and sustainable development of an economy. Export growth helps to utilize the unemployed resources, increase the productivity, expand the market size, and helps to reap the benefits of scale economies. Gradually, the focus of international economics is shifted from country or industry to firm. Micro econometric analysis emphasizes on the study of firms' behavior in international market. Melitz (2003) provides a theoretical backdrop of international activities of heterogeneous firms. Two streams of literature evolve to understand the impact of firm-level heterogeneity on their trade behavior. Linkage between productivity and international activity of a firm is the main hypothesis of the first type of literature, whereas second type of literature discusses about the importance of sunk cost in determining the variation of firm-level export performances.

Productivity and efficiency are two indigenous characteristics of a firm that is important in determining the competitiveness of the firm in national and international market. There are two alternate hypotheses. The first hypothesis is based on self-selection theory of a behavioral firm and the second hypothesis is based on the "learning-by-exporting" theory. The first hypothesis states that a more productive and efficient firm chooses to enter the export markets. Exports involve various costs like transportation costs, cost of gathering information about foreign markets,

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advertising or marketing cost, hiring cost of off-shore managers, modifying cost of current domestic products according to international taste and preference (Wagner, 2012). A more productive and efficient firm is able to bear these costs more easily vis-à-vis an inefficient firm. Foresighted firms, with a desire to enter into the export market in future, improve their performance and competitiveness in pre-entry period. According to this hypothesis, firm-level productivity differences can be one of the causes of entry into the export market.

The second hypothesis states that exporting firms become more productive after their entry to export market. This hypothesis is based on "learning-by-exporting" theory. Knowledge transfer and international competition improve the productivity and efficiency of the exporting firms. Bernard and Jensen (1999, 2004) examined the first hypothesis and found that exporting firms are relatively more productive than non-exporting firm. Wagner (2007) has studied the second one and has failed to conclude any definite result. Balakrishnan et al. (2000) have not observed any acceleration in the productivity growth after trade liberalization in the Indian manufacturing industry. Sharma and Mishra (2011) investigated the self-selection hypothesis and learning-by-exporting hypothesis in the context of Indian manufacturing firms over the time period 1994–2006. They observed evidence of self-selection but not the presence of learning by export. Ranjan and Raychaudhuri (2011) found the evidence of self-selection hypothesis in the context of Indian manufacturing firms using CMIE—Prowess database. They also found out the positive impact of learning-by-exporting on the performance of exporting firms. Fernandes and Isgut (2015) examined the learning-by-exporting hypothesis and found a positive effect of learning-by-exporting on the performance of Colombian manufacturing firms.

There is another stream of literature discussing the importance of sunk cost on firm-level export performance. Export performance is perpetual in nature due to the presence of sunk costs. It implies that current export market participation is affected by past experience. Roberts and Tybout (1997) investigated the impact of sunk cost on export decision. Following them, sunk cost and past export experience are regarded to be important in increasing the probability of a firm to export. Baldwin (1988), Dixit (1989a, 1989b), and Krugman (1984) proposed that firms need to incur the sunk entry cost before entering into the export market. Now, it is expected that productive firms are more capable to bear such costs. Once the firm has incurred the sunk cost, it tries to remain in the export market. Hence, exporting behavior of a firm is usually perpetual in nature. The presence of sunk entry cost and sunk exit cost produce hysteresis export behavior of a firm. The present paper is unable to examine the sunk cost hysteresis hypothesis as it intends to undertake cross-sectional study of Indian manufacturing firms. Besides these productivity and sunk cost-related hypothesis, many other factors are also important in determining the export behavior of the firms. Market demand, availability of close substitute, relative prices of the substitute, world income, taste and preferences, etc., are the demand side factors, whereas, production capacity, productivity, managerial efficiency, world price versus domestic price, quality standard, etc., are the supply side variables (Sinha Roy, 2001; Raychaudhuri et al., 2003).

This paper intends to study the export decision as well as export performances of Indian manufacturing firms. Availability of information and increasing global market accessibility are expected to improve the firm-level export performance (Srinivasan and Archana, 2011). However, there is a wide variation in the export performance across firms in organized manufacturing sector. Larger and productive firms are expected to be the better performers in the export market (Helpman, 2006; Fu et al., 2010; Bas and Causa, 2013; Pradhan & Zohair, 2015; Kemme et al., 2014). Ownership pattern is also an important factor in determining the firm-level export performance. Existing literature highlights two types of ownership issues; foreign vs. domestic ownership and state vs. private ownership. Foreign-owned firms are better performer than the domestic firms in the export market (Filatotchev et al., 2008; Fu et al., 2010; He et al., 2012; Ghosh & Roy, 2016). Foreign ownership along with foreign management improves the export performances of the firms. There is a debate on state versus private ownership issue. Zhang et al. (2001) show that state-owned enterprises are less competitive and poor performers in the export market whereas Yi et al. (2012) show that state ownership has improved the export performance of the Chinese firm during 2005–2007. However, there are limited numbers of literature addressing the issue of state versus private ownership in the context of the Indian manufacturing industry. The present research intends to analyze the impact of state versus private ownership in determining inter-firm variation in the context of their export decision and export performance.

Technical efficiency, high productivity, quality standard, and usage of advance technology make a firm relatively more competitive in the export market (Granér and Isaksson, 2009; Aggrey et al., 2010; Bangwayo-Skeete and Moore, 2015). It is expected that the efficient firm will export more. Few sector-specific studies are available to examine the impact of technical efficiency in determining variation in inter-firm export performance (Bhavani & Tendulkar, 2001). There is no study that addresses the issues of technical efficiency and firm-level export performance considering the whole Indian manufacturing industry. The present paper tries to bridge that research gap. It uses stochastic frontier analysis to calculate firm-level efficiency.

Usage of advance technology can be instrumented by import intensity (Pant, 1993; Dholakia & Kapur, 2004), R&D intensity (Kemme et al., 2014), and in-house R&D expenditure (Ghosh & Roy, 2016). Bangwayo-Skeete and Moore (2015) empirically show that having international quality standard certification helps the manufacturing firms of developing countries to penetrate the export market.

This cross-sectional study intends to analyze the impact of firm-level heterogeneity in explaining inter-firm variation in the export decision and export performances in the context of the Indian organized manufacturing industry. The paper is structured in the subsequent manner. Following two sections delineate the methodology, data description, and data exploration. Fourth section contains empirical analysis. The last section summarizes the major findings and provides some concluding remarks.

2 Data Description and Methodology

Most firm-level studies in the Indian context use CMIE-Prowess database (Pradhan & Zohair, 2015, Ghosh & Roy, 2016). Here, ASI unit-level data for the year 2011–12 has been considered (MoSPI Annual Survey of Industries, 2009). ASI unit-level data is relatively more comprehensive and larger in size. ASI firm-level data also provides the information on NIC classification. This information is not available in CMIE-Prowess database. The total number of firms is 84806, but a large number of firms either have no information or have incomplete information. Hence, 11,188 firms have been considered for the final analysis. These firms are located in 30 states and Union Territories. Sixty-six three-digit manufacturing industries have been considered here.

Two equations are estimated here using the Heckman regression technique. First equation addresses the issue related to export decision, known as selection equation, whereas the second one addresses the issue related to export performance of the firms, known as outcome equation.

- *Selection Equation*:

Dependent Variable:

$$\text{Decision to Export } = 1,\ \text{if firm decides to export} \\ = 0,\ \text{otherwise}$$

$$\begin{aligned}\text{Decision to Export} = \beta_0 + \beta_1 \text{technical efficiency} + \beta_2 \text{urban code} + \beta_3 \text{ownership} + \\ \beta_4 \text{Skill intensity} + \beta_5 \text{usage of imported inputs} + \\ \beta_6 \text{quality standard} + \beta_8 \text{State - wise location dummy} + U_1\end{aligned} \quad (1)$$

Here, decision to export is a binary variable.

- *Outcome Equation*:

Dependent Variable:

Share of Export (it is a continuous variable), if decision to export = 1 then only share of export variable is observable.

$$\begin{aligned}\text{Share of Export } = \alpha_0 + \alpha_1 \text{ technical efficiency } + \alpha_2 \text{ urban code } + \alpha_3 \text{ ownership} \\ + \alpha_4 \text{ Skill intensity } + \alpha_5 \text{ usage of imported inputs } + U_2\end{aligned} \quad (2)$$

U_1 and U_2 follow normal distributions. Heckman–Tobit model formulation requires that at least one variable included in the selection model must be omitted from the outcome equation. In this case, the variables "***State-wise location dummy***" and "***quality standard***" are excluded from the outcome equation. The rationale is given as follows: For the Indian firms, location is very important for their cost efficiency, as not all states are equally endowed with infrastructural facilities. It generally affects their export decision. Secondly, the binary variable "quality standard" assumes that quality certification is important a value equal to unity, if the firm has ISO certification. Again, following the "self-selection hypothesis" a firm with higher quality standard is more likely to opt for export market. However, export performance will not depend on the place of location or ISO certification. Thus, the above variables are incorporated in the selection equation but omitted from the outcome equation. Maximum likelihood method is used for estimation along with robust standard error assumption.

Detailed description of the variables are given below,

- $\begin{aligned}\text{Export decision } &= 1,\ \text{if Firm exports}\\ &= 0,\ \text{otherwise}\end{aligned}$
- Share of Export = Share of export is expressed as a percentage of gross output
- Technical efficiency = Efficiency is one of the important factor in determining the export decision as well as export performance of the firm. To calculate firm-level efficiency, stochastic frontier analysis is used (detailed discussion on stochastic frontier analysis is given in the next section)
- $\begin{aligned}\text{Urban\_code } &= 1,\ \text{if firm is situated in urban area}\\ &= 0,\ \text{otherwise}\end{aligned}$
- $\begin{aligned}\text{Ownership } &= 1,\ \text{for private firm}\\ &= 0,\ \text{for State} - \text{owned firm}\end{aligned}$
- $\begin{aligned}\text{ISO\_code } &= 1,\ \text{if firm has ISO certification}\\ &= 0,\ \text{otherwise}\end{aligned}$
- $\begin{aligned}\text{Usage of imported inputs } &= 1,\ \text{if firm uses imported input}\\ &= 0,\ \text{otherwise}\end{aligned}$
- Skill intensity = wages to the managerial stuffs, supervisor, administrative staff, etc.,/wages to the production workers
- $\begin{aligned}\text{Usage of computer } &= 1,\ \text{if firm uses computer}\\ &= 0,\ \text{otherwise}\end{aligned}$

Annual Survey of Industry provides definition of the variables,

Gross Output: Gross output is defined as the ex-factory value of products and by-products manufactured during the accounting year, and the net value of the semi-finished goods, work-in-process and also the receipts for industrial and non-industrial services rendered to others.

Gross Fixed Capital Formation: Gross fixed capital formation (GFCF) refers to the net increase in physical assets within an accounting year. Physical assets are those, which have a normal productive life of more than one year. Fixed capital covers all type of assets, new or used or own constructed, deployed for productions, transportation, living or recreational facilities, hospitals, schools, etc., for factory personnel. It would include land, buildings, plants and machineries, transport equipments, etc. It includes the fixed assets of the head office allocable to the factory and also the full value of assets taken on hire-purchase basis (Whether fully paid or not) excluding interest element. It excludes intangible assets and assets solely used for post-manufacturing activities such as sale, storage, distribution, etc.

Production Workers: Number of workers directly employed or involved in the production process.

Non-production Workers: Total number of employees less the Production workers. It includes persons holding position of supervision or management or engaged in administrative office, store-keeping section and welfare section, watch and ward staff, sales department as also those engaged in the purchase of raw materials, etc., and production of fixed assets for the factory. It also includes all working proprietors and their family members who are actively engaged in the work of the factory.

2.1 Stochastic Frontier Analysis

Efficiency is one of the important factors in determining the export decision as well as export performance of the firm. It is expected that the efficient firm will export more. To calculate firm-level efficiency, stochastic frontier analysis has been used (Kumbhakar and Lovell, 2000; Roy Biswas and Ghose, 2012; Ghose, 2016). Firms have been classified industry-wise and sixty-six three-digit manufacturing industries have been considered. Here three-digit NIC 2008 classification has been followed.

The measurement of Technical Efficiency (TE) was effectively started with the analysis of Farrell (1957). Output-oriented TE is a comparison between observed output and the maximum potential output obtained using given inputs. In this study, Stochastic Frontier Production Model (developed by Aigner et al., 1977) is adopted to estimate TE.

Considering a Stochastic Frontier Production Function (SFPF)

$$Y_i = f(X_i, t; \beta) \exp(v_i) \tag{3}$$

representing the maximum producible output by the ith producing unit given the non-negative input vector X_i with

$\beta =$ the corresponding vector of technology parameters and

$v_{\mathrm{i}} =$ a random variable seeking to capture all the random factors that are outside the control of the producer (such as weather, strikes, factor intensity, implementation of some reform policies, etc.). These random factors are likely to affect the production of maximum possible output.

$t =$ time period.

Actually, the ith producing unit's observed output; Y_i may lies below the frontier output due to factors like the presence of workers with lower ability, poor management decisions, or inadequate monitoring efforts, etc. These shortfalls are captured by technical inefficiency of the producing unit. Since, the actual output cannot be higher than the frontier output, Eq. (3) can be modified as

$$Y_i = f(X_i, t; \beta)\exp(v_i)\exp(-u_i) \tag{4}$$

with $u_i \geq 0$ implying that $\exp(-u_i) \leq 1$.

So, an output-oriented Farrell measure of time-varying TE of the ith-producing unit can be presented as:

$$\mathrm{TE}_i = \frac{Y_i}{f(X_i, t; \beta)\exp(v_i)} = \exp(-u_i) \tag{5}$$

for $u_i \geq 0$ and TE_i varies inversely with u_i, $0 \leq \mathrm{TE}_i \leq 1$. u_i may be taken as index of inefficiency.

It is to be noted that $v_i$and $u_{i,}$ i.e. the two error terms are included in the expression. v_i is the usual error term of the model and is independently, identically, normally distributed with mean = 0 and variance = σ^2. u_i measures the magnitude of technical inefficiency in production of the ith producing unit. It is independently distributed from a normal distribution with mean = μ_i and variance = σ_u^2, truncated at zero. Further, it is assumed that there is no correlation between v_i and u_i.

Five variables are used in the empirical analysis. Definitions of concepts like ex-factory value, fixed asset, and man-days are given below:

Output (Y):	total value of ex-factory products and by-products produced by the firm during the year in question.
Capital (FA):	net value of fixed assets of the firm at the beginning of a year.
Labour (L):	total number of man-days worked during the year.
Intermediate inputs (I):	nominal value of inputs (both indigenous and imported, including power and fuels) used by the firm during the year.
Age (A):	difference between the current year and firm's initial production year.

To estimate the time-varying technical inefficiency prevailing across different firms in a particular industry, the methodology of Battese (1993) and Lundvall and Battese (2000) is followed. The stochastic frontier production function is taken to be a translog form due to its flexible nature:

$$\ln Y_i = \left[\beta_0 + \sum_{j=1}^{4}\beta_j x_{ji} + \sum_{j\leq}^{4}\sum_{k=1}^{4}\beta_{jk}x_{ji}x_{ki}\right] + (v_i - u_i)$$

Here, the subscript i refers to the ith firm, $i = 1, 2, 3\ldots\ n$, where n is the number of unit-level firms

$$X_{ji} = \text{the amount of } j\text{th input used by the } i\text{th firm, and}$$
$$x_{ji} = \text{the natural logarithm of } X_{ji},\ j = 1, 2, 3, 4.$$

3 Data Exploration

This section first presents some basic descriptive statistics and then undertakes some intrinsic analysis.

Tables 1 and 2 describe the basic distribution pattern of explanatory variables. Table 1 shows that the average technical efficiency of 11,188 firms is 0.875779, with maximum value 0.98 and minimum value 0.03, whereas skill intensity has average at 1.105617 with maximum at 701.4879 and minimum at 0. It indicates that skill intensity has a wide range of variation than technical efficiency.

Table 2 describes the proportional distribution of Urban location dummy, quality standard dummy, usage of imported input dummy, and ownership dummy.

Table 1 Descriptive statistics of technical efficiency and skill-intensity

Variable name	Mean	Std. dev.	Min.	Max.
Technical efficiency	0.875779	0.093303	0.03	0.98
Skill-intensity	1.105617	6.958826	0	701.4879

Source Authors' calculation on the basis of ASI data, MoSPI Annual Survey of Industries, 2011–12

Table 2 Proportional distributional of urban-location dummy, quality standard dummy, usage of imported input dummy, and ownership dummy

Name of the variables	Proportion	Std. err
Urban location dummy		
Rural	0.40202	0.00463
Urban	0.59798	0.00463
Quality standard dummy		
Not having certificate	0.86718	0.00321
Having certificate	0.13282	0.00321
Usage of imported input dummy		
Not using imported input	0.83052	0.00354
Using imported input	0.16948	0.00354
Ownership dummy		
Private firm	0.22505	0.00394
State-owned firm	0.77495	0.00394

Source Authors' calculation on the basis of ASI data, MoSPI Annual Survey of Industries, 2011–12

Table 2 describes that around 40% of the firms are located in rural area and the rest 60% is located in urban area. Most of the firms, around 87%, does not have ISO-quality certificate, whereas around 83% of firms are not using imported inputs. Majority of the firms, around 77%, are privately owned whereas the rest 23% is state-owned.

Thirty states and union territories and 66 3-digit industries are considered here. Table 3 provides the individual state-wise distribution of exporting and non-exporting firms. ASI unit-level database reveals that Bihar, Sikkim, Nagaland, Manipur, Tripura, Meghalaya, and Andaman & Nicobar Island do not have any exporting firms. Haryana has the highest percentage of exporting firm followed by Delhi and Uttar Pradesh. Kerala, Maharashtra, Karnataka, and Tamil Nadu are the other better-performing states. Punjab, West Bengal, Gujarat, and Rajasthan have moderate percentage of exporting firms.

Table 4 shows the ownership-wise distribution of exporting and non-exporting firms for the year 2011–2012. It shows that the percentage of exporting firm is higher for state-owned firms than private-owned firms. 20.41% state-owned firms are exporting, whereas the share is only 15.88% for the private-owned firm. Another interesting observation shows that average technical efficiency is higher for state-owned firms than private firms.

Table 5 describes the industry-wise distribution of exporting and non-exporting firms and their average technical efficiency. Service (residential and social), refined petroleum products, motor vehicles manufacture, man-made fibers, domestic appliances, basic precious and other non-ferrous metals, vegetable and animal oils and fats, irradiation, electro-medical and electrotherapeutic equipment, and installation of industrial machinery and equipment industry have average technical efficiency of more than 90%, whereas publishing of books, periodicals, and other publishing activities, air and spacecraft and related machinery, repair of fabricated metal products, machinery and equipment, and warehousing and storage sector have average technical efficiency of less than 80%. On the other hand, the share of exporting firms is more than 40% in processing and preserving of fish, crustaceans and mollusks, wearing apparel, except fur apparel, tanning and dressing of leather; manufacture of luggage, handbags, saddlery and harness; dressing and dyeing of fur, jewelry, bijouterie and related articles, manufacture of knitted and crocheted apparel, and sports goods industry.

Data exploration fails to establish one-to-one mapping among export performance, ownership pattern, and technical efficiency. This demands a more comprehensive econometric analysis. Next section delineates the results of that analysis.

Table 3 Individual state-wise firm-level export performance

State	% of non-exporting firms	% of exporting firms
J&K	98.48	1.52
H.P	93.56	6.44
Punjab	80.68	19.32
Chandigarh	96.88	3.13
Uttarakhand	94.67	5.33
Haryana	67.36	32.64
Delhi	70.05	29.95
Rajasthan	84.83	15.17
U.P	70.05	29.95
Bihar	100.00	0.00
Sikkim	100.00	0.00
Nagaland	100.00	0.00
Manipur	100.00	0.00
Tripura	100.00	0.00
Meghalaya	100.00	0.00
Assam	95.11	4.89
West Bengal	81.80	18.20
Jharkhand	97.64	2.36
Odisha	92.54	7.46
Chhattisgarh	95.00	5.00
M.P	95.19	4.81
Gujarat	84.30	15.70
Maharashtra	73.61	26.39
A.P	87.30	12.70
Karnataka	78.03	21.97
Goa	92.55	7.45
Kerala	71.63	28.37
T.N	78.30	21.70
Puducherry	88.46	11.54
A&N. Island	100.00	0.00

Source Authors' calculation on the basis of ASI data, MoSPI Annual Survey of Industries, 2011–12

Table 4 Ownership-wise exporting and non-exporting firms (in percentage) 2011–2012

Decision to export	State-owned firms	Private-owned firms	Total
% of exporting firms	20.41	15.88	16.9
% of non-exporting firms	79.59	84.12	83.1
Mean technical efficiency	0.891221	0.871295	–

Source Authors' calculation on the basis of ASI data, MoSPI Annual Survey of Industries, 2011–12

4 Empirical Analysis

Empirical research explains two issues; export decision and export performance at firm level. The Heckman selection model is used here to address these issues simultaneously. Estimation of selection equation analyses the role of firm-level characteristics in determining the inter-firm variation in their export decision. Table 6 provides the estimation result of selection equation.

Empirical estimation shows that the probability of a firm to export increases with the increase in technical efficiency. The technically efficient firms have a relatively high probability to enter into the export market supporting the hypothesis of self-selection decision (Helpman, 2006; Wagner, 2012). This finding is consistent with the few sector-specific research (Bhavani & Tendulkar, 2001). Urban locational advantages, quality standard and usage of imported input also have significant positive impact on the probability of a firm to export. Connectivity and transportation facility are better in urban areas, this increases the probability of a firm to enter into the export market. Having ISO certification ensures the information regarding quality of the product and hence helps the domestic firm to penetrate the international market (Bangwayo-Skeete & Moore, 2015). Importation of inputs may involve technological transfer that may increase the probability of a firm to export. Skill intensity does not have any significant effect on the probability of a firm to export. State-specific geographical location has a significant positive impact on the export decision of a manufacturing firm. There is an interesting observation noticed regarding ownership pattern of exporting firm. Empirical results confirm that public or government-owned firm has a significant advantage over the private firm in case of entry in international market (like Yi et al., 2012). Estimated marginal effect shows that a government firm has around 1.8% more probability than a private firm to be an exportable firm. Results of other marginal effects demonstrate that technical efficiency, usage of imported input, and urban location are the three most important factors to increase the probability of a firm to export. Increase in technical efficiency and usage of imported input raise the probability of a firm to export by more than 10%. Having the quality standard increases the probability of the firm to export by more than 3%.

Table 5 Industry-wise distribution of exporting and non-exporting firms (in percentage) and their average technical efficiency (2011–2012)

Name of the industry	Industry	Non-exporting	Exporting	Mean technical efficiency
Processing and preserving of meat	101	65.71	34.29	0.85371
Processing and preserving of fish, crustaceans, and mollusks	102	39.58	60.42	0.88125
Processing and preserving of fruit and vegetables	103	77.42	22.58	0.85355
Vegetable and animal oils and fats	104	96.64	3.36	0.90248
Dairy products	105	97.4	2.6	0.8924
Grain mill products, starches, and starch products	106	94.26	5.74	0.86533
Manufacture of other food products	107	88.62	11.38	0.86989
Manufacture of prepared animal feeds	108	94.34	5.66	0.88472
Tobacco product	120	90.41	9.59	0.87644
Spinning, weaving and finishing of textiles	131	85.08	14.92	0.82566
Manufacture of other textiles	139	67.76	32.24	0.86927
Wearing apparel, except fur apparel	141	41.57	58.43	0.88181
Manufacture of knitted and crocheted apparel	143	58.33	41.67	0.86201
Tanning and dressing of leather; manufacture of luggage, handbags, saddlery, and harness; dressing and dyeing of fur	151	50	50	0.86931
Footwear	152	69.51	30.49	0.87335
Sawmilling and planning of wood	161	100	0	0.83385
Products of wood, cork, straw, and plaiting materials	162	88.03	11.97	0.87855
Paper and paper products	170	92.64	7.36	0.8804
Printing and service activities related to printing	181	84.94	15.06	0.8388

(continued)

Table 5 (continued)

Name of the industry	Industry	Non-exporting	Exporting	Mean technical efficiency
Coke oven products	191	96.15	3.85	0.86423
Refined petroleum products	192	85.71	14.29	0.91393
Basic chemicals, fertilizer, and nitrogen compounds, plastics, and synthetic rubber in primary forms	201	77.81	22.19	0.89749
Other chemical products	202	85.64	14.36	0.89332
Man-made fibers	203	66.67	33.33	0.908
Pharmaceuticals, medicinal chemicals, and botanical products	210	80.22	19.78	0.89171
Rubber products	221	80.95	19.05	0.88673
Plastics products	222	90.13	9.87	0.88456
Glass and glass products	231	79.41	20.59	0.87338
Non-metallic mineral products n	239	92.4	7.6	0.84991
Basic iron and steel	241	88.52	11.48	0.89301
Basic precious and other non-ferrous metals	242	83.33	16.67	0.90256
Casting of metals	243	85.28	14.72	0.87939
Structural metal products, tanks, reservoirs, and steam generators	251	89.16	10.84	0.86486
Weapons and ammunition	252	100	0	0.824
Other fabricated metal products; metalworking service activities	259	78.77	21.23	0.87438
Electronic components	261	79.52	20.48	0.88205
Computers and peripheral equipment	262	75	25	0.81563
Communication equipment	263	80.95	19.05	0.86
Measuring, testing, navigating, and control equipment; watches and clocks	265	84.62	15.38	0.89154
Irradiation, electro-medical and electrotherapeutic equipment	266	69.23	30.77	0.90231

(continued)

Table 5 (continued)

Name of the industry	Industry	Non-exporting	Exporting	Mean technical efficiency
Optical instruments and equipment	267	100	0	0.87778
Electric motors, generators, transformers, and electricity distribution and control apparatus	271	80.66	19.34	0.89155
Batteries and accumulators	272	94.59	5.41	0.88486
Wiring and wiring devices	273	85.96	14.04	0.87702
Electric lighting equipment	274	77.08	22.92	0.89292
Domestic appliances	275	87.5	12.5	0.90361
Other electrical equipment	279	91.14	8.86	0.89899
General purpose machinery	281	80.8	19.2	0.88827
Special-purpose machinery	282	82.63	17.37	0.87793
Motor vehicles manufacture	291	92.11	7.89	0.91211
Parts and accessories for motor vehicles	293	82.88	17.12	0.8875
Railway locomotives and rolling stock	302	93.33	6.67	0.88956
Air and spacecraft and related machinery	303	71.43	28.57	0.78857
Transport equipment n.e.c	309	87.98	12.02	0.8912
Furniture	310	93.33	6.67	0.87947
Jewelry, bijouterie, and related articles	321	54.76	45.24	0.895
Sports goods	323	59.38	40.63	0.88125
Medical and dental instruments and supplies	325	68.29	31.71	0.87634
Other manufacturing	329	75.41	24.59	0.8623
Repair of fabricated metal products, machinery, and equipment	331	100	0	0.78444
Installation of industrial machinery and equipment	332	83.33	16.67	0.9
Electric power generation, transmission, and distribution	351	100	0	0.892

(continued)

Table 5 (continued)

Name of the industry	Industry	Non-exporting	Exporting	Mean technical efficiency
Gas; distribution of gaseous fuels through mains	352	91.67	8.33	0.88417
Warehousing and storage	521	100	0	0.42857
Publishing of books, periodicals, and other publishing activities	581	100	0	0.794
Service (residential and social)	893	100	0	0.92

Source Authors' calculation on the basis of ASI data, MoSPI Annual Survey of Industries, 2011–12

Table 6 Inter-firm variation in the export decision

Dependent variable: decision to export				
Variables	Coefficient	Significance	Marginal effect	Significance
Technical efficiency	1.276***	0.000	0.312***	0.000
Urban code	0.242***	0.000	0.059***	0.000
Ownership	–0.075**	0.034	–0.018**	0.034
Skill intensity	–0.0002	0.846	–0.00006	0.846
Usage of imported inputs	0.427***	0.000	0.104***	0.000
Quality standard	0.143***	0.000	0.035***	0.000
State-wise location dummy	0.006***	0.000	0.001***	0.000
Constant	–2.320***	0.000	–	–

Source Authors' calculation
Note "***" indicates 1% level of significance, "**" indicates 5% level of significance, "*" indicates 10% level of significance

After analyzing the export decision at firm level, Table 7 delineates the impact of various factors in determining the variation in inter-firm export performances. Urban locational advantages and usage of imported input have a significant positive impact on the export performance, measured by the share of export, at firm level. Positive significant coefficient of urban location dummy implies that the urban firms export more than the rural firms. On the other hand, the usage of imported inputs ensures the transmission of sophisticated technology and global standard, which in turn improves the export performances of the manufacturing units. Skill intensity, however, has a significant negative impact on export performance of a firm, implying that the share of export increases with the increase in the proportion of production workers relative to the non-production workers. Exporting firms reduce the top-level managers and supervisor relative to the direct production workers to be more cost-effective.

Ownership pattern has a significant positive impact on the export performance of the firm. Private firms export a larger share of their output than the state-owned

Table 7 Inter-firm variation in the export performance

Dependent variable: share of export		
Variables	Coefficient	Significance
Technical efficiency	−13.817	0.274
Urban code	12.318***	0.000
Ownership	17.385***	0.000
Skill intensity	−0.863**	0.048
Usage of imported inputs	5.460**	0.017
Constant	−12.202	0.382
Wald test of indep. eqns. (rho = 0): chi2(1) = 52.59 Prob > chi2 = 0.000		

Source Authors' calculation
Note "***" indicates 1% level of significance, "**" indicates 5% level of significance, "*" indicates 10% level of significance

firms. It implies that ownership pattern enhances the export performance of the manufacturing firms though it has some conflicting impact on the export decision. At the entry-level, state-owned firms enjoy the advantage over private one; however, the latter one is the better performer than the former one in terms of export share. Technical efficiency does not have any significant impact on export performances.

After investigating the direct impact of technical efficiency and ownership pattern on firm-level export performance, the paper intends to explore the indirect effect of ownership pattern on export decision and export performance of a firm through improving technical efficiency. Ownership patterns may influence the technical efficiency and productivity of a firm, which in turn may affect the firm-level export decision and export performance. Table 8 describes the indirect impact of ownership on export decision of an Indian manufacturing firm. Empirical results illustrate that ownership pattern does not have any significant influence on the impact of technical efficiency on export decision. It implies that ownership pattern does not influence the positive impact of technical efficiency on export decision of the firm. Other explanatory variables, however, have the expected impacts on the entry decision of the firm.

Table 9 describes the indirect effect of the ownership pattern on the export performance of the manufacturing units. It delineates that technical efficiency has a significant positive impact on the export performance of a private firm; however, there is no significant effect of the same export share of a public firm. Other control variables have the usual expected impact on export share of a firm.

Table 8 Indirect effect of ownership pattern on export decision at firm level

Dependent variable: decision to export				
Variables	Coefficient	Significance	Marginal effect	Significance
Technical efficiency	1.258301***	0.000	0.301361***	0.000
Technical efficiency X ownership pattern	−0.05887	0.131	−0.0141	0.131
Urban code	0.221372***	0.000	0.053018***	0.000
Skill intensity	−0.00056	0.810	−0.00013	0.810
Usage of imported inputs	0.406614***	0.000	0.097384***	0.000
Usage of Computer	0.785924***	0.000	0.188228***	0.000
Quality standard	0.115756***	0.005	0.027723***	0.005
State-wise location dummy	0.004188***	0.002	0.001003***	0.002
Constant	−3.04559***	0.000	–	–

Source Authors' calculation
Note "***" indicates 1% level of significance, "**" indicates 5% level of significance, "*" indicates 10% level of significance

Table 9 Indirect effect of ownership pattern on the export performance

Dependent variable: share of export		
Variables	Coefficient	Significance
Technical efficiency	9.615	0.780
Technical efficiency X ownership pattern	16.613***	0.000
Urban code	21.188***	0.000
Skill intensity	−0.833**	0.014
Usage of imported inputs	23.953**	0.010
Usage of computer	66.145***	0.001
Constant	−189.729**	0.031

Source Authors' calculation
Note "***" indicates 1% level of significance, "**" indicates 5% level of significance, "*" indicates 10% level of significance

5 Conclusion

In the conclusion, it can be stated that firm-level heterogeneity explains the variation in export decision and export performance of Indian organiszed manufacturing firms. This heterogeneity can be explained in terms of technical efficiency, spatial location, ownership pattern, technological advancement, and quality standard and skill intensity. It is observed that the efficient firms are better performers in the export market. Firms located in urban area have high potential to export due to spillover effect. Ownership pattern has diverging impacts on export decision and export performances across the manufacturing units. State-owned firm has higher probability than private firm to enter into the international market, whereas the latter one exports more than the former one. Certification of international quality standards helps Indian organized manufacturing firms to penetrate the export market. Usage of imported input involves technological transfer. Technological transfer enhances the export performance of the firm. Empirical research shows that Indian export-oriented firms are relatively production worker intensive. Besides this direct effect, indirect effects of ownership patterns on the export performance through enhancement of technical efficiency have also been examined. Estimated result confirms that technical efficiency raises the share of export significantly only for private firm and not for state-owned firm in Indian organized manufacturing sector.

Due to unavailability of information, we restrict our analysis to the state versus private ownership. Foreign ownership versus domestic ownership has not been considered here. Besides, we have not considered the sunk cost theory in explaining firm-level export performance. A detailed research in panel framework is required to capture the impact of sunk cost in explaining firm-level export performance.

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The Impact of Global Financial Crisis on the Efficiency of Indian Banks: Evaluation with Data Envelopment Analysis

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1 Introduction

From 2007 to 2008, the financial system around the world was hit hard by the Global Financial Crisis (GFC). Since the Indian financial system is dominated by the banking sector, which accounts for most of the financial resources, it was expected that the Indian banking sector would feel the same heat. However, GFC has not knocked as hard in the Indian banking system as globally (Gulati & Kumar, 2016) although, the shock of the GFC has led to an increase in non-performing loans, affecting the operational performance of the Indian banks (Gulati, 2022).

Commercial banks in India, as per the ownership, can be divided into three broad categories: public sector banks (PSBs), where Indian government is stakeholder; private banks (PVBs), owned by private entities; and foreign banks owned by overseas companies. Foreign banks on Indian soil operate with limited clientele, primarily focusing on institutional investment and international trade financing. The domestic banks (PSBs and PVBs) are the major players both in terms of the geographical reach and number of customers.

In 2017, amongst commercial banks, the domestic banks held about 96% of total deposits of which around 76% lie with PSBs (authors' calculation). Though PSBs and PVBs compete with each other, they face a somewhat different operating environment. Thus, their comparison using the same benchmark will be misleading. In fact, recent empirical studies (Casu et al., 2013; Gulati & Kumar, 2016; Goyal et al., 2019) find that there is a difference in the technologies with which they operate.

Globally, there is a large amount of literature on the analysis of banks' efficiency. Sharma et al. (2013) methodically review such studies published between 1994 and

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2011. The authors find that, in the multi-input multi-output production system, most of the studies have utilized data envelopment analysis (DEA) as the prominent tool to measure performance of banking industry, Further, they find that nearly half of the efficiency studies focus on technical efficiency (TE). In the efficiency analysis of banking services, there is no consensus on the inputs and outputs. However, it is observed that intermediation approach[1] is the most favored approach for technology set selection. Chaluvadi et al. (2018) provide a glimpse of the variety of technology sets used in banking studies across the world. We observe two salient features in the filtered literature: (i) except for a couple of studies, almost all the studies use radial TE models and (ii) most of the studies focus on the pre-global financial crisis period or compare the pre-crisis period and the crisis period. As per the authors' knowledge this is possibly the first study which, by using non-radial efficiency model, delves into evaluation of efficiency of Indian banks disaggregated across individual components of technology set. The composite efficiency scores obtained from traditional models, due to overlooking of possible input or output slacks in optimal solution, indicate same corrective action across all the components of technology set. The non-radial approach, by providing disaggregated scores, will help managers to focus on specific underperforming inputs and outputs to enhance productive efficiency.

Hence, there is a need for updating the efficiency studies on Indian banks using advanced DEA models and through this paper we intend to fill the gaps mentioned above. Given the tiny footprint of foreign banks on the Indian commercial banking landscape, we focus only on their domestic counterparts. More specifically, through this paper we try to address the following research questions: (i) how do PSBs and PVBs perform on the non-radial Russell measures of TE? (ii) how do the Russell measures affect the ranking of banks in comparison to conventional radial measures? (iii) was the non-radial TE of banks affected during the global financial crisis (GFC) of 2008? (iv) do the non-discretionary and production environment variables influence the Russell efficiency of PSBs and PVBs in a similar way? and (v) to identify the consistently poor-performing banks. The rest of the paper is organized in four sections. Section 2 gives a brief review of recent literature on DEA-based TE analysis of the Indian banking sector. Section 3 gives the methodological framework which includes both the theoretical as well as empirical models used in the study. Section 4 comprises of results and discussion, while Sect. 5 concludes the paper.

2 Literature Review

In the following paragraphs, we review some of the recent studies (since 2005) analyzing TE of Indian commercial banks using DEA. Das et al. (2005) evaluate the TE of 71 commercial banks from 1997 to 2003 for both input orientation and output

[1] As per the intermediation approach, banks operate as intermediaries of financial services between entities and facilitate the transfer of unemployed financial resources for productive utilization to generate financial assets.

orientation with variable returns to scale (VRS) assumption. They consider a four-inputs (borrowed funds, number of employees, fixed assets, and equity) and three-outputs (investments, performing loan assets, and other incomes) technology set. Using a common frontier for PSBs, PVBs, and foreign banks, they find that the banks are highly efficient across both the orientation with median annual efficiency score being above 0.98. Das and Ghosh (2006) investigate the performance of 98 commercial banks (unbalanced panel) from 1992 to 2002. They define a technology set comprising of five inputs (demand deposits, savings deposits, fixed deposits, capital-related operating expenses, and employee expenses) and two outputs (advances and investments). They compare the input-oriented constant returns to scale (CRS) and VRS TE scores and find that the annual mean TE varies between 0.81 (in the year 2002) and 0.96 (in the year 1999). Based on second-stage Tobit regression analysis, they observe that ownership (PSBs versus others), Capital Adequacy Ratio (CAR), and management quality (defined as ratio of operating expenses to total assets) significantly affect the TE scores. While state ownership and CAR have a positive impact, management quality has a negative impact on TE.

Kumar and Gulati (2008) study the efficiency of 27 PSBs for the year 2005. They use an input-oriented CRS model for three inputs (physical capital, labor, and loanable funds) and two outputs (net interest income and non-interest income) technology set to find that the TE scores vary between 0.63 and 1.0 with mean being 0.88. They perform second-stage ordinary least squares (OLS) regression and find that bank's size, bank's market share of deposits, and off-balance sheet activities have significant impacts on efficiency. Market share and off-balance sheet activities positively affect TE while size impacts negatively. Another paper from the same authors focuses on PSBs for the year 2007, and there they have used a different technology set. Kumar and Gulati (2010) use two outputs (advances and investments) and three inputs (physical capital, labor, and loanable funds) to calculate output-oriented CRS TE scores for comparison of banks' performance. They observe that the efficiency scores range between 0.78 and 1.0, with an average of 0.91. Further, they find that the mean efficiency score of large banks (asset size larger than median size) is more than that of the small banks.

Tandon et al. (2014) evaluate the productive efficiency of 44 commercial banks of different ownership for the period 2009–2012. They utilize a two-input (deposits and assets) and two-output (interest income and non-interest income) technology set to calculate the input-oriented VRS TE from the common frontier. They find that PVBs are most efficient with mean TE score of 0.96, followed by PSBs (mean TE score of 0.95) and then foreign banks with mean TE score of 0.93. To identify the important factors affecting the TE they conduct second-stage regression. Their results imply that business per employee and CAR positively impact efficiency, whereas profit per employee and non-interest income impact negatively. In another study, Tzeremes (2015) evaluates the impact of GFC on the productive performance of commercial banks. He calculates input-oriented VRS TE score of 64 banks for the period 2004–2012. The technology set utilized comprises three inputs (fixed assets, employees, and deposits) and two outputs (loans and other earning assets). The results indicate that, for all the years in the study period, PSBs are more efficient than PVBs. Further, the study reveals that PSBs are more consistent performers than private and foreign banks. The mean efficiency for the sample varies from 0.73 (in 2006) to 0.86 (in 2012).

Kumar et al. (2016) analyze output-oriented VRS TE of Indian domestic banks (19 PSBs and 14 PVBs) for the period 1996–2010. They calculate the TE scores from a common frontier using total cost and total deposits as inputs, and total loans and other earning assets as outputs. They observe that across the study period, for both PSBs and PVBs the mean TE score is around 0.94 with little difference between the categories. They further find that during pre-GFC period the PSBs and PVBs have similar efficiency with mean TE around 0.94. However, during GFC time PVBs with mean TE score of 0.97 slightly outperform PSBs (TE score of 0.95). Tamatam et al. (2019) analyze output-oriented TE of 21 PSBs and 17 PVBs for the period 2008–2017. The study employs two inputs (total assets and total deposits) and four outputs (advances, interest income, total income, and operating profit) technology set for calculation of efficiency. Over the study period, they observe the mean TE to be 0.97 and 0.98 for PSBs and PVBs respectively. Additionally, they compare the TE results obtained from 18 different DEA models across different orientations and returns to scale assumptions.

Recently, Khati and Mukherjee (2020) investigate the performance of Indian domestic banks in the post-global financial crisis period using Pareto–Koopmans (PK) efficiency scores to overcome the restrictive nature of radial and orientation-specific efficiency measures. The authors utilize a balanced panel of 26 PSB and 19 PVB from 2011 to 2017. Three inputs (loanable funds, physical capital, and labor) and three outputs (advances, investment, and other incomes) are used to define the technology set. The disaggregation of efficiencies into input- and output-specific components reveals that for PSB the inefficiencies primarily result due to fixed assets and other income while for PVB it is mainly because of other incomes, labor, and fixed assets. Second-stage regression analysis reveals that the PK efficiency has a non-linear relationship with size of the bank. Deposit to liability ratio negatively impacts the PK efficiency while priority sector lending has a positive influence on it.

3 Methodology

3.1 Theoretical Framework

Within the DEA framework, Charnes et al. (1978) provided the popularly known CCR model to measure TE in multi-input multi-output, CRS technology setup. Later, Banker et al. (1984) extended it to VRS technology which is commonly denoted as the BCC model. In both the models, the TE measure depends on the orientation of the benchmarking problem. For an input-oriented model, the efficiency score is calculated on the basis of maximum possible proportional reduction of all inputs (X) given the output bundle (Y_0). While in output-oriented model, the efficiency score is calculated on the basis of maximum possible proportional expansion of all outputs (Y) given the input bundle (X_0). To calculate the input-oriented VRS TE score for the 0th decision-making unit (DMU), we solve the following linear programming problem (LPP):

$$\begin{aligned}
&\min \theta \\
&\text{s.t.} \quad \sum_{j=1}^{N} \lambda_j Y_{rj} \geq Y_{r0}\, \forall\, r = 1, 2, \ldots m \\
&\sum_{j=1}^{N} \lambda_j X_{ij} \leq \theta X_{i0}\, \forall\, i = 1, 2, \ldots n \\
&\sum_{j=1}^{N} \lambda_j = 1;\ \lambda_j \geq 0\, \forall\, j = 1, 2, \ldots N
\end{aligned} \tag{1}$$

where, N is the number of DMUs, m is the number of outputs, n is the number of inputs, θ is the proportion to which all the inputs are reduced and λ_j is the component of jth DMU which is used to make the benchmark DMU. Solving the above LPP we get $\theta*$ which results in the efficiency score as ${\text{TE}^{\text{I}}}_0 = \theta*$. Following the same notations, the output-oriented VRS TE score for 0th DMU can be calculated by solving the following LPP:

$$\begin{aligned}
&\max \phi \\
&\text{s.t.} \quad \sum_{j=1}^{N} \lambda_j Y_{rj} \geq \phi Y_{r0}\, \forall\, r = 1, 2, \ldots m \\
&\sum_{j=1}^{N} \lambda_j X_{ij} \leq X_{i0}\, \forall\, i = 1, 2, \ldots n \\
&\sum_{j=1}^{N} \lambda_j = 1;\ \lambda_j \geq 0\, \forall\, j = 1, 2, \ldots N
\end{aligned} \tag{2}$$

Solving the above problem gives us the optimum value ϕ^* and the efficiency is given as ${\text{TE}^{\text{O}}}_0 = \frac{1}{\phi^*}$. The stated models have two shortcomings which limit their scope for fair comparison. First, the orientation employed in the TE score calculation model leads to different results for a given DMU. Thus, in a multi-input multi-output technology setup a DMU, which is efficient for input-oriented model, may become inefficient when evaluated using output-oriented model and *vice-versa*. Secondly, these models follow radial approach in contraction (expansion) of inputs (outputs) to obtain the efficient level of performance, i.e., the changes in either all inputs or all outputs are equi-proportional. However, this strategy may not always work as the radial models leave the possibility of slacks even in case of optimal solution.

For instance, in case of input-oriented radial efficiency we put the restriction that all the inputs should be reduced by same proportions. Yet, there may be the possibility that some inputs can be reduced by a larger proportion than the others. Thus, the restriction of changes by the same proportion will lead us to a non-optimal solution.

One possible way to overcome the shortcomings of radial efficiency models is to use non-radial DEA model. In the non-radial measure of efficiency, also known as the Russell measure, unlike the radial measures, the restriction of proportionate adjustment in outputs and inputs is relaxed. Thus, in calculating the Russell measure for input-orientation, given the outputs, different inputs are reduced by different proportions. The input-oriented Russell measure of TE (IRTE) for 0th DMU can be computed by solving the following LPP (Ray, 2004):

$$\begin{aligned}
&\rho_X = \min \frac{1}{n} \sum_i \theta_i \\
&\text{s.t.} \quad \sum_{j=1}^{N} \lambda_j Y_{rj} \geq Y_{r0} \, \forall r = 1, 2, \ldots, m \\
&\sum_{j=1}^{N} \lambda_j X_{ij} \leq \theta_i X_{i0} \, \forall i = 1, 2, \ldots, n \\
&\sum_{j=1}^{N} \lambda_j = 1; \lambda_j \geq 0 \, \forall j = 1, 2, \ldots, N.
\end{aligned} \tag{3}$$

where θ_i is the proportion to which ith input is reduced to reach the efficient level of use, and rest of the notations are already explained above. Solving the above problem gives the optimal value $\rho_X{}^*$ and IRTE $= \rho_X{}^*$. It is worth noting that the input-oriented BCC score (TE^{I}) can be computed from LPP (3). If we impose the condition $\theta_i = \theta$, and solve for θ^*, then $\mathrm{TE}^{\mathrm{I}} = \theta^*$. Similarly, the Russell efficiency measure can be obtained for output-orientation where different outputs can be increased by different proportions given the inputs. The output-oriented Russell measure of TE (ORTE) for 0^{th} DMU can be computed by solving the following LPP (Ray, 2004):

$$\begin{aligned}
&\rho_Y = \max \frac{1}{m} \sum_r \phi_r \\
&\text{s.t.} \quad \sum_{j=1}^{N} \lambda_j Y_{rj} \geq \phi_r Y_{r0} \forall r = 1, 2, \ldots, m \\
&\sum_{j=1}^{N} \lambda_j X_{ij} \leq X_{i0} \, \forall i = 1, 2, \ldots, n \\
&\sum_{j=1}^{N} \lambda_j = 1; \lambda_j \geq 0 \, \forall j = 1, 2, \ldots, N.
\end{aligned} \tag{4}$$

where ϕ_r is the proportion to which rth output is increased to reach the efficient level and the other notations remain same as defined previously. Solving the above problem gives the optimal value ρ_Y* and ORTE = $1/\rho_Y$*. Further, if in LPP (4) we impose the condition $\phi_r = \phi$, and solve for ϕ*, then output-oriented BCC score $(\mathrm{TE^O}) = \frac{1}{\phi^*}$.

The number of DMUs in the sample (N) influences solution to DEA LPP and TE scores consequently. For a small value of N, relatively larger number of DMUs will be on the frontier and thus the efficiency scores are not credible for practical purposes. Charnes et al. (1985) suggest that for panel data the number of observations can be increased by employing window analysis. In this method the efficiency calculations are performed after pooling the observations of two or more time periods (duration of window) into single dataset thus increasing the number of observations. A DMU is treated as a distinct unit for different time periods. For instance, we have a balanced panel of N DMUs for three consecutive years represented as *t–1*, *t,* and *t+1*. We have to calculate the efficiency of a DMU for the year *t* on the basis of two-year window. We obtain the efficiency scores of the DMU through two windows: first by pooling observations from the years *t–1* and *t*, and then by pooling the observations from the years *t* and *t+1*. The average of the efficiency scores obtained from the two windows is considered the efficiency of the DMU for the year *t*. However, for the first and last year of the panel, only one window is possible so the single window score is considered as the efficiency score. The crucial consideration in size of window is that there should be little change in technology during this window period.

Once the TE scores of the DMUs are obtained, it is pertinent to analyze the role of possible exogenous factors, which may affect efficiency scores, through the second-stage regression. Most studies, presuming that efficiency scores need to be considered as censored variable, have used the Tobit regression model. However, the use of Tobit regression in second-stage regression analysis has been criticized by McDonald (2009). Since DEA scores are not a censored variable but rather a fractional variable, it does not reflect the true data-generating process (DGP) of the DEA scores, leading to biased results (Simar & Wilson, 2007). Consequently, we applied bootstrapped truncated regression method approach proposed by Simar and Wilson (2007) to investigate the influence of the exogenous variables on the computed radial and non-radial efficiency scores. For the second stage, we assumed relationship between efficiency scores and exogenous variables can be expressed as

$$\mathrm{TE} = \beta Z_j + \epsilon_{j.} \quad (5)$$

Note that here β and Z_j are the vectors of the regression parameter and exogenous variables, respectively, while $\epsilon_j \sim \left(0, \sigma^2\right)$ and TE denotes the statistical noise in the bootstrapped truncated regression and technical efficiency scores obtained from the DEA model, respectively. In the current study, specifically, we have employed algorithm 1 of Simar and Wilson (2007) using "simarwilson" package available in

Stata14. Algorithm 1 is usually preferred for the externally obtained DEA scores. Following steps have been undertaken to bootstrapped DEA scores.

1. Calculate the DEA scores ($\hat{\delta}_j$) for all the firms.
2. Take a reciprocal of the DEA scores, in case of input-oriented DEA model.
3. For $m < j$, select $\hat{\delta}_j > 0$ for the truncated regression model (truncated left at 1) and regress $\hat{\delta}_j$ on Z_j to score the coefficients of the regression ($\hat{\beta}$) and variance parameter σ^2 using maximum likelihood approach.
4. Repeat the following steps 4.1–4.3 for B (1, 2, ... B) times, to get the bootstrap estimates of ($\hat{\beta}^b$, $\hat{\sigma}^b$) for each B.

    4.1 For each firm, select an artificial error $\tilde{\epsilon}_j$ from the normal truncated distribution with left truncation at $1 - \hat{\beta} Z_j$.

    4.2 Compute artificial efficiency score $\tilde{\delta}_j$ from $\tilde{\beta}\ Z_j + \tilde{\epsilon}_j$ for all firms.

    4.3 Run a truncated regression (truncated left at 1) of $\tilde{\delta}_j$ on Z_j to get bootstrap scores of $\hat{\beta}^b$ and $\hat{\sigma}^b$.

5. Calculate the confidence interval and standard error of $\hat{\beta}$ and $\hat{\sigma}^2$ from the bootstrap distribution of $\hat{\beta}^b$ and $\hat{\sigma}^b$.

3.2 Empirical Model and Data

The literature on the bank efficiency reveals different approaches to bank's production process and leads to different input–output variables. Following the opinion of Berger and Humphrey (1997), we use the intermediation approach with three-input and three-output technology set. The inputs considered are: (i) loanable funds viz. sum of deposits and borrowings in millions of rupees (X_1); (ii) physical capital viz. fixed assets in millions of rupees (X_2); (iii) labor viz. number of employees (X_3). The outputs utilized are: (i) advances in millions of rupees (Y_1); (ii) investment in millions of rupees (Y_2); (iii) other incomes in millions of rupees (Y_3). In this study, we focus on the performance of domestic commercial banks from 2005 to 2017.[2] In view of the differences in technology amongst bank categories (e.g., Goyal et al., 2019), we consider PSBs and PVBs as separate groups for efficiency evaluation. Thus, we calculate the efficiency with respect to the group frontier rather than meta-frontier. For proper comparison, only the banks for which the data is available throughout the study period are considered. Thus, the dataset are two 13-year balanced panels of 26 PSBs and 19 PVBs. The data are extracted from Statistical Tables Relating to Banks in India, published by the Reserve Bank of India (RBI). Value of all financial variables has been adjusted to the year 2005 using the wholesale price index, 2004–05 series.

[2] In Indian accounting system financial year is different from the calendar year. So, the year 2005 pertains to the financial year 2004–2005.

Sample size is an important criteria for suitability of DEA in efficiency score calculation. Cooper et al. (2007) suggest that, for n-input and m-output technology set, the number of DMUs should be more than, either $(m \times n)$ or $3(m + n)$, whichever is larger. Considering the above criteria, for the present study, the number of DMUs should be more than 18. This condition is fairly satisfied for PSB (26 banks), but for PVB (19 banks) it is on the margin. Thus, we apply window analysis, with two-year window, for calculation of efficiency scores. We presume little change in the technology in a two-year span.

For second-stage regression, on the basis of literature, we identify potential exogenous variables and check for correlation amongst them to avoid the multicollinearity issue and finally, we choose seven regressors. These variables are: SIZE (logarithm of total assets in million rupees); DEPLIB (deposit to liability ratio); PRIORITY (ratio of priority sector advances to total advances); MANAGE (ratio of intermediation cost to total assets); CAR (capital adequacy ratio); and NPA (ratio of non-performing assets to advances). To check for non-linear relationship between TE and size of banks, we include quadratic term $SIZE^2$ as a regressor. The recent GFC originated in late 2007 and turned into a full-blown international crisis in September 2008 with the collapse of the Lehman Brothers. However, we presume the impact of GFC may have percolated well into the year 2009. To account for the impact of the GFC we include dummy variable CRISIS which takes value 1 for three crisis years (2008, 2009, and 2010) and 0 otherwise. To see how efficiency changed in the post-GFC period we incorporate another dummy variable POSTCRISIS. Variable POSTCRISIS takes value 1 for seven years (2011–2017) and 0 otherwise.

4 Results and Discussion

In this study, we mainly focus on the Russell efficiency measure but for comparison we have also calculated BCC TE scores.[3] We initiate the section with a brief glimpse into the growth of average values of inputs and outputs per bank. The size of PSBs in terms of total assets has tripled from 2005 to 2017 and in the same duration the PVBs have expanded to five times. If we consider the number of employees, then while for PVBs it has almost quadrupled, the PSBs employee size has increased marginally to 1.2 times. It seems that the PSBs have focused considerably on increasing employee productivity by reducing the excess manpower. In terms of investments, advances, other incomes, and loanable funds the PVBs show considerably larger proportional growth than that by PSB. In the span of 13 years, while PVBs have doubled the average physical capital per bank, PSBs have increased it to almost five times.

Before proceeding with the results and analysis, we illustrate the calculation of Russell measures for Allahabad Bank for the year 2006 considering a two-year window. Thus, we have to solve the LPP model twice, once for each window. Table 1 reproduces the optimum values obtained by solving the LPPs for input orientation as

[3] The individual bank specific Russell scores and BCC scores will be made available on request.

well as output orientation. W1 represents the first window (2005 and 2006 pooled) while W2 denotes the second window (2006 and 2007 pooled). Since we have two-year window, we get two efficiency scores for the bank (one from W1 and another from W2). The resultant efficiency score is the average of efficiency scores obtained from separate DEA for W1 and W2. For input orientation, the Russell measure in each window is the average of θ's corresponding to three inputs obtained by solving the LPP for that window. Thus, for W1, the Russell measure is 0.650 (that is average of 0.930, 0.522, and 0.498). Similarly, for W2 the Russell measure is 0.695 (average of 0.983, 0.567, and 0.535). Hence, the Russell efficiency score of the bank for 2006 is 0.672 (average of 0.650 and 0.695). The efficiency score of an individual input is the average of efficiency values obtained in the two windows. Thus, for input loanable funds the efficiency is 0.957, i.e., the average of 0.930 and 0.983. Similar calculations can be done to obtain the output-oriented Russell efficiency scores. However, one has to keep in mind that the case of output orientation the efficiency score is inverse of ϕ. For the years 2005 and 2007, the efficiency scores result from the single window as only one window is possible.

We start the discussion with a descriptive summary of input-oriented efficiency scores and their analysis followed by a summary and analysis of output-oriented efficiency scores. Table 2 displays the summary of input-oriented BCC TE and IRTE scores. Due to the paucity of space, we report the summary of efficiency scores at an interval of three years starting from 2005. Panel A of the table depicts PSBs-specific scores, while Panel B shows values for PVBs. It is evident that the efficiency scores are high when we employ the radial model. The average BCC TE scores for all the years of study are 0.980 and 0.969 for PSBs and PVBs respectively. This indicates very high

Table 1 Russell scores calculation of Allahabad bank for the year 2006

Input/output	Proportion	W1	W2	Efficiency
Input orientation				
Loanable funds	θ_1	0.930	0.983	0.957
Physical capital	θ_2	0.522	0.567	0.544
Labor	θ_3	0.498	0.535	0.517
	ρ_X*	0.650	0.695	
Russell measure	IRTE = ρ_X*	0.650	0.695	0.672
Output orientation				
Investment	$\emptyset_1$	1.106	1.000	0.952
Advances	$\emptyset_2$	1.007	1.113	0.946
Other incomes	$\emptyset_3$	2.254	1.834	0.494
	ρ_Y*	1.456	1.316	
Russell measure	ORTE = $1/\rho_Y*$	0.687	0.760	0.723

Source Authors' calculations
Note (i) IRTE is input-oriented Russell technical efficiency and ORTE is output-oriented Russell technical efficiency

efficiency for both the groups of banks, a result consistent with the literature discussed in Sect. 2. Compared to that, for Russell measure, the overall mean IRTE scores are 0.901 and 0.873 for PSBs and PVBs respectively. Thus, there is a considerable drop in efficiency scores for both groups. Another noteworthy observation is the minimum value of efficiency scores. The minimum efficiency score for PSBs, drops from 0.817 (Central Bank of India for the year 2017) to 0.601(Central Bank of India for the year 2008) when we compare the BCC and Russell scores. It indicates a vast scope of improvement in non-radial efficiency for some of the banks. For instance, in the case of Central Bank of India for the year 2017, the input-oriented BCC TE score is 0.817 while IRTE is 0.704. If we put the restriction of radial contraction then each input can be reduced by a maximum of 18.3% given the output. Nevertheless, if we remove the restriction of radial contraction, as is the case of IRTE, then the average possible reduction in inputs is 29.6%. This is because the individual inputs loanable funds, physical capital, and labor can be reduced by 10.7%, 56.4%, and 21.6% respectively. The picture remains the same for PVBs where the minimum efficiency score drops from 0.806 (Dhanlaxmi Bank for the year 2005) to 0.410 (Jammu and Kashmir Bank for the year 2017) when we shift from BCC to Russell measure. When we compare the efficiency scores of PSBs and PVBs we find that the PSBs have higher efficiency scores than PVBs in either of the cases. We find that for either of the bank groups and for both radial and non-radial measures, the median score is higher than mean. The efficiency scores are concentrated on the higher side, i.e., the majority of banks is closer to the frontier. In addition, if we consider the standard deviation of efficiency scores within a particular group, then we observe that the variation is higher for Russell scores than the BCC scores for all the years. When we compare the group of banks, then the variation in efficiency scores is higher for PVBs than PSBs, under both measures.

Next, we move on to Table 3 which displays the summary of output-oriented BCC TE scores and ORTE scores. Panel A and B present efficiency scores for PSBs and PVBs respectively. Again, it is evident that the efficiency levels are high when we employ the radial model. The average BCC TE scores for all the years of study are 0.979 and 0.971 for PSBs and PVBs respectively. However, the mean ORTE scores are 0.91 and 0.827 for PSBs and PVBs respectively. Thus, we observe a substantial drop in efficiency scores moving from radial to non-radial measure. The minimum efficiency score for PSBs drops from 0.839 (Central Bank of India for the year 2017) to 0.250 (Bank of Maharashtra for the year 2006) when we employ Russell measure in place of BCC measure. Similar is the case for PVBs, where the efficiency score drops from 0.807 (Dhanlaxmi Bank for the year 2005) to 0.021 (Lakshmi Vilas Bank for the year 2014) when we shift from BCC to Russell measure. There is tremendous scope for improvement in non-radial efficiency for some of the DMUs. For example, in the year 2005, Dhanlaxmi Bank has output-oriented BCC TE and ORTE scores of 0.807 and 0.443 respectively. Under the restriction of radial expansion, each output can be expanded by a maximum of 23.9%, given the input. Whereas, if we relax the restriction, as is the case of ORTE, then the average possible expansion in outputs is 125.7%. This is because the individual outputs i.e. investments, advances, and other incomes can be increased by 31.4%, 19.3%, and 327.3% respectively. It is

Table 2 Summary of input-oriented efficiency scores

	2005	2009	2013	2017	All years
Panel A: Public sector banks (PSBs)					
BCC scores					
Mean	0.968	0.980	0.988	0.969	0.980
Median	0.981	0.985	0.997	0.989	0.992
Standard deviation	0.038	0.022	0.014	0.045	0.027
Minimum	0.876	0.921	0.960	0.817	0.817
No. of banks on frontier	11	9	11	9	
IRTE scores					
Mean	0.894	0.881	0.911	0.891	0.901
Median	0.926	0.886	0.957	0.907	0.945
Standard deviation	0.110	0.112	0.107	0.101	0.108
Minimum	0.676	0.667	0.681	0.704	0.601
No. of banks on frontier	11	9	11	9	
Panel B: Private banks (PVBs)					
BCC scores					
Mean	0.954	0.967	0.964	0.980	0.969
Median	1.000	0.981	0.968	1.000	0.997
Standard deviation	0.066	0.043	0.042	0.032	0.044
Minimum	0.806	0.845	0.871	0.907	0.806
No. of banks on frontier	11	6	9	12	
IRTE scores					
Mean	0.889	0.875	0.865	0.852	0.873
Median	1.000	0.889	0.869	1.000	0.960
Standard deviation	0.142	0.121	0.145	0.214	0.154
Minimum	0.606	0.620	0.626	0.410	0.410
No. of banks on frontier	10	6	9	12	

Source Authors' calculations
Note (i) BCC is radial technical efficiency
(ii) IRTE is input-oriented Russell technical efficiency

evident that PSBs have higher efficiency scores than PVBs for both radial and non-radial measures. Comparing the mean and median, we observe the efficiency score distribution pattern similar to what we observed in case of input-oriented models. The standard deviation of efficiency scores indicates higher variation in Russell scores than the BCC scores for all the years, similar to the case of input orientation. Variation in efficiency scores is higher for PVBs than PSBs.

In the preceding discussion, our focus is primarily on the analysis of bank group level aggregate results. However, stakeholders may be interested in the consistency of individual bank's TE performance across the two orientations. We identify the

Table 3 Summary of output-oriented efficiency scores

	2005	2009	2013	2017	All years
Panel A: Public sector banks (PSBs)					
BCC scores					
Mean	0.969	0.978	0.988	0.968	0.979
Median	0.979	0.984	0.997	0.988	0.991
Standard deviation	0.036	0.023	0.014	0.044	0.027
Minimum	0.881	0.923	0.960	0.839	0.839
No. of banks on frontier	11	9	11	9	
Russell scores					
Mean	0.917	0.923	0.878	0.932	0.910
Median	0.916	0.947	0.949	0.957	0.945
Standard deviation	0.090	0.085	0.149	0.078	0.112
Minimum	0.688	0.715	0.538	0.718	0.250
No. of banks on frontier	11	9	11	9	
Panel B: Private banks (PVBs)					
BCC scores					
Mean	0.954	0.966	0.972	0.980	0.970
Median	1.000	0.980	0.979	1.000	0.994
Standard deviation	0.065	0.045	0.031	0.033	0.043
Minimum	0.807	0.837	0.915	0.906	0.807
No. of banks on frontier	11	6	9	12	
Russell scores					
Mean	0.858	0.913	0.648	0.916	0.827
Median	1.000	0.955	0.802	1.000	0.959
Standard deviation	0.176	0.101	0.378	0.143	0.241
Minimum	0.443	0.627	0.072	0.484	0.021
No. of banks on frontier	10	6	9	12	

Source Authors' calculations
Note (i) BCC is radial technical efficiency
(ii) ORTE is output-oriented Russell technical efficiency

banks which fall in the same Russell efficiency score bracket for both the input and output orientations. Table 4 enumerates such PSBs and PVBs for the year 2005 and 2017. In 2005, we observe that 15 PSBs (out of 26) and 14 PVBs (out of 19) maintain their position in the same bracket, while for the rest of the banks there is a change if the orientation in TE measurement is altered. In comparison, for 2017 16 PSBs (out of 26) and 13 PVBs (out of 19) maintain their position. Thus, the relative number of consistent performers across the two orientation has remained fairly the same over the study period. Another interesting aspect to visualize from the table is the consistent performers over the study period. For PSBs, eight banks and for PVBs,

Table 4 Efficiency-wise distribution of PSBs and PVBs for the year 2017

Russell efficiency	2005	2017
Panel A: Public sector banks (PSBs)		
Less than 0.5	–	–
0.501–0.600	–	–
0.601–0.700	–	–
0.701–0.800	–	Central Bank of India
0.801–0.900	Bank of Baroda Vijaya Bank	Bank of Baroda Dena Bank UCO Bank
0.901–1.00	Andhra Bank Canara Bank Corporation Bank IDBI Bank Punjab And Sind Bank Punjab National Bank State Bank of Bikaner and Jaipur State Bank of Hyderabad State Bank of India State Bank of Mysore State Bank of Patiala State Bank of Travancore United Bank of India	Andhra Bank Bank of Maharashtra Corporation Bank IDBI Bank Indian Bank Punjab and Sind Bank State Bank of India State Bank of Mysore State Bank of Patiala Union Bank of India United Bank of India Vijaya Bank
Panel B: Private banks (PVBs)		
Less than 0.5	–	Jammu & Kashmir Bank
0.501–0.600	–	–
0.601–0.700	Catholic Syrian Bank	–
0.701–0.800	Karur Vysya Bank	–
0.801–0.900	IndusInd Bank South Indian Bank	–
0.901–1.00	Axis Bank DCB Bank HDFC Bank ICICI Bank Karnataka Bank Kotak Mahindra Bank Nainital Bank RBL Bank Tamilnad Mercantile Bank Yes Bank	Axis Bank Catholic Syrian Bank City Union Bank Dhanlaxmi Bank Federal Bank HDFC Bank ICICI Bank IndusInd Bank Nainital Bank RBL Bank Tamilnad Mercantile Bank Yes Bank

Source Authors' calculations

seven banks have managed to remain in the same efficiency score bracket. Evidently, the consistent performers, whether we consider the orientation or over the study span, are mainly the banks which are closer to the frontier. However, the performance of poorly performing banks shows movement across the efficiency brackets.

Unlike the BCC efficiency calculation, where all the inputs or the outputs (depending on the orientation) have been adjusted in same proportion, in the Russell measure, the proportions of change may be different. This gives us the opportunity to find the productive efficiencies of the individual inputs or outputs depending on the orientation. Panel A of Table 5 displays the efficiencies of individual inputs when we employ input-oriented Russell efficiency measure. For PSBs, considering the mean values for all the years, the major contributor to inefficiency is the input physical capital followed by the input labor with efficiency scores of 0.792 and 0.919 respectively. For PVBs as well, the prime contributors to inefficiency are the inputs physical capital and labor with efficiency scores of 0.816 and 0.813 respectively. For either of the bank groups, loanable funds input is highly efficient. Similar to the input efficiencies, we can calculate efficiencies of individual outputs in case of output-oriented Russell measures. Panel B of Table 5 presents the individual outputs' efficiencies for output-oriented case. We observe that for PSBs, investments, and advances are highly efficient with mean values of 0.966 and 0.989, respectively. The inefficiency mainly arises because of other incomes having an average efficiency level of 0.836. The results for PVBs are similar, and inefficiency is mainly due to other incomes with an average efficiency level of 0.749. However, the contribution of other incomes in inefficiency is considerably more for PVBs than PSBs. The results carry crucial managerial implications. The banks can considerably improve efficiency if they focus on better management of physical capital and labor, and increase the sources of other incomes.

This study utilizes contemporaneous (cross-section) data-based frontier for comparison across the study period of 13 years. However, the distribution of efficiency scores may change over the study period. We conduct median test to ascertain if the median efficiency score for 2017 is different from the one in 2005. Median test is a non-parametric test wherein the null hypothesis assumes same median value across all samples. We calculate the test statistics for IRTE, ORTE, and the individual components of technology set. For PSBs, we observe that there is no significant difference in median IRTE scores over the study period, and the observation is similar in case of ORTE scores. If we consider the components of technology set then the test statistic is significant for investments and advances. For investments, there is a drop in median efficiency score implicating a downward shift in efficiency but for that there is no significant economic difference in the median efficiency score. The PSBs need to improve their performance in terms of investment to improve efficiency. The evaluation of test statistics corresponding to PVBs reveals that there is no significant change in the efficiency score distribution whether we consider gross scores (IRTE or ORTE) or the individual technology set components.

While the overall mean efficiency score gives us a general picture, for various stakeholders it might be interesting to know the relative performance of smaller banks in comparison to their larger counterparts. Hence, we explore the variation of

Table 5 Average input and output specific efficiencies

	2005	2009	2013	2017	All years
Panel A: Inputs					
Public sector banks (PSBs)					
Loanable funds	0.979	0.996	1.000	0.980	0.991
Physical capital	0.837	0.703	0.777	0.728	0.792
Labor	0.867	0.944	0.956	0.963	0.919
Private banks (PVBs)					
Loanable funds	0.960	0.995	0.990	0.991	0.990
Physical capital	0.947	0.833	0.732	0.820	0.816
Labor	0.760	0.796	0.872	0.746	0.813
Panel B: Outputs					
Public sector banks (PSBs)					
Investments	0.984	0.955	0.981	0.925	0.966
Advances	0.971	0.989	0.994	0.973	0.989
Other incomes	0.835	0.860	0.777	0.914	0.836
Private banks (PVBs)					
Investments	0.938	0.953	0.954	0.996	0.958
Advances	0.961	0.981	0.994	0.990	0.984
Other incomes	0.770	0.853	0.565	0.843	0.749

Source Authors' calculations

efficiencies of banks on the extremes of the total asset size spectrum. For the analysis we take the three smallest banks, grouped as "small banks," and three largest banks, as "large banks," on the basis of total assets for the year 2005. Thus, the three largest PSBs are State Bank of India, Punjab National Bank, and Canara Bank, and the three smallest are Punjab and Sind Bank, State Bank of Mysore, and State Bank of Bikaner and Jaipur. In the case of PVBs, small banks include DCB Bank, Nainital Bank, and RBL Bank and large banks are ICICI Bank, HDFC Bank, and Axis Bank.

Figure 1 displays the grouped mean IRTE scores of small banks and large banks for PSBs and PVBs. The small PSBs perform above the overall annual mean efficiency scores for all the years, and there is little variation in their performance. Also, the small PSBs consistently perform better than large PSBs for all the years. In contrast, the large PSBs show a lot of variation in efficiency, and in some years their performance has dipped below the average annual efficiency scores. For PVBs, both the categories of banks are more efficient than the overall annual mean efficiency scores across the study period. However, we find that for most of the years, small PVBs have outperformed their large counterparts. Also, the performance of small PVBs is more consistent than that of the large PVBs. Figure 2 exhibits the ORTE scores of small and large banks for both groups. The performance of small PSBs is similar to that observed in IRTE, showing better performance than large PSBs and the annual PSBs average. Large PSBs are able to beat the annual average in most of the years, though failing in some. However, in the case of PVBs both the categories of banks show very small variation and consistently perform better than the PVBs annual average for all the years.

The efficiency scores are often used to rank the DMUs. As the Russell scores are different from BCC scores, not surprisingly, the non-radial approach may lead to a difference in ranking. To see whether the efficiency calculation approach significantly influences the rank order of the banks, we check the rank correlation between BCC scores and the Russell scores. For the purpose, we employ Kendal's Tau-b

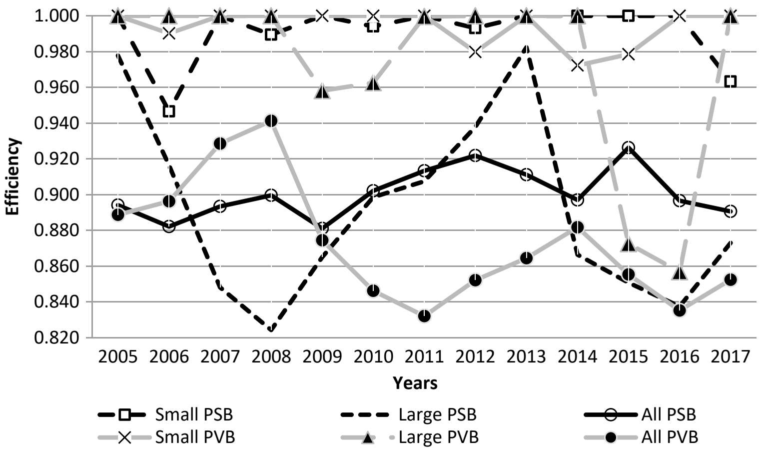

Fig. 1 Input-oriented Russell efficiency scores of smallest and largest banks

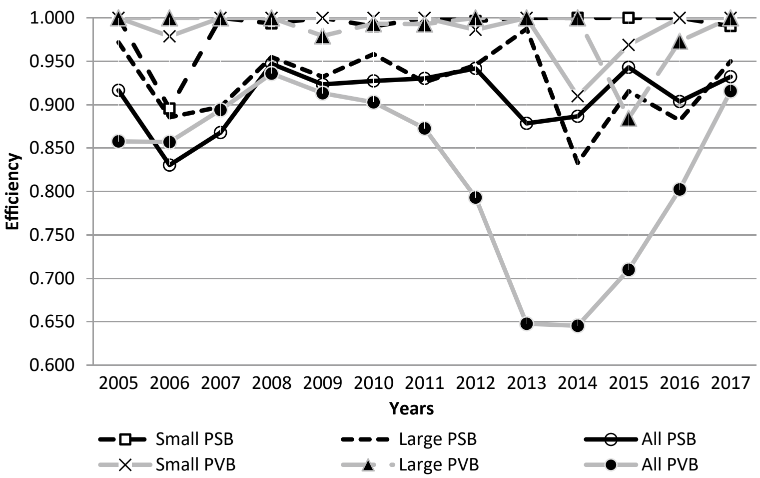

Fig. 2 Output-oriented Russell efficiency scores of smallest and largest banks

measure which makes adjustment for ties (Agresti, 2010). The value of Kendal's Tau-b ranges between 1 and –1, wherein 1 and –1 indicate perfectly positive and perfectly negative correlations respectively, and 0 means no correlation. We find that, in all the cases, there is high correlation amongst input-oriented and output-oriented efficiency scores whether it is radial or non-radial model. However, if we compare the ranks based on radial BCC efficiency with that of non-radial Russell efficiency, we obtain low values of the correlation coefficient. For instance, for the year 2005, the rank correlation between input-oriented BCC TE and IRTE scores has values of 0.625 and 0.762 for PSBs and PVBs respectively. For the same year, if we consider output orientation, rank correlation values are 0.761 and 0.727 for PSBs and PVBs respectively. The results are similar for the year 2017. For PSBs, the rank correlation values are 0.628 and 0.749 for input orientation and output orientation respectively, and for PVBs the corresponding values are 0.634 and 0.739 respectively. The implication is that changing the efficiency measuring approach from radial to non-radial, not only changes the efficiency scores but also considerably influences the rank order of DMUs.

The results of second-stage bootstrapped truncated regression on Russell efficiency scores are displayed in Table 6. Panel A and Panel B show the coefficients for PSBs and PVBs respectively. We observe that the regression results are similar for most of the variables for both PSBs and PVBs. The coefficient of SIZE is negative and significant and SIZE^2 positive and significant which implies a U-shaped relationship between efficiency and size of bank and indicates that as the size of the bank increases, initially the efficiency decreases, reaches a low point, and then starts increasing. Kumar and Gulati (2008) find a similar relationship between size and efficiency though they do not account for the possibility of non-linear relationship. DEPLIB coefficient is negative and significant for both the PSBs and PVBs. This shows that as the deposits increase, the bank is not able to create more advances proportionate to the deposits and thus becomes inefficient. CAR, the measure of risk preparedness of banks, has a positive and significant impact on efficiency scores of PSBs and PVBs. A higher CAR means more stability in the face of turbulence. This stability attracts people and companies to do business with such banks and thus leads to higher efficiency. The results on CAR are similar to the findings of Das and Ghosh (2006). The coefficient of NPA is significant only for PVBs' ORTE scores and has a negative sign. Non-performing assets represent those assets on which the bank cannot recover its advances, and this not only erodes the asset size of the bank but also reduces the resources that can be employed profitably. Intuitively, as the NPA increases the productive performance of banks decreases (Sanjeev, 2006). The coefficient MANAGE is significant only in the case of IRTE for PSBs. It has a negative sign, which is in accordance with expectation. As the proportion of intermediation cost increases, it implies poor management and it leads to decrease in efficiency (Das & Ghosh, 2006). The PRIORITY coefficient is positive and significant on ORTE scores for categories of banks implying that higher lending to priority sector increases their output-oriented efficiency scores but has no significant impact on efficiency when input-orientation is considered. In this context, it is worth noting that Kumar and

Gulati (2008) do not find priority sector lending significantly affecting the efficiency of PSBs.

CRISIS has positive and significant coefficient in case of PSBs but negative for PVBs. It implies that the efficiency of PSBs increased during the GFC. Traditionally, the Indian banking industry has limited exposure to the overseas markets and mostly depends on domestic demand for its business. However, at the onset of crisis RBI took various measures to stabilize the Indian banking industry (Sinha, 2010). In addition, because of the decrease of overseas financing sources, the demand for advances from Indian banks increased and there was a flight of deposits from non-PSBs to PSBs (Eichengreen & Gupta, 2012). These factors may have led to a positive impact on the efficiency of PSBs while a negative impact on the efficiency of PVBs. The coefficient of POSTCRISIS is significant and positive for PSBs indicating that the efficiency of PSBs is increasing even in the post-crisis period. However, the efficiency of PVBs has further deteriorated in the post-crisis period.

5 Conclusion

The paper strives to analyze the productive efficiency of Indian domestic banks utilizing the Russell measure, which is a non-radial DEA concept within the framework of generalized efficiency measures. Given the shortcomings of conventional radial DEA models, we employ the non-radial approach, assuming variable returns to scale. Also, to ascertain the possible impact of recent financial crisis (2007 to 2009) on efficiency we employ a balanced panel of 26 PSBs and 19 PVBs from the year 2004–05 to 2016–17. We decide to calculate the efficiency scores relative to the bank-group specific frontiers, as there is a possibility of difference in technology amongst them. Following the intermediation approach, we define a three-input and three-output production technology for the calculation of both radial (BCC) and non-radial (Russell) technical efficiency scores.

The results suggest that if we consider the BCC efficiency scores, then both the groups of banks are extremely efficient. In comparison, the Russell efficiency scores are significantly low and indicate the possibility of improvement in productive performance of many banks. We find that inputs physical capital and labor are the main contributors to input-oriented Russell inefficiency, while output, other income contributes most to the output-oriented inefficiency. The rank correlation analysis indicates that using non-radial measure against radial measure affects the ranking of banks so these models cannot be used interchangeably for the purpose of ranking. Second-stage bootstrapped truncated regression reveals that the Russell efficiency scores show a U-shaped relationship with total asset size of banks. Non-performing assets and deposit to liability ratio have negative impact on the efficiency of banks while capital adequacy ratio positively affects efficiency. Further, global financial crisis has positive impact on the non-radial TE of PSBs while impacting negatively the same in the case of PVBs.

Table 6 Second-stage pooled bootstrap truncated regression results

	Panel A: Public sector banks (PSBs)						Panel B: Private banks (PVBs)					
	IRTE			ORTE			IRTE			ORTE		
	Coef.		Std. err.	Coef.		Std. err.	Coef.		Std. err.	Coef.		Std. err.
SIZE	−3.990	***	0.932	−0.952	***	0.229	−0.919	**	0.452	−0.336	**	0.123
$SIZE^2$	0.138	***	0.033	0.033	***	0.008	0.039	**	0.018	0.014	***	0.005
DEPLIB	−0.029	***	0.007	−0.005	***	0.000	−0.016	***	0.006	−0.009	***	0.002
PRIORITY	0.001		0.004	0.002	*	0.001	0.006		0.004	0.007	**	0.003
MANAGE	−0.214	***	0.065	0.004		0.029	−0.054		0.053	−0.008		0.018
CAR	0.021	**	0.013	0.010	***	0.003	0.063	***	0.016	0.005	**	0.002
NPA	0.004		0.007	−0.001		0.001	−0.025		0.019	−0.029	**	0.013
CRISIS	−0.040		0.051	0.107	***	0.010	−0.272	***	0.081	−0.006		0.013
POSTCRISIS	0.044		0.051	0.118	***	0.011	−0.310	***	0.077	−0.164	***	0.049
Constant	3.286	***	6.754	7.909	***	1.665	7.074	**	2.892	3.342	***	0.818
Wald Chi square	39.250	***		18.44	**		41.660	***		38.453	***	
N	338			338			247			247		

Note (i) * significant at10% significance level, ** significant at 5% significance level, *** significant at1% significance level
(ii) IRTE is input-oriented Russell technical efficiency and ORTE is output-oriented Russell technical efficiency

Though this is possibly the first study on the Indian banking sector, which utilizes non-radial Russell model to the calculation of TE, it can be extended along multiple directions. In calculation of Russell efficiency score, we have assigned equal weights to all the inputs and outputs but different weights, depending on relative importance of individual components, may be assigned. Further extension of the study can be non-radial orientation free approach to calculate even more sophisticated generalized measures of technical or productive efficiency. Another possibility is inclusion of non-performing assets as bad outputs in the core model for calculation of efficiency.

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Does Government Effectiveness and Regulatory Framework of a Country Influence the Performance of MFIs? an Empirical Study on Selected Asian Countries

Chandralekha Ghosh and Ankana Das

1 Introduction

The microfinance can be defined as the provider of microcredit. Microfinance Institutions (MFIs) provide microcredit to the micro entrepreneurs who need economic support and have willingness and ability to pay. The clients of MFIs are mainly risky since they cannot provide real collateral as they tend to work in informal sector of the society (Ada Microfinance, 2020). Thus MFIs are the institutions which provide accessibilities of micro finances to rural people. They enjoy greater acceptability among the poor and have flexibility in operations providing a level of comfort to their clients. The basic objective behind the setup of MFIs was to provide financial help with social development. MFIs are lucrative compared to the commercial banks as they provide microcredit to the economically active poor who include microenterprises, small farmers, low-income salaried employees, pensioners and poor households, without any collateral. The commercial banks are always profit oriented whereas the MFIs mainly provide loans for social development. Thus commercial microfinance is a complement to, not a substitute for government and donor alleviation and employment generation programs for the extremely poor (Delfiner and Peron, 2007).

The phenomenon of mission drift captures the process that MFIs are departing from the social mission and continuously increasing its focus on financial assessment (Ghosh & Guha, 2017; Kar, 2012). Given this scenario one of the main objectives is to determine the factors affecting the performance of MFIs namely, social as well

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as financial. Moreover one important objective is to examine how the country-level macro variables are affecting the performance of MFIs. MFIs of selected countries have different background and consequently the governance factors also differ from country to country.

Ghosh and Das (2020) have shown how regulatory framework and the government effectiveness of MFIs of seven South Asian countries influence the performance of MFIs in these countries by using panel data model. The paper of Ghosh and Das (2020) have found that MFI-specific variables like real yield on gross loan portfolio is positively influencing return on assets (ROA), operational self-sufficiency (OSS) and per cent of female borrower but cost per borrower is negatively influencing all the dependent variables. Regulatory quality of the country has a positive influence on ROA and profit at margin of the MFIs. Domestic credit and growth of gross domestic product (GDP) per capita have positive impact on percent of female borrower, the representative of the social variable.

Ahmed et al. (2016) employed financial ratio analysis, multiple regression models and considered various performance indicators that have been standardized by the Consultative Group to Assist the Poor (CGAP, 2003 and 2005) to measure the financial performance or the profitability of MFIs in South Asia. They recommended that interest rate charged by MFIs is one of the barriers for clients' loan repayment. It also suggests that MFIs should maintain a close relation with the client.

Kar and Swain (2014) investigated the impact of competition on microfinance institutions' (MFIs) outreach, financial performance and quality of loan portfolio by using Boone indicator. They suggested that increased competition in the microfinance industry leads to a decline in the loan portfolio quality. The paper by Rupa (2014) analysed the financial performance of MFIs in India, using data from the period 2007 to 2011. They have used descriptive statistics and growth rates to analyse the data. The paper suggested that in terms of overall financial performance, Indian MFIs have good performance in terms of Operational Self Sufficiency (OSS) and Return on Equity (ROE).

Shahzad (2015) has examined the outreach and financial stability of 372 institutions from different countries namely India, Nepal, Bangladesh and Sri Lanka. The period of their study is from 1982 to 2013 and they have used stochastic frontier analysis and DEA methods. The study by Sharif Mohd (2018) showed the performance and role of microfinance institution in the development of India. The paper has used the descriptive method to analyse the data of the period from 2012–13 to 2016–17. The findings of this paper show that the proportion of income generating loan remained same during the year 2015 and it increased up to 94 per cent in the year 2017. The indicators relating to overall financial structure such as Return on assets, Return on equity and capital adequacy ratio have increased over this period and have found sharp decline in total assets of MFIs.

From the above literature review it can be said that till now the performances are estimated by descriptive methods or GMM methods or stochastic frontier method. This paper has used a new technique, i.e., multilevel model to analyse the data of the time period 2004 to 2013. This paper has analysed the differential impacts of the variables both at the microfinance institution level as well as at country level which have not been analysed before. Multilevel model incorporates features of both fixed effects and random effects model. The multilevel or the mixed effect model is a better model as it helps to generalize the population and it helps to analyse the data within the groups. There are data at two levels at cross section; that is microfinance institutions level data as well as at country level data. It estimates the effects at both the levels simultaneously. It recognizes the existence of data hierarchy by allowing the residual component at each level of hierarchy. It also explains the longitudinal studies where individual's responses over time are correlated with each other.

Ghosh and Das (2020) have shown that different countries have different history of development of MFIs and the governance of these countries also differs. There exists a vast literature which shows that governance variables have important influence on performance of MFIs (Kar & Swain, 2014). They have used panel data analysis but not the multilevel modelling. The studies like Kar and Swain (2014), Ghosh and Das (2020) have used different governance variables like Estimates of Control of Corruption, Government effectiveness, Political Stability and absence of violence and regulatory quality, but no study has yet studied differential impact of different governance variables on the performance related variables of MFIs using multilevel modelling. So the main research gap that has been dealt in this paper is that whether the difference in the governance-related factors are differently influencing the performance of MFIs.

The major issue of this study is to examine whether the impact of different governance-related factors on both financial and social performance vary from country to country. This set of countries namely Afghanistan, Pakistan, Bangladesh, India, Indonesia, Vietnam and Thailand have different background of evolution of MFIs and have differences in their regulatory frameworks and government effectiveness and other governance-related factors. Most of the previous studies have used different methods of analysis to analyse the performance of MFIs but this study has used the multilevel longitudinal model for examining the country-level differences in terms of government effectiveness, regulatory framework and other governance-related variables like estimates of control of corruption, political stability and absence of violence in case of examining the impact of these variables on the performance of microfinance institution. From this viewpoint the following research questions arise:

How differences in Government Effectiveness of respective countries affect the performance of MFIs?

What is the differential impact of regulatory framework of different countries on the performance of the MFIs?

What is the differential impact of other governance-related variable on the performance of MFIs?

The paper is trying to find out the determinants influencing the performance of the MFIs. The financial performance is being measured by Operational Self Sufficiency (OSS), Return On Assets (ROA) and Profit at the margin (PM). Social performance is being measured by the percent of female borrowers (PERFB) and Average loan size per borrower adjusted by GNI per capita (AVLB). This paper actually examines the role of country-specific factors as well as MFI-related factors in influencing the performance of MFIs in seven selected Asian countries. The research has used data on 91 MFIs of these selected seven Asian countries for the period from 2004 to 2013. The paper is divided into following sections. Section 1 is the introductory section containing the literature review, Sect. 2 represents methodology, data and variable used, Sect. 3 illustrates the results and analysis and Sect. 4 concludes the paper.

This research paper will help in policy prescription that will try to improvise the effectiveness of the Government and regulatory framework of the country so that the economy can grow. MFIs mostly look upon on the social as well as the economical perspective of the country, thus this paper will help MFIs to improvise its policies.

2 Methodology

Multilevel models are also called hierarchical linear model. This method is used where the data is hierarchical or nucleated in nature or "nested data structure" (Hair and Fávero 2019). It allows and/or forces researchers to hypothesize relationship at each level of the analysis. The main advantage of this model over traditional OLS model is that it uses nested data structure (Hair and Fávero 2019) to estimate cross-level effects. It provides us with an opportunity to estimate the variance structure using a parsimonious, parametric structure. Moreover, these relationships at the second and higher levels are of theoretical interests and represent the main focus of the study. Multilevel models allow analysts to address problems of heterogeneity with samples of repeated measurement. The interest is to understand the level 2 relationships but a better picture can be observed by incorporating the level 1 model of individual effects. It also allows the prediction of quantities at both level 1 and level 2. It is clearly explained in Hamilton (2013).

This paper considers the country as the basic unit of observation which is level 1 unit of observation. The next level up is called level 2 and so forth. The second level is the microfinance institution level units of observations. Multilevel models are specified through conditional relationship where relationships described at one level are conditional on random coefficient of upper level. Due to this conditional modelling framework multilevel data and models are also known as hierarchical.

$$y_{it} = z'_{1,it}\left(\alpha_i + X_{2,i}\beta_2\right) + x'_{1,it}\beta_1 + \varepsilon_{it} = z'_{it}\alpha_i + x'_{it}\beta + \varepsilon_{it} \tag{9.1}$$

Using the notations $x'_{it} = \left(z'_{1,it}x'_{1,it}X_{2,i}\right)$, $z_{it} = z_{1,it}$ and $\beta = \left(\beta'_1\beta'_2\right)'$.

In this equation, to assess the achievements of MFIs the paper considers n countries and for the ith country the paper randomly chooses n_i MFI.) explains that this linear relationship is to vary by country. The notations β_{0i} and β_{1i} are for country-specific intercepts and slopes. The variable t = 1,….,T_1 represents time period for the i^{th} individual. According to) the unit of analysis for the level -1 model is an observation at a point in time, not the individual. Thus the paper uses the subscript "t" as an index for time. The $z_{1,it}$ and $x_{1,it}$ explains the sets of level 1 explanatory variables. The associated parameters that may depend on the ith individual appear as a part of the β_i vector, whereas parameters that are constant appear in the β_1 vector. Conditional on the subject, the disturbance term ε_{it} is a mean-zero random variable that is uncorrelated with β_i (). This model is clearly explained in Hamilton (2013) and Hair and Fávero (2019).

2.1 *Data Analysis*

The variables that have been used in this paper are similar to the variables used in the paper by Ghosh and Das (2020) and some of the variables are same as variables used in Kar & Swain, 2014. One important contribution of the paper is that this paper has estimated multilevel model or the mixed effect model, as it contains both the fixed effect and random effects. It helps to analyse the data at both the levels namely country level and microfinance institution level. By using this model this paper tries to analyse the impact of each governance-related variable on the performance of MFIs. The model helps us to explain the variations of the variables and it provides the graphical description of influence of each of the governance-related variables at country level on the performance-related variables. With the help of the graphical descriptions the policy makers can easily identify the impact of the variables and formulate policies accordingly. This paper has used the multilevel model which has been already explained in Sect. 2.1. This method helps us to explain the cross-level effect and it also explains the variations among the variables. MFI-related data has been obtained from Microfinance Information Exchange (MIX) database whereas country-level data were collected from the World Development Indicators (WDI) and the Worldwide Governance Indicators (WGI) databases of the World Bank respectively. The time period of the data is 10 years mainly 2004–2013. The paper has considered 91 MFIs of seven selected South Asian countries mainly Afghanistan, Bangladesh, India, Pakistan, Indonesia, Philippines and Vietnam.

The STATA software has been used to analyse the data of 10 years (2004–2013) of seven selected South Asian countries.

2.1.1 Variables Used

The paper considers two types of dependent variables—financial dependent variables that include Operational Self Sufficiency (OSS), Profit Margin (PM), Return On Assets (ROA), portfolio at risk past 30 days (PAR 30) and social variables that include Average loan size per borrower adjusted by GNI per capita (AVLB) and percent of female borrowers (PERFB). Social performance is mainly the indicator of MFIs depth of outreach. ROA indicates how well an institution uses its total assets to generate return. OSS is used to measure profitability and self-sustainability of MFIs. Portfolio quality is being measured by portfolios-at-risk past 30 days (PAR 30). PAR ratio is calculated by dividing the PAR by the Gross Loan Portfolio (GLP). Low repayment performance or high loan risk is indicated by larger PAR.

The explanatory variables are mainly of three types namely macroeconomic indicators, MFI characteristics and governance indicators. The MFI-related explanatory variables are: Real yield on gross loan portfolio (RYGLP), Capital asset ratio (CAR), Cost per borrower (CPB), Log assets (LnA), Log number of deposit account (Ln DA), Log number of active borrower (LnAB), Log offices (LnOFF) and Log debt to equity ratio(LnDER). Apart from these variables, other MFI-related variables are namely age of the institutions, target market and outreach. Age is being represented by three dummies namely New_MFI, Young_MFI and Mature_MFI. Mature_MFI has been taken as the base category. The variable outreach indicates the number of borrowers which has been categorized into three types namely, Large_OUTREACH, Medium_OUTREACH and Small_OUTREACH. The Small_OUTREACH has been taken as base category. The Target Market variable explains the depth of market. This variable has been represented by three dummies namely Low_TARGET, Broad_TARGET, Small_TARGET and High_TARGET. The High_TARGET has been taken as the base category. The variable regulated is taken as an independent variable so to avoid multicolinearity problem we haven't taken the current legal status as independent variable as there will be high correlation between regulated dummy and legal status-related dummy. By incorporating regulated dummy variable this paper tries to show whether the MFIs which are regulated by Government or by some non-government regulatory institutions have differential impact on the performance of the MFIs. The dummy corresponding to regulated MFI is Regulated Dummy _MFI. Those who are not regulated have been taken as base category (see Appendix Table A1 for details of all the variables description with acronyms and sources).

The Governance variables used in this paper are: Control of Corruption estimate (COCR:EST), defined as "the estimation of capturing perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' of the state by elites and private interests". Government Effectiveness Estimate (GE:EST) has been explained as "the capturing perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies". Political Stability and Absence of Violence/Terrorism estimates (PSAV:EST) has been defined by "the estimation of capturing perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism" and Regulatory Quality estimates (RQ:EST) is "the estimation of capturing the perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development" (Kaufmann et al., 2010). Apart from these variables other macro variables are Domestic Credit (DC), Growth of GDP per capita (GRGDP_PERC) and Inflation (INF).

The descriptive statistics like mean, median, standard deviation, range of the dependent variables as well as explanatory variables have been computed and they confirm standard statistical results. The correlation statistics of the explanatory variables have been also checked and they are below the critical level to cause multicollinearity problem. The descriptive statistics results as well as correlation statistics are with the author if asked they will be provided.

3 Multilevel Model Analyses

Mixed-effects modelling is basically regression analysis allowing two kinds of effects: fixed and random, indicating intercepts and slopes meant to describe the population as whole, just as in ordinary regression, and also random effects, representing intercepts and slopes that can vary across subgroups of the sample randomly. The dependent variable Y represents financial variables namely OSS, ROA, PAR 30 and PM and social variables are PERFB and AVLB. All the explanatory variables are mentioned above as well as in Table A1. The mixed model of Gross loan Portfolio per 30 days (PAR 30), Operational Self Sufficiency (OSS) and Average loan size per borrower adjusted by GNI per capita (AVLB) are not significant so the results have not been provided. Wald test for these regressions has rejected mixed models.

Tables 1 and 2 represent mixed effect model. Table 1 shows the fixed effect part of the model. A likelihood ratio test, i.e., WALD test is reported in Table 1 which confirms that mixed effect model should be accepted over fixed effect regression model. In the random intercept model, intercepts vary randomly across different countries. This model implies seven separate intercepts, one for each country divisions, but they are not directly estimated. Instead, Table 2 provides an estimated standard deviation of the random intercepts (0.02), along with standard error (0.01) and 95% confidence interval for that standard deviation. This confirms mixed effect model over fixed effect model. The countries differ in terms of intercept term which varies randomly.

Tables 3 and 4 represent mixed effect model. Table 3 represents the fixed part of the mixed effect model. In the mixed model the country-specific variable, regulatory quality estimate has been taken as the predictor variable to vary randomly across different countries. From Table 3 we find that $p = 0.00$ corresponds to the Wald Statistic so we can conclude that adding random slopes brought significant improvement in the model. So the mixed model is accepted over fixed effect model. Table 4 depicts the estimation of standard deviation of the coefficient on the country-specific variable regulatory quality. The estimate is 0.03 which is greater than the standard error suggesting that there exists significant country-to-country variations in the slope coefficients for the regulatory quality variable. This result shows that regulatory quality has differential impact on ROA for different countries. In Fig. 1, vertical axis denotes seven countries and the horizontal axis is representing the slope coefficients deviations of regulatory quality from the mean value. It shows how regulatory quality affects differently across different countries.

In Bangladesh, ROA of MFI decreases as the regulatory quality increases. But in other countries with increase in regulatory quality ROA increases. It can be due to

Table 1 Results of mixed effects model on ROA

Dependent variable: Return On Assets (ROA)		
Explanatory variables	Coefficient	p value
RYGLP	0.09*	0.00
CAR	0.15*	0.00
CPB	−0.0006*	0.00
LnA	0.00001	0.11
Ln DA	0.0018*	0.01
LnAB	0.00001	0.50
LnOFF	−0.0055***	0.07
LnDER	0.02*	0.00
New_MFI	−0.05*	0.00
Young_MFI	0.01	0.13
Large_OUTREACH	−0.02	0.11
Medium_OUTREACH	0.0052	0.77
Low_TARGET	−0.10**	0.03
Broad_TARGET	−0.08***	0.06
Small _TARGET	0.12*	0.01
Regulated Dummy_MFI	0.0075	0.38
COCR:EST	−0.02	0.38
RQ:EST	0.05***	0.08
DC	0.0002	0.39
GRGDP_PERC	0.0002	0.86
INF	0.0001	0.82
Constant (CONS)	−0.07	0.31
No.of observations	910	
Wald Statistic and prob	285.12	0.00
Chi2(2) and prob	19.45	0.00

* Significant at 1% level, ** Significant at 5% level, and *** Significant at 10% level

Table 2 Estimates of standard deviations of the model on ROA

Random effect parameters	Estimate	Standard error	95% conf	Interval
Country: independent				
Sd (cons)	0.02	0.01	0.01	0.06
Sd(residual)	0.09	0.00	0.08	0.09

Table 3 Results of mixed effect model with variations of the country-specific variable

Dependent variable: Return On Assets (ROA)		
Explanatory variables	Coefficient	P value
RYGLP	0.09*	0.00
CAR	0.14*	0.00
CPB	−0.0006*	0.00
LnA	0.0065***	0.07
LnDA	0.0017**	0.01
LnAB	0.0024	0.51
LnOFF	−0.0065**	0.03
LnDER	0.02*	0.00
New_MFI	−0.05*	0.00
Young_MFI	0.01	0.15
Large_OUTREACH	−0.01	0.13
Medium_OUTREACH	0.0040	0.74
Low_TARGET	−0.10**	0.03
Broad_TARGET	−0.09***	0.05
Small_TARGET	0.11**	0.02
Regulated Dummy_MFI	0.0055	0.45
COCR:EST	0.0016	0.94
RQ:EST	0.02	0.38
DC	0.0001	0.56
GRGDP_PERC	0.0008	0.56
INF	0.0001	0.88
CONS	−0.07	0.28
No.of observations	910	
Wald Statistic and prob	285.12	0.00
Chi2(2) probability	19.45	0.00

* Significant at 1% level, ** Significant at 5% level, and *** Significant at 10% level

Table 4 Estimates of standard deviations of the model on ROA with variations of the country-specific variable

Random Effect Parameters	Estimate	Standard error	95% conf	Interval
Country: independent				
Sd (regulatory quality: estimates)	0.03	0.01	0.01	0.07
Sd (cons)	0.00	0.00	0.00	0.09
Sd(residual)	0.09	0.00	0.08	0.09

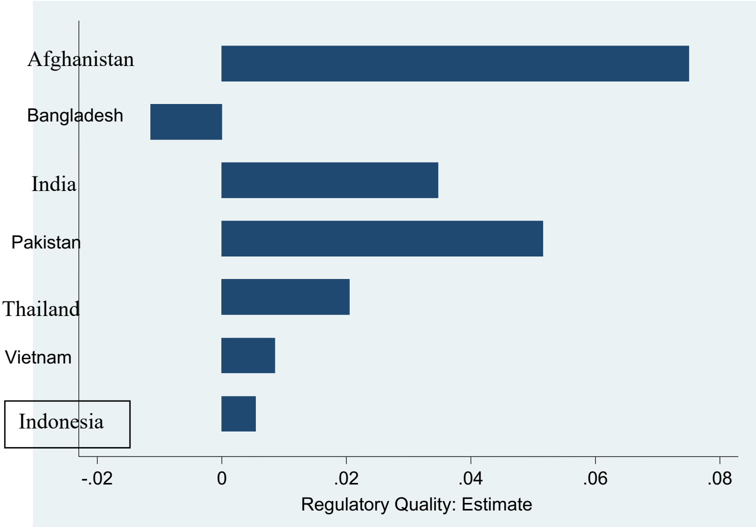

Fig. 1 Graph showing the effect of regulatory quality on ROA

the fact that most of the MFIs in Bangladesh are NGO MFIs (almost 96%, Appendix Table A2) so with high regulation the NGOs cannot provide loans to the maximum number of persons. The paper also finds that for Bangladesh outreach is large (see Appendix Table A3) which states that with high outreach large number of NGOs provides loans to the maximum number of persons so with decline in regulation quality of the country there is increase in ROA. This is suggestive of the fact that quality of regulation is now very important and with its better functionality the sampled MFIs may not achieve higher financial performance in case of Bangladesh.

Tables 5 and 6 depict the results of mixed effect model on profit margin. The explanation is similar to that of the explanation given in the section above Table 1. In Table 6 we find that an estimated standard deviation of the random intercepts (0.97), along with standard error (0.42) and 95% confidence interval for that standard deviation which implies that there is variation in the intercept of different countries and the random intercept model is accepted over fixed effect model.

Tables 7 and 8 represent mixed model results with random variation of government effectiveness across countries. The explanation is similar to that of the explanation represented in the section above Table 3. The result in Table 8 depicts that the standard deviation of the coefficient of the country-specific variable government effectiveness estimate is 5.05 which is greater than the standard error (1.47) suggesting that there exists significant country-to-country variations in the slope coefficients for government effectiveness. So mixed model is accepted. From Fig. 2 we can observe that the impact of government effectiveness on profit margin is not same across all the countries. To look more closely at how the government effectiveness estimate varies across countries, we can predict the random effects and from these we can estimate the total effects. Apart from India and Vietnam, government effectiveness has negative impact

Table 5 Estimates of mixed effect model on profit margin

Dependent variable: Profit Margin(PM)		
Explanatory variables	Coefficient	p value
RYGLP	0.11	0.62
CAR	2.65*	0.00
CPB	−0.0088*	0.00
LnA	0.06	0.18
LnDA	0.0068	0.52
LnAB	0.03	0.49
LnOFF	−0.09***	0.05
LnDER	0.33*	0.00
New_MFI	−0.30	0.14
Young_MFI	0.27***	0.07
Large_OUTREACH	0.14	0.44
Medium_OUTREACH	0.49*	0.00
Low _TARGET	−2.77*	0.00
Broad_TARGET	−2.23	0.00
Small_TARGET	0.69	0.34
Regulated Dummy_MFI	0.03	0.77
GE:EST	−2.38*	0.00
COCR:EST	−0.54	0.16
PSAV:EST	0.20	0.36
RQ:EST	1.40*	0.00
DC	0.01**	0.01
GRGDP_PERC	0.10*	0.00
INF	−0.00	0.79
CONS	−1.60	0.15
No.of observations	910	
Wald Statistic and prob	353.72	0.00
Chi2(2) with prob	19.35	0.00

* Significant at 1% level, ** Significant at 5% level, and *** Significant at 10% level

Table 6 Estimates of standard deviation of the model on profit margin

Random Effect Parameters	Estimate	Standard error	95% conf	Interval
Country: independent				
Sd (cons)	0.97	0.42	0.41	2.29
Sd(residual)	1.28	0.03	1.23	1.35

on profit margin in all other countries. This denotes that as the government becomes effective the profit margin falls but in India and Vietnam as the government effectiveness gets enhanced the performance of MFIs in terms of profit margin increases. The MFIs of India have faced a severe problem in the year 2011–2012, especially in the second half. To overcome this situation, Malegam Committee has provided many recommendations such as creation of a separate category of NBFCs operating in the microfinance sector to be designated as NBFC-MFIs. They have decided that there should be an imposition of a margin cap and interest rate cap on individual loans and requirement of transparency in interest charges. Apart from these other suggestions are namely, lending by not more than two MFIs to individual borrowers, creation of one or more credit information bureaus and many more (Sinha, 2012). On the basis of the recommendations, RBI and Government of India have provided comprehensive guidelines to protect the borrowers. According to Sinha, 2012, governance and regulatory framework are essential for increasing the wealth of the shareholders as well as maintaining the transparency and accuracy and it will enhance the profit margins of MFIs. A strong regulatory system always helps to protect borrower's interest as well as provides financial health for MFIs. In the long-term perspective, it is clear that a strong regulatory framework will enable the growth of MFIs to reach out to more needed persons and will also reduce risks associated with it.

In Vietnam the Vietnamese Bank for Poor (VBP) is the main arm of the government's policy for extending micro-financial services to the poor and it is the largest provider of micro-financial services nationwide. Because of its proximity to the government and its position of quasi-monopoly as a provider of micro-financial services, it can be considered as the de facto supervisory and regulatory device of the industry. In Vietnam, the Vietnamese Bank for Poor (VBP) and People's Credit Fund were created as a specialized extension of the Vietnamese Bank of Agriculture (VBA) to provide collateral-free credit facilities to the borrowers at lower interest rates. They have adopted "Credit Institution Law in 2010" for sustainable financial inclusion (Nguyen, 2019). According to Nguyen, 2019, many regulations have been taken by the Government of Vietnam to regulate MFIs so that the customers are benefitted. Bui (2017) has observed that Grameen Bank of Bangladesh started providing loans to the financially weaker section of the society in small scale where as the Government of Vietnam has gone through different methods of regulatory practices to strengthen the financial base of the country. According to Nguyen, 2019, government has reformed the banking sector and thus it had led to the expansion of the MFIs. Since 2005 Government of Vietnam has taken a series of regulatory measures to regulate microfinance institutions as it was suggested by Fallavier(1998). These measures have helped in the establishment of new MFIs as well as increase in the numbers of borrowers. A sound system requires removal of interest ceiling and more approach to market-based interest rate, professional management, formalization of non-banking financial intermediaries and a clear accountability. These factors have helped to improve the MFIs of Vietnam and thus have enhanced the profit margin of MFIs in Vietnam (Nguyen, 2019).

Tables 9 and 10 represent mixed effect model results on the percent of female borrowers. The explanation is already explained in section above the Table 1. In

Table 7 Estimates of mixed effect model with variations of the country-specific variable

Dependent variable: Profit Margin (PM)		
Explanatory variables	Coefficient	p value
RYGLP	0.09	0.62
CAR	2.53*	0.00
CPB	−0.0077*	0.00
LnA	0.06	0.15
LnDA	0.16	0.60
LnAB	0.05	0.32
LnOFF	−0.10**	0.02
LnDER	0.33*	0.00
New_MFI	−0.01	0.94
Young_MFI	0.10	0.48
Large_OUTREACH	−0.0045	0.98
Medium_OUTREACH	0.24	0.15
Low_TARGET	−1.84*	0.00
Broad_TARGET	−1.45**	0.02
Small_TARGET	1.54**	0.02
Regulated Dummy_MFI	0.03	0.77
GE:EST	−2.14*	0.30
COCR:EST	−0.54	0.16
PSAV:EST	0.20	0.36
RQ:EST	0.09	0.86
DC	−0.0003	0.96
GRGDP_PERC	0.01	0.60
INF	0.0088	0.49
CONS	−3.61	0.21
No.of observations	910	
Wald Statistic and prob	253.04	0.00
Chi2(2) with prob	91.91	0.00

[*] Significant at 1% level, ** Significant at 5% level, and *** Significant at 10% level

Table 8 Estimates of standard deviation of the model on profit margin with variations of the country-specific variable

Random effect parameters	Estimate	Standard error	95% conf	Interval
Country: independent				
Sd (government effectiveness: estimate)	5.05	1.47	2.85	8.97
Sd (cons)	7.17	2.03	4.11	12.50
Sd(residual)	1.20	0.02	1.15	1.26

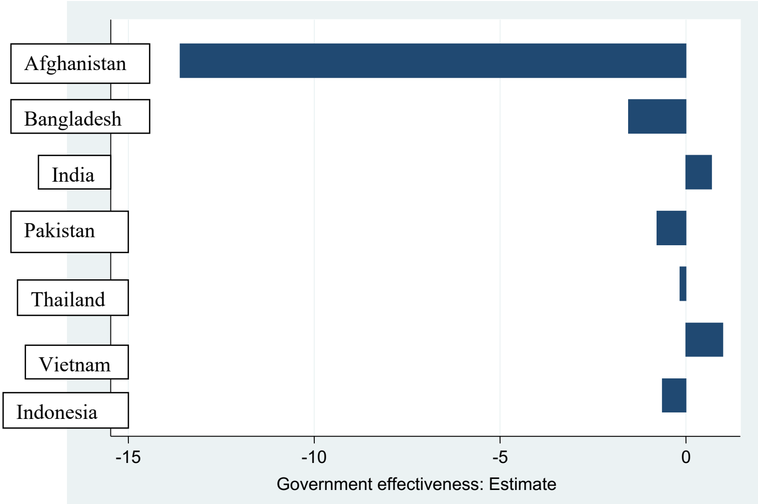

Fig. 2 Graph showing the effect of government effectiveness: estimate on profit margin

Table 10, estimated standard deviation of the random intercepts (0.12), along with standard error (0.03) and 95% confidence interval for that standard deviation implies that there is a variation of intercept across countries. So the mixed model is accepted.

Tables 11 and 12 represent mixed model results with random variation of domestic credit on female borrower. The explanation is similar to that of the explanation given in the section above Table 3. The result in Table 12 depicts that the standard deviation of the coefficient of the country-specific variable domestic credit is 0.0008 is less than the standard error (0.001) suggesting that there exists no significant country-to-country variations in the slope coefficients. Fig. 3 depicts the total effects of domestic credit on female borrower. All the countries have positive impact on domestic credit for female borrower. Percent of female borrower reflects the outreach of the society. From the graph 3 we find that India is having the maximum impact of domestic credit on female borrower. Kar and Swain (2014) mentioned that MFIs have recognized that females have a major role in the development of the economy. So they try to focus on providing more credits to the female. It implies MFIs are providing loans either to the females who are better off economically or female who can afford bigger sized loans.

4 Conclusions

This paper tried to examine whether regulatory quality and Government effectiveness have any influence on the performance of MFIs. To examine the performance of the MFIs the study has used multilevel model. The multilevel model is used

Table 9 Estimates of mixed effect model on percent of female borrowers

Dependent variable: Percent of Female Borrower (PERFB)		
Explanatory variables	Coefficient	P value
RYGLP	0.26*	0.00
CAR	−0.09*	0.00
CPB	−0.008*	0.00
LnA	−0.003	0.64
LnDA	−0.001	0.23
LnAB	−0.01	0.17
LnOFF	0.009	0.17
LnDER	−0.01***	0.08
New_MFI	0.07**	0.01
Young_MFI	0.05**	0.01
Large_OUTREACH	−0.006	0.81
Medium_OUTREACH	−0.03	0.24
Low_TARGET	0.19**	0.04
Broad_TARGET	0.08	0.38
Small_TARGET	−0.002	0.98
Regulated Dummy_MFI	−0.07*	0.00
GE:EST	−0.14**	0.05
COCR:EST	−0.06	0.27
PSAV:EST	−0.01	0.73
RQ:EST	0.10	0.15
DC	0.002*	0.00
GRGDP_PERC	0.002	0.37
INF	−0.0001	0.93
CONS	0.63*	0.00
No.of observations	910	
Wald Statistic and prob	274.65	0.00
Chi2(2) with prob	111.36	0.00

* Significant at 1% level, ** Significant at 5% level, and *** Significant at 10% level

Table 10 Estimates of the standard deviation of the model on percent of female borrowers

Random effect parameters	Estimate	Standard error	95% conf	Interval
Country: independent				
Sd (cons)	0.12	0.03	0.06	0.21
Sd(residual)	0.18	0.00	0.17	0.19

Table 11 Estimates of mixed effect model with variations of the country-specific variable on percent of female borrower

Dependent variable: Percent of female borrower (PERFB)		
Explanatory variables	Coefficient	Level of significance
RYGLP	0.26*	0.00
CAR	−0.09*	0.00
CPB	−0.0009*	0.00
LnA	−0.004	0.57
LnDA	−0.001	0.26
LnAB	−0.01	0.17
LnOFF	0.009	0.16
LnDER	−0.01***	0.09
New_MFI	0.07**	0.01
Young_MFI	0.05**	0.01
Large_OUTREACH	−0.005	0.83
Medium_OUTREACH	−0.02	0.26
Low_TARGET	0.19**	0.04
Broad_TARGET	0.08	0.38
Small_TARGET	−0.0005	0.99
Regulated Dummy_MFI	−0.07*	0.00
GE:EST	−0.14**	0.05
COCR:EST	−0.06	0.27
PSAV:EST	−0.006	0.84
RQ:EST	0.10	0.15
DC	0.002**	0.01
GRGDP_PERC	0.002	0.36
INF	−0.0002	0.89
CONS	0.63*	0.00
No.of observations	910	
Wald Statistic and prob	276.20	0.00
Chi2(2) with prob	111.60	0.00

* Significant at 1% level, ** Significant at 5% level, and *** Significant at 10% level

Table 12 Estimates of the standard deviation of the model on percent of female borrowers with variations of the country-specific variable

Random effect parameters	Estimate	Standard error	95% conf	Interval
Country: independent				
Sd (Domestic credit)	0.0008	0.01	0.0006	0.10
Sd (cons)	0.11	0.04	0.05	0.24
Sd (residual)	0.18	0.004	0.17	0.19

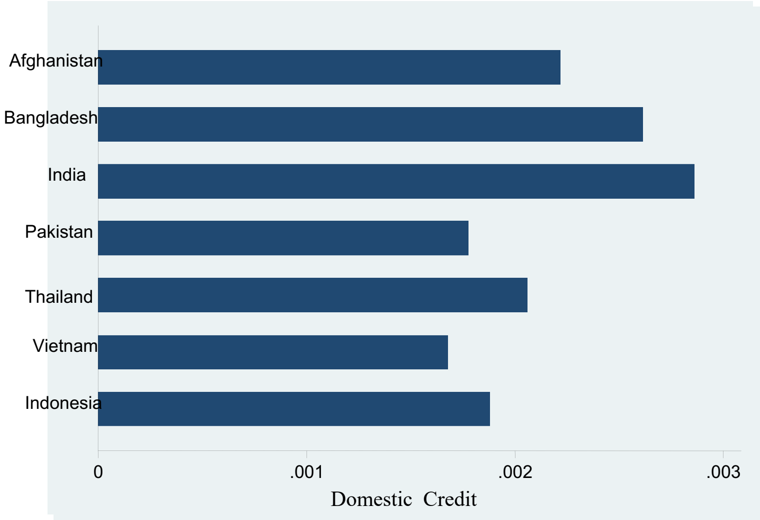

Fig. 3 Graph showing the effect of domestic credit on female borrower

because it shows differential impact of country-specific variables on the performance of the MFIs among different countries. As different countries have different historical perspective of evolution of the MFIs so it is necessary to analyse the performance of the MFIs at the institution level as well as at country level.

The important observations are that regulatory quality of countries has differential impact on ROA across different countries. The regulatory quality influences ROA positively for all the countries except for Bangladesh. Government effectiveness influences the profit margin negatively except for India and Vietnam. The domestic credit (DC) has positive influence on percent of female borrowers (PERFB) and the impact is highest for India followed by Bangladesh. On the basis of the above observations few policies can be prescribed. Countries like Bangladesh and Afghanistan should look after the regulatory quality and effectiveness of the Government respectively. Although Bangladesh has NGO-based MFIs, the regulatory quality of the country must improve to increase ROA as well as profit margin of the MFIs. RQ:EST ensures the security of the customers which will in turn lead to growth of the MFIs and ultimately it will result in the enhancement of ROA of the MFIs. Afghanistan should look after the government effectiveness as it has negative impact on profit margin in this country. Government needs to be more effective and responsible to increase profit of the institutions. The government of the country must take some policies and programmes to improve the quality of the institutions. This improvement will attract more customers which will thus improve the profit margin. The study has already found positive relation between domestic credit and percent of female borrower. India has strong regulatory quality and Government effectiveness so it enables the female borrower to rely on the MFIs. So it is necessary for all the countries to be more effective and reliable to provide loans to the customers.

Appendix

See Tables A1, A2 and A3.

Table A1 Variable descriptions

Variable name	Definition	Source
Dependent variables		
Financial variables:		
Return on Assets (ROA)	Net operating income after taxes/Average total assets	MIX Market
Operational Self Sufficiency (OSS)	Total operating revenues / total administrative and financial expenses	MIX Market
Portfolio at risk past 30 days(PAR 30)	Portfolio-at-risk past 30 days / Gross loan portfolio	MIX Market
Profit margin(PM)	Net Operating Income/ Financial Revenue	MIX Market
Social Variables:		
Percent of female borrower(PERFB)	Percent of female borrowers	MIX Market
Average loan balance per borrower adjusted by GNI per capita(AVLB)	Average loan balance per borrower/GNI per capita	MIX Market
Explanatory variables:		
Control of corruption: Estimate(COCR:EST)	Aggregate governance indicator of 'control of corruption'	WGI
Government effectiveness: Estimate(GE:EST)	Aggregate governance indicator of 'government effectiveness'	WGI
Political stability and absence of violence/ terrorism: Estimate(PSAV:EST)	Aggregate governance indicator of 'political stability'	WGI
Regulatory quality: Estimate(RQ:EST)	Aggregate governance indicator of 'regulatory quality'	WGI
Domestic credit(DC)	Domestic credit provided by the banking sector (% of GDP)	WDI
Growth of GDP per capita(GRGDP_PERC)	Growth of real GDP per capita	WDI
Inflation(INF)	Rate of inflation, GDP deflator	WDI
Log assets(LnA)	The natural logarithm of total assets (Total net asset accounts) in US$	MIX Market

(continued)

Table A1 (continued)

Variable name	Definition	Source
Real yield on gross loan portfolio(RYGLP)	[Yield on gross portfolio (nominal) – Inflation rate] / (1 + Inflation rate)	MIX Market
Capital/asset ratio(CAR)	Ratio of total capital to total assets	MIX Market
Cost per borrower(CPB)	Operating Expense/ Number of Active Borrowers	MIX Market
Log number of active borrower(LnAB)	The natural logarithm of number of active borrowers an MFI has	MIX Market
Log number of deposit account(LnDA)	The natural logarithm of number of any type of deposit account held by an MFI	MIX Market
Log offices(LnOFF)	The natural logarithm of number of staffed points of service and administrative sites	MIX Market
Log debt to equity ratio(LnDER)	The natural logarithm of ratio of total debt to equity	MIX Market
Age	Dummy variable, New_MFI = 1, Young_MFI = 2 and Mature _MFI = 3. Mature _MFI is taken as base category	MIX Market
Current legal status	Dummy variable, NGO = 1, Other = 2, Bank = 3, NBFI = 4, rural bank = 5, credit union = 6	MIX Market
Outreach[a]	Dummy variable, Large_OUTREACH = 1, Medium _OUTREACH = 2, Small_ OUTREACH = 3. Small_OUTREACH is taken as base category	MIX Market
Target market[b]	Dummy variable, Low End Business = Low_ TARGET = 1, Borad End Business = Broad_ TARGET = 2, Small End Business = Small_ TARGET = 3, High End Business = High_ TARGET = 4. High_TARGET is taken as base category	MIX Market
Regulated(Regulated Dummy_MFI)	Dummy variable If yes = 1 then Regulated Dummy_ MFI = 1, zero otherwise	MIX Market

Source Microfinance Information Exchange (MIX), Worldwide Governance Indicators (WGI) and the World Development Indicators (WDI) of the World Bank

[a]Indicates number of borrower. Large outreach = number of borrowers > 30,000 , medium outreach = number of borrowers between 10,000 to 30,000, and small outreach = if number of borrowers<10,000.

[b]Indicates depth of the market. Low end target market = depth<20%, broad end target market = depth between 20% and 149%, high end target market = depth between 150% and 250% and small end target market = depth over 250%.

Table A2 Country wise observations and current legal status

	Current legal status						
Name of countries	Non Governmental Organization(NGO)	Other financial institutions	Bank	Non Bank Financial Institution(NFBI)	Rural bank	Credit Union	TotaL
Afghanistan	10(20%)	10(20%)	10(20%)	20 (40%)	0	0	50
Bangladesh	280(96.55%)	0	10(3.44%)	0	0	0	290
India	70(25%)	9(3.21%)	0	181(64.64%)	10(3.57%)	10(3.57%)	280
Pakistan	102(68%)	0	28(18.66%)	20(13.33%)	0	0	150
Thailand	0	0	0	10(100%)	0	0	10
Vietnam	39(78%)	0	11(22%)	0	0	0	50
Indonesia	20(25%)	0	10(12.5%)	10(12.5%)	30(37.5%)	10(12.5%)	80
Total	521 (57.25%)	19 (2.08%)	69(7.58%)	241(26.48%)	40(4.39%)	20(2.97%)	910

Source MIX, 2014, 2017

Table A3 Country wise observations and outreach

Outreach				
Name of countries	Large (%)	Medium (%)	Small (%)	Total
Afghanistan	19(38)	14(28)	17(34)	50
Bangladesh	254(90.71)	20(7.14)	16(5.71)	290
India	228(102.82)	35(12.5)	17(6.07)	280
Pakistan	91(60.66)	35(23.33)	24(16)	150
Thailand	0	0	10(100)	10
Vietnam	22(44)	11(22)	17(34)	50
Indonesia	22(27.5)	11(13.75)	47(58.75)	80
Total no of MFIs	636 (69.89)	126(13.84)	148(16.26)	910

Source MIX, 2014, 2017

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Development Fundamentals: Demography and Social Sector

Subaltern Urbanization: The Birth of Census Towns in West Bengal

Saumyabrata Chakrabarti and Vivekananda Mukherjee

1 Introduction

Urban growth in India over the last five decades can broadly be divided into four components, namely (a) growth due to natural increase in population; (b) growth due to net rural-urban migration; (c) growth due to reclassification from rural to urban settlement and (d) growth due to areal expansion. Figure 1 shows the share of these components in Indian urban growth in the last five decades.

From Fig. 1, as Chakrabarti and Mukherjee (2020) pointed out, the largest component of urbanization in India is the urbanization out of natural increase in population that explains more than 50% of urban growth, while the migration-driven urbanization stayed almost stable in the last five decades explaining only 20% of the same. The growth due to areal expansion had never exceeded 10% and remained particularly insignificant in the last decade, 2001–2011. On the other hand, reclassification-driven urbanization whose role remained marginal before 2001–2011, has become more prominent during the same period. As Chakrabarti and Mukherjee (2020) observed in the Indian Census the reclassification of villages in small towns (called Census Towns (CTs)) happens if a village satisfies the following criteria: (1) it has a population of 5000 or more; (2) its population density is at least 400/km^2; and (3) 75% of its male main workforce working in non-farm sector. The CTs are administered

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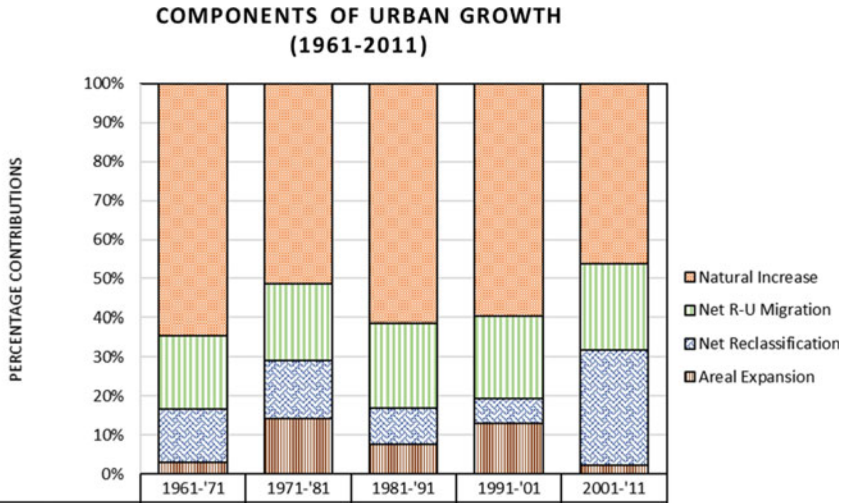

	1961-'71	1971-'81	1981-'91	1991-'01	2001-'11
Natural Increase	64.6	51.3	61.3	59.4	46.3
Net R-U Migration	18.7	19.6	21.7	21.0	22.0
Net Reclassification	13.8	14.8	9.4	6.2	29.5
Areal Expansion	2.9	14.2	7.6	13.0	2.2

Fig. 1 Components of urban growth in India (1961–2011). *Source* Census of India (1971, 1981, 1991, 2001 and 2011); Chakrabarti and Mukherjee (2022)

by rural local governments.[1] As per Census (2011), the upsurge in number of CTs from 1362 to 3894 during the decade of 2001–2011, had contributed toward almost 30% of urbanization. Denis et al. (2012) call it 'subaltern urbanization'. This chapter focuses on the determinants of this particular kind of urbanization.

There are three different kinds of theoretical argument that attempt to explain the dynamics of formation of the CTs. The first is related to the impact of developments in the large city in the neighborhood. The factors like fall in formal sector employment, the rise in congestion, house-rent and pollution may incentivize the existing population living in the large city to relocate in the villages bordering the city. It is also possible that the rural population, who looks for opportunities to relocate in the large city for better livelihood, for the same reasons mentioned above, are dissuaded in doing so. Some may resort to commuting rather than living within the city limit. The papers like Kundu (2011) and Sharma (2013) spell out such possibilities. The second is related to the development at the village level. The development of local infrastructure like schools, health facilities, stable electricity connection, development of banking facilities at the villages, generates forces of agglomeration at the village level. They not only facilitate relocation from neighboring villages but also

[1] In India the rural local governments are called 'Panchayats'. The three tier Panchayat system consists of 'Gram Panchayat' at the bottom, 'PanchayatSamiti' at the middle and 'ZillaParisad' at the top.

from the large city located nearby. The papers like Aggarwal (2018) and Mukhopadhyay et al. (2016) take this view. Third, the development of transport infrastructure connecting the villages to the neighboring large city may play a role in the formation of CTs. The reduced transport cost may either decelerate the formation of the CTs by strengthening the forces of agglomeration toward the existing cities, or it may accelerate the same by strengthening the forces of dispersion away from the existing cities. The effect of transport infrastructure in the formation of CTs is discussed by papers like Ghani et al. (2012) and Chakrabarti and Mukherjee (2022).

This chapter attempts to find out which of the factors mentioned above explain the birth of CTs in West Bengal, an Eastern state of India, during 2001–2011. We work on West Bengal data, since West Bengal is the state which has experienced maximum increase in terms of number of CTs during 2001 and 2011, as shown in Table 1. It accounts for two-thirds of the urbanization in the state during the period.

The table above shows that all the major states have experienced a jump in the number of CTs between 2001 and 2011 with West Bengal leading the list. In

Table 1 Distribution and growth of census towns in Indian states

States	Number of census towns in 2011	Number of new census towns between 2001 and 2011
West Bengal	780	526
Kerala	461	346
Tamil Nadu	376	269
Uttar Pradesh	267	206
Maharashtra	278	171
Andhra Pradesh	228	137
Jharkhand	188	107
Odisha	116	86
Gujarat	153	83
Karnataka	127	81
Assam	126	80
Rajasthan	112	76
Punjab	76	55
Bihar	60	52
Haryana	74	49
Madhya Pradesh	112	46
Uttarakhand	41	29
Jammu and Kashmir	36	27
Chhattisgarh	14	10
Others	269	162
India	3894	2600

Source Census of India (2011) and author's calculation (Chakrabarti & Mukherjee, 2020, 2022)

West Bengal, out of 780 CTs 526 have born during 2001–2011. In earlier papers Chakrabarti and Mukherjee (2020, 2022) explored the role of neighboring city, development of village-specific factors, and transport infrastructure in the birth of CTs in West Bengal. Chakrabarti and Mukherjee (2020) explain the birth of CTs around existing cities by considering city-specific factors like its formal sector wage, population density, area, and transport cost from the neighborhood village to the city where the jobs are located. They find that high formal sector wage along with a low urban extension is conducive for the birth of Census Towns in the neighborhood of a city. Chakrabarti and Mukherjee (2022), on the other hand, found that the existence of state/national highways in the neighborhood increases the probability of a village, designated as a 'would be Census Town', being transformed in a Census Town, whereas the development of rail infrastructure did not stimulate such transformation. Further, Chakrabarti and Mukherjee (2022) noted that density of local road network in a district complements the highways in explaining the formation of the CTs for districts that are not adjacent to Kolkata, the capital city of West Bengal, indicating that in these districts the transport infrastructure creates the forces of dispersion away from the existing cities. On the contrary, the districts that are bordering Kolkata local roads oppose the dispersing influence of the highways in formation of CTs, and decrease the concentration of non-farm activities at the 'would be CTs'. The paper by Chakrabarti and Mukherjee (2022) did not find significant impact of Golden Quadrangle (GQ) project, implemented during the study period for connecting the four major metropolitan cities of India, in birth of the Census Towns in West Bengal. They also found that the village-specific factors play a positive significant role in conversion of a village to a Census Town.

Since the city-specific, village-specific, and the transport infrastructure-related variables are correlated with each other as one causes the other, we cannot use them as explanatory variables in a single regression framework. However, from the policy perspective it is important to know their relative contribution in formation of Census Towns. The present chapter attempts to solve this problem. It uses Principal Component Analysis (PCA)[2] to reduce the dimensionality of the explanatory variables. The principal components are a blend of all the control variables used in Chakrabarti and Mukherjee (2020, 2022) and are orthogonal to each other. The varimax rotation of these variables identifies control variables, which have the highest correlation with each of the extracted principal components. We identify the principal components with the variable having the highest correlation with them and use them in the regression analysis to find out how they explain the conversion of villages in Census Towns in West Bengal. The chapter finds, in similar spirit as Chakrabarti and Mukherjee (2022), the explanatory factors play out differently in the districts bordering Kolkata, the capital city of West Bengal, and the other districts. The districts bordering Kolkata are North 24 Parganas, South 24 Parganas, and Haora. While the presence of highways within 5 km. radius of a village plays an important role in creation of CTs for both types of districts, in the districts bordering Kolkata density

[2] See papers like Savić (2006), Chen and Ma (2015), Nugrahadi et al. (2020), for applications of PCA in different context.

of population in the nearby city/Statutory Town (ST) plays a significant role. In the districts not bordering Kolkata the CTs are created away from the nearby STs and cities. It appears, among the city-specific factors, the importance of density that we find in this chapter is a new finding. It was not significant when Chakrabarti and Mukherjee (2020) analyzed the importance of city-specific factors in formation of CTs in West Bengal. Similarly, when Chakrabarti and Mukherjee (2022) analyzed the transport infrastructure-specific factors, nearness did not appear as a significant variable. Therefore, this is also a new finding of the chapter. We obtain the new results as we take all the three types of variables in a single framework and eliminate correlation between them. The results suggest that the forces of dispersion created from the congestion at the existing cities/STs are important in explaining the birth of CTs in West Bengal both at the districts around Kolkata and the other districts. The highways help the dispersion. In the districts outside Kolkata, commuting to the nearest city/ST is not important for formation of CTs. It highlights the process of the local agglomeration in and around the villages converted into CTs. However, in the districts bordering Kolkata, it seems the density of population in existing cities/STs plays an important role in dispersion process.

The plan of the chapter is as follows. The second section surveys the existing literature on the birth of Census Towns. Section 3 describes the methodology and the data and derives the results. The section following concludes the paper.

2 The Survey of Literature

Kundu (2011) discussed the issue of low rates of in-migration in metropolis and large cities like Delhi, Chandigarh, Kolkata, Hyderabad, Chennai, and Mumbai. According to this study, in urban metropolis various drives like removal of encroachments, shantytowns, petty commercial establishments, squatter settlements, and judicial interventions to curb the unplanned extension of urban growth caused the in-migration less attractive for poorer section of the population. Sharma (2013) points out that due to improved transport facilities workers travel daily to cities for jobs, which in turn led to the developments of CTs near the existing urban centers.

In a theoretical paper Marjit and Kar (2014) argue that in an open economy reform in labor market may lead to development of urban formal sector and shrinkage of urban informal sector coupled with a decline in wage in urban informal sector and an increase in the same in rural informal sector. These lead to a reverse migration in the economy with a fall in the average wage until there is a substantial growth of urban organized sector. Krugman and Elizondo (1996) with the example of Mexico point out that due to a shift of the economy from an inward looking strategy to liberalization of international trade the manufacturing sector scatters with the mitigation of backward and forward linkages in Mexico City to northern states adjacent to US border causing the dispersion of non-farm labor force in the economy. Zhu (2017) recognizes that the phenomenon of in situ urbanization in a wide range of areas in south eastern coastal provinces of China after 1970s was an outcome of China's urbanization process after liberalization in line with Krugman and Elizondo (1996).

Among village centric views, according to Aggarwal (2018) development of roads and transport facilities in rural areas leads to a greater market integration, reduced price of non-local goods, and wider variety of consumption basket in rural areas and more participation of local youths in the expanded labor market. Mukhopadhyay et al. (2016) in the context of certain CTs in northern India observed that, improved transport and communication facilities along with growing rural income stimulate the growth of small scale non-tradable services which are the main sources of non-farm employment in these settlements.

There are some notable studies that discuss the role of transport infrastructure and urbanization. The study by Krugman (1991) on economic geography, argues that lowering of transport cost encourages agglomeration by attracting both labor and capital to the city. However, Helpman (1998) predicts that rising housing price due to rise in population in the larger region acts against agglomeration in the city, in favor of dispersion of economic activities and consequently the labor force. However, the technological progress in manufacturing sector may mitigate the dispersing forces (Zhu, 2017). Proost and Thisse (2019) argue that owing to the improvement in transport infrastructure and falling transport cost there is first agglomeration and then dispersion of production and consequent regional disparity and in the later stage regional integration occurs. Chandra and Thompson (2000), with the result of a study on the effect of highways show that the highways improve the income of the rural countries they go through and reduce the same in the adjacent countries in USA between 1969 and 1993. Baum-Snow et al. (2020) show with the example of China that investing in local transport infrastructure to promote the growth of hinterland often has an opposite impact of losing economic activities and specialization in agriculture. In Indian context, Ghani et al. (2012) found that district-level infrastructure is partly dispersing organized manufacturing to rural locations while the unorganized manufacturing is relocating to urban locations. Such movement seems to be partially explained by the development of national-level highways especially the construction of Golden Quadrangle, a highway project undertaken by the Government of India that was implemented in the study period. However, there is a very limited impact of Golden Quadrangle on unorganized manufacturing outside the nodal districts where more than one highways meet. Balakrishnan (2013) cited instances of Bangalore-Mysore highway and Pune-Nasik highway to establish that the urbanization along highways has been the emerging pattern of urbanization in developing countries. According to the study of Mahajan and Nagraj (2017) using NSSO 55th round (1999–2000), 66th round (2009–2010), and 68th round (2011–2012) datasets, the construction of highways and rural road networks during 2000–2012 boosted up construction demand and employment in rural areas. Chakrabarti and Mukherjee (2020, 2022) in search of the reasons behind the birth of CTs show the relative significance of certain city-specific, transport infrastructure-specific, and village infrastructure-specific variables in formation of CTs in the state of West Bengal in India. They find that factors like high formal sector wage rate at the nearest city of a village, the larger area of the city, development of highways and local roads in the village-neighborhood, provision of banking facility, and availability of stable electricity connection at the village help conversion of the village in a CT.

3 The Principal Component Analysis

The Principal Component Analysis (PCA) is a technique that reduces the dimension of correlated variables into new variables, called principal components (PC) which are uncorrelated with each other and describe most of the information in the full dataset to explain its common variation.

The control variables used in the literature for explaining the birth of CTs are mainly of three different types: (1) variables related to transport infrastructure; (2) variables related to village-specific infrastructure; (3) variables related to the nearest city/statutory towns.

An improvement of transport infrastructure in a village can occur in three different ways: (i) development of a highway that connects cities may pass through the village neighborhood; (ii) improvement of rail-connectivity of the village to the cities; (iii) improvement of local road network near the village (Chakrabarti & Mukherjee, 2022). The improvement of transport infrastructure reduces the cost of traveling to the city, which may have both positive and negative influence on a village in terms of its conversion to a CT. On the one hand, it facilitates migration from village to city and reduces its chance of being converted to a CT; on the other, it shelters the firms and workers who relocate from the city for avoiding the congestion and increases its chance of being converted to a CT. The increased commuting of non-farm workers, due to ease of commuting, to the nearest city/ST also helps the conversion of a village to a CT. The set of variables related to transport infrastructure are:

HIGHWAY 5: A dummy variable that takes value of 1, if a highway passes through a neighborhood of 5 km radius around the center of village i in district j;

RAIL 5: A dummy variable that takes value of 1, if there is at least one railway station within 5 km radius neighborhood around the center of village i in district j;

NEARNESS: Reciprocal of the nearest city/ST distance from the center of village i in district j.

ROAD: The length of rural roads per 1000 km^2. area in district j. We assume uniform distribution of rural roads across all villages of the district.

The development of non-tradable services like availability of electricity services, rural banks, other financial services, etc., offers a better quality of life to village residents, creates more non-farm jobs, and therefore, attracts more population in it (Chakrabarti & Mukherjee, 2022). The set of variables related to local development are:

RBANK: A dummy variable that takes value of 1, if at least one branch of a commercial bank is present in village i at district j;

POWER: Represents percentage of electrified villages in district j, where village i is located. This indicates the probability of availability of power in village i in district j.

The presence of an urban center in the neighborhood may impact CT dynamics meaningfully (Chakrabarti & Mukherjee, 2020). Let us describe the variables related to the developments at the nearest city/statutory towns. First, in the short run a rise in the formal wage although reduces the employment in urban formal sector, has an uncertain effect on the expected wage in the urban sector, and consequently on the CT dynamics. As the wage expected in the urban area rises, labor starts migrating to the city; the city with its defined boundary and density of population cannot accommodate the migrants from the rural area, causing them to revert back to the village and be absorbed in rural non-farm sector. However, the wage rate in the rural area rises and the farm sector is forced to shed-off labor. They find jobs in the rural non-farm sector causing non-farm employment to expand and helping a village to transform to a CT. On the contrary, if the expected wage in the city falls, reverse migration starts leading to a fall in rural wage. Then the farm sector with limited absorption capacity accommodates more labor compared to rural non-farm sector and the village ceases to transform to CT. Since the wage in the formal sector is credited through banks, the number of branches of commercial banks has been used as proxy variable for formal wage in the urban sector. Second, a fall in the population density in the city causes a fall in the participation in the urban informal sector. These labors find jobs in rural non-farm sector since the rural farm sector with limited absorption capacity does not employ them. Therefore, the villages near the city have greater chance to be transformed into CTs. Last, an expansion in the boundary of the city reduces the chance of a neighboring village being transformed into a CT. This happens as given the size of its formal sector, expansion of the city leads to an expansion of urban informal sector. The labor relocates from the rural non-farm sector to urban informal sector, which reduces the chance of the neighboring village transforming into a CT. The city-specific variables used in analysis are:

DENS: Population density in the nearest city/ ST; a proxy variable for 'formalization and sanitization' in the city/ST; a lower value of DENS implies more 'formalization and sanitization';

AREA: Area of the nearest city/ST;

UBANK: Number of commercial bank branches in the nearest city/ST, a proxy variable for formal wage in the nearest city.

The three types of variables described above are likely to be correlated with each other. For example, the improvement of transport infrastructure connecting a village to a city or in the neighborhood of a village may improve the village-specific infrastructure as agglomeration forces are created around the village. The number of bank branches can increase. The power supply can improve. It may also increase population density in the city as both the migration and the daily commuting to the city becomes less costly. The improvement of local infrastructure also leads to the development of transport infrastructure. The development of the city, which leads to congestion, as argued by Helpman (1998) obviates development of infrastructure away from the city. Therefore, we cannot use all these variables together in a regression analysis for finding their influence on the growth of Census Towns.

Hence the empirical exercise consists of two parts. The first part uses PCA to reduce the number of variables described above into few principal components (PCs) which are the linear combination of original variables containing most of the information of original variables capturing majority of the variation in the dataset. The analysis helps us to extract those PCs which have the highest Eigen values. The varimax rotation of them tells us which variables have the highest association with the chosen PCs. Then, for finding out relative significance of the variables which have the highest association with chosen PCs (dominant variables) in explaining the formation of CTs, we run the following regression specification:

$$y_{ij} = \alpha + \mu\beta + D_j + \varepsilon_{ij} \quad (1)$$

In Eq. (1) the dependent variable y_{ij} represents the status of a village in Census 2001 which was identified as 'would be CT'. It takes a value of 1 on the successful conversion of the village in Census 2011. Otherwise, it takes a value of $0.X_{ij}$ represents the set of dominant variables that indicate the dominant variable chosen from significant PCs at the i th village in the j th district. The district-specific fixed factors of district j, which are shared by all the villages located in district j, are captured through the dummy variable D_j. The unobserved village-specific factors are captured through ε_{ij}, which we assume to be independently identically distributed across the villages.

3.1 The Data

We use the dataset pertaining to CTs/Villages Directory of West Bengal for 2001 and 2011 extracted from the Census of India (2001 and 2011)) and also from the State Statistical Handbook of West Bengal for various years. Table 2 describes the data.

The descriptive statistics presented in Table 2 depicts that majority of the villages (80%) designated as 'would be' census town in 2001 got transformed into CT in 2011. Among the set of explanatory variables related to connectivity to city/local connectivity of village i, the dummy variable HIGHWAY5 has a mean of 0.78 implying 78% of such villages were located in the 5 km radius neighborhood of either nearest national highway or state highway (Chakrabarti & Mukherjee, 2022). Similarly, the dummy variable RAIL5 having the mean of 0.38 implies that 38% of the 'would be CTs' villages in the Census 2001 were located in the 5 km radius neighborhood of the nearest rail station. For the NEARNESS variable, for the sampled villages the mean is 0.11, with maximum of 2 and minimum of 0.01. There exists, an inverse relation between distance of a village from the nearest city/ST and the value of NEARNESS variable. The minimum distance that we have found in our data was 0.5 km (the reciprocal of 2) and the maximum distance was 100 km (the reciprocal of 0.01). The average distance was 9.09 km (the reciprocal of 0.11) (Chakrabarti & Mukherjee, 2022). For the variable ROAD, data was unavailable at the village level. Therefore, we used the data on the roads maintained by the local administrative bodies like Gram Panchayats, Panchayat Samitis, and Zilla Parishads aggregated at the district level as a proxy for the ROAD variable as in Chakrabarti and Mukherjee (2022). The

Table 2 Descriptive statistics

Variable name	Mean	Standard deviation	Minimum value	Maximum value
Dependent variable (=1, for villages transformed to CT) (=0, for villages not transformed to CT)	0.80	0.40	0	1
Transport related variables				
HIGHWAY5 (=1, neighborhood of highways within 5 km radius from the village center; 0, otherwise)	0.78	0.41	0	1
RAIL5 (=1, neighborhood of railheads within 5 km radius from the village center; 0, otherwise)	0.38	0.48	0	1
NEARNESS (reciprocal of the distance from nearest city/ST from the village)	0.11	0.18	0.01	2
ROAD (the length of rural road in the district 2007–2008 per 1000 km^2)	11.46	9.50	3.09	30.77
Variables related to local non-traded services				
RBANK (=1, if 1 commercial banks in the village 2007–2008; 0 otherwise)	0.51	0.50	0	1
POWER (percentage of electrified village in the district 2001)	93.7	11.86	53.7	100
City/ST specific variables				
DENS (population/ km^2) Population density of the nearest city/ST	12,618.62	6901.34	1884	24,841
AREA (km^2) Area of the nearest city/ST	56.11	62.92	5.85	185

(continued)

Table 2 (continued)

Variable name	Mean	Standard deviation	Minimum value	Maximum value
UBANK Number of bank branches of the nearest city/ST	189	369	15	1007

Source Census of India (2001 and 2011) and State Statistical Handbook of West Bengal (various years)

data has been normalized per 1000 km^2 area of the district. The average length of local roads per 1000 km^2 in the districts of West Bengal by 2007–08 was 11.46 km with a minimum of 3.09 km in the district of Darjeeling and maximum of 30.77 km in the district of South 24 Parganas. We assume that the road allocation is uniformly distributed among all villages in a district (Chakrabarti & Mukherjee, 2022).

Among the non-tradable services RBANK is taken at village level but in the absence of proper village-level data, the data on POWER is taken at the district level. RBANK is a binary variable with mean of 0.51 which implies that 50% of 'would be CTs' villages have had at least one commercial branch in 2007–2008 before the Census operation of 2011. On an average, 93.70% of villages were electrified across all districts in West Bengal in 2001 with a minimum of 53% and a maximum of 100%.

It is not that all the villages in West Bengal, which were identified as 'would be CTs' in Census 2001, had a nearby city with population exceeding 1lac. In the absence of such cities we have used those urban bodies, which have the status of Statutory Towns (STs) and we have taken their population density and area as explanatory variable for our analysis. But, all STs are not large enough to trigger migration/commuting from nearby villages. For solving this problem, we looked at the distribution of bank branches at the city and STs of West Bengal and considered only those STs in which the number of bank branches is above the median (turns out as 15).

Among the city-specific attributes, population density of the nearest city/ST from a 'would be CTs in 2001' vary from 1884/km^2 to 24,841/km^2 with the mean at 12,618.6/km^2. The maximum is corresponding to the city of Kolkata. The area of such city/ST has a mean of 56.11 km^2 with a standard deviation 62.92. The number of branches of the banks in the nearest urban bodies from the 'would be CTs in 2001', which has been considered as a proxy for wage at the nearest urban locality, vary from 15 to 1007 with a mean of 189. The maximum number of bank branches belongs to the city of Kolkata. We take log transformation of the variables POWER, DENS, AREA, and UBANK while doing the empirical exercise.

We also run separate regressions for the districts bordering Kolkata and the other districts of West Bengal. The districts bordering Kolkata are North 24 Parganas, South 24 Parganas, and Haora. Of the 551 villages, which were 'would be CTs in 2001', 171 belonged to these districts.

3.2 The Principal Components

We perform the PCA with the variables described above. First, we calculate Eigen values and Eigen vector of each Principal Components. While the Eigen values represent the variances of the dataset, the Eigen vectors are the coefficients of the original variables in each principal component representing the correlation between a variable and the principal component. A PC qualifies for incorporation in the analysis if it has its Eigen value greater than one. Then we perform the orthogonal varimax rotation of the original Eigen vector matrix corresponding to Eigen values. The objective is to determine the association between the variables and corresponding principal components clearly which the original Eigen vector matrix fails to show in some cases. The rotated component vectors after varimax rotation represent clearly the correlation between the original variables and the chosen Principal Component. This method helps us to identify those variables with the highest load (dominant variables) in each PC.

3.3 The Regression

The regression specification (1) has binary dependent variable. Hence, the Probit regression method is applied. We allow the corresponding probability distribution to be associated with a cumulative normal distribution,

$$Z = \varnothing(x\mu + \varepsilon) \in (0, 1)\text{sothat}x\mu + \varepsilon = \varnothing^{-1} \tag{2}$$

Notice,$Z' = x\mu + \varepsilon$

Since the dependent variable takes the value 0 and 1, we assume,Z' takes the value 0 and 1. The above function $Z\prime = x\beta + \varepsilon$ is called the Probit function whose parameters are estimated.

3.4 The Results

First we report the results as we use data from all the districts of West Bengal. The Eigen values of the principal components and corresponding rotated varimax table of Eigen vector matrix are shown in the following tables.

Table 3 shows the number of principal components to be extracted based on Eigen values. From the table we choose first four PCs whose Eigen values are greater than one explaining 70% common variation in data. The second column of this table shows each PC's individual contribution in explaining the data. The principal components are ordered according to their ability to explain the variation in the data in decreasing order. We observe that the first principal component individually explains 25% of the

Table 3 Principal components and their Eigen values: all districts

Component	Eigen value	Proportion	Cumulative
PC1	2.30	0.25	0.25
PC2	1.50	0.21	0.46
PC3	1.17	0.13	0.59
PC4	1.05	0.11	0.70
PC5	0.89	0.10	0.80
PC6	0.85	0.09	0.89
PC7	0.77	0.08	0.97
PC8	0.33	0.02	0.99
PC9	0.11	0.01	1.00

variation in the data, the second, third, and fourth individually explain 21%, 13%, and 11% respectively.

In order to identify the mostly associated control variable with a particular PC, the varimax orthogonal rotation for the first four PCs is carried out. The results are shown in Table 4. The varimax orthogonal rotation represents the correlation between a variable and a principal component. We have chosen that variable from a principal component, which has the highest association with the principal component. The dominant variables in the four principal components that we have chosen are as follows: ROAD for PC1, DENS for PC2, RAIL5 for PC3, and POWER for PC4. The associations indicate that transport-specific rural road network and railheads within 5 km from a village has been the dominant variables in PC1 and PC3. City-specific population density and village non-tradable rural electrification also find their place in terms of dominance in PC2 and PC4 respectively. Keeping their dominant role in explaining the PCs in mind, henceforth, in our analysis we will identify PC1 by ROAD, PC2 by DENS, PC3 by RAIL5, and PC4 by POWER. These variables are regressed on the dependent variable as in (1). The results obtained are reported in Table 5.

We run two different specifications of (1). The first is without the inclusion of the district-specific fixed effect and the second is with the inclusion of it. In both the specifications, the variables DENS and POWER turn out to be significant at 1% level. The result is interesting on the one hand because the partial approach taken by Chakrabarti and Mukherjee (2020) did not find a significant impact of DENS on the birth of Census Towns in West Bengal. On the other, Chakrabarti and Mukherjee (2022) found ROAD as a significant variable affecting the birth of CTs, which is no longer true in the present analysis. However, since from Chakrabarti and Mukherjee (2022) we know that because of uneven development the districts neighboring Kolkata show a different trend in the case of the transport infrastructure and the village-specific variables, we bifurcate the entire dataset in two parts and repeat the same exercise with each of them as above. First, we report the results of the dataset that contains data only on the villages in the districts bordering Kolkata. The districts bordering Kolkata are North 24 Parganas, South 24 Parganas, and Haora.

Table 4 Principal component table: all districts (rotated component matrix with varimax rotation)

Variable	PC1	PC2	PC3	PC4
HIGHWAY5	−0.19	0.01	0.51	0.33
RAIL5	0.04	−0.04	0.71	−0.03
NEARNESS	0.03	−0.06	0.35	−0.58
ROAD	0.60	−0.06	0.05	−0.09
BANK	0.15	0.42	0.28	−0.13
POWER (LOG TRANSFORMED)	0.06	−0.02	0.16	0.70
DENS (LOG TRANSFORMED)	−0.08	0.74	−0.05	0.02
AREA (LOG TRANSFORMED)	0.54	−0.30	−0.02	0.12
U.BANK (LOG TRANSFORMED)	0.51	0.40	−0.06	0.10
N	551	551	551	551

Table 5 The regression results: all districts

Explanatory variables	Probit1	Marginal effect	Probit2	Marginal effect
ROAD	0.01 (0.01)	0.01	0.01 (0.01)	0.01
DENS	0.36*** (0.07)	0.11	0.49*** (0.13)	0.16
RAIL5	0.10 (0.12)	0.02	0.11 (0.12)	0.04
POWER	0.92*** (0.41)	0.41	1.01*** (0.52)	0.45
District fixed effect	No		Yes	
N	551		551	
Pseudo R^2	0.02		0.03	

Dependent Variable Transformation of a village which was 'would be Census Town' of Census 2001 to Census Towns in Census 2011
Note Robust standard errors in the parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Of the 653 villages present in the entire dataset, which were 'would be CTs in 2001' in West Bengal, 171 belonged to these districts.

The Eigen values of the principal components of the above exercise and the corresponding varimax table of Eigen vectors are reported in Tables 6 and 7.

Here as before four principal components have their Eigen values greater than 1, which are taken up for the analysis. These PCs explain 73% of the common variation in the data. The dominant variables in the four principal components that we have chosen are as follows: AREA for PC1, DENS for PC2, RAIL5 for PC3, and HIGHWAY5 for PC4. Keeping their dominant role in explaining the PCs in mind, henceforth, in our analysis we will identify PC1 by AREA, PC2 by DENS, PC3 by

Table 6 Principal components and their Eigen values: the districts bordering Kolkata

Component	Eigen value	Proportion	Cumulative
PC1	2.86	0.31	0.31
PC2	1.61	0.18	0.49
PC3	1.04	0.13	0.62
PC4	1.00	0.11	0.73
PC5	0.87	0.09	0.82
PC6	0.70	0.07	0.89
PC7	0.62	0.06	0.95
PC8	0.19	0.03	0.98
PC9	0.04	0.02	1.00

Table 7 Principal component table: the districts bordering Kolkata (rotated component matrix with varimax rotation)

Variable	PC1	PC2	PC3	PC4
HIGHWAY5	−0.07	−0.01	0.11	0.83
RAIL5	0.04	−0.02	0.81	0.10
NEARNESS	−0.19	−0.09	0.36	−0.23
ROAD	0.56	0.07	0.15	−0.17
BANK	0.09	0.50	0.32	0.05
POWER (LOG TRANSFORMED)	0.29	0.03	−0.19	0.44
DENS (LOG TRANSFORMED)	−0.11	0.71	−0.11	−0.01
AREA (LOG TRANSFORMED)	0.57	−0.28	−0.01	0.02
U.BANK (LOG TRANSFORMED)	0.44	0.37	−0.04	−0.07
N	171	171	171	171

RAIL5, and PC4 by HIGHWAY5. As these variables are regressed on the dependent variable, the results obtained are reported in Table 8.

The first specification of the regression is without the inclusion of the district-specific fixed effect and the second is with inclusion of it. In both the specifications, the variables DENS and HIGHWAY5 turn out to be significant at 1% level. Notice that the role of density of the nearest city/ST, which we derived in the regression consisting of all the districts is preserved in this regression as well. However, in the districts bordering Kolkata it seems the existence of a highway within 5 km radius of a village plays a significantly positive role in its transformation to a CT. While the result confirms the finding of Chakrabarti and Mukherjee (2020), it is interesting to note that POWER, the variable which turned out to be significant in overall regression, no longer plays a role here.

Table 8 The regression results: the districts bordering Kolkata

Explanatory variables	Probit1	Marginal effect	Probit2	Marginal effect
AREA	0.05 (0.11)	0.01	0.24 (0.12)	0.05
DENS	0.60*** (0.18)	0.10	0.65*** (0.18)	0.15
HIGHWAY5	0.62*** (0.19)	0.15	0.47** (0.20)	0.10
RAIL5	0.17 (0.19)	0.04	0.24 (0.19)	0.05
DSFE	NO		YES	
N	171		171	
Pseudo R^2	0.18		0.21	

Dependent Variable Transformation of a village which was 'would be Census Town' of Census 2001 to Census Towns in Census 2011
Note Robust standard errors in the parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Next, we report the results of the dataset that contains data on the villages in the districts not bordering Kolkata. The Eigen values of the principal components and the corresponding varimax table of Eigen vectors are reported in Tables 9 and 10.

The four principal components having their Eigen values greater than 1 here explain 64% of common variation in the data. The dominant variables in these PCs are: AREA for PC1, ROAD for PC2, HIGHWAY5 for PC3, and NEARNESS for PC4. Keeping their dominant role in explaining the PCs in mind, our analysis identifies PC1 by AREA, PC2 by ROAD, PC3 by HIGHWAY5, and PC4 by NEARNESS. As these variables are regressed on the dependent variable, the results are reported in Table 11.

Table 9 Principal components and their Eigen values: the districts not bordering Kolkata

Component	Eigen value	Proportion	Cumulative
PC1	1.81	0.22	0.22
PC2	1.44	0.17	0.39
PC3	1.25	0.13	0.52
PC4	1.08	0.12	0.64
PC5	0.98	0.10	0.74
PC6	0.78	0.09	0.83
PC7	0.77	0.08	0.91
PC8	0.50	0.06	0.97
PC9	0.35	0.03	1.00

Table 10 Principal component table: the districts not bordering Kolkata (rotated component matrix with varimax rotation)

Variable	PC1	PC2	PC3	PC4
HIGHWAY5	0.05	0.03	0.66	0.13
RAIL5	−0.18	0.35	0.47	0.01
NEARNESS	−0.05	−0.15	0.13	0.73
ROAD	0.01	0.75	0.13	0.09
BANK	0.12	−0.17	0.50	0.22
POWER (LOG TRANSFORMED)	0.05	−0.35	0.10	−0.59
DENS (LOG TRANSFORMED)	−0.35	−0.29	0.16	−0.09
AREA (LOG TRANSFORMED)	0.65	0.11	−0.04	−0.04
U.BANK (LOG TRANSFORMED)	0.62	−0.14	0.12	−0.08
N	380	380	380	380

Table 11 The regression results: the districts not bordering Kolkata

Explanatory variables	Probit1	Marginal effect	Probit2	Marginal effect
AREA	0.05 (0.09)	0.02	−0.01 (0.12)	−0.01
ROAD	0.01* (0.03)	0.01	0.01* (0.04)	0.01
HIGHWAY5	1.15*** (0.20)	0.18	1.10*** (0.27)	0.11
NEARNESS	- 0.90*** (0.35)	−0.10	−1.01*** (0.40)	−0.15
DSFE	No		Yes	
N	380		380	
Pseudo R^2	0.21		0.25	

Dependent Variable Transformation of a village which was 'would be Census Town' of Census 2001 to Census Towns in Census 2011
Note Robust standard errors in the parentheses
$*p < 0.10, **p < 0.05, ***p < 0.01$

Notice that the variables HIGHWAY5 and NEARNESS turn out to be significant at 1% level. While the HIGHWAY5 has a positive effect on the formation of CTs as expected, NEARNESS has a negative effect. The negative sign of NEARNESS implies that in the districts, which are not bordering Kolkata, commuting is not an important factor for the birth of the CTs. In the districts not bordering Kolkata, it appears that only the transport infrastructure-related variables play a significant role in explaining the emergence of CTs: there is no significant role played by either the village infrastructure-specific factors or the city-specific factors.

4 Conclusions

The burgeon of CTs in India during 2001–2011 has been astounding and allures economists to analyze in deep the reasons behind it. The earlier literature pointed out the importance of city-specific factors like its formal-sector wage and area (Chakrabarti & Mukherjee, 2020); transport infrastructure-related factors like availability of highways near the villages and the local road network, the village infrastructure-related factors like availability of electricity and banks (Chakrabarti & Mukherjee, 2022) in conversion of villages in CTs. However, since these variables have mutual dependence on each other, no study before takes up all these factors together in a single framework to study their relative importance in formation of the CTs. The present chapter takes it up in a dataset of West Bengal, which have seen the birth of maximum number of CTs among the states in India during 2001–2011. The analysis has been carried out using the Principal Component Analysis, which consolidates the set of nine explanatory variables in four uncorrelated principal components. We identify the principal components with the dominant variable correlated with them and subsequently use them in the regression analysis to find their role in explaining the formation of CTs. The results show that the factors play their roles differently in the districts bordering Kolkata, the capital city of West Bengal, and the other districts of the state. While in both types of districts the availability of a highway within 5 km radius of a village, which was a 'would be CT' in 2001, helped the village to get converted into a CT in 2011, the density of nearby city/ST played a significant role in the districts bordering Kolkata. Commuting was not an important factor in the districts not bordering Kolkata. The results suggest that the forces of dispersion away from the existing cities/STs are important to understand subaltern urbanization in West Bengal. The improvement of the highway infrastructure is an important instrument in the process. The partial analysis that is present in the existing literature often emphasizes the role of local infrastructure in the villages and city-specific developments like rise in urban wages and areal expansion of the cities, in explaining the emergence of CTs. But a more general framework adopted in the present study do not support these views. The chapter shows that the subaltern urbanization in all over West Bengal is a fallout of policy of improving highway infrastructure. Whether it has improved welfare of the state, remains a future research agenda.

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Gendered Occupational Segregation and Its Cost in India: Evidence from NSSO Data

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1 Introduction

Gender-based occupational segregation is one of the most persistent aspects of gender inequality in the labour market, creating a barrier to a country's welfare (Chaudhury & Verick, 2014; Khitarishvili et al., 2018). It is usually associated with a relatively higher concentration of females in lesser quality jobs that offer lower pays and poor working conditions (Anker et al., 2003). The ILO Convention on Discrimination (Employment and Occupation) (1958) (No. 111) acknowledged the importance of occupational segregation based on gender as a form of discrimination in the labour market. While some authors (Anker, 1998; Lewis, 1985) chose to use the concept of segregation and concentration interchangeably, another group of analysts argued that these two concepts have fundamental differences. According to Blackburn et al. (1993) 'segregation concerns the tendency for men and women to be employed in different occupations from each other across the entire spectrum of occupations under analysis' and the concept of segregation is symmetric, i.e. male or female workers cannot be segregated from each other to a different degree, however concentration can vary across the spectrum of occupational categories making the concept of concentration asymmetric (Blackburn et al., 1993; James & Taeuber, 1985; Siltanen et al., 1995).

The literature on occupational segregation is mostly limited to the measurement of occupational segregation only (Albelda, 1986, Anker, 1998, Anker & Hein, 1985, Beller, 1982, Ferber, 1992, Boulding, 1976, Karmel & Maclachlan, 1988, King, 1992, Watts & Rich, 1993). Again, there are studies based on the kinds of profession that are more segregated than others. In low- and lower-middle income countries, agriculture is one of the primary occupations of females whereas in high-income countries, they are mostly concentrated in health, education, or other service sectors

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(Cartmill, 1999; Grigoli et al., 2018, ILO, 2016, World Bank, 2015). It has been found across the globe that female workers are usually under-represented in managerial[1] and technical categories of occupation or jobs that involve repairmen and production (Brown, 1999; Cartmill, 1999; Charles, 1992; Coré, 1999; Valentova et al., 2007). The services and sales occupations where the females are concentrated are mainly jobs with the lowest pay, limited mobility (Ward, 1988), the worst working conditions, under flexible contracts and with no benefits—and are the first to be laid off, forming a flexible buffer labour force (Anker, 1998, Charles & Grusky, 1995, Standing, 1999, Seguino, 2000, World Bank, 2011).

The literature on occupational segregation in the developing countries is relatively sparse and there are even fewer instances in case of India. In India, the initial studies were carried out at the national level combining all the occupations together but not by occupation-wise classification (Anker, 1998; Swaminathan & Majumdar, 2006; Uppal, 2007). Subsequent studies have measured occupational segregation considering disaggregated occupations both at national level with rural-urban variation (Chakraborty & Bharati, 2013; Rustagi, 2010) and at state level (Duraisamy & Duraisamy, 2014; Sharma, 2018) by using unit-level data from the National Sample Surveys on employment and unemployment (NSSO) and the decennial census, following National Classification of Occupations (NCO). Women are overrepresented in primary sector (especially in rural areas), craft-related and elementary occupations while the share of men in executive categories is higher (Chakraborty & Bharati, 2013, Duraisamy & Duraisamy, 2014; Rustagi, 2010). Swaminathan and Majumdar (2006) observed that females are more concentrated in non-manufacturing sector. Although gender segregation across India's manufacturing sector appears to have decreased over the period from 1989/90 to 2000/01, the apparent movement was due to changes in the industrial structure of employment, not desegregation per se (Chattopadhyay et al., 2013).

Occupational segregation may be estimated using different measures; a brief overview is given by Blackburn (1995: https://doi.org/10.1080/13645579.2011.610616). Among such measures are Index of Dissimilarity (Duncan & Duncan, 1955), WE Index (OECD, 1980), Sex ratio (Hakim, 1981), IP index (Karmel-Maclachlan, 1988), Marginal matching measure (Blackburn & March, 1991), and Gini Coefficient (Silber, 1989). Most of the existing studies on occupational segregation (Albelda, 1986, Anker, 1998, Anker & Hein, 1985, Beller, 1982, Blau & Ferber, 1992, Boulding, 1976, Jacobs & Lim, 1992, King, 1992, Sharma, 2018, Watts & Rich, 1993, Weeden et al., 2018) use the standard Duncan and Duncan Index of Dissimilarity (Duncan & Duncan, 1955). However, these measures cannot decompose the segregation that occurred due to the difference in endowments among male and female workers and due to the discrimination faced by the female. Brown et al. (1999) developed a Dissimilarity Index based on a multinomial logit model for Mexico using 1987–93 National Urban Employment Survey data. This regression-based calculation of Duncan and Duncan Index captures the issue of discrimination

[1] World Bank Report, 2015 shows that very few women are found to be in managerial positions and on average, women earn 10–30 percentage points lower than men.

while measuring the segregation explaining the gendered wage gap. According to this study, most of the male-female differences in earnings in Mexico in both 1987 and 1993 can be explained by differences in rewards to individual endowments rather than gender differences in endowments.

Using two rounds of NSSO data (61st and 68th rounds), this paper starts with the calculation of Duncan and Duncan Index of Dissimilarity for all major states in India. The study then attempts to decompose the labour market segregation into endowment effect and an 'unexplained' component (or discrimination) to understand whether segregation is a result of differences in endowment among males and females, or whether it is a manifestation of discriminatory practices against female workers in the labour market, or there is presence of both. The study further contributes to the literature by estimating the economic cost of gender-based labour market segregation in terms of wage loss of female workers.

2 Objectives

The objectives of the present paper are as follows:

- Estimating gender-based occupational segregation at all India level and for different states in India.
- Decomposing gender-based segregation into endowment effect and 'unexplained' component (referred to as discrimination).
- Estimating the cost of gender-based segregation in terms of wage loss of female workers.

3 Data and Methodology

3.1 Data

The study employs unit-level data from the 'Employment and Unemployment Survey' conducted by National Sample Survey Organization (NSSO) for the following two rounds—NSSO 61st Round (July 2004–June 2005) and NSSO 68th Round (July 2011 to June 2012). In this analysis, individuals aged between 16 and 65 years have been classified into workers and unemployed according to their Usual Principal Activity as displayed in Table 1. The rest of the categories have been omitted due to lack of relevance to this discussion.

Workers have been recoded into seven occupational categories based on the codes of the National Classification of Occupation (NCO) across the two NSSO rounds (Table 2). The 61st round (2004–05) uses codes of NCO-1968 while the 68th round (2011–12) uses codes of NCO-2004.

Table 1 Definition of worker using NSSO activity status

Usual principal activity	Category
Worked in household enterprise (self-employed)	
Employer Worked as helper in household enterprise (unpaid family worker) Worked as regular salaried/wage employee Worked as casual wage labour: in public works In other types of work	Workers
Did not work but was seeking and/or available for work	Unemployed

Table 2 Recoding occupations into seven occupational categories

Occupation	2004–2005 code: NCO 1968	2011–2012 code: NCO 2004	Occupational category
Legislators, administrative and executive officials, directors, and managerial workers	200–299	100–199	Legislators
Teaching, health, engineering, science and social science professionals and technicians, accountants, auditors, and artists	000–199	200–399	Professionals
Office and customer service clerks and clerical-related workers	300–399	400–499	Clerks
Workers (domestic and institutional), shop and market sales workers personal and protective service	400–599	500–599	Service

3.2 Measuring Occupational Segregation

The level of occupational segregation has been measured using an Index of Dissimilarity proposed by Duncan and Duncan (1955). This Index measures the minimum proportion of male or female workers who need to change their occupation to equalize the occupational distribution. The Index is calculated using the following formula:

$$\boldsymbol{DI} = 0.5 \times \sum_{i=1}^{n} \left| \frac{\boldsymbol{F_i}}{\boldsymbol{F}} - \frac{\boldsymbol{M_i}}{\boldsymbol{M}} \right| \tag{1}$$

F_i and M_i are the frequencies of females and males in the *i*th occupation category respectively, and F and M are the overall female and male frequencies respectively. The value of the Index ranges from 0 to 1 where 0 means no segregation and 1 implies total segregation.

The Index has been estimated using one-digit occupational codes for all India level, and for the states. In addition, the level of segregation within each occupation category (defined using the one-digit codes) has also been estimated for the different occupational classes given in Table 2.

Choropleth maps have been used to identify the variations in occupational segregation across states. The states are divided into three groups based on the estimated segregation level:

- States with low segregation levels (below 0.3827)
- States with medium segregation levels (0.3827–below 0.5325)
- States with high segregation levels (0.5325 and above).

3.3 Gender-Based Discrimination in Occupational Choice

The next part of the analysis examines occupational choice, and the extent to which discriminatory practices in the labour market pose barriers to such choices. A multinomial logit model (MNL) is used to model occupational choices of workers. It is assumed that occupational choices of individuals depend upon the following variables:

- Socio Religious Groups (SRG): Categories are Hindu Forward Class (HFC), Hindu Other Backward Classes (HOBC), Hindu Scheduled Caste or Schedule Tribe (HSC/ST), Muslims and Others.
- Age of the respondent (RAGE): Categories are 16–25, 26–40, 41–50, 51–60 and 61–65 years
- Marital Status (RMARITAL): Categories are Never Married, Currently Married and Divorced/Separated/Widowed
- Educational Profile of the respondent (REDU): No Formal Education (NFE), Below Primary Education (BPE), Primary Education (PE), Middle School Education (ME), Secondary Education (SE), Higher Secondary Education (HSE), and Above Higher Secondary Education (AHSE)
- State dummies (SD) for 29 states and 6 union territories indicating the place of residence.

The choice of variables is determined by the availability of information in the NSSO database. This model is estimated for male and female workers separately using the same set of covariates. This implies that it is not possible to incorporate factors that determine the decision to work for women exclusively (like gender norms, fertility, etc.).

Using the estimated coefficients of the model estimated for *male* workers and characteristics of *female* workers, we have estimated the predicted probability for occupational choices. It implies the probability of a female worker choosing a particular occupation if they did not face any discrimination in the labour market but is treated at par with a male worker with similar characteristics. Using these predicted probabilities, we re-estimate the endowment adjusted Dissimilarity Index (DI) following Brown et al. (1999) as follows:

$$\boldsymbol{DI}_1 = 0.5 \times \sum_{j=1}^{J} \left| \boldsymbol{A}_p^f - \boldsymbol{P}_j^f \right|$$

when A^f_p is the actual proportion of females employed in the jth occupation and $\boldsymbol{p}_j^f$ is the MNL-based predicted proportion of females employed in the jth occupation. DI1 indicates the proportion of female required to switch their occupation to realize the model-predicted distribution. This captures the segregation due to presence of discrimination in the labour market. Here, we are assuming that males are getting a fair deal from the market.

3.4 Cost of Occupational Segregation

Finally, we calculate the *cost of occupational segregation*. This is the loss in wage earning of female workers due to occupational segregation; it is expressed as a proportion of GDP. It is based on works by Oaxaca (1973), Blinder (1973), Fairlie (2005), and Brown et al. (1999).

To isolate the effects of labour market constraints in occupational choice faced by female workers we assume that there is no gender gap in wages across each occupational category. Based on the results of the multinomial logit model we estimated W_{11} (total wage income of female workers), w_{12} (total wage income of female workers if there is no gender discrimination in the labour market), and w_{13} (total wage income of female workers if there is neither gender discrimination in the labour market nor any gender differences in characteristics of workers) in terms of average female wage ($\overline{\boldsymbol{w}_j^f}$). Since female workers are paid less than similarly endowed male counterparts (Agarwal, 2013; Duraisamy & Duraisamy, 2016), this estimate of the costs of segregation will be an underestimate.

The estimation requires us to multiply the predicted number of males and females with wages paid to a worker in the absence of any gender-based discrimination ($\overline{w}$). Since this is not observable, we will use either average female wages ($\overline{\boldsymbol{w}_j^f}$) or average male wages ($\overline{\boldsymbol{w}_j^m}$) as a proxy of $\overline{w}$. In this study we have used average female wages ($\overline{\boldsymbol{w}_j^f}$).

The total wage income of female workers (w_{11}) has been calculated by estimating the product of predicted probability that a female is in jth occupation ($\overline{\boldsymbol{f}_j^f}$), total female workers as per Census (T_f) and the mean female wage in each occupational category ($\overline{\boldsymbol{w}_j^f}$), and then adding this product across the seven occupational categories. The predicted probability that a female is in jth occupation ($\overline{\boldsymbol{f}_j^f}$) is estimated using the results of the multinomial logit model estimated for female workers.

Table 3 Wage differentials indicating loss in GDP

Cause of loss	Estimated loss
Loss due to discrimination and difference in endowments	$L_{11} = \frac{12X(w_{13}-w_{11})X100}{GDP}$
Loss due to restriction in occupational choices or discrimination	$L_{12} = \frac{12X(w_{12}-w_{11})X100}{GDP}$
Loss due to difference in endowments between male and female workers	$L_{13} = \frac{12X(w_{13}-w_{12})X100}{GDP}$

$$\boldsymbol{W}_{11} = \sum_{j=1}^{7} \left(\widehat{\boldsymbol{f}_j^f} \times \boldsymbol{T}_f \times \overline{\boldsymbol{w}_j^f} \right) \tag{2}$$

Similarly, w_{12} is estimated as above, but using the results of the multinomial logit model estimated for male workers to predict the probability that a female is in *j*th occupation ($\widehat{\boldsymbol{f}_j^m}$)

$$\boldsymbol{W}_{12} = \sum_{j=1}^{7} \left(\widehat{\boldsymbol{f}_j^m} \times \boldsymbol{T}_f \times \overline{\boldsymbol{w}_j^f} \right) \tag{3}$$

Finally, w_{13} is estimated as above, but using the predicted probability that a male is in *j*th occupation ($\widehat{\boldsymbol{m}_j^m}$) based on the results of the multinomial logit model estimated for male workers:

$$\boldsymbol{W}_{12} = \sum_{j=1}^{7} \left(\widehat{\boldsymbol{m}_j^f} \times \boldsymbol{T}_f \times \overline{\boldsymbol{w}_j^f} \right) \tag{4}$$

As the wages are in monthly terms, they (w_{11}, w_{12} and w_{13}) are multiplied by 12 to get annual earnings. The losses due to the discrimination faced by female workers are calculated as shown in Table 3.

4 Findings

4.1 Sample Profile

In this section, the differences between the distribution of male and female workers across occupational categories, age groups, educational standards, socio-religious groups, and marital status have been examined. Table 4 shows that the proportion of male workers is higher than the proportion of female workers for both the rounds across all occupational categories.

Table 4 Sample profile across NSSO rounds (all figures in percentage)

Variables	2004–2005						2011–2012					
	Rural		Urban		Total		Rural		Urban		Total	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Legislators	83.13	16.87	87.38	12.62	85.63	14.37	85.39	14.61	88.17	11.83	86.98	13.02
Professional	75.95	24.05	68.08	31.92	72.23	27.77	77.44	22.56	74.04	25.96	75.58	24.42
Clerks	89.16	10.84	81.48	18.52	84.48	15.52	88.62	11.38	80.06	19.94	83.05	16.95
Service	80.10	19.90	78.48	21.52	79.19	20.81	83.54	16.46	85.30	14.70	84.48	15.52
Primary	64.39	35.61	66.68	33.32	64.54	35.46	70.27	29.73	77.42	22.58	70.91	29.09
Crafts	75.03	24.97	80.98	19.02	78.01	21.99	86.38	13.62	86.82	13.18	86.58	13.42
Elementary	89.00	11.00	89.79	10.21	89.35	10.65	73.20	26.80	74.52	25.48	73.60	26.40
Age-cohort												
16–25	50.73	49.27	52.10	47.90	51.22	48.78	50.63	49.37	52.28	47.72	51.27	48.73
26–40	48.98	51.02	50.16	49.84	49.41	50.59	48.57	51.43	49.50	50.50	48.94	51.06
41–50	51.41	48.59	52.22	47.78	51.70	48.30	51.97	48.03	51.62	48.38	51.83	48.17
51–60	50.59	49.41	50.81	49.19	50.67	49.33	50.44	49.56	50.51	49.49	50.47	49.53
61–65	50.73	49.27	49.29	50.71	50.25	49.75	50.64	49.36	50.10	49.90	50.43	49.57
Educational Standard												
No Formal Education	40.94	59.06	41.44	58.56	41.07	58.93	39.41	60.59	40.33	59.67	39.69	60.31
Below Primary	54.03	45.97	52.11	47.89	53.44	46.56	52.02	47.98	51.96	48.04	52.00	48.00
Primary Education	54.70	45.30	52.10	47.90	53.83	46.17	52.26	47.74	51.30	48.70	51.92	48.08
Middle School Education	59.01	40.99	54.32	45.68	57.25	42.75	55.47	44.53	52.77	47.23	54.44	45.56

(continued)

Table 4 (continued)

Variables	2004–2005						2011–2012					
	Rural		Urban		Total		Rural		Urban		Total	
	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Secondary Education	63.13	36.87	56.53	43.47	60.22	39.78	59.27	40.73	54.44	45.56	57.16	42.84
Higher-Secondary Education	65.65	34.35	57.21	42.79	61.46	38.54	59.95	40.05	54.97	45.03	57.52	42.48
Above HS		26.56	62.25	37.75	66.55	33.45	68.83	31.17	60.54	39.46	63.62	36.38
Religion and Social Group												
Hindu Forward Caste	51.01	48.99	52.18	47.82	51.53	48.47	51.07	48.93	52.05	47.95	51.55	48.45
Hindu OBC	51.03	48.97	50.99	49.01	51.02	48.98	51.03	48.97	51.81	48.19	51.30	48.70
Hindu SC/ ST	51.03	48.97	51.54	48.46	51.16	48.84	51.01	48.99	51.14	48.86	51.05	48.95
Muslim	51.07	48.93	51.37	48.63	51.19	48.81	50.83	49.17	51.36	48.64	51.07	48.93
Others	51.42	48.58	50.41	49.59	51.12	48.88	50.64	49.36	49.82	50.18	50.34	49.66
Marital Status												
Never married	56.11	43.89	56.30	43.07	56.18	43.82	56.19	43.81	56.87	43.13	56.45	43.55
Currently married	48.60	51.40	50.06	49.94	49.09	50.91	48.75	51.25	49.96	50.04	49.21	50.79
Divorced/seperated	24.40	75.60	18.25	81.75	22.20	77.80	23.54	76.46	18.29	81.71	21.41	78.59

The average percentage of male workers in the sample across occupational categories is 79.06% in the 61st round while it increases marginally to 80.16% in the 68th round. For the female workers, there has been an increase in participation only in "elementary" occupation across the rounds. The remaining categories are showing a fall in the proportion of female workers. The highest level of reduction has been observed in the category "crafts" across the NSSO rounds.

The proportion of males and females among the working population is more or less similar for all the age cohorts across the NSSO rounds. The average proportion of males across the age cohorts is 50.65% in the 61st round and 50.59% in the 68th round.

The proportion of females without formal education in the sample is higher than the proportion of males and it increases marginally from 58.93 to 60.31% across the rounds. For rest of the categories the proportion of males is higher than the proportion of females, for both the rounds. There is a difference of 33.1% in the proportion of males and females who have higher education (above HS) in 61st round and this reduces to 27.24% in the 68th round.

4.2 Duncan and Duncan Index Across Sectors, Occupational Categories and States

First, we consider the Duncan and Duncan Index of Dissimilarity across the all India and rural and urban sub-samples. Table 5 presents the level of segregation for the two rounds of NSSO. The Index represents the average of the differences in female and male workers engaged across all occupations. Thus, in 2004–2005, on an average the proportion of male and female workers engaged in an occupation differs by about 34%. It increases marginally to 35% in 2011–12.

It can be noted that segregation has increased both at all India level and in the rural sector. However, the segregation has decreased by 0.041 points in urban area between the two rounds. The reduction in the level of segregation in the urban sector can be attributed to greater awareness about rights of workers and efforts to have parity in wages of males and females, along with higher level of parity in terms of education and skill attainment between males and females.

Table 6 presents the values of occupational category-wise Duncan and Duncan Index of Dissimilarity across rounds to analyse the condition of segregation across the occupational categories. It is the average of the differences in female and male

Table 5 Duncan and Duncan index of dissimilarity—all India

Place	2004–2005	2011–2012
Total	0.347	0.355
Rural	0.274	0.306
Urban	0.453	0.412

workers engaged in occupations at 3-digit level for each major occupational class (two-digit level).

Table 6 reveals the following:

(a) Segregation has increased across the rounds for “Professionals”, however, it has decreased for all other occupational categories.
(b) The marked decrease in the level of segregation in the category “Legislators” could be partly attributed to the increase in quota for females in the legislative occupations in India.
(c) In the 61st Round of NSSO, the level of segregation in the urban sector has been higher than the segregation level in the rural sector in all occupational categories, other than the category “Legislators”.
(d) In the 68th Round of NSSO, level of segregation in the urban sector is higher than segregation levels in the rural sector in all categories, except “Legislators” and
(e) “Service”.
(f) The increasing level of segregation in the category “Professional” indicates the discriminatory labour market constraints persistently faced by females, preventing them to reach their true potential.

The following figures (Figs. 1 and 2) present the picture of occupational segregation in 29 states and 6 union territories in India across two rounds of NSSO. According to Fig. 1, the states with measure of segregation as 0.5 or higher include Chandigarh, Punjab, Delhi, and Haryana in the North and Goa, Pondicherry, and Kerala in the South. Other than Kerala and Rajasthan, the measure of segregation in West Bengal is on the higher side in the 61st round.

According to Fig. 2, the states with measure of segregation as 0.5 points or higher include Punjab, Haryana, and Chandigarh in the North and Goa, Kerala, and Pondicherry in the South. The level of segregation in these states indicates that discriminating socio-cultural norms present in labour markets are persisting. States like Rajasthan, Sikkim, Jharkhand, and Andhra Pradesh are close to crossing over to the higher side of the level of segregation and focus should be given to prevent that

Table 6 Duncan and Duncan index of dissimilarity—across occupational categories

Occupational category	2004–2005			2011–2012		
	Total	Rural	Urban	Total	Rural	Urban
Legislators	0.267	0.353	0.197	0.023	0.026	0.022
Professional	0.326	0.320	0.451	0.388	0.330	0.457
Clerk	0.201	0.205	0.207	0.111	0.097	0.137
Service	0.412	0.308	0.486	0.260	0.287	0.279
Primary	0.116	0.110	0.200	0.063	0.059	0.144
Crafts	0.557	0.538	0.584	0.543	0.529	0.565
Elementary	0.449	0.401	0.512	0.373	0.333	0.473

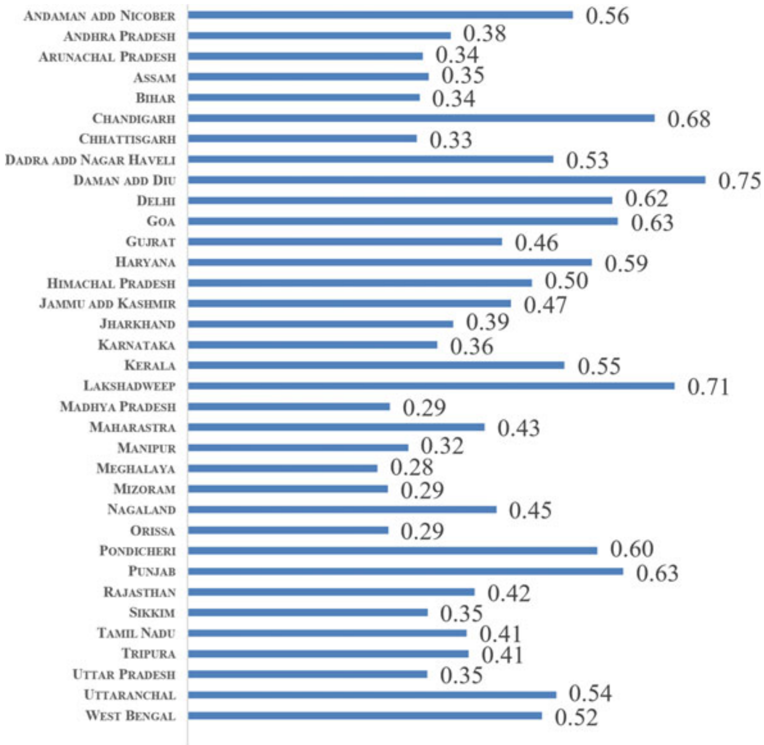

Fig. 1 State-wise Duncan and Duncan index of dissimilarity for 61st round

from happening. Chhattisgarh, Madhya Pradesh, Orissa, and Tripura have the lowest levels of segregation among all the states.

4.3 Choropleth Maps of Duncan and Duncan Index

Choropleth maps have been used to understand the state-wise variation in segregation as well as to locate the hotspots. The maps are drawn for both the rounds to identify whether there has been any change in the level of segregation over the years.

Comparing Figs. 3 and 4, we find that the level of segregation has increased across the rounds in the Northern states namely, Bihar, Uttar Pradesh, Punjab, Orissa, Rajasthan, Jharkhand, and Madhya Pradesh as well as in the Southern states like Karnataka and Arunachal Pradesh. The North-Eastern States of Mizoram, Meghalaya, Manipur, and Assam are also indicating an increase in the level of segregation across NSSO rounds. Jammu and Kashmir is also showing an increase in the level of segregation across rounds. Chandigarh shows the highest decrease in the measure of

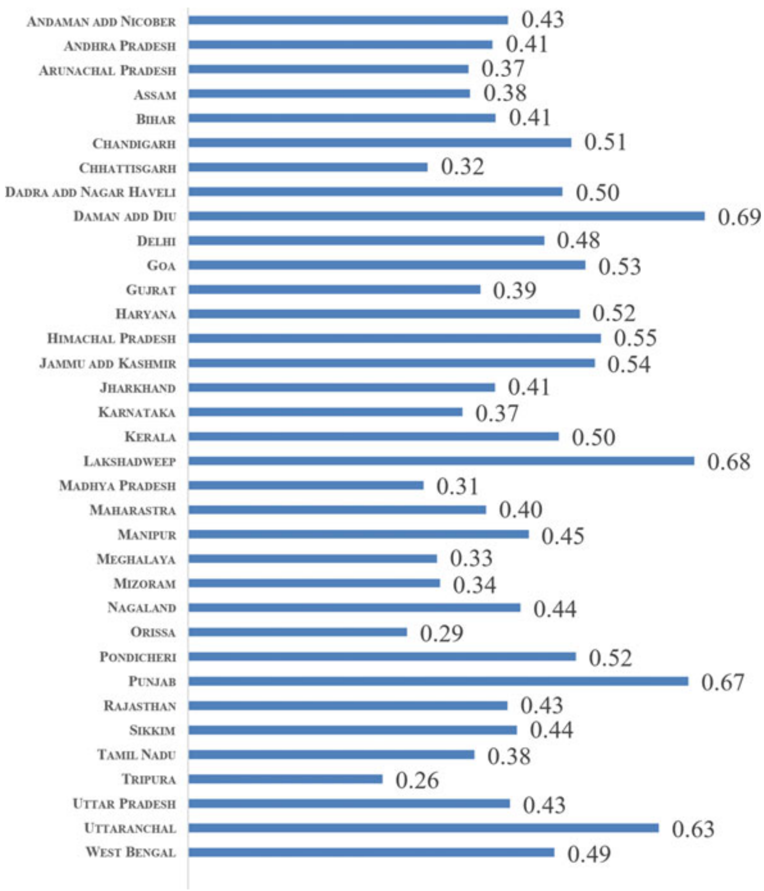

Fig. 2 State-wise Duncan and Duncan index of dissimilarity for 68th round

segregation followed by Tripura and Delhi across the NSSO rounds, while Manipur presents the highest increase in the level of segregation across the NSSO rounds.

4.4 Calculation of Dissimilarity Index with Labour Market Discrimination

We find that there is a decrease in the value of the Dissimilarity Index from the 61st to the 68th round for all India as well as the rural sector (from Table 5). In Table 7, The Duncan and Duncan Dissimilarity Index given in (1) (Duncan & Duncan, 1955) has been calculated based on the difference between the predicted and tabulated female occupational distributions using the method suggested by Brown et al. (1999).

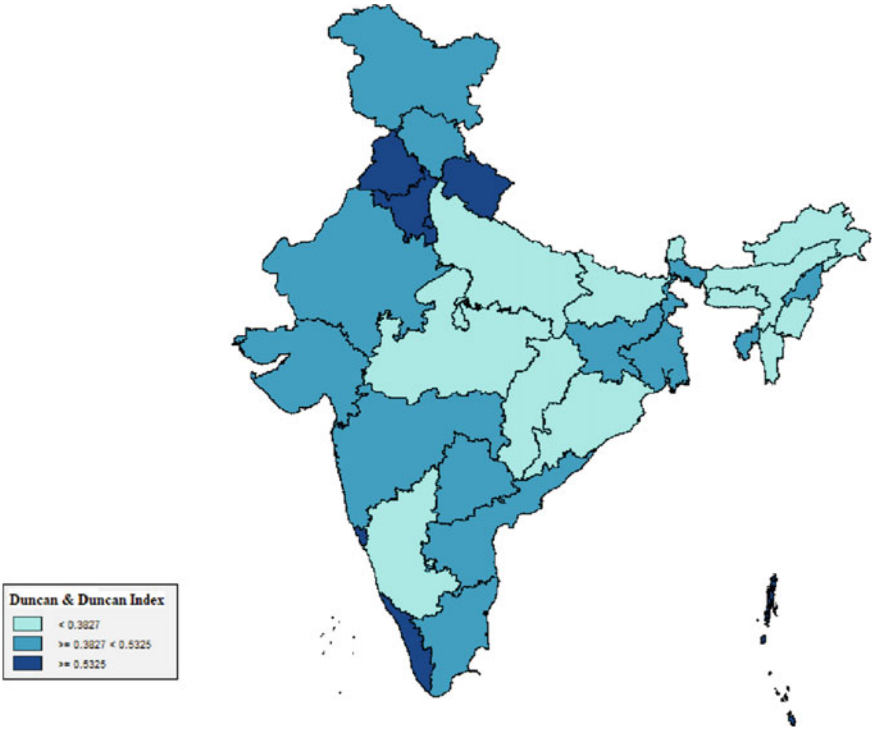

Fig. 3 Choropleth map of Duncan and Duncan index of dissimilarity for 61st round

Here, the value for the Index falls from 29.38% (i.e. 0.294) in the 61st round to 21.65% (i.e. 0.217) in the 68th round for all India which indicates that the extent of the "unexplained" observed occupational differences declined. In other words, the percentage of females who could change occupations to equalize the actual and predicted female occupational distributions declined over the rounds.

The drop in occupational segregation is very clear in the primary and elementary occupational categories, which show the highest absolute declines across the rounds. However, it is important to note that high paying occupational categories like legislators and professionals show a different picture. For example, in 61st round 1.71% of female workers were employed as legislators, but if females could enjoy the same labour market opportunities as males, our model predicts that about 3.35% of females would actually be employed as legislators (a 1.64% point higher than the existing scenario). In the 68th round this differential had gone up to 3.01% points.

A similar reduction in the value of the Dissimilarity Index is observed for the sector-wise data where the value declined from 23.75% (i.e. 0.238) to 19.78% (i.e. 0.198) and from 20.44% (0.204) to 17.22% (0.172) for the rural and urban sectors respectively, indicating that females faced less restrictions in occupational choice in the 68th round compared to the 61st round. Here also, we find the major fall in primary and elementary occupational categories.

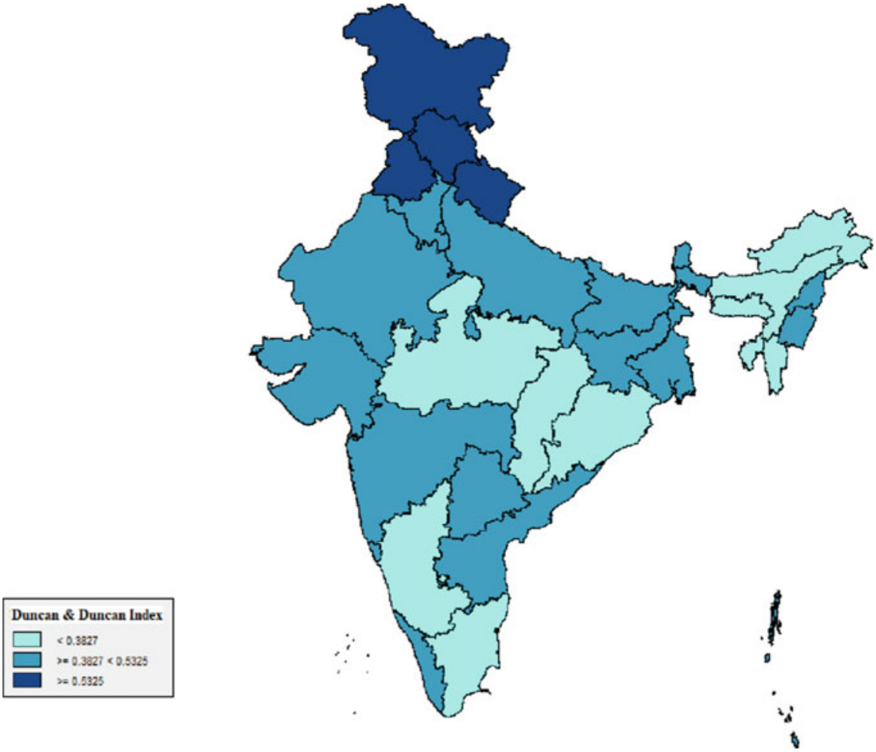

Fig. 4 Choropleth map of Duncan and Duncan index of dissimilarity for 68th round

4.5 Estimation of Cost of Segregation

In this section, we have tried to estimate the loss due to discrimination in occupational choices. For this, we assume that female workers face the same labour market constraints that are faced by the male workers. The loss constitutes of two parts:

- First, the loss due to difference in endowments between male and female workers,
- Second, the loss due to restriction in occupational choices.

Restrictions may appear from the gender discrimination in workplace, or it may be due to female workers self-select themselves for a certain type of occupation in order to conform to gendered social expectations.

Table 8 indicates the actual values of the losses calculated from the multinomial logit model (MNL) which considers the situation where male workers avail ideal employment opportunities, but female workers face occupational segregation. W_{11}, W_{12}, and W_{13} are estimated by generating occupational distribution of female workers facing the same labour market opportunities as male workers. Later, the costs have been expressed in terms of earning differential and as a proportion of national income in Table 9.

Table 7 Dissimilarity index across NSSO rounds

Occupational category	2004–2005			2011–2012		
	Predicted female distribution (%)	Actual female distribution (%)	Dissimilarity index (%)	Predicted female distribution (%)	Actual female distribution (%)	Dissimilarity index (%)
Legislator	3.35	1.71	0.82	7.17	4.16	1.50
Professional	2.36	4.09	0.86	5.59	7.87	1.14
Clerk	2.17	1.42	0.37	1.50	1.53	0.02
Service	15.69	8.78	3.45	10.74	5.13	2.80
Primary	43.55	71.2	13.82	21.90	34.22	6.16
Crafts	12.02	8.07	1.98	24.98	11.95	6.52
Elementary	20.86	4.73	8.07	28.12	35.14	3.51
All India			**29.38**			**21.65**
Legislator	2.17	1.05	0.56	5.06	2.29	1.38
Professional	1.53	2.02	0.24	3.61	3.72	0.05
Clerk	1.11	0.43	0.34	0.75	0.34	0.20
Service	10.06	4.87	2.60	7.57	3.27	2.15
Primary	58.18	81.45	11.63	29.77	42.64	6.43
Crafts	8.81	6.39	1.21	21.72	9.42	6.15
Elementary	18.12	3.80	7.16	31.52	38.32	3.40
Rural			**23.75**			**19.78**
Legislator	6.27	5.39	0.44	11.46	10.81	0.32
Professional	3.84	15.54	5.85	8.88	22.64	6.88
Clerk	4.68	6.88	1.10	2.87	5.76	1.45
Service	28.70	30.40	0.85	16.65	11.74	2.46
Primary	9.75	14.59	2.42	6.07	4.26	0.91
Crafts	19.01	17.35	0.83	31.13	20.95	5.09
Elementary	27.74	9.86	8.94	22.94	23.83	0.44
Urban			**20.44**			**17.22**

Table 8 Estimates for predicted earnings and earning differentials

Estimates	2004–2005 (Rs. crores)	2011–2012 (Rs. crore)
W_{11}	1,73,308	4,90,175
W_{12}	1,75,003	4,91,985
W_{13}	1,89,787	5,48,372
$L11 = W13 - W11$	51,568	8,243
$L12 = W12 - W11$	1,603	851
$L13 = W13 - W12$	49,964	7,391
Gross domestic product at constant (2011–2012) prices	54,80,380	87,36,330

Table 9 Percentage loss in GDP

Loss	2004–2005 (%)	2011–2012 (%)
Income loss	11.29	1.13
Loss due to difference in endowments	10.94	1.02
Loss due to restriction in occupational choice	0.35	0.12

We find that, the loss in GDP is 11.29% in 61st round and 1.13% in 68th round. Out of this, discrimination in labour market results in a loss of 0.35% in 61st round and 0.12% in 68th round. Difference in endowments between male and female workers amounts to a loss of 10.94% in 61st round and to that of 1.02% in 68th round. The values indicate that the loss in GDP has fallen across the rounds.

The reduction in loss due to difference in endowments indicates increasing educational attainment of females over time. The decrease in loss due to discrimination reflects change in society's perception towards gender equality—females are getting better job opportunities than before. This is consistent with the previous exercises where it is observed that Dissimilarity Indices have been reduced over time.

5 Discussion and Conclusion

Our analysis reveals the presence of gender-based occupational segregation in India, and observes that it has increased over the study period. The increase is observed at all India level, and also for the majority of states, including Uttar Pradesh, Bihar, Orissa, Rajasthan, and Assam. Northern states like Punjab, Haryana, and Chandigarh persistently have high levels of segregation across the NSSO rounds. While the occupational category "Professional" has shown an increase in the level of segregation at all India level as well as in the rural and urban sectors, other occupational categories have all recorded a decrease in the level of segregation at all India level across NSSO rounds.

Moving on to the analysis of endowment adjusted Dissimilarity Index, it has been observed that the difference in occupational attainment between male and female workers results from the differences in rewards, i.e., discrimination. From the values of the regression-based Dissimilarity Index, we find that the extent of the "unexplained" observed occupational differences declined from the 61st to the 68th round for all India as well as the rural and urban sectors. At all India level, the value for the Index falls from 29.38% (i.e., 0.294) in the 61st round to 21.65% (i.e., 0.217) in the 68th round. So, the percentage of females (or males) that would have to change occupations to equalize the actual and predicted female occupational distributions has declined over the rounds and this fall is particularly evident in the primary and elementary occupational categories while high paying categories show a rise in gender differentials.

The total cost of segregation, as a proportion of GDP, constitutes two parts. One is the cost due to difference in endowments between male and female workers and the other is the cost due to segregation. We found that, the loss in GDP is 11.29% in 61st round and 1.13% in 68th round. The figures obtained indicate that the losses in GDP have fallen across two rounds, indicating that the labour market situation has improved during the period 2004–2005 to 2011–2012 for female workers.

The findings of this study are consistent with existing studies reporting gendered occupational segregation in both developed countries sectors (Brown, 1999, Cartmill, 1999, Charles, 1992, Coré, 1999, Grigoli et al., 2018, ILO, 2016, Valentova et al., 2007, World Bank, 2015) and India (Chakraborty & Bharati, 2013, Duraisamy & Duraisamy, 2014; Rustagi, 2010; Sharma, 2018; Swaminathan & Majumdar, 2006). The pattern of segregation is also similar. The former occupational categories gender segregation is reported to have decreased over the period from 1989/90 to 2000/01 (Chattopadhyay et al., 2013), which contradicts the findings of this study. Existing studies report that women are over-represented in the primary sector, sales and service sector and under-represented in the executive and professional categories, and in manufacturing and technical categories. While we find broadly similar findings in this study, in India, the representation of women is low in the service sector also.

As this study is modelled by Brown et al. (1999), a comparison of the results between these two studies is interesting. Brown et al. report that the Dissimilarity Index declined in Mexico over the period 1987 to 1993; it is observed for the original Duncan and Duncan Index as well as the index adjusted for gender segregation. The results imply that in both Mexico and India the residual factors responsible for gendered occupational segregation have become less important over time. The occupational segregation across gender has resulted in an increase in the wage gap from 20.8% (1987) to 22.0% (1993), mainly due to changes in the characteristics of male and female workers. In contrast, this study found that wage gap had decreased mainly as a result of increase in educational attainments of female workers.

This study contributes to the existing literature in several ways. It uses a large sample of over a lakh respondents based on a nationally representative survey. This study also extends analysis of gendered occupational segregation to cover issues like the underlying causes of such segregation and the resultant reduction in earnings of female workers. These are under-researched areas with considerable policy implications. However, the study is based on data from the pre-pandemic period. Examining how the economic recession and the COVID-19 pandemic affected occupational segregation is important given the tight conditions prevailing in the labour market. It comprises an interesting extension of the research undertaken in this study.

To sum up, even though the level of occupational segregation has fallen over time with the entry of female workers into occupations which were previously male dominated, policy interventions are still required to minimize the negative consequences of gender-based discrimination. Policy interventions should include encouraging educational programmes for school-going female students to promote the choice of atypical occupations, making the provision for vocational training programmes for female employees and addressing gender biases in institutional practices like selection, recruitment, and promotion. Such measures would ensure further reduction in occupational segregation, and the corresponding costs associated with segregation.

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Does Job Prospect Influence School Enrolment for Women in South Asia?

Saibal Kar and Archita Pramanik

1 Introduction

Why do people with similar economic characteristics end up with different levels of schooling? Why should there be a strong gender difference in schooling enrolment in many countries, especially, those in South Asia? Do women in the South Asian countries respond positively to job market prospects? These and similar questions integral to the enormous literature on human capital beginning with Yoram Ben-Porath and Gary Becker in the 1960s are obviously not new, but the empirical literature surrounding such issues in developing countries has informed next to nothing so far. One of the common obstacles regarding tracing the connection from schooling to the returns in the vein of the famous Mincer equation has been the inadequate data sources on schooling, and much less on female schooling. Over time, the data has improved, but to the extent female school participation is influenced by labor force participation, contemporaneous, as well as that derived from prior responses remains unexplored. This chapter is invested in this particular exercise, such that, we explore functional relationships between female job market prospects in industries, in the manufacturing sector, or in the service sector and the high-school enrolment in eight South Asian countries from 1994 to 2018.

The extant literature points out that differences in cognitive abilities across a distribution of the population, access to credit, household size, public policies, etc., can be the determining factors behind educational attainments. However, in many cases, these variables can be endogenous—an issue that has been often underestimated in the vast literature on production or accumulation of human capital. Indeed,

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it is well known that the estimation of the returns to education is sensitive to the presence of measurement errors, typically because unobserved ability can affect both educational choice and the returns to education. One of the strategies used to deal with this problem consists of selecting instrumental variables that are correlated with schooling but not with earnings (conditional on schooling). The typical instruments used in the literature are school reforms, family background variables, information on siblings and twins, etc. (Card, 1999). These endogenous variables may offer useful information on the degree of risk (see for example Brunello (2002) for inclusion of absolute risk as a determinant) that the households get exposed to regarding the choice of type and level of schooling. Further, using a mean-variance frontier Hartog and Vijverberg (2007) identify the types of schooling that insure against the uncertainties in the labor market. The effect of risk on human capital investment being a very important topic in the analysis of earnings uncertainty appeared in the early work of Levhari and Weiss (1974), where risk has been treated exogenously. More recently, however, studies by Hogan and Walker (2002), Belzil and Hansen (2002), Hartog and Diaz-Serrano (2007), etc., used stochastic dynamic programming approaches that reach somewhat opposite conclusions. To remind, Levhari and Weiss (1974) developed a two-period model with exogenously determined labor supply to show that an increase in uncertainty about the returns to human capital reduces the level of investment in schooling under good states that generate higher marginal returns to schooling. However, uncertainty may also encourage investment in human capital. Are the mean values of returns and the associated volatility of the critical variables then impactful for the choice of schooling, and to what degree?

The present paper attempts to estimate these by invoking an empirical strategy where we test contemporaneous and lagged effects of industrial and service sector opportunities on schooling decision among women. Section 2 offers a brief literature review; Sect. 3 describes the data and empirical specifications. Section 4 presents the main results and Sect. 5 concludes.

2 A Brief Literature Review

The studies on the production or accumulation of human capital at an individual level draw largely on the seminal contributions by Becker (1962) and Ben-Porath (1967) and were later enhanced by Buiter and Kletzer (1995), Snow and Warren Jr. (1990), Graham (1981), Nitzan and Paroush (1980), Ritzen and Winkler (1977), Donaldson and Eaton (1977), and many others. Since the literature is wide and multi-faceted, we refer to a few in order to motivate our point of departure. Over the last two decades, Pecorino (1994), Becker et al. (1990), etc., study human capital investment and growth; while Hanushek et al. (2004), Seshadri and Yuki (2004), Caucutt and Kumar (2003), Benabou (2000, 2002) and others, emphasized skill formation for children facing credit constraints and parental altruism. Recently, Cooray et al. (2014) investigated the influence of human capital disaggregated by gender on economic growth. However, up till 1974 the literature of human capital investment was under perfect foresight with respect to future earnings for every level of education. The effect of risk on the production of human capital by an individual was first formalized by Levhari and Weiss (1974) and was subsequently followed by Williams (1978, 1979), Kodde (1986), Hogan and Walker (2002), Pereira and Martins (2002), Hartog and Vijverberg (2002), and others. Still later, a number of country-specific evidence supporting the intricate analytical basis of human capital acquisition are available in Harmon et al. (2003), Palacios-Huerta (2006), Christiansen et al. (2007), Grochulski and Piskorski (2010) and others. Notwithstanding, prevalence of uncertainty in acquiring human capital remains a subject of contemporary interest. The two sources include: one, when schooling decisions are made and two, when perceived distribution of the random variables are realized in the post-schooling period. The optimal production of human capital in the face of a risk-return trade-off affects individuals' demand for higher education considerably (see Hartog et al. 2007; Diaz-Serrano & Hartog, 2006; Hartog & Diaz-Serrano, 2007; Jacobs et al., 2009, etc.).[1]

It is also well known that individual decision making toward choice of education is guided by various micro and macroeconomic policies of the government (see Beladi et al., 2016). Government provides public education system, public libraries and fund projects to improve the situation. A vast literature that studies the effect of education subsidies and labor income taxes on the formation of human capital is also integral to this idea. The returns to education especially at the higher levels often outweigh benefits from reduction of inequality of opportunities, such as schooling, (see Lam et al., 2015) and this has been a dominant feature of rising wage inequality in South Africa.

The above review does not explain how job prospects and industrial activities may impart influence on the choice of type and level of schooling. Presently, we refer to a few studies that have done so in the recent past. It would further show that the possible impact on female school enrolment—high school and beyond, has received little or no attention. This clearly justifies our attempt at tracing this link for South Asia (Fig. 1), which clearly shows low (Afghanistan, Pakistan, <50%) to mediocre turnouts (India, Bhutan) for 7 out of 8 countries for most of the years under consideration. Except for Sri Lanka (approximately 80% enrolment rates), all other countries fall short by 10–60% in terms of comparable female enrolment rates in developed countries. In terms of the connection, however, Kerr et al. (2020) show that as part of a randomized control experiment, intervention in the form of information on labor market prospects offered to 97 randomly chosen high schools in Finland led graduating students ready to update their beliefs, apply to programs associated with higher earnings. In terms of loss of prospects, as one experienced in Palestine owing to closure of the Israeli labor market, dropouts from high school was an unambiguous outcome (Saad & Fallah, 2020). However, ironically, strong labor market prospects as well as higher individual ability may also lower efforts in school (see Chadiet al., 2019 for German students). If such lack of effort becomes pervasive however, or suffers from lack of interest and investments from the government, as fairly common in developing countries then

[1] Further, see Beladi et al. (2016) on this issue for analytical proximity, but with more general applicability.

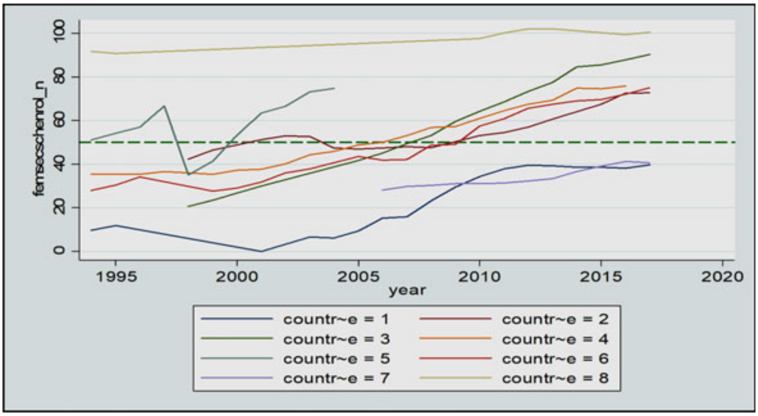


Fig. 1 Female secondary school enrolment for South Asian countries. *Note* Country 1—Afghanistan; Country 2—Bangladesh; Country 3—Bhutan; Country 4—India; Country 5—Maldives; Country 6—Nepal; Country 7—Pakistan; Country 8—Sri Lanka. *Source* Author's calculation

wage inequality across educated and uneducated workers remains low but they also receive less welfare benefits (Hromcova & Agnese, 2019). These evidences clearly offer important empirical lessons that the present study takes forward.

3 Data and Empirical Method

3.1 Data

The data for eight South Asian countries collected between 1994 and 2018 forms a panel data set. Admittedly, given many missing data points about crucial variables like school enrolment, the total number of observations has at times gone down approximately to 150 when the most populated variable returns 200 data points. The countries of South Asia, namely Afghanistan, Bangladesh, Bhutan, India, Maldives, Nepal, Pakistan, Sri Lanka have improved in terms of school participation among the women to some extent, but not remarkably for most. Yet, a relationship between employment prospects controlled for a set of standard predictors and school enrolment among women is a worthy candidate to focus on various economic consequences. The data is collected from the World Development Indicators for all these years.

The dependent variable is *female secondary school enrolment*, as percentage of gross enrolment[2] (*femsecscenrol_n*). The set of explanatory variables include, (i) per

[2] Gross enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education shown. Secondary education completes the

capita gross domestic product (*gdppercap_n*); (ii) Employment in industry, female (% of female employment, modeled ILO estimate, *femempind*). This is our main independent variable, but we also test (iii) similar relations with service sector job prospects for women (*femlemlservice*) (iv) As we depict shortly, secondary school enrolment for women against both industrial employment for women, and per capita GDP for the country are concave. Naturally, we use squared terms for each of these variables in order to capture the non-linearity in the relationships (*femindsq* and *gdpsq*, respectively). (v) Since we are dealing with aggregative, cross-country data, industry value added as percentage of GDP (*industryva_n*) should serve as an adequate control for heterogeneity apart from information regarding the industrial depth in each of these countries. To elaborate on this variable, according to WDI, the choice of industry corresponds to ISIC divisions 10–45 and includes manufacturing (ISIC divisions 15–37). It comprises value added in mining, manufacturing (also reported as a separate subgroup), construction, electricity, water, and gas. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. It is calculated without making deductions for depreciation of fabricated assets or depletion and degradation of natural resources. The origin of value added is determined by the International Standard Industrial Classification (ISIC), revision 3 or 4. (vi) It is important to remember that a large body of the related literature has identified women workers as "added workers" who help to smooth consumption during economic downturns (for a detailed survey, see Killingsworth & Heckman, 1986, Chap. 2). Consequently, high degrees of labor force participation and industrial and service sector employment for men (*malemservice*) may have negative impact on female labor force participation and hence, women school enrolment (vii) The industrial employment for men (*maleempind*, [I1]) renders such effect on women schooling, in addition to (viii) an interaction effect, where, *memptr* represents male secondary school enrolment interacted with male industrial employment. We also consider (ix) manufacturing value added separately (*manufacturingva_n*), as defined above and (x) share of imports in gdp (*imports_n*), which for South Asian countries might be conduits of exports as well as production of non-traded goods.

Before the panel data is applied to the empirical specification, the first step is to check whether the series is stationary in order to avoid spurious correlations arising from non-stationary series. Among several tests developed for identifying unit roots in panel data the most frequently used test under the assumption of heterogeneous slopes is Im-Pesaran-Shin (ips) unit-root test. We used Im-Pesaran-Shin unit-root test for stationarity of the variables. The null hypothesis of ips test states that all panels contain unit roots [presence of unit root or I(1)], while the alternative hypothesis states that Some panels are stationary [I(0)]. The results of the unit root test show that except for male industrial employment, none of the series is non-stationary allowing us to conduct the regression analysis at levels.

provision of basic education that began at the primary level, and aims at laying the foundations for lifelong learning and human development, by offering more subject- or skill-oriented instruction using more specialized teachers (definition as per World Development Indicators, World Bank). For South Asia, primary and secondary school enrolment are more readily reported as compared to tertiary education at the aggregate.

Based on the available data, we also offer some graphical representations. For example, Fig. 2 shows a projected positive but decreasing relation between female industrial employment and female secondary schooling. Subsequently, Fig. 3 shows that the relation between female service sector employment and female secondary school enrolment is even more concave, rising sharply up to 40% of employment and falling rapidly beyond that. Indeed, the aggregate outcomes clearly suggest that more disaggregated micro-econometric analysis should be the key to identifying the sharp reductions, and could be an important factor in explaining the ever-shrinking female labor force participation in some of the South Asian countries, including India, in recent decades.

However, Fig. 4 shows that male industrial jobs promote secondary school attendance for women in South Asia. The main outcome might be owing to the income effect, while the nature of jobs could in part be complementary as well.

In fact, the positive impact of industrial jobs for men is also carried forward in terms of industry value added in respective countries. Figure 5 shows that female school enrolment falls briefly as industry value added rises at low depths of industrialization but rises steadily beyond 20% industry value added. The projection is significant at 5% confidence intervals.

Figure 6 shows that female secondary school enrolment rises up to the 40% mark for imports-to-GDP ratio and subsequently declines. A few other relations are relegated to the appendix.

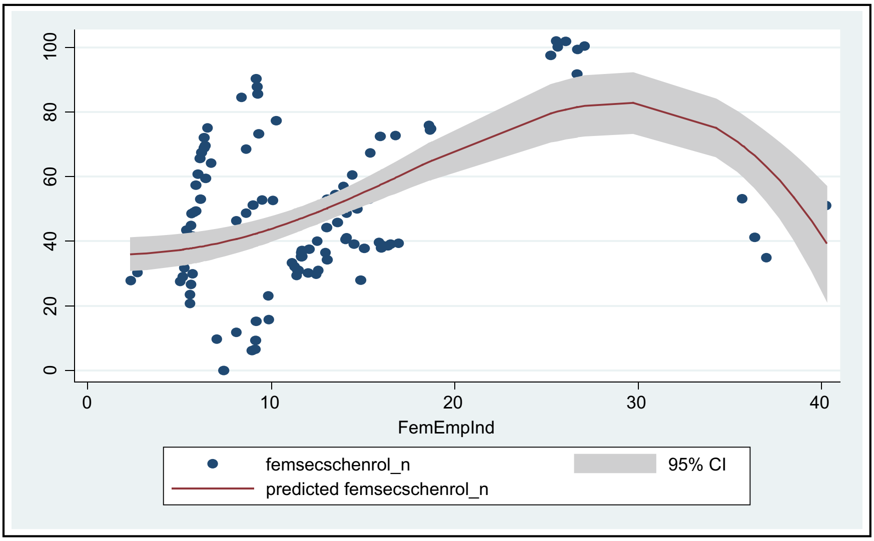


Fig. 2 Relation between female secondary school enrolment and female industrial employment. *Source* Author's calculation

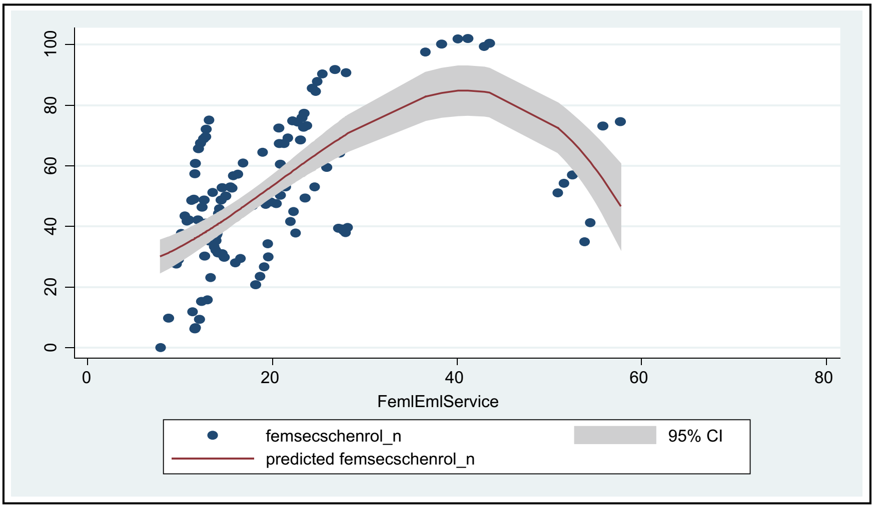


Fig. 3 Relation between female secondary school enrolment and female service employment. *Source* Author's calculation

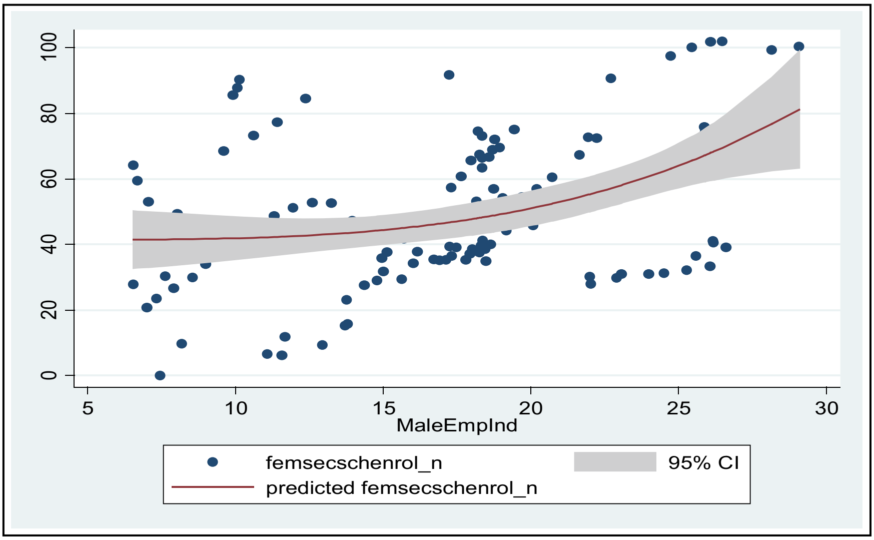


Fig. 4 Relation between female secondary school enrolment and male industrial employment. *Source* Author's calculation

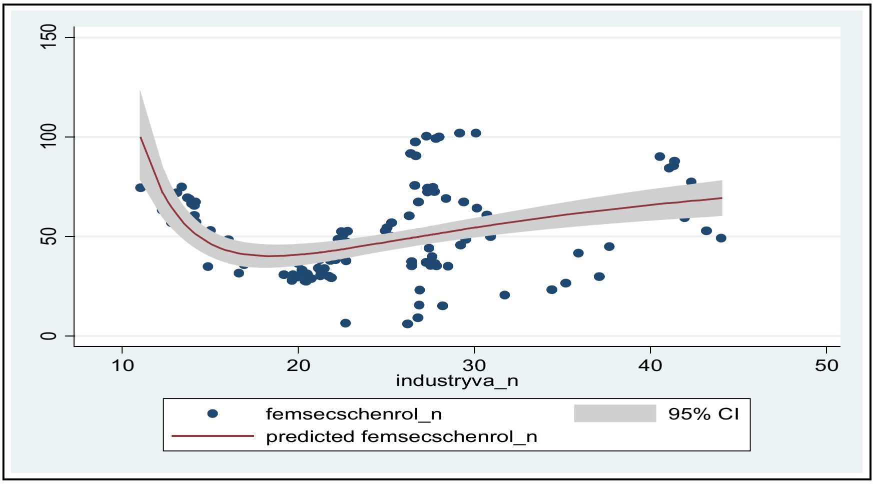


Fig. 5 Relation between female secondary school enrolment and industrial value added. *Source* Author's calculation

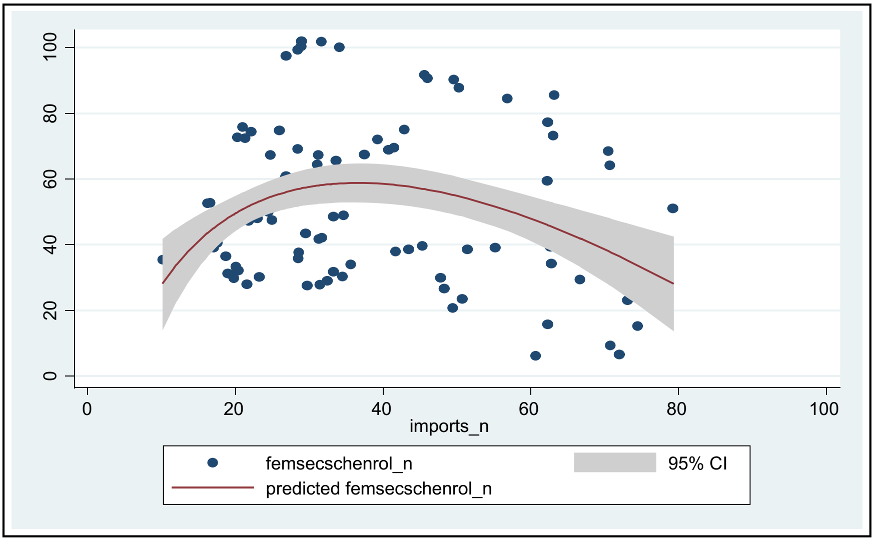


Fig. 6 Relation between import share and female secondary school enrolment. *Source* Author's calculation

3.2 Empirical Methods

Overall, we present an empirical relation in Eq. (1) below:

$$\begin{aligned} femseschenrol\_n_{it} =&\alpha_0 + \beta_1 femempind_{it} \\ &+ \sigma_i \sum_{i=1}^{k} \underline{X}_{it} + \beta_2\gamma_i + \beta_3\theta_t + \varepsilon_{it} \qquad i = 1 \ldots k \end{aligned} \tag{1}$$

where all variables are reported for ith country in the tth year. $\underline{X}_{it}$ stands for the vector of covariates (plus one interaction variable as defined above) and σ_i is the ith regression coefficient for the control variables. α_0 is the regression constant, while β_1 is the coefficient of regression for (*femempind*) the main independent variable. γ_i and θ_t stand for country fixed and time fixed effects, respectively, while ϵ_{it} represents the idiosyncratic error term. Note that, in recent times, several studies use the cross-country panel data methods of the similar genre as presented here, including some dealing with South Asia only (viz, Cooray et al., 2014; Moazzam, 2022; Saha et al., 2021, etc.). The interaction term offers further point estimates for the panel of countries. In this case, we are interested in observing if male secondary school enrolment interacted with male industrial employment for the panel of countries yields meaningful marginal estimates. The marginal estimates take the following form, such that we can predict the critical values of male industrial employment or male school enrolment for their influence on female secondary school enrolment. Formally,

$$\frac{\delta(femsecschenrol)_{\mathrm{it}}}{\delta(\mathrm{malempind})_{\mathrm{it}}} = \sigma_{\mathrm{m}} + \sigma_{\mathrm{int}}(\overline{malescenrol})_{it} \tag{2}$$

where, σ_{m} is the direct coefficient for the effect of male industrial employment on female secondary school enrolment, while σ_{int} is the coefficient of the interaction term for the mean value of male school enrolment. Putting the above equation to zero, we get,

$$(\overline{malescenrol})_{it} = -\frac{\sigma_{\mathrm{m}}}{\sigma_{\mathrm{int}}} \tag{3}$$

In other words, from (3) one can estimate the critical mean level of male school enrolment that leaves no impact on female secondary enrolment. Instead of the mean value, we can also check for other quartiles to reflect on the female school enrolment as an outcome when male industrial employment rises. The regression tables in the next section shall offer this critical value.

Now, as far as the technicality of the panel regression is concerned, we offer two sets of results. (i) First, we use the well-known static fixed effects (*FE*) to trace any relation between female employment in industries *and the female secondary school* *enrolment.*[3] The panel fixed effects is the chosen model after we have tested for panel random effects and the efficacy of the applications of panel data over linear regression models via LM tests. For want of space, we do not report these preparatory stages and move directly to the applications of the *FE*. (ii) Second, we use the dynamic panel data estimates, in particular system GMM (Generalized Method of Moments with further details in Arellano & Bond, 1991 and recent applications and explanations in Dutta et al., 2020). Prior applications of SGMM show that inclusion of a lagged dependent variable as a regressor violates strict exogeneity, because the lagged dependent variable is necessarily correlated with the idiosyncratic error. When the strict exogeneity assumption is violated, commonly used static panel data techniques such as fixed effects (FE) estimators are inconsistent. The method via which we resolve concerns about endogeneity is the Dynamic Panel estimators. In recent decades, the use of dynamic panel estimators for cross-country panels (or firm-level, state-level panels) has steadily increased. The dynamic processes in economic activities make dynamic panel estimation useful especially to control for unobservable heterogeneity. For OLS or fixed effect models, the unobserved individual effects can be correlated not only with endogenous regressors but also with predetermined regressors. The dynamic panel estimators, as described below, use internal instruments generated via moment conditions employing several lags of the endogenous covariates. This reduces the sample size considerably. While this would not be a concern for an extensive sample, it is definitely a concern in our case given that the panel is not balanced and that many countries and variables have missing entries. In the process, we control for the maximum number of differences to be chosen as instruments for the system GMM exercises. We find that the number of instruments is substantially lower than the number of groups, allowing us to conduct the exercises with much lower probability of encountering the well-known Nickell bias.

3.3 Identification and Causal Relation

There is no easy way to establish that the causation is invariably from the set of dependent variables to the measure of school enrolment as proposed in this study. Theoretically speaking, we argue that industrial job prospects, and subsequently adding prospects in services, that of male counterparts in these economies and effects of trade, are all distinctly capable of causing school attendance. Yet, it is a short step to argue that unless school enrolment and graduation rates are high, certain kinds of activities would not flourish in a given region or for an economy in the aggregate. This violates strict exogeneity in the independent variables and raises concerns about simultaneity apart from omitted variables bias that are natural for developing countries with insufficient enumeration on variables of interest integral to the literature on education and labor market outcomes. Consequently, we look into possible causality between schooling and employment variables, in particular,

[3] The Hausman test is conclusive in favor of fixed effects panel regression.

how industrial employment and service sector employment Granger cause female secondary school enrolment in the South Asian countries. Note that, the test for causality is only to ascertain the functional relation, and is not a test for endogeneity. We report the panel VAR-based Wald test for Granger causality to inform regarding the causation in Table 1. In addition, we report the impulse response functions in Fig. 7a, b. Figure 7a shows that a 1% shock in female employment at industries raises school enrolment among women significantly and commensurately and retains it for several forward lags (top figure, right panel). On the other hand, female school enrolment does not have any impact on female industrial employment (bottom figure, left panel). Figure 7b invokes both industrial employment and service sector employment as drivers of female secondary school enrolment and finds that while a positive shock to industrial employment raises and then slightly reduces female school enrolment after 3 periods, a positive shock to service sector reduces and then steadily raises school enrolment among women. The reverse causation does not seem valid, however. Table 1 enumerates these results and establishes that the causation indeed runs from industrial and service sector employment to female school enrolment and not vice versa.

Granger causality Wald tests

Set I

H0:female industry does not granger cause female school can be rejected.
H0:female service does not granger cause female school can be rejected (<25%).

Set II

H0:female school does not granger cause female industry cannot be rejected.
H0:female service does not granger cause female industry cannot be rejected (<25%).

Set III

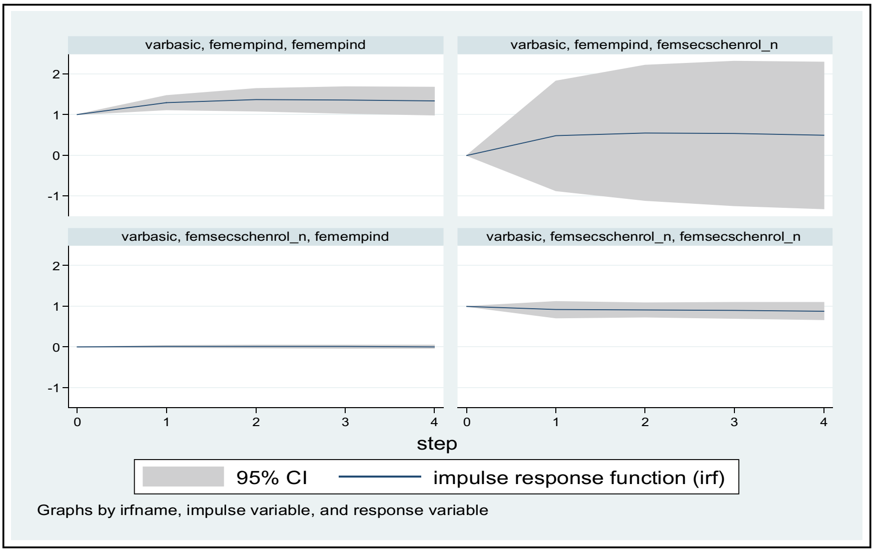
H0:female school does not granger cause female service cannot be rejected.

Table 1 Granger causality Wald tests

Equation	Excluded	Chi^2	Df	Prob > Chi^2
femsecschenrol_n	femempind	4.9753	2	0.083
femsecschenrol_n	femlemlservice	4.084	2	0.130
femsecschenrol_n	ALL	5.1535	4	0.272
femempind	femsecschenrol_n	2.6525	2	0.265
femempind	femlemlservice	2.6043	2	0.272
femempind	ALL	5.6072	4	0.230
femlemlservice	femsecschenrol_n	0.38595	2	0.825
femlemlservice	femempind	13.892	2	0.001
femlemlservice	ALL	14.378	4	0.006

Note Author's calculation

a



b

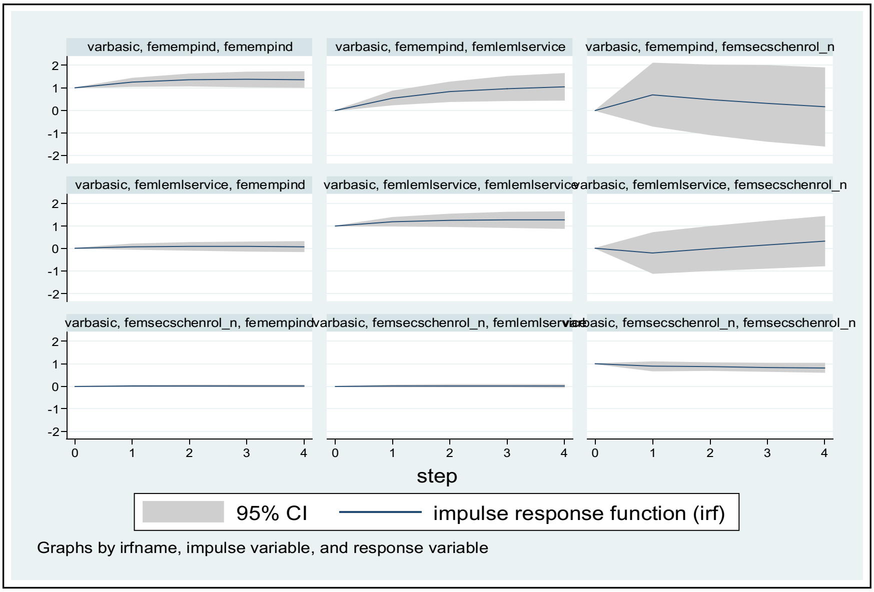


Fig. 7 **a** Impulse response functions between female industrial employment and female secondary school enrolment. **b** Impulse response functions between female industrial employment and female secondary school enrolment. *Note* Author's calculation

H0:female industry does not granger cause female service can be rejected.

There should still be concerns regarding endogeneity arising from functional relations between one or more explanatory variables, such as industrial prospects for women positively influencing service sector employment. Therefore, resorting to system GMM is the best redress to concerns regarding endogeneity especially because the model chooses lagged values of the independent variables while estimating the contemporaneous impact on the independent variable. Nevertheless, we have conducted further robustness analysis to buttress available results.

To briefly reiterate, GMM estimator generates estimates that are more efficient than the ones generated by the difference GMM estimator (of Arellano & Bond, 1991) in the presence of series that are persistent (as lagged levels of such series are weak instruments for subsequent first difference series; for example, Bond et al., 2001). Additionally, the difference GMM estimator magnifies gaps in the context of unbalanced panel dataset (Roodman, 2009). Blundell et al. (2001) have noted that the system GMM estimator relies on relatively weaker restrictions on the initial condition process, and is considerably asymptotically efficient (Table 2).

4 Empirical Results

We begin by presenting the benchmark results through the panel fixed effects. As convention, we report the direct impact of female industrial employment on female secondary school enrolment in Table 3 column 1. The variable is supported by its own square term along with GDP and its square terms as well. The effect of industrial job prospects is positive and highly significant (at 1% level) for female schooling in South Asia. As rise in per capita GDP is expected to raise female schooling as well, the own coefficient rise almost 6 times for a unit rise in industrial employment for women. The square terms show convergence properties. In column 2, female employment in service sector over and above employment in industries, however, does not improve school enrolment and might actually reduce it marginally. In column 3 we include manufacturing value added and in column 4, industry value added in its place. Both show negative and significant (1% level) impact on female secondary school enrolment, which tends to document that an improvement in the depth of industrial and service sectors do not motivate women to choose schooling, unlike the more direct impact of industrial jobs. In fact, greater industrialization might lower school enrolment—an outcome which needs further research into the deeper connections between the two. Apparently, if industrialization is low-skill intensive, as could be for South Asian economies high formal education might not be necessary to facilitate jobs. The other aspect which the panel data does not capture is the extent of informalization in South Asian countries that push a substantial part of manufacturing and industrial activities into the realm of low technology, household activities that engage a large number of women without formal education. In column 5, the first difference of male industrial employment remains positive but non-significant.

Table 2 Panel fixed effects. Dependent variable: female secondary school enrolment

Variables	(1)	(2)	(3)	(4)	(5)
	Femsecschenrol	femsecschenrol	femsecschenrol	femsecschenrol	femsecschenrol
fememppind	6.142***	6.932***	5.254***	5.997***	4.563***
	(1.125)	(1.179)	(0.909)	(1.118)	(1.262)
gdppercap_n	0.0317***	0.0335***	0.0459***	0.0413***	0.0467***
	(0.00488)	(0.00490)	(0.00394)	(0.00491)	(0.00529)
Femindsq	−0.138***	−0.145***	−0.117***	−0.116***	−0.0886**
	(0.0398)	(0.0394)	(0.0299)	(0.0373)	(0.0402)
Gdpsq	−3.34e−06***	−3.24e−06***	−4.60e−06***	−3.76e−06***	−4.20e−06***
	(9.13e−07)	(9.03e−07)	(6.98e−07)	(8.49e−07)	(8.96e−07)
fememservice		−0.631**	−1.212***	−0.953***	−0.663**
		(0.318)	(0.248)	(0.305)	(0.324)
manufacturingva_n			−3.951***		
			(0.430)		
industryva_n				−1.375***	−1.536***
				(0.321)	(0.320)
D.maleempind					0.962
					(0.984)
Constant	−29.61***	−28.56***	35.23***	8.017	11.48
	(5.641)	(5.593)	(8.121)	(10.00)	(9.836)
Observations	124	124	124	124	121
R-squared	0.742	0.751	0.859	0.786	0.799
Number of countries	8	8	8	8	8

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

In Table 3, we assign a number of other variables as potential explanatory factors for the female school enrolment as conceived of in this exercise. Columns 1–4 in Table 3 now include female employment in the service sector, which despite being negative is not significant everywhere. The first four variables repeated from Table 3 maintain the sign and statistical significance all through. We do not find the coefficient of male industrial employment to be significant at first difference, still. However, the interaction term (*memptr*) between male industrial employment and school enrolment is positive and significant (1% level, column 3). The marginal impact as explained in Eqs. (2) and (3) bears significance here. The coefficients in Table 3 suggest that unless the mean male school enrolment is fairly low industrial employment for men is likely to raise women school enrolment. Indeed, unless growth in male school enrolment (the coefficient being in the first difference) falls below zero, women choose secondary enrolment unambiguously with rise in male

Table 3 Panel fixed effects. Dependent variable: female secondary school enrolment. *Interaction Effects: memptr = male sec school enrol * male indusemp*

Variables	(1)	(2)	(3)	(4)^
	femsecschenrol	femsecschenrol	femsecschenrol	femsecschenrol
femempind	6.115***	3.410***	4.669***	5.997**
	(1.308)	(1.178)	(1.095)	(2.177)
gdppercap_n	0.0409***	0.0747***	0.0274***	0.0413**
	(0.00557)	(0.00896)	(0.00571)	(0.0125)
femindsq	−0.118***	−0.0663*	−0.105***	−0.116**
	(0.0401)	(0.0374)	(0.0349)	(0.0425)
gdpsq	−3.74e−06***	−1.12e−05***	−2.54e−06***	−3.76e−06*
	(8.60e−07)	(1.83e−06)	(8.47e−07)	(1.67e−06)
femempservice	−0.868	−0.905***	−1.162***	−0.953
	(0.572)	(0.285)	(0.290)	(0.647)
industryva_n	−1.355***	−1.350***	−0.691**	−1.375
	(0.341)	(0.278)	(0.344)	(0.845)
malemservice	−0.0905			
	(0.515)			
imports_n		−0.0339		
		(0.116)		
maleempind			0.891	
			(0.766)	
memptr			0.0205***	
			(0.00499)	
Constant	8.610	11.46	5.578	8.017
	(10.60)	(10.05)	(9.374)	(26.51)
Observations	124	114	124	124
R-squared	0.786	0.859	0.815	0.786
Number of countries	8	7	8	8

Standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$
^Robust SE by country clusters

industrial jobs. Finally, column 4 in Table 3 uses robust standard errors by country clusters and the results continue to display statistical significance.

As already mentioned, the benchmark FE analysis is corroborated with system GMM specifications and analyses in Tables 4 and 5, respectively. Importantly, the first lag of the dependent variable is also chosen as a regressor in the system GMM. Column 1 Table 4 shows that female employment in industries is still positive but weakly significant (10%) than before, although in subsequent specifications (columns 3–5) it remains highly significant. The lagged value of the dependent variable being positive and significant at 1% suggests presence of strong peer effect, wherein the school enrolment benefits from history of observing moderate to high enrolment in previous years. The prevalence of various school enrolment and attendance programs as initiated in many parts of South Asia should be instrumental in maintaining such steady enrolment patterns for female students. Nevertheless, as symmetric to Table 2, column 2 includes female employment in services which is positive but not significant. Columns 3 and 4 include manufacturing and industry value added at the national level, both of which have negative and significant impact on school enrolment among women. In other words, the set of results discussed under Table 2, with a possibility of being fraught with endogeneity, holds true even when concerns about endogeneity is rigorously addressed. As part of further robustness checks, we delineate that the Sargan test for validity of over-identifying restrictions have been conducted and reported as footnote to Table 5.

Table 4 System GMM. Dependent variable: female secondary school enrolment

Variables	(1)	(2)	(3)	(4)	(5)
	Femsecschenrol	femsecschenrol	femsecschenrol	femsecschenrol	femsecschenrol
L.femsecschenrol_n	0.835***	0.831***	0.778***	0.743***	0.746***
	(0.0450)	(0.0455)	(0.0494)	(0.0547)	(0.0551)
gdppercap_n	0.00626***	0.00566***	0.00706***	0.0147***	0.0147***
	(0.00186)	(0.00208)	(0.00213)	(0.00387)	(0.00389)
fememplnd	0.547*	0.548	1.496***	0.766**	0.688*
	(0.281)	(0.382)	(0.529)	(0.380)	(0.391)
Femindsq	−0.0215**	−0.0232**	−0.0425***	−0.0424***	−0.0405***
	(0.00946)	(0.00984)	(0.0123)	(0.0119)	(0.0121)
Gdpsq	−5.28e−07**	−5.21e−07**	−8.20e−07***	−1.62e−06***	−1.60e−06***
	(2.54e−07)	(2.55e−07)	(2.78e−07)	(4.72e−07)	(4.75e−07)
Fememservice		0.122	0.0813	0.237	0.220
		(0.184)	(0.182)	(0.184)	(0.186)
manufacturingva_n			−0.680**		
			(0.265)		
industryva_n				−0.484***	−0.473***
				(0.177)	(0.179)
D.maleempind					0.593
					(0.619)
Constant	1.449	0.327	3.212	7.559*	7.690*
	(2.691)	(3.210)	(3.358)	(4.093)	(4.119)
Observations	110	110	110	110	110
Number of countrycode	8	8	8	8	8

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

Table 5 System GMM. Dependent variable: female secondary school enrolment. *Interaction Effects: memptr = male sec school enrol * male indusemp*

Variables	(1)	(2)	(3)^
	femsecschenrol	femsecschenrol	femsecschenrol
L.femsecschenrol_n	0.660***	0.974***	0.535***
	(0.0590)	(0.0305)	(0.0430)
gdppercap_n	0.0170***	0.00748***	0.0102***
	(0.00384)	(0.00240)	(0.00272)
Fememp ind	1.505***	−0.520*	−2.454***
	(0.433)	(0.296)	(0.411)
Femindsq	−0.0647***	0.0213*	0.0220**
	(0.0134)	(0.0119)	(0.0104)
Gdpsq	−2.04e−06***	−1.56e−06***	−7.10e−07**
	(4.78e−07)	(4.69e−07)	(3.40e−07)
Femempservice	0.828***	−0.213**	0.310**
	(0.254)	(0.0966)	(0.128)
industryva_n	−0.676***	−0.0520	−0.211*
	(0.183)	(0.0814)	(0.126)
Malemservice	−0.555***		
	(0.165)		
imports_n		0.0714***	
		(0.0205)	
D.maleempind			0.873*
			(0.438)
Memptr			0.0215***
			(0.00209)
Constant	17.93***	3.306	17.55***
	(5.009)	(2.380)	(3.010)
Observations	110	100	110
Number of countrycode	8	7	8

Standard errors in parentheses
***p < 0.01, **p < 0.05, *p < 0.1
^Sargan test of overidentifying restrictions. H0: overidentifying restrictions are valid
$chi^2(84) = 204.543$; $Prob > chi^2 = 0.0000$ (null hypothesis rejected)

Table 5 column 1 shows that female secondary school enrolment rises more than proportionately for a unit rise in female industrial employment and it is statistically significant at 1%. However, rise in male employment in the service sector seems to lower female secondary school enrolment. Once again, the precise mechanism which dissuades women from school enrolment needs better qualification, which the aggregative data under consideration does not reveal adequately. Imports in column 2 and the interaction variable in column 3 (*memptr*) is also positive and significant at 1% level. These coefficients taken together clearly impart a positive influence on female school enrolment across countries of South Asia, which simple depictions as in Fig. 1 has already revealed. Further, with regard to the interaction variable, column 3 Table 5 the ratio of the coefficients maintains that a significant drop in male school enrolment on average would be warranted in order to nullify the positive impact of male industrial employment on female school enrolment. These results are supported by Sargan test which shows that over-identifying restrictions do not pose threats for the validity of the system GMM specifications in these columns. In essence, an attempt to relate job market prospects to school enrolment among women is both challenging and problematic in view of many other considerations that influence labor market performance and school attendance among female participants in developing countries. Yet, recent micro-econometric relations between the two suggest that similar connections might also exist in the aggregate. The above results showed that despite substantial loss of data based on the more intricate questions to be explored, the majority of the specifications showed invariant support toward the fact that expansion in industrial jobs leads to higher school enrolment among women in South Asia.

5 Concluding Remarks

Many developing countries continue to be deficient in educational infrastructure, typically because the allocation of funds is perpetually inadequate and that private facilities remain outside the scope of millions in such countries. Countries of South Asia have made major progress in the last few decades as far as women schooling, and in general, women empowerment is concerned. One of the sources of such empowerment obviously comes from financial independence, whether through engagement in industrial activities, service-related activities or through self-employment. Since the socio-cultural context within countries of South Asia is both complex and deep, the exact mechanism that drives women empowerment through persistence in schools; by achieving better educational outcomes and economic power remains somewhat unclear.

The legal capacities could facilitate but not directly deliver economic advantages unless the transition from school to work remains strong. Yet another feature of the female labor market in South Asia is a significant withdrawal from the workforce. In India for example, the recent fall in women labor force participation to only 17% is puzzling. Is this owing to longer school years? Has rise in income to male counterparts the main factor behind such withdrawal, or is it that women are not even going to school and therefore falling out of employment opportunities? While we do not directly address these questions in this paper, but the role of industries in motivating women to attend and finish school has been explicitly addressed. In other words, poor industrial employment opportunities might be a reason why men and more so, women find school attendance and completion, economically not very useful. While this takes us back to the early questions on human capital formation, as we have already discussed in the introduction, yet it seems that the labor market outcomes do play a role. Our results, across various empirical specifications that control for sources of endogeneity establish that industrial job prospects motivate women to attain a higher level of secondary school enrolment. The same is not true about service sector expansion and growth, perhaps owing to the nature of the expertise required, or the job profile. While industrialization per se does not influence this decision directly, yet depth of industries translating into female jobs undoubtedly influences positive turnout. There are many related questions that the present paper does not answer but opens up possibilities to look into country-specific data or even sector-specific information to establish the relation much more convincingly, and perhaps explain the falling labor market participation among women in some of these countries.

Appendix 1

This is robust; service sector-led development in the country implies that people start considering school enrollment secondary level graduation in the country as a source of insurance—also for female. The above three relations tell us that the Asian countries are at different stages of growth where the combination of all these possibilities generate the final aggregate outcome (See Figs. 8 and 9).

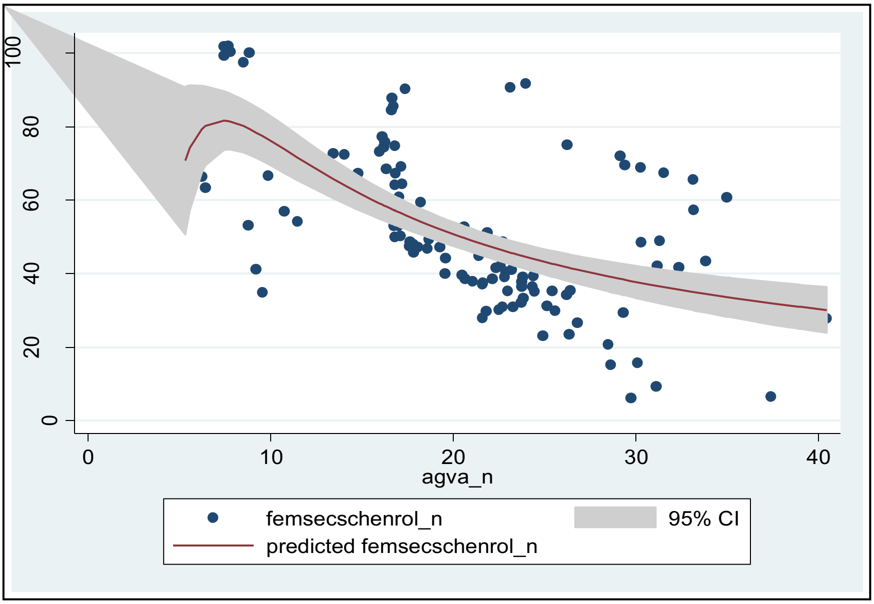


Fig. 8 Relation between female secondary school enrolment and agricultural value added. *Source* Author's calculation

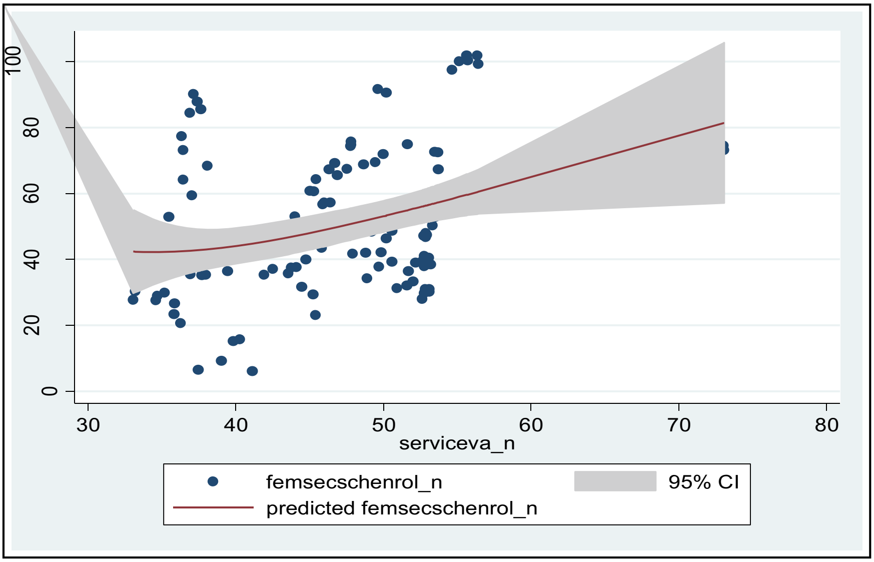


Fig. 9 Relation between female secondary school enrolment and service sector value added. *Source* Author's calculation

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Regional Patterns and Dynamics of Learning Outcomes in India

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1 Introduction

Education plays an important role in human capital formation by enhancing the productivity and earning prospects of individuals (Card, 1999; Colclough et al., 2010). The quality of human capital also augments the returns to physical capital, adding to the benefits of education in the economic process (Cervellati & Sunde, 2005; Doyle et al., 2013; Schultz, 1961). Due to its private and social returns, the quality of education is crucial for the development of a society (Hanushek & Kimko, 2000). Therefore, improving the quality of education provision is an important aspect of public policy.

Over the last few decades, in India, public policies on education have tried to improve access to education, especially for remote and backward communities in the country. Some of these policies, such as the Right to Education Act (RTE), have been successful in improving school participation, as reflected by high levels of enrolment rates at the elementary level. While the major policies have concentrated on providing better access and higher enrolment, the discourse on education has gradually shifted toward the quality of education and learning outcomes. In his book "The Rebirth of Education," Lant Pritchett has highlighted that enrolment is not automatically translating into better cognitive outcomes (Pritchett, 2013). This phenomenon is prevalent worldwide, especially in developing and emerging economies such as India (Banerjee & Duflo, 2015).

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Multiple nationally representative surveys have shown that learning levels have remained stagnant over the last many years. The Annual Status of Education Report (ASER) has been instrumental in measuring the trends in learning outcomes of school-age children over the last decade.[1] Even though 96 percent of children aged 6 to 14 years are in school, nearly 60 percent of students in Grade 4 in rural areas cannot read at a Grade 2 level, and only less than 18 percent can do basic division (ASER 2018). Therefore, understanding the causes of low learning outcomes and finding remedial policies are important areas for current research in education. The quality of an individual's human capital is a significant determinant of future labor market outcomes. Moreover, quality of the workforce can also have a cascading effect on economic growth.

The National Education Policy (NEP), released in 2020, has incorporated various aspects related to the quality of learning. One of the most relevant components of NEP-2020 in this context is the importance accorded to universal foundational literacy and numeracy. This demonstrates a significant shift from the input policies of infrastructure development to the output-oriented evaluation of learning outcomes, although it overlooks several structural aspects of inequality in education (Roy, 2019). Given this background, we take a stock of the current state of education in India, with a particular focus on the inequality in cognitive outcomes. Recent studies highlight a great extent of heterogeneity in cognitive outcomes both within and across schools (Muralidharan & Singh, 2021). While the patterns and trends in *average* learning outcomes have been discussed widely in academic and policy circles, a discourse focusing on the distribution of learning outcomes is less explored and wanting. The distributional aspect becomes even more important in the context of the Covid-19 pandemic when schools have remained closed for over 1.5 years. The pandemic is likely to have wreaked havoc on the formative learning of children, primarily from backward communities, thus, exacerbating the pre-existing inequality in education (Engzell et al., 2021; Hevia et al., 2022; Kim et al., 2021). This is likely to have multipronged and long-term implications on various economic outcomes, including the quality of human capital, productivity, income, and inequality.

Our study utilizes multiple rounds of ASER data from 2007 to 2018 to construct district-level indicators on learning outcomes of school-age children, along with other supply-side variables obtained from three other datasets, viz. Census 2001, District Information System for Education (DISE), and night-time light data. In the existing literature, analysis of regional economic disparity in India has been mainly based on state-level data; in contrast, we use district-level information. Use of district-level data is critical in analyzing regional inequalities in India on account of at least two reasons. First, in a country like India, wherein states are not only large and populous (comparable with even many countries) but also heterogeneous, analysis carried out using state-level data may miss significant patterns or trends in inequalities (Chander et al., 2014). Second, considering that districts are one of

[1] ASER is a nationally representative survey conducted by the NGO Pratham in every year across all districts of India. The survey measures children's basic literacy, numeracy, etc. among other information.

the most important administrative units of the country, district-level analysis, by unearthing localized problems, helps in mapping inequalities and its determinants for attracting policy attention (Wanmali & Islam, 1995). This aspect is especially true for the education system, where some important policies, such as the District Primary Education Program (DPEP), have been implemented explicitly through the district-level administrative machinery.

We analyze regional inequality in learning outcomes using the concepts of convergence, which has been extensively used to analyze trends in per capita GDP and similar indicators. The literature on economic growth postulates two types of convergence: beta convergence and sigma convergence. From the neoclassical theory of economic growth, it follows that national economies may converge to the same level because of diminishing returns to physical capital. Beta convergence is further separated into unconditional (or absolute) beta and conditional beta convergence, where the latter helps us to reflect on factors that determine the rate of convergence. Sigma convergence happens when income dispersion across regions falls over time, while beta convergence occurs when the partial correlation between growth rate in income and the initial level of income is negative (Barro & Salai-i-Martin, 1992; Durlauf et al., 2005).

We apply the methodology of convergence to study the temporal changes in the regional distribution of learning outcomes across the Indian districts over a decade. First, we explore whether regional disparity in learning outcomes is increasing or decreasing over time. Then, we analyze the impact of various educational supply-side factors, such as infrastructure, quality of teachers, grants provided, etc., on the changing patterns of regional disparity in learning outcomes. Thus, our study reflects on some of the policy relevant factors that determine the inequality in learning outcomes.

Our findings reveal that there is an absolute convergence taking place in learning outcomes across districts in India over time. However, convergence speed increases substantially once we control other factors in the conditional convergence model, indicating the importance of having equality of opportunity. We also examine the convergence coefficients for primary and post-primary-aged children separately. The results follow similar patterns as in the basic model. We also conduct additional analyses to understand the nature of convergence. Beta convergence can happen due to two reasons: lower-performing districts can grow faster and catch up with better-performing districts, or there can be a decline in the quality of better-performing districts. To isolate these two processes as the drivers of convergence, we investigate the distribution of learning outcomes over the years. The result shows that the dispersion of the arithmetic score has slightly decreased over time, and there is no substantial change in the dispersion of other outcome variables. However, the all-India level mean has reduced over time for all the outcome variables (i.e., reading, arithmetic, and overall test scores). This result indicates that the convergence is mainly due to a fall in learning outcomes among the districts which were performing better in the initial year. This result is a matter of concern from the perspective of the overall quality of learning outcomes in the country.

This chapter is divided into five sections. Section 2 discusses the datasets and the main variables for our analysis. Section 3 illustrates the empirical model. We discuss the results of our analysis in Sect. 4. Section 5 includes the concluding remarks.

2 Background and Data Description

There are four datasets involved in our study: Annual Status of Education Report (ASER), District Information System for Education (DISE), Census 2001, and night-time lights data. The main variables capturing learning outcomes have been obtained from ASER. Education-related variables such as school infrastructure, teacher qualification, pupil-teacher ratio, teacher-gender ratio, and developmental grants are obtained from DISE which is a census of all recognized schools in India, including government, private aided, and private unaided schools. Some of the population characteristics such as literacy rate, sex ratio, and location of residence are captured by the Census; this information is also readily available in DISE. We have used the night-time light data to proxy the district's economic development and activities. List of all relevant variables and respective data sources has been given in Table 1. After generating the relevant variables from each dataset and aggregating them at the district level, we merged them using the 2001 Census district names since our final analysis is based on district-level data. In the following paragraphs, we provide further details of these datasets and the variables used in our analysis.

ASER is the largest annual household survey carried out in India to collect information on children's schooling and basic learning levels. This provides estimates at district, state, and national levels. ASER samples households, not children. Since it is a household-based survey, it enables all children in the household to be included—irrespective of their school enrollment status. It also includes those children who have never been to school or have dropped out in between. The sampling strategy used in ASER generates a representative picture of each rural district in India. From each district, ASER selects 30 villages from the Census 2001 village list. This selection is based on Probability Proportional to Size (PPS), a widely used sampling technique. Then, from each village, ASER randomly selects 20 households. This gives a total number of 600 households in each rural district, or about 3,00,000 households at the all-India level. Approximately 600,000 children over 16,000 villages across the country in the age group of 3–16 are surveyed every year.

All children in the age group of 3–16 from the sampled households are included in the survey. Enrolment status in school or pre-school is recorded for all such children, while learning assessments are done with children only in the age group of 5–16. As part of the learning assessment, children are tested in basic reading in their first language, arithmetic, and basic reading in English. The same test is given to all children across the years irrespective of their age, enrolment status, and class standard. The reading assessment has four levels: a child is asked to read letters, common words, a paragraph with four simple sentences (Grade 1 level text), and a

Table 1 Descriptive statistics

Data source	Variables	Obs	Mean	Std.Dev
ASER	Reading score in 2007	548	2.76	0.37
	Reading score in 2018	549	2.62	0.38
	Arithmetic score in 2007	548	2.61	0.39
	Arithmetic score in 2018	549	2.3	0.34
	Overall learning score in 2007	548	5.38	0.74
	Overall learning score in 2018	549	4.92	0.69
	Reading growth rate	548	-0.05	0.14
	Arithmetic growth rate	548	-0.13	0.16
	Overall learning growth rate	548	-0.09	0.14
DISE	Infrastructure index	548	0.02	0.98
	Pupil-teacher ratio	548	33.64	12.94
	Teacher gender ratio	548	0.87	0.88
	Proportion of teachers trained	548	0.45	0.27
	Proportion of qualified teachers	548	0.46	0.16
	Grants	548	0.09	0.91
Census	Literacy rate	544	63.02	12.26
	Sex ratio	544	0.94	0.06
	Percentage of urban population	537	21.55	14.82
DMSP/OLS	Night-time luminosity	549	4.78	4.68

Note: Learning outcome growth rates have been calculated by taking the difference in learning outcomes between 2007 and 2018 after making a log transformation. The literacy rate is presented in percentages. The infrastructure index is generated using PCA, capturing the quality of school building, conditions of classrooms, availability of blackboards, separate toilet for girls, and drinking water facility. The pupil-teacher ratio is the ratio of students to the number of teachers. The teacher-gender ratio captures the average number of female teachers per male teacher. The proportion of teachers trained means the ratio of trained teachers out of total teachers. Proportion of qualified teachers captures the proportion of teachers with qualifications of graduation or above, among all the teachers. Grants is a PCA index generated using different types of grants received by the school. Sex ratio is scaled down by 1000. The night-time luminosity captures the average nightlights for the district. All the control variables are measured in the initial year, 2007 with the demographic variables sourced from Census 2001.

short story of 10 to 12 sentences (Grade 2 level text). Similarly, the arithmetic assessment consists of four levels: single-digit number recognition, double-digit number recognition, two-digit subtraction with borrowing, and three-digit by one-digit division. The highest level of arithmetic tested corresponds to what is expected in Grade 3 or 4, depending on the state. We have converted these levels into a scale of 0 to 4 in our main analysis. Children who cannot read even letters or recognize single-digit numbers are marked with 0. Since our final analysis is based on district-level data, we aggregated these learning outcomes by calculating their average for each district in India. Although the original learning outcome at the child level is a categorical variable, the district-level average is a continuous variable in the range of 0–4.

The National University of Educational Planning and Administration, with the support from the Ministry of Human Resource Development (MHRD) and UNICEF, initiated a comprehensive data collection on elementary education in India, known as the District Information System for Education (DISE). It provides district-level information about students, teachers, and infrastructure at both primary and upper primary levels for all districts in the country. It is a census of all recognized schools in India and collects information about 1.4 million elementary schools each year. The variables collected in the DISE include enrolment, teachers by gender, teachers' qualifications, development grants to schools, infrastructure facilities in schools, etc. The dataset is updated annually. Population-related variables captured by the Census, such as literacy rate, sex ratio, and share of urban population, which are relevant to our study, are also readily available in the DISE.

Henderson et al. (2012) have shown that night-time light data is a useful proxy for measuring economic growth. After that, many studies in economics literature have used this as a proxy for GDP because it is highly correlated with economic activities, objectively measured, and available for almost all places in the world at the subnational level. For example, in India, we do not have a standard measure of output at the district level. Chanda and Kabiraj (2020) have used night-time light data to examine regional differences in economic growth in India. They have also added a new dimension by exploring the rural–urban variations that are not easily done by current official data. Therefore, in our study, we use night-time light data as a proxy to capture economic activities at the district level. The most widely used luminosity data in the economics literature is an annual composite available for every year from 1992 to 2013, usually referred to as Defense Meteorological Satellite Program/ Operational Linescan System (DMSP/OLS) night-time lights. This data is provided by National Oceanic and Atmospheric Administration/National Geophysical Data Center (NOAA/NGDC) Earth Observation Group.[2] Light intensity is reported as a 6-bit Digital Number (DN) for each arc-second grid (approximately 0.86 km at the equator). DN is a unitless integer that measures the stable light and takes a value from 0 to 63, where 0 means no light, and 63 is the highest luminosity observed. We use the district-level annual average night-time luminosity obtained from the DMSP/OLS data. We have converted each value in the light intensity scale (0–63) to its total value by multiplying with its total count in that district and aggregated it at the district level. After that, the district aggregate light intensity value is divided by its total number of grid points to adjust for the variation in the district's size.

The important control variables in our study are district-level literacy rate, infrastructure index, pupil-teacher ratio, teacher-gender ratio, the proportion of trained teachers, teacher qualification, school grants, sex ratio, percentage of urban population, and night-time light data. These variables are measured in the initial year. We discuss the rationale for including these variables below.

[2] The data can be downloaded from https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html.

Literacy rate: Literacy rate and educational development are considered to be key variables affecting the demographic indicators and significantly contribute to improving the quality of life. Higher levels of literacy and academic development lead to greater awareness and assist in acquiring new skills. Educated parents play a vital role in children's learning (Hoover-Dempsey & Sandler, 1997). Researchers have shown that an educated mother directly impacts children's education level in that household (Guryan et al., 2008). The literacy rate can also indicate the presence of skilled labor in the district, thus affecting the returns to better quality human capital. For these various reasons, districts with a higher literacy rate may have an initial advantage in learning outcomes. Therefore, we include the district-level literacy rate, i.e., the percentage of literate individuals in the district, taken from the Census 2001. A person aged seven and above who can read and write with understanding in any language is treated as literate.[3]

School infrastructure index: An increase in government funding for school infrastructure has been shown to affect educational outcomes (Card & Krueger, 1996). The importance of public investments in schools may reach beyond direct benefits; it may increase enrolment and learning levels by demonstrating the importance of schooling to families and society (Masino & Nino-Zarazua, 2016). Typical investments in school facilities include expanding the number of schools as well improving the quality of existing school infrastructure. Across countries, better instructional materials, hygiene sanitation, and well-maintained classrooms are associated with higher performance in reading and mathematics (Hungi, 2011). Therefore, if the governments invest more in the school infrastructure of poorer regions with lower performance, that could reduce learning inequality and lead to faster convergence among the districts. In our study, an index has been created for infrastructure using Principal Component Analysis (PCA). This index captures the quality of the school building, conditions of classrooms, availability of blackboard facility, separate toilet for girls, and drinking water facility.

Teacher-related variables: The smaller the Pupil-Teacher Ratio (PTR), the higher is the teacher's focus on individual students (Krueger & Whitmore, 2011). In some lower-income settings, including India, lower PTR predicted improved learning outcomes and higher enrolment, especially for girls (Dreze & Kingdon, 2003). In India, female teachers at primary and upper primary levels have been much more effective in accelerating learning outcomes than male colleagues (Hungi, 2011; Muralidharan & Sundararaman, 2006). Therefore, we have included teacher-gender ratio as well in our control variables. Similarly, teacher training and their qualification also play a significant role. Trained and qualified teachers are more effective and equally important as better infrastructure to enhance the quality of educational outcomes (Angrist & Lavy, 2001). Though defining a good teacher is a challenging exercise, better training and higher qualification can lead to better teaching in the

[3] Based on expert advice, the age limit was raised to seven in the 1991 Census. It is observed that children below this age limit don't ordinally develop the skill required to understand the text properly. To be literate, there is no requirement for formal education.

classroom. Therefore, we have considered the proportion of teachers with graduation or above as qualified teachers.

School grants: There are various grants provided through the Sarva Shiksha Abhiyan (SSA) program to all the government schools in India, and they arrive with clear expenditure guidelines. It is the primary vehicle for implementing various educational policies for the country's overall provision of elementary education. In our model, a PCA index is generated using two major grants received by the schools: School Development Grant and Teacher Learning Material Grant.

Demographic characteristics of the district: In our model, the sex ratio is used to capture the effect of the gender composition of the population on learning outcomes. It is defined as the size of female population per thousand male population. Sex ratios are likely to reflect education and job opportunities for women (Rosenzweig & Schultz, 1982). We have also controlled the percentage of the urban population in a district. The percentage of the urban population to the total population captures the extent of urbanization. Jayasuriya and Wodon (2003) have shown that urbanization positively impacts learning outcomes. It may be because that urban setup provides more options for schooling and better orientation for the future career. Besides, the nature of jobs in urban cities may require different types of education than in rural areas, impacting the learning outcomes of students (World Bank, 2018).

Night-time luminosity: Research has shown that increased income and economic activities have led to increased human capital formation (Acemoglu & Pischke, 2001). Therefore, we use night-time light data as our proxy to capture economic activities since information on GDP is not available at the district level. This variable records the average amount of light emitted from the districts using satellite images, as explained earlier in this section.

3 Empirical Model

This study looks at regional inequality in learning outcomes, how it has changed over the years, and the different factors affecting it. To explore this, we adopt convergence models from growth theory in macroeconomics. Various studies have used convergence models to study the regional inequalities across Indian districts and over time (Chanda & Kabiraj, 2020; Das et al., 2015; Tiwari et al., 2020). Using a similar framework, we seek to investigate the dynamics of inequality in learning outcomes. Generally, there are two convergence models: beta convergence and sigma convergence. Beta convergence has two specifications—with and without control variables, known as conditional and unconditional beta convergence. These models were initially used to analyze the hypothesis of cross-country convergence in economic growth (Baumol, 1986; Durlauf et al., 2005, Barro & Salai-i-Martin, 1992). In the Indian context, Das et al. (2015) have examined the evidence of convergence in per capita incomes at the district level using these models. Li et al. (2018) have also applied a similar approach to studying districts' convergence based on household expenditure data.

The empirical concepts of these models were then extended to many fields not related to growth or GDP. Royuela and Garcia (2015) have studied the convergence process in Colombia during 1975–2005, considering not only economic variables but also social indicators of education, health, and crime. Anton et al. (2021) have explored whether there is a convergence in non-monetary working conditions using data from European regions from 1995 to 2015. Ortega et al. (2016) have investigated how corruption affects the convergence process in human development across countries using information from 69 countries for the period 1990–2012. Also, these models have been applied to look at the convergence in health outcomes among Indian states (Hembram & Haldar, 2020; Purohit, 2012).

We begin with unconditional beta convergence, also known as absolute beta convergence. In this model, we estimate a regression model of growth rate in learning outcomes against the initial level of learning outcomes, not including any other covariate. Our dependent variable measures the growth rate in learning outcomes between 2007 and 2018. The regression equation is as follows:

$$log(Y_{i,1}) - log(Y_{i,0}) = \beta_0 + \beta_1 log(Y_{i,0}) + \varepsilon_i \tag{1}$$

where, $Y_{i,1}$ is the learning outcome in 2018 for district i, and $Y_{i,0}$ is the learning outcome at the base year 2007 for district i. The left-hand side of Eq. (1) can be approximated as the transitional growth rate in learning outcomes from 2007 to 2018. The inclusion of the logarithm of initial learning outcomes as an explanatory variable is a standard procedure for studying convergence in the literature. β_1 indicates the extent and direction of convergence. A negative β_1 implies that districts with lower levels of initial learning outcomes will experience a higher transitional growth rate of learning outcomes compared to the districts with higher levels of initial learning outcomes. Similarly, a positive β_1 would imply divergence.

In the unconditional convergence model that does not include any other covariate, all that matters is the initial level of the learning outcomes. However, there might be many other factors affecting this growth rate apart from the initial level of the outcome variable. Moreover, these factors may also be correlated with the initial level of learning outcome. Therefore, in the conditional convergence model, these variables are taken into account and controlled in the regression. The model specification is given by Eq. (2).

$$log(Y_{i,1}) - log(Y_{i,0}) = \beta_0 + \beta_1 log(Y_{i,0}) + X'_{i,0}\,\gamma + \varepsilon_i \tag{2}$$

where $X_{i,0}$ is the vector of variables used to control for the effect of other confounding factors at the base year. A negative β_1 in the conditional model implies that districts with lower levels of initial learning outcomes will experience a higher transitional growth rate of learning outcomes than the districts with higher levels of initial learning outcomes keeping all other covariates ($X_{i,0}$) constant. In other words, a negative coefficient in this model means convergence in the growth rate of learning outcomes among districts that are similar in terms of the socio-economic indicators included in the set of covariates in the model. By comparing the direction and magnitude of β_1 between the unconditional and conditional models, we can also reflect on the influence of the covariates on the rate of convergence.

We next estimate sigma convergence that measures the disparity of learning outcomes across districts over time. The widely used indicator of sigma convergence is the standard deviation or the coefficient of variation. For example, we can say that districts are sigma-convergent if the standard deviation of the outcome at $t + k$ ($k > 0$) is lower than that at t. In addition to the standard deviation, we also illustrate the extent of sigma convergence by estimating kernel density functions of test scores for various years. Both the concepts of beta and sigma convergence are related; however, some economists (Friedman, 1992; Quah, 1993) believe that sigma convergence is more revealing of reality since it directly looks at the distribution of the interested variables across different periods without relying on particular specifications of econometric models. Also, the beta convergence does not reveal whether the poorer states are converging to higher levels or better states are converging to lower levels; however, these two possibilities can be isolated by looking at the sigma convergence, especially by the movement of the distribution of the test scores over time.

4 Results

Descriptive Statistics: Our final data consists of district-level variables from four different datasets; the descriptive statistics of all relevant variables are given in Table 1. Our dependent variable, i.e., the growth rate in learning outcomes, has been calculated by taking the difference in learning outcomes between 2007 and 2018 after making a log transformation. The major control variables included in our study are literacy rate, school infrastructure index, pupil-teacher ratio, teacher-gender ratio, the proportion of trained teachers, the proportion of teachers with higher educational qualifications, the proportion of schools that received development grants, sex ratio, percentage of urban population and night-time luminosity data (proxy of economic development). In the school infrastructure index, we have incorporated a few variables that capture the quality of infrastructure provided in school, such as classroom conditions, availability of blackboards, school building materials, the proportion of schools with separate female toilets, and drinking water facilities.

In Table 1, we can observe that there has been a decline in learning outcomes over the years. For example, the district reading score is 2.62 in 2018, while it was 2.76 in 2007. This decrease has been reflected in the growth rates of these variables, with the most significant decrease recorded in the arithmetic growth rate. In Fig. 1, we have plotted a district map of India showing the average learning outcomes to demonstrate how it has changed over the years. Panel (a) shows the average learning score (it is the average of reading and arithmetic score) in 2007, and Panel (b) shows the average learning score in 2018. The graphical representation clearly indicates that the learning performance has deteriorated over time. We have presented similar graphs separately for the reading and arithmetic scores in the Appendix (Figs. 5, 6, 7, 8, 9, 10, 11 and 12). Also, we did this for younger (age: 5–10) and older children (age: 11–16) to look at the heterogeneity in learning performance among different age groups over the years, and found similar patterns.

Regression Results for Beta Convergence: Now, we look at the results from the regressions estimating the absolute beta convergence, given in Table 2. The results have been presented separately for each outcome variable: reading, arithmetic, and overall (sum of reading and arithmetic score). It can be seen that the sign of the beta coefficient is significant and negative for all three outcome variables, implying that there is convergence in district-level learning outcomes over time.

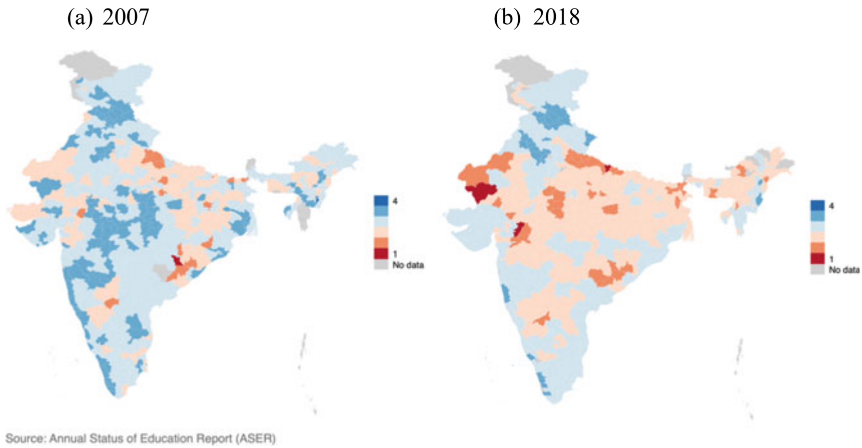

Fig. 1 District-wise average learning performance, India

Table 2 Absolute convergence

Variables	(1)	(2)	(3)
	Reading	Arithmetic	Overall
Log(Reading_07)	−0.4390*** (0.0391)		
Log(Arithmetic_07)		−0.5444*** (0.0380)	
Log(Overall_07)			−0.4967*** (0.0377)
Constant	0.3881*** (0.0393)	0.3884*** (0.0356)	0.7411*** (0.0625)
Observations	548	548	548
R-squared	0.1909	0.2841	0.2484

Robust standard errors in parentheses
*** p < 0.01, ** p < 0.05, * p < 0.1

Next, we look at the results of conditional convergence. We have reported results only for the overall learning outcome in Table 3. The results for reading and arithmetic scores follow a similar pattern and are provided in Tables 4 and 5 in the Appendix. Column 1 presents the results of the unconditional convergence for the overall score, as it was given in Table 2, for ease of comparison. Column 2 illustrates the results of convergence conditioning on initial literacy rate. The convergence speed has increased substantially after conditioning on literacy rate compared to the magnitude of absolute convergence, indicating that literacy rate is highly correlated with the initial level of learning outcome and its growth rate. It can also be noted that the positive and significant coefficient of literacy rate implies that districts with initially higher levels of literacy rate experience a higher transitional growth rate.

Table 3 Conditional convergence

Variables	(1)	(2)	(3)	(4)	(5)
	Absolute	Control1	Control2	Control3	All Controls
Log(Overall_07)	-0.4967*** (0.0377)	-0.8221*** (0.0456)	-0.5028*** (0.0379)	-0.6813*** (0.0458)	-0.8916*** (0.0457)
Literacy rate		0.0068*** (0.0005)			0.0061*** (0.0007)
Infrastructure Index			0.0166*** (0.0055)		0.0013 (0.0070)
Pupil-teacher ratio				-0.0026*** (0.0005)	-0.0013*** (0.0004)
Teacher gender ratio				0.0392*** (0.0052)	0.0040 (0.0054)
Teachers trained				0.0685*** (0.0198)	0.0798*** (0.0187)
Teacher Qualification				0.0673** (0.0290)	0.0515 (0.0334)
Grants					-0.0008 (0.0076)
NTL Luminosity					0.0065*** (0.0020)
Sex ratio					0.1123 (0.1039)
Percentage of urban population					-0.0017*** (0.0004)
Constant	0.7411*** (0.0625)	0.8582*** (0.0558)	0.7511*** (0.0630)	1.0414*** (0.0854)	0.8958*** (0.1110)
Observations	548	543	547	547	536
R-squared	0.2484	0.4765	0.2604	0.3870	0.5520

Robust standard errors in parentheses
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

In column 3, the control variables include an infrastructure index that captures the quality of school infrastructure. As expected, its coefficient is positive and significant, implying that having better school infrastructure facilities leads to a higher growth rate in learning outcomes. However, the beta coefficient remains almost unchanged from the unconditional convergence model, implying that infrastructure facilities in schools do not affect the rate of convergence in learning outcomes. This may be because that infrastructure is not associated with the initial level of learning outcome.

In column 4, the model considers the role of teacher-related variables in the convergence rate. As compared to school infrastructure, teacher-related variables facilitate the growth rate of learning at a faster pace. As expected, we find that the pupil-teacher ratio is significant, and it negatively affects the growth rate. The other control variables, like a higher proportion of trained and qualified teachers, are significant, and they positively impact the growth rate. When conditioned on these teacher-related variables, the learning growth rate across the districts converges faster than the unconditional model.

Finally, in the last model, along with all previous control variables, we further added some key variables such as economic activities captured by night-time luminosity, sex ratio, percentage of the urban population, and the average school grants. The literacy rate is still positive and it significantly affects the growth rate of learning outcomes. As expected, the coefficient of trained teachers and night-time luminosity (NTL) is positive and significant, while the effect of the pupil-teacher ratio (PTR) is negative and significant. It may be because the trained teachers are more efficient at teaching, increased economic activities proxied by NTL are leading to better human capital formation, and higher the PTR, the lower is the focus of a teacher on an individual student. Once we control for all the variables, infrastructure index, and grants become insignificant. Also, both teacher-gender ratio and sex ratio become insignificant in the final model. However, the percentage of the urban population is negatively associated with the growth rate of learning outcomes. Students living in urban areas may have higher learning growth if urban places have higher levels of development fostering learning. However, since we already control for night-time luminosity, the developmental effect of urbanity is already captured. The residual effect of urban areas may be negative, for instance, if urban areas also have higher incidence of pollution. Thus, it seems from our result that after controlling for the developmental effect, the negative channels of urbanity are relevant for learning outcomes. After controlling all the variables in column 5, we find that the convergence rate is amplified. This implies that the districts would converge at a faster rate if all the districts had a similar level of development at the beginning.

Furthermore, we have also examined the convergence in the learning outcomes for younger and older children separately. So far, in our main analysis, we have considered all the children in the age group of 5–16 to measure the district average learning outcomes. To investigate the difference in the convergence between the primary and post-primary children, we have classified the children into two groups: younger children (aged 5 to 10) and older children (aged 11 to 16), and calculated the district average learning outcomes. We have given the regression results separately for these two groups in Tables 6 and 7 in the Appendix. There is no substantial difference in the convergence coefficients compared to our basic model, where we have considered all the children together. However, there are variations in the effect of covariates on the growth rates of learning outcomes. For example, the teacher-gender ratio is positive and significant for older children, while it is not significant for younger children. This result is consistent with the literature highlighting that for adolescent students, female teachers are better than male teachers for girls' learning outcomes, especially in mathematics (Muralidharan & Sheth, 2016; Rakshit & Sahoo, 2023). The "role model effect" of female teachers is one of the channels that explains this effect. The existing studies also point out that there is no negative impact of female teachers on male students, thus, having a greater number of female teachers may be beneficial for overall learning of students. The effect of teachers' gender on girls' learning is more prominent for adolescents rather than younger children because the perception of gender identity of the teacher may not be salient for children at a very young age.

Sigma Convergence: Next, we analyze sigma convergence in learning outcomes. This will uncover the mechanism behind the beta convergence we have already found, i.e., whether the poor-performing districts are growing faster and catching up with better-performing districts or there is a decline in the performance of the better-performing districts and their quality is decreasing over the years, relative to the poor-performing districts. If the convergence occurs through the first channel, it is a preferred outcome for the economy and society. On the other hand, if the convergence occurs through the second pathway, it is not a desirable outcome.

We begin the analysis of sigma convergence using graphs. Figure 2 plots the distributions of learning outcomes separately for reading, arithmetic, and average learning score.[4] We have also plotted the mean and standard deviation over the years for these three variables in Fig. 3. We can observe that the standard deviation of reading scores has increased over time. In the arithmetic score, the dispersion has slightly decreased, and it has led to a reduction in the dispersion of the average learning score as well. However, there is a reduction in the mean of all three learning outcomes.

Further, in Fig. 4, we compare the distribution of learning outcomes over the years. We show the figure for a few years, i.e., 2007, 2011, and 2018, to highlight the overall dynamics. We find that the outcomes of 2007 first order stochastically dominate the distribution of 2011 which in turn also dominates the distribution of 2018. This result shows that there is a gradual decline throughout the distribution of learning outcomes. A Kolmogorov–Smirnov test[5] shows that there is a significant difference between the distribution for the years 2007 and 2018. These results support the second mechanism behind the observed beta convergence. From the perspective of economic policies, this is not an encouraging result since the reason for convergence is not because poorer districts are performing better and catching up with developed districts but due to a reduction in the quality of better-performing districts.

[4] We use a non-parametric estimator, specifically, the kernel density function for this analysis.

[5] The Kolmogorov–Smirnov test is a nonparametric test for comparing two samples and test whether they are drawn from the same probability distribution.

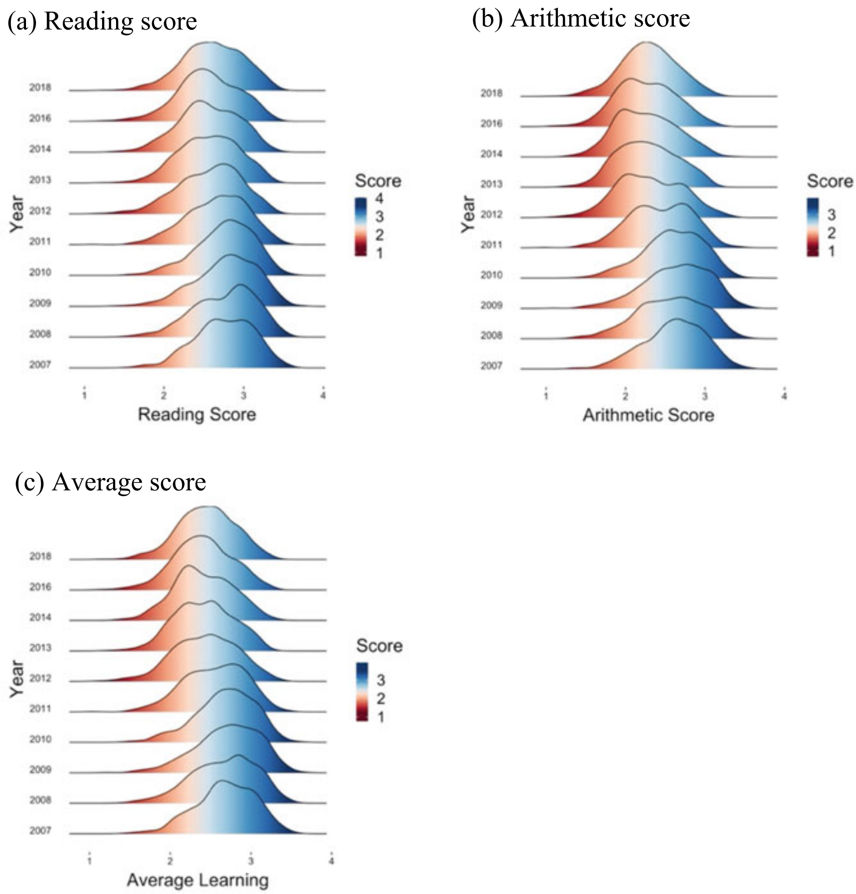

Fig. 2 Distribution of learning outcomes over the years

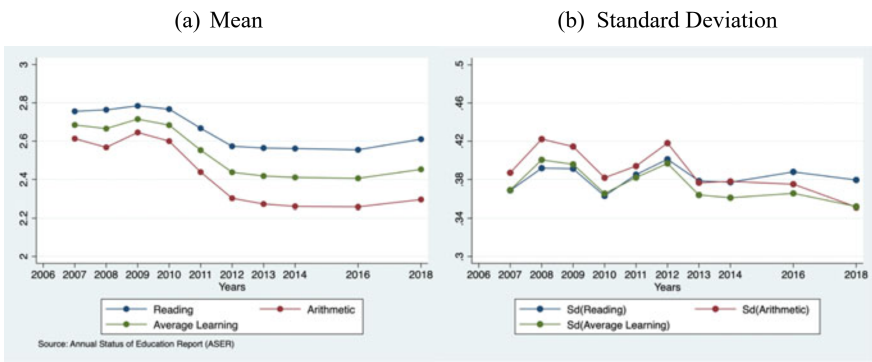

Fig. 3 Mean and standard deviation of learning outcomes over the years

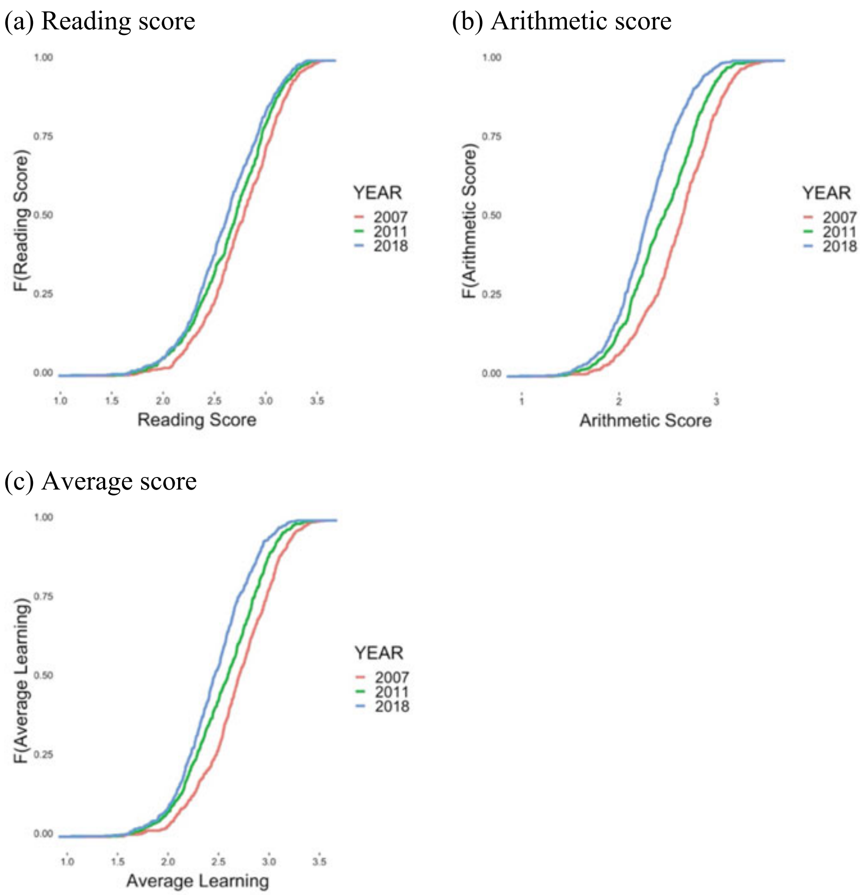

Fig. 4 Cumulative density function of learning outcomes over the years

5 Conclusion

This chapter looks at the transition of learning outcomes in India over the last decade. We use convergence models from the growth literature to see whether the learning outcomes are converging among the districts over the years. Specifically, we use the measures of beta and sigma convergence to understand the dynamics of average learning across the Indian districts over time. Our empirical exercise shows that there is beta convergence across the districts in India. The convergence rate increases when we control other relevant variables capturing the initial conditions of the districts. This implies that convergence occurs faster among the districts with similar socio-economic characteristics. Our analysis shows the importance of creating equality of opportunity through public policies to achieve faster convergence or a reduction in inequality in learning outcomes among the districts. Further, we have studied the sigma convergence to determine whether the lower districts are catching up or better districts are getting worse in terms of learning outcomes. The dispersion has reduced slightly for arithmetic outcome. However, the average learning outcome has decreased in all three measures, reading, arithmetic, and average learning score. These results are concerning from the perspective of the potential demographic dividend and indicate that public policies need to prioritize building foundational literacy and numeracy skills, as suggested in the National Education Policy, 2020.

The issue of regional disparity in learning becomes even more critical in the context of the COVID-19 pandemic. It has led to the largest disruption of the educational system, affecting more than 1.6 billion students worldwide (UNICEF, 2020). A joint report by World Bank, UNESCO, and UNICEF has revealed that learning losses from the pandemic could cost this generation of students close to $17 trillion in lifetime earnings or the equivalent of 14% of today's global GDP (World Bank et al., 2021). Even before the pandemic, the world was experiencing a learning crisis and inequality for many vulnerable sections of society, like girls, students with disabilities, students from low-income families, and students from religious and ethnic minorities. The COVID-19 pandemic has exacerbated this crisis, and it might be long-lasting beyond the current generation. As the education system shifted toward remote learning in early 2020, many moved quickly by deploying multiple strategies like online, television, and radio education to sustain learning continuity. However, the accessibility of remote learning varied greatly, with marginalized students often not able to benefit from remote learning opportunities because of multiple reasons like lack of electricity, internet connectivity, electronic devices, and discrimination and gender norms. Besides, teachers in low and middle-income countries have limited training in the transition toward online teaching, leaving them unprepared to deliver quality education to the students (World Bank et al., 2021).

Additionally, contraction in family income and government fiscal pressures increase the risk of school dropout and insufficient funds in the educational sector for the coming years. Early evidence from several high-income countries has already revealed tremendous learning losses and increases in inequality (Contini et al., 2021; Engzell et al., 2021; Maldonado & De Witte, 2020). The unprecedented situations over the last many months can have a substantial negative impact with variations by grades, schools, and students' characteristics (Hevia et al., 2022; Kim et al., 2021). Therefore, focusing on equity and fast recovery is most critical as children return to school. In this context, our results show that inequality in background characteristics such as existing literacy rates, teacher quality, and regional development can hinder the progress toward reducing inequality in learning outcomes. It confirms the importance of promoting equality of opportunity through government interventions in reducing learning inequalities. Policy makers should identify regions where learning outcomes are falling behind and specifically target to improve outcomes in those regions. Our findings suggest that recruiting more teachers to reduce pupil-teacher ratio and training the teachers are likely to be relevant in this context.

There are several limitations that should be considered while interpreting the findings from our study. First, we may have omitted other policy-relevant factors that may have affected the convergence rate in learning outcomes during the period considered. On the supply side, these factors may include the quality of school management, teacher absenteeism, teacher motivation, etc. On the demand side, we have omitted factors such as parental motivation, returns to education, and various structural barriers such as caste composition of the population in the districts. Second, we have not exploited any exogenous variation in the independent variables, preventing us from making any strong claim of causality in the relationship. Third, our analysis is aggregated at the district level and masks any intra-district heterogeneity in learning outcomes. Addressing these issues constitutes an agenda for future research.

Appendix

See Tables 4, 5, 6, 7.

See Figs. 5, 6, 7, 8, 9, 10, 11 and 12.

Table 4 Conditional convergence (reading score)

Variables	(1)	(2)	(3)	(4)	(5)
	Absolute	Control1	Control2	Control3	All Controls
Log(Read_07)	−0.4390*** (0.0391)	−0.8376*** (0.0507)	−0.4533*** (0.0394)	−0.6155*** (0.0465)	−0.9142*** (0.0490)
Literacy rate		0.0074*** (0.0006)			0.0070*** (0.0007)
Infrastructure Index			0.0175*** (0.0056)		0.0114* (0.0066)
Pupil-teacher ratio				−0.0029*** (0.0005)	−0.0017*** (0.0004)
Teacher gender ratio				0.0302*** (0.0055)	−0.0129** (0.0054)
Teachers trained				0.0824*** (0.0212)	0.0900*** (0.0194)
Teacher Qualification				0.0265 (0.0299)	−0.0028 (0.0334)
Grants					0.0043 (0.0075)
NTL Luminosity					0.0057*** (0.0019)
Sex ratio					0.1864* (0.0991)
Percentage of urban population					−0.0015*** (0.0004)
Constant	0.3881*** (0.0393)	0.3189*** (0.0323)	0.4021*** (0.0397)	0.5888*** (0.0585)	0.2816*** (0.0917)
Observations	548	543	547	547	536
R-squared	0.1909	0.4580	0.2049	0.3271	0.5443

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5 Conditional convergence (arithmetic score)

Variables	(1)	(2)	(3)	(4)	(5)
	Absolute	Control1	Control2	Control3	All Controls
Log(Arithmetic_07)	−0.5444*** (0.0380)	−0.7775*** (0.0428)	−0.5450*** (0.0381)	−0.7131*** (0.0459)	−0.8517*** (0.0444)
Literacy rate		0.0059*** (0.0005)			0.0050*** (0.0007)
Infrastructure index			0.0139** (0.0060)		−0.0092 (0.0082)
Pupil-teacher ratio				−0.0021*** (0.0005)	−0.0007 (0.0005)
Teacher gender ratio				0.0486*** (0.0055)	0.0227*** (0.0066)
Teachers trained				0.0528** (0.0206)	0.0687*** (0.0210)
Teacher Qualification				0.1088*** (0.0322)	0.1076*** (0.0381)
Grants					−0.0070 (0.0085)
NTL Luminosity					0.0076*** (0.0024)
Sex ratio					0.0407 (0.1223)
Percentage of urban population					−0.0020*** (0.0006)
Constant	0.3884*** (0.0356)	0.2392*** (0.0338)	0.3887*** (0.0357)	0.5021*** (0.0547)	0.2529** (0.1207)
Observations	548	543	547	547	536
R-squared	0.2841	0.4367	0.2910	0.4118	0.5191

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6 Conditional convergence (younger children (age: 5–10))

Variables	(1)	(2)	(3)	(4)	(5)
	Absolute	Control1	Control2	Control3	All Controls
Log(Overall_07)	−0.5192*** (0.0420)	−0.8215*** (0.0435)	−0.5171*** (0.0423)	−0.7103*** (0.0446)	−0.8952*** (0.0414)
Literacy rate		0.0101*** (0.0007)			0.0089*** (0.0009)
Infrastructure Index			0.0146* (0.0077)		−0.0149 (0.0094)
Pupil-teacher ratio				−0.0052*** (0.0006)	−0.0025*** (0.0006)
Teacher gender ratio				0.0547*** (0.0069)	0.0009 (0.0072)
Teachers trained				0.1069*** (0.0283)	0.1211*** (0.0265)
Teacher Qualification				0.0558 (0.0421)	0.0342 (0.0478)
Grants					0.0020 (0.0107)
NTL Luminosity					0.0115*** (0.0031)
Sex ratio					0.1190 (0.1506)
Percentage of urban population					−0.0026*** (0.0007)
Constant	0.5846*** (0.0584)	0.3762*** (0.0466)	0.5812*** (0.0587)	0.9080*** (0.0759)	0.4561*** (0.1460)
Observations	548	543	547	547	536
R-squared	0.2376	0.4901	0.2418	0.4150	0.5867

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7 Conditional convergence (older children (age:11–16))

Variables	(1)	(2)	(3)	(4)	(5)
	Absolute	Control1	Control2	Control3	All Controls
Log (Overall_07)	−0.5958*** (0.0394)	−0.8330*** (0.0426)	−0.6106*** (0.0400)	−0.7473*** (0.0439)	−0.8833*** (0.0428)
Literacy rate		0.0039*** (0.0003)			0.0033*** (0.0004)
Infrastructure Index			0.0105** (0.0043)		0.0039 (0.0053)
Pupil-teacher ratio				−0.0016*** (0.0003)	−0.0006* (0.0003)
Teacher gender ratio				0.0271*** (0.0035)	0.0111*** (0.0041)
Teachers trained				0.0295** (0.0137)	0.0407*** (0.0140)
Teacher Qualification				0.0790*** (0.0209)	0.0753*** (0.0237)
Grants					−0.0040 (0.0054)
NTL Luminosity					0.0027* (0.0014)
Sex ratio					0.0418 (0.0743)
Percentage of urban population					−0.0011*** (0.0003)
Constant	1.0734*** (0.0756)	1.2844*** (0.0716)	1.1015*** (0.0767)	1.3445*** (0.0877)	1.3479*** (0.1077)
Observations	548	543	547	547	536
R-squared	0.3026	0.4693	0.3124	0.4361	0.5210

Robust standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

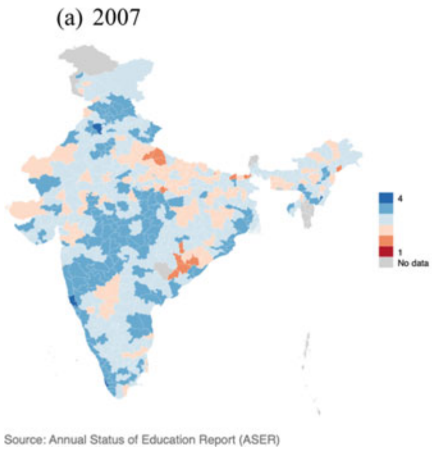

Fig. 5 District-wise reading performance, India

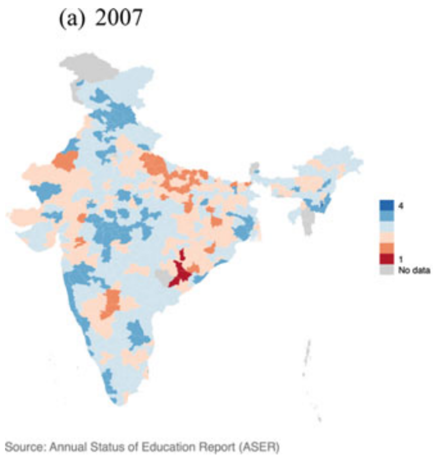

Fig. 6 District-wise arithmetic performance, India

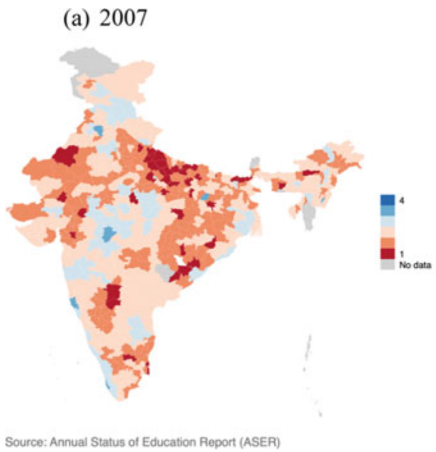

Fig. 7 District-wise average learning performance for younger children (age: 5–10), India

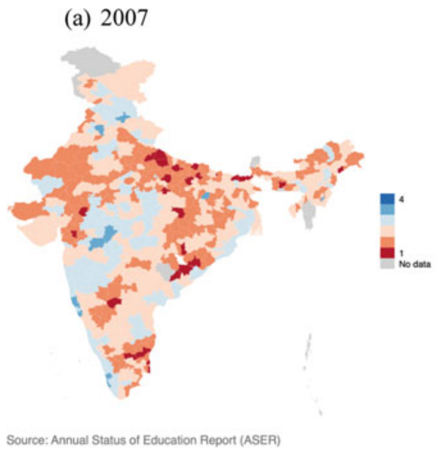

Fig. 8 District-wise reading performance for younger children (age: 5–10), India

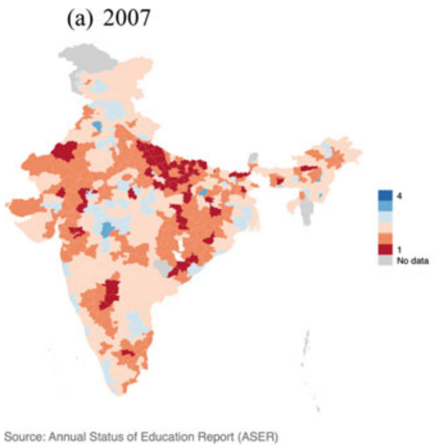

Fig. 9 District-wise arithmetic performance for younger children (age: 5–10), India

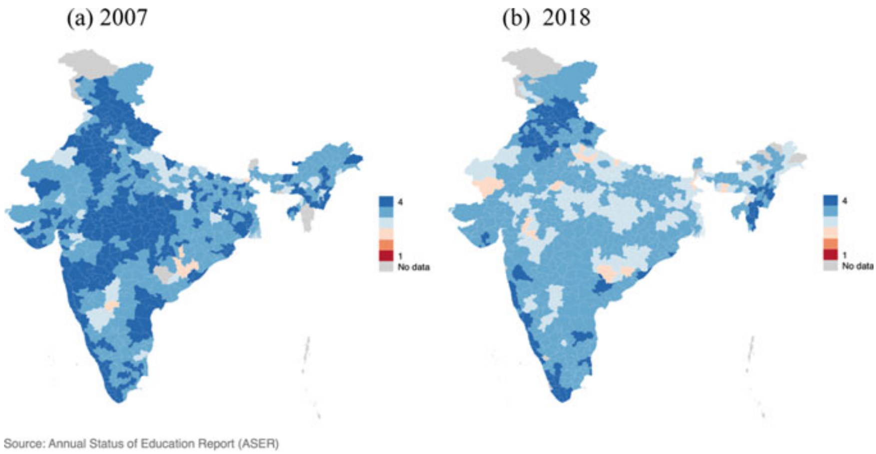

Fig. 10 District-wise average learning performance for older children (age: 11–16), India

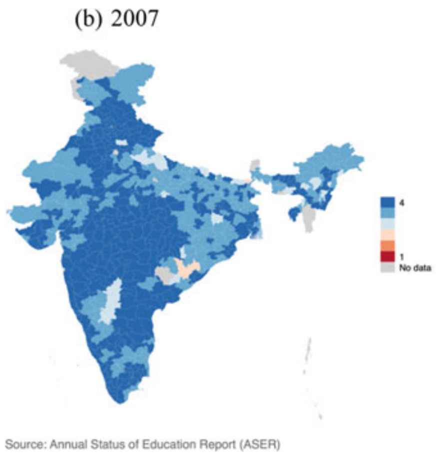

Fig. 11 District-wise reading performance for older children (age: 11–16), India

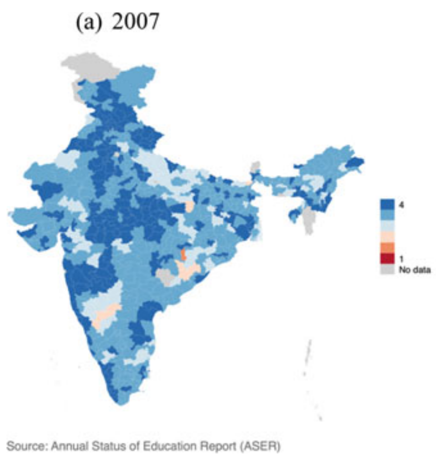

Fig. 12 District-wise arithmetic performance for older children (age: 11–16), India

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Gender Differential of Educational Outcomes in India: How Does Space Matter?

Antara Bhattacharyya and Sushil Kr. Haldar

1 Introduction

Inclusive growth with a special focus on gender issues has been considered an important national objective in India. Both males and females have equal potential to acquire educational endowment but due to unequal opportunity, there exists wide range of gender disparity in respect of educational outcomes. A woman has to face different sorts of unequal treatments from her childhood onwards. The declining child sex ratio is one of its examples; even there exists spatial neighbourhood impact of this declining child sex ratio. However, in this paper we have considered only the gender inequality in educational aspect. Accessibility to proper education for all helps to improve a nation and go ahead in right direction. However, India's economic growth has failed to narrow the gender gap. The existing literature shows India is lagging way behind in gross enrolment ratio than that of the world average (Rami, 2017). Lack of equality in education harms not only the present generation but it is also responsible for creating a depressing society for the future generation (Katiyar, 2016). The gender inequality in education results in more demand for equal opportunity program. Promoting female education may encourage more enrolment in education for women (Kapur, 2019). This inequality imposes a great challenge for the policy makers and the researchers to suggest or implement some policies relevant to tackle this diversified complex challenge to improve the women's position in educational attainment (Karak, 2016). Though, some of the affirmative actions have played a significant role to improve this scenario; the Mahila Samakhya Programme, Jan Shikshan Sansthans and Sarba Sikhsha Abiyan are among some of the examples (Pietkiewicz-Pareek, 2019). India has been experiencing a wide range of variations of gender inequality in education at the sub-national level (Pal, 2004). Gender differential in educational outcomes are more observed in northern states. In states like Uttar Pradesh, parental

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discriminatory attitude can be observed in case of girl child's education (Kingdon, 2002). Even educated parents and developed village infrastructure has a positive effect on lowering the gap between male and female in Bihar and Uttar Pradesh (Chaudhury & Roy, 2009). In case of Jammu and Kashmir, developmental programs towards achieving the women's role in equal education, have failed to achieve its desired goals. Even in Assam, mid-day meal scheme fails to address the problem of gender inequality (Nayak & Mahanta 2013). In Andhra Pradesh and Telengana, in some villages, discouragement towards girls' education causes negative impact on the educational attainment of women (Gouri, 2017). Family background plays a crucial role in determining the women's participation in education (Mishra & Mishra, 2015). Variation in socio-cultural and familial factors resulted in divergence between the male–female educational attainment rates (Batra & Reio, 2016). However, higher economic development results in lower gender differential and migration of wives to reside with the husband's family may have a negative impact on women's educational achievement (Rammohan & Vu, 2017). In case of middle class society, no evidence can be found on the matter of egalitarian educational attainment (Vaid, 2004). The most interesting factor to state is that India is now slowly moving towards gender equality in primary and upper primary educational enrolment ratio (Ghosh, 2018). However, backward and vulnerable part of the society is still facing an unequal access (Kundu, 2014; Sharma & Vats, 2019). Even for higher education, participation of women is still lagging behind that of male (Kesarwani, & Bala Komaraiah, 2019); inspite of the fact that the equality in higher education is considered to be a powerful tool for advancement of a society in the right direction (Chauhan, 2011). Most of the women, who pursue education in abroad, have mothers who are either university-literate or are involved in jobs other than regular household chores (Sondhi, 2016). Support by the spouse and in-laws, awareness related to changing gender role and gender stereotypical thinking, parental encouragement towards a girl child can make huge difference in higher education attainment (Hassan et al., 2020, Dandapat & Sengupta 2013). Proper implementation of policies and its improved qualities have a positive impact on narrowing the gender gap in elementary schooling (Velaskar, 2010). Even, in rural India the gender gap between male and female is getting reduced for gross enrolment ratio and elementary schooling (Virendra et al. 2013). This is mainly due to the fact that in rural India, males go outside to find a job after the completion of mainly upper primary education. Even, after successful completion of education women lag behind of their male counterparts in terms of economic opportunities (Bhattacharyya & Haldar, 2020a, 2020b).

The earlier literature clearly suggests that numerous factors are responsible in explaining the variations of gender differential in educational outcomes. However, the previous studies could not capture the role of space and its neighbourhood impacts (through Moran's Index). How does space and neighbour's effect on gender differential of literacy rate and enrolment rate matter? Our study tries to answer this question and we assume that this makes our paper distinct from earlier studies. Moreover, the role of income, urbanization and social expenditure in explaining the variations in net enrolment ratio as well as literacy rate have not been discussed systematically in earlier studies. Giving spatial weights to the explanatory variables and considering its impact on the variation of the inequality indices of education has not been studied; this broadens the scope of the present study. Our present study considers the public schools only; however, the importance of private schools are not been considered here because of lack of data. However, it may be true that there is a shift in the preference from public to private schools due to improved infrastructural facilities.

2 Objective, Data and Methods

The first objective of our paper is to estimate the gender disparity in literacy and enrolment rate using coefficient of inequality and Sopher's Disparity Index. The second objective is to study the effect of space on gender disparity in literacy and enrolment. The third objective is to find out the socio-economic factors (along with space) determining such differential educational outcomes in a spatial panel data regression framework.

The data regarding urbanization (URB), per capita social expenditure (PCSE), female workforce participation rate (FWFPR) and male and female literacy rate have been collected from Census 2001 and 2011 and yearly PCNSDP has been drawn from RBI. Data regarding Net Enrolment ratio has been collected and calculated from the data source of National Institute of Educational Planning and Administration, New Delhi, Here we have considered four-time points (viz. 2000, 2005, 2010 and 2015). The Census data are adjusted accordingly using appropriate interpolation and extrapolation techniques. Here, 24 states in India have been considered. The states are Andhra Pradesh, Arunachal Pradesh, Assam, Bihar, Goa, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Manipur, Meghalaya, Mizoram, Nagaland, Orissa, Punjab, Rajasthan, Sikkim, Tamil Nadu, Tripura, Uttar Pradesh and West Bengal.

The popular measure of disparity between male and female in educational achievement is coefficient of inequality (CI) as shown in Eq. (1).

$$CI = \frac{X_m - X_f}{X_f} \tag{1}$$

where, X_m and X_f are the male and female achievements in education respectively. However, the Sopher's Disparity Index (1974) is a well-accepted measurement technique for identification the disparity between male and female in educational attainment (say, literacy rate) but the index fails to satisfy the additive monotonicity axiom as pointed out by Kundu and Rao (1986); they have proposed the following modified formula for measuring disparity in educational outcomes:

$$DI = \ln\left(\frac{X_m}{X_f}\right) + \ln\left(\frac{\theta - X_f}{\theta - X_m}\right) \tag{2}$$

where, X_m and X_f are the male and female achievements in education, respectively, as mentioned earlier, and $\theta = Max\{X_m + X_f\}$.

A panel data regression model has been considered for finding out the determinants or explanatory factors that can play a role to explain the variation in the dependent variable and that the equation of the model has been written as followed:

$$Y_{it} = \beta' X_{it} + \eta_i + \mu_t + \varepsilon_{it}. \tag{3}$$

X_{it} = vector of the explanatory variables, η_i = captures the space effect, μ_t = captures the time effect and ε_{it} stands for white noise term. Here, i = 1, 2, 3,… 24 and t = 1, 2, 3 and 4. As different explanatory variables have been considered here we have run a VIF test and to avoid the muliticolinearity problem we have formulated separate models. Here fixed effect has been supported by the Hausman test. Therefore, space and time may have an effect on the dependent variable. To capture the space-related impact we have considered the Spatial Lag and Spatial Error models. **Moran Index** has been used to capture the neighbourhood impact between states in case of gender disparity in educational outcomes. This index basically captures the spatial auto-correlation. We define Moran Index Anselin (1988, 1995) and Hongfei et al. (2007)] as:

$$MI = \frac{N}{W} . \frac{\sum_i \sum_j w_{ij}\left(X_i - \overline{X}\right)\left(X_j - \overline{X}\right)}{\sum_i \left(X_i - \overline{X}\right)^2} \tag{4}$$

where N is the number of state indexed by i and j. These are the spatial units. Sum of the spatial weights are represented by $W = \sum_i \sum_j w_{ij}$. Here a matrix (w_{ij}) of spatial weights has been set up with zero on the diagonal ($w_{ii} = w_{jj} = 0$) and the variable of interest is X. The mean ($\overline{X}$) is also been calculated. There are several ways by which spatial weights matrix can be defined. However, for our study, it is relevant to use Rook's contiguity matrix (Anselin, 1988). In this matrix formulation, we construct a binary matrix ($w_{ij} = 1$ if both the states share the border or zero otherwise). This matrix is formulated by keeping in mind the geographical proximity. We had to make this matrix row standardise. We transform Eq. (4) to Z which is normalised value for statistical significance testing (Anselin, 1988).

$$Z_{MI} = \frac{MI - E[MI]}{\sqrt{V(MI)}} \tag{5}$$

where, $E[MI] = -\frac{1}{N-1}$ and

$$V(MI) = \frac{NS_4 - S_3 S_5}{(N-1)(N-2)(N-3).W^2} - (E[MI])^2$$

where, $S_1 = \frac{1}{2}\sum_i\sum_j\left(w_{ij}+w_{ji}\right)^2$, $S_2 = \sum_i\left(\sum_j w_{ij}+\sum_j w_{ji}\right)^2$, $S_3 = \frac{N^{-1}\sum_i (X_i-\overline{X})^4}{\left[N^{-1}\sum_i\left(X_i-\overline{X}\right)^2\right]^2}$, $S_4 = \left(N^2-3N+3\right)S_1 - NS_2 + 3W^2$,

$S_5 = \left(N^2-N)\right)S_1 - 2NS_2 + 6W^2$.

To measure the spatial autocorrelation we have formulated a null hypothesis (no spatial autocorrelation). We have mentioned Z scores along with its ‘p’ value for Moran Index. This ‘p’ value gives us the level of statistical significance which ultimately helps us to conclude whether there exists spatial autocorrelation or not. High and positive value of Z score indicates clustering of High-High or Low-Low value state. That means similar value states are clustering together. This is clubbed or clustered geographically (Anselin, 1995). On the contrary, negative significant values indicate a possibility of outlier. That means on the basis of the variable of interest, both the neighbour sharing states is dispersed spatially. Equation 4 is meant for measuring the Global Moran Index. Global Moran Index is mainly used for detecting the spatial autocorrelation on an aggregate level. However, it fails to identify the spatial autocorrelation on a disaggregate level. For that, we need to construct Local Moran Index.

Local Moran Index can find out individually which states are having positive or negative spatial autocorrelation with its neighbouring states (Anselin, 1995).

Analysis of local Moran’s I is very similar to that of global Moran’s I, as shown in Eq. (6).

$$MI_i^L = \frac{X_i-\overline{X}}{S_i^2}\sum_{j=1,i\neq j} w_{ij}\left(X_j-\overline{X}\right) \tag{6}$$

where, $S_i^2 = \frac{\sum_{j=1,\, i\neq j}^{N} w_{ij}}{N-1} - \overline{X}^2$.

For a randomization hypothesis, the expected value is:

$$E(I_i) = -\frac{\sum_{j=1,i\neq j}^{N} w_{ij}}{N-1}$$

and the variance of MI_i^L is given as:

$$Var(MI_i^L) = \frac{(N-B_2)\sum_{j=1,i\neq j}^{N} w_{ij}^2}{N-1} - \frac{(2B_2-N)\sum_{k=1,k\neq i}^{N}\sum_{k=1,k\neq i}^{N} w_{ik}w_{ik}}{(N-1)(N-2)} - \left[E(MI_i^L)\right]^2$$

where, B_2 is defined as: $B_2 = \frac{N \sum_{i=1, i \neq j}^{N} (X_i - \overline{X})^4}{\left[\sum_{i=1, i \neq j}^{N} (X_i - \overline{X})^2 \right]^2}$

This Moran Index only indicated the spatial autocorrelation between the states on the basis of some variable of interest. However, to explain the spatial variation of a particular variable by its explanatory variable two basic regression model has been used for our study. These are spatial Lag and Spatial Error model. Spatial or geographical impact has to be incorporated if there exist a spatial influence.

We assume that any dependent variables in the i-th state at time t, namely y_{it} for linear spatial lag model (SLPM):

$$y_{it} = \rho \sum_{j=1}^{N} W_{ij} y_{jt} + X_{it}\beta + +\mu_i + \varepsilon_{it}$$
$$where\ i = 1, 2, \ldots N; i = 1, 2, \ldots N; t = 1, 2, \ldots T; \tag{7}$$

where ρ is the spatial autoregressive parameter, β is the (*K* × *1*) parameters, X_{it} stands for (*1* × *K*) vector of explanatory variables. Here μ_i becomes random (Anselin & Bera, 1998; Baltagi & Griffin, 1997), with zero mean and constant variance, $IID(0, \sigma^2)$; ε_{it} is white noise, $IID(0, \sigma^2)$; *W* is the spatial standardized weight matrix of order (*N x N*) defined earlier. The endogenous interaction effects of the dependent variable, y_{it} is, $\sum_{j=1}^{N} W_{ij} y_{jt}$. Interaction effects among the error terms have been considered in SEPM (Spatial Error panel Model) model. The SEPM model is presented below:

$$y_{it} = X_{it}\beta + +\mu_i + \phi_{it}\ where \phi_{it} = \lambda \sum_{j=1}^{N} W_{ij}\phi_{jt} + \varepsilon_{it} \tag{8}$$

where, ϕ_{it} is spatially auto-correlated error term, λ is the spatial autocorrelation coefficient of the error term (Bhattacharyya & Haldar, 2020a, 2020b, Hembram et. al, 2020, Bhattacharyya et al, 2021).

3 Empirical Analysis

3.1 Descriptive Statistics

In the following Table 1, summary statistics of all variables have been given. It can be seen that mean of URB is 28.14 (%), PCNSDP is Rs. 35992.32, FWFPR is 45.74(%) and PCSE is Rs. 5632.97. Wide differences between maximum and minimum value and high standard deviation (especially in PCNSDP) confirm that there exists a variation of these variables across the states. Here, an interesting phenomenon is observed. Average value of net enrolment ratio is higher in case of female than male. However, in case of literacy rate, we find an exact opposite scenario; however, the mean value of literacy shows that male are 15% more literate than that of female. India still fails to narrow this significant gap. However, relatively higher standard deviation and differences in maximum and minimum value support the existence of variability across states.

Here we have tried to capture the scenario of disparity between male and female in the net enrolment ratio and literacy rate across 24 states for four-time points viz. 2000, 2005, 2010 and 2015. As discussed earlier, here, we have considered two measurements of disparity that is coefficient of inequality and Sopher's Disparity Index. We define, CIE = Coefficient of inequality of Enrolment; DSE = Sopher's

Table 1 Descriptive statistics

Variable (Notation)	Obs	Mean	Std. Dev	Min	Max
Urbanization (URB)	96	29.14831	12.8582	9.678495	66.40166
Per Capita Net State Domestic Product (PCNSDP)	96	35,992.32	20,300.67	11,006.94	130,181.6
Female Work Force Participation Rate (FWFPR)	96	45.74336	13.7064	21.95462	71.414
Per Capita Social Expenditure (PCSE)	96	5632.971	5331.08	729.8527	24,956.85
Net Enrolment for upper primary level (Female)	96	39.58672	24.62221	16.21936	93.6
Net Enrolment for upper primary level (Male)	96	37.51291	23.13096	13.18	91.5
Female Literacy Rate (FLR)	96	67.92	12.7	33.12	94.11
Male Literacy Rate (MLR)	96	82.43	8.02	59.68	97.76

Source Author's estimation

Disparity Index of Enrolment; CIL = Coefficient of inequality of Literacy Rate, DSL = Sopher's Disparity Index of Literacy Rate; T1 = 2000; T2 = 2005; T3 = 2010 and T4 = 2015.

In case of net enrolment ratio, the disparity between male and female is found to be negative; this means female is better off compared to male. This contrasting feature is found in almost all the states except Rajasthan, Orissa and Bihar as shown in Table 2. However, gender disparity in literacy rate does prevail in all the states; it is noticed that the disparity is found to be declining over time in respect of literacy rate as shown in Table 3.

The disparity between male and female in respect of enrolment and literacy is found to be counterintuitive. We find more female enrolment compared to male in same−age cohort! Why is it happening? One possible explanation would be the prevalence of child labor in poor economies. Male child is more mobile than female

Table 2 Trends of CIE and DSE of 24 states for 4 time points

State	CIE(T)	CIE(T2)	CIE(T3)	CIE(TIE4)	DSE(T1)	DSE(T2)	DSE(T3)	DSE(T4)
An. Pradesh	−0.088	−0.051	−0.047	−0.06	−0.044	−0.026	−0.026	−0.041
Arunachal	−0.160	−0.128	0.0298	−0.107	−0.083	−0.065	0.014	−0.081
Assam	−0.118	−0.11	−0.11	−0.107	−0.061	−0.05	−0.06	−0.081
Bihar & Rg	−0.132	−0.077	0.1159	0.0184	−0.067	−0.038	0.0528	0.014
Goa	−0.013	−0.012	−0.09	−0.055	−0.006	−0.006	−0.052	−0.043
Gujrat	0.0117	0.0154	0.1613	−0.029	0.0057	0.0076	0.0762	−0.020
Harayna	−0.010	−0.002	−0.023	−0.109	−0.005	−0.001	−0.012	−0.077
Himachal	0.0125	0.0133	−0.033	−0.020	0.0062	0.0067	−0.018	−0.015
Karnataka	−0.046	−0.04	−0.037	−0.024	−0.023	−0.024	−0.019	−0.017
Kerala	−0.03	−0.039	−0.109	−0.017	−0.016	−0.020	−0.062	−0.012
M.P. & Rg	0.0279	−0.001	0.035	−0.08	0.013	−0.0001	0.0167	−0.057
Maharashtra	0.027	0.017	−0.043	−0.050	0.013	0.0087	−0.022	−0.037
Manipur	−0.015	−0.022	−0.003	−0.022	−0.007	−0.011	−0.001	−0.018
Meghalaya	−0.275	−0.221	−0.187	−0.083	−0.155	−0.122	−0.097	−0.059
Mizoram	−0.07	−0.06	−0.150	−0.022	−0.038	−0.035	−0.083	−0.018
Nagaland	−0.184	−0.132	−0.089	−0.074	−0.099	−0.070	−0.045	−0.056
Orissa	0.012	−0.0008	0.004	0.0108	0.0059	−0.0004	0.0022	0.0073
Punjab	−0.127	−0.103	−0.138	−0.075	−0.067	−0.054	−0.073	−0.061
Rajasthan	0.1103	0.097	0.2572	0.0122	0.050	0.0456	0.113	0.007
Sikkim	−0.084	−0.064	−0.150	−0.099	−0.043	−0.033	−0.077	−0.077
Tamilnadu	−0.007	−0.018	-0.055	−0.030	−0.003	−0.009	−0.033	−0.022
Tripura	−0.03	−0.032	−0.035	−0.107	−0.019	−0.016	−0.017	−0.081
U.P. & Rg	−0.025	−0.010	0.0293	−0.179	−0.012	−0.004	0.014	−0.123
WB	−0.057	−0.063	−0.099	−0.122	−0.029	−0.032	−0.052	−0.095

Source Author's Estimation. CIE = Coefficient of inequality of Enrolment, DSE = Sopher's Disparity Index of Enrolment; T1 = 2000, T2 = 2005; T3 = 2010; T4 = 2015

Table 3 Trends of CIL and DSL of 24 states for 4 time points

State	CIL(T1)	CIL(T2)	CIL(T3)	CIL(T4)	DSL(T1)	DSL(T2)	DSL(T3)	DSL(T4)
Andhra Pradesh	0.394408	0.324135	0.264814	0.214069	0.206361	0.179037	0.154001	0.130801
Arunachal	0.466345	0.333851	0.237032	0.16319	0.226586	0.178621	0.138403	0.103424
Assam	0.305255	0.231457	0.171547	0.121943	0.168584	0.136868	0.108262	0.081957
Bihar & Rg	0.801932	0.539271	0.376149	0.264996	0.331023	0.257225	0.202539	0.159135
Goa	0.173146	0.152789	0.134042	0.116721	0.117388	0.106993	0.096945	0.08719
Gujrat	0.378201	0.298553	0.233456	0.179256	0.211802	0.179637	0.150461	0.123511
Harayna	0.357958	0.289349	0.233281	0.186605	0.201174	0.174357	0.150366	0.128493
Himachal	0.265945	0.223302	0.18577	0.152482	0.165519	0.145841	0.127212	0.109423
Karnataka	0.33814	0.2716	0.216058	0.168994	0.189161	0.161576	0.136358	0.112962
Kerala	0.074327	0.058765	0.043923	0.029752	0.057118	0.046133	0.035223	0.024371
M.P. & Rg	0.512428	0.419545	0.341719	0.275564	0.261714	0.227744	0.196469	0.167349
Maharashtra	0.28256	0.233527	0.189984	0.151057	0.174812	0.151254	0.128678	0.106896
Manipur	0.323461	0.246191	0.182688	0.129575	0.186686	0.152561	0.121195	0.091848
Meghalaya	0.097635	0.069046	0.045947	0.026897	0.058846	0.044264	0.031334	0.019529
Mizoram	0.045764	0.047062	0.048322	0.049545	0.034931	0.036361	0.037798	0.039244
Nagaland	0.157826	0.117988	0.086061	0.059902	0.095168	0.07635	0.059744	0.044648
Orissa	0.491784	0.373292	0.280298	0.205373	0.252626	0.208542	0.169292	0.13356
Punjab	0.187342	0.1634	0.142136	0.123125	0.114044	0.103342	0.09337	0.084003
Rajasthan	0.72634	0.618589	0.528864	0.452992	0.336197	0.304265	0.275358	0.248901
Sikkim	0.25894	0.193671	0.142091	0.100302	0.151609	0.122978	0.097651	0.074572
Tamilnadu	0.279218	0.223733	0.175332	0.132739	0.168775	0.142328	0.117205	0.093135

(continued)

Table 3 (continued)

State	CIL(T1)	CIL(T2)	CIL(T3)	CIL(T4)	DSL(T1)	DSL(T2)	DSL(T3)	DSL(T4)
Tripura	0.24819	0.169796	0.108599	0.059499	0.15143	0.113764	0.079704	0.047816
U.P. & Rg	0.630033	0.459007	0.337158	0.245943	0.292381	0.237734	0.192677	0.154025
West Bengal	0.292065	0.221152	0.161748	0.111263	0.168786	0.136121	0.105754	0.077127

Source Author’s Estimation. Notes: CIL = Coefficient of inequality of Literacy Rate, DSL = Sopher’s Disparity Index of Literacy Rate; T1 = 2000, T2 = 2005; T3 = 2010; T4 = 2015 and parents from subsistence family generally prefer to send their male child outside home for income-earning activities compared to female child. The nature of role of children in a poor family at their very early stage of life is different for male and female. Under patriarchal society, poor family generally prefers more number of children; female child usually looks after domestic chores whereas male child goes outside home for cash. Since, outside job opportunity of a female child is restricted compared to that of a male, the female children go to school, thus female enrolment outweighs male enrolment.

The literacy rate takes into account all the age cohorts. This makes a huge difference between male and female. Both the enrolment and literacy have the asymptotic upper bound (viz. 100 percent), therefore, we find a declining trend of disparity between male and female in respect of literacy rate.

3.2 Econometric Analysis

Before analysing the econometric results, we have estimated the coefficient of inequality between male and female in respect of literacy and upper primary net enrolment; the same is estimated using Sophers Disparity Index as shown in Tables 2 and 3. In the following Table 4, panel data regression has been performed for four dependent variables that are coefficient of inequality of Net Enrolment for upper primary level between male and female (CIE), coefficient of inequality of literacy rate between male and female (CIL), Sopher's Disparity Index of Net Enrolment for upper primary level between male and female (DSE) and Sopher's Disparity Index of literacy rate between male and female (DSL). In Appendix 1, we have tried to represent the graphical representation of gender inequality in net enrolment ratio and literacy. As discussed earlier, here two inequalities measurement have been considered. Here, we have four-time points (viz. 2000, 2005, 2010 and 2015) and for each time point, we estimate CIE, DSE, CIL and DSL.

Here four explanatory variables such as urbanizations (URB), per capita net state domestic product (PCNSDP), per capita social expenditure (PCSE) and female workforce participation rate (FWFPR) have been taken to capture the variation of the dependent variables. All the explanatory variables have been taken together in the models due to low multi-collinearity (VIF = 2.19). Eight models have been formulated and for each dependent variable; fixed effect and random effect models have been set up for finding out the cause variation: Is it purely due to random effect or is it due to space or time? Model 1 captures the fixed effect and model 2 captures the random effect for CIE. Similarly, model 5 and model 6 are meant for DSE. Low value of the Hausman test supports random effects over the fixed effect for both CIE and DSE. However, none of the explanatory variables stand significant to capture the variation of the CIE and DSE. On the contrast, higher values of Hausman test support fixed effect over random effect for both CIL and DSL (viz. model 3, model 4, model 7 and model 8).

Table 4 Econometric analysis: using panel data regression

Dep var	CIE		CIL		DSE		DSL	
Exp var	FE Mod 1	RE Mod 2	FE Mod 3	RE Mod 4	FE Mod 5	RE Mod 6	FE Mod 7	RE Mod 8
URB	0.004 (0.002)	0.001 (0.001)	0.006 (0.003)	−0.0006 (0.002)	0.002 (0.001)	0.0007 (0.0006)	0.002* (0.001)	−0.00006 (0.0008)
PCNSDP	−1.85e-06(0.1.12e-06)	−7.80e-07 (8.14e-07)	−4.17e-06 (1.40e-06)	−2.50e-06 (1.22e-06)	−9.80e-07 (6.10e-07)	−4.02e-07 (4.39e-07)	−1.71e-06***(5.18e-07)	−1.12e-06**(4.72e-07)
PCSE	1.54e-06 (2.63e-06)	−2.72e-07 (2.24e-06)	−3.73e-06 (3.30e-06)	−5.10e-06 (3.17e-06)	−2.39e-07(1.43e-06)	−1.22e-06(1.21e-06)	−1.95e-06 (1.22e-06)	−2.44e-06** (1.20e-06)
FWFPR	−0.002 (0.003)	0.0001 (0.0009)	−0.0134 (0.004)	−0.001 (0.0018)	−0.001 (0.001)	0.0002 (0.0005)	−0.004*** (0.001)	−0.001 (0.0007)
Constant	0.0006 (0.134)	−0.063 (0.055)	0.846 (0.169)	0.466*** (0.097)	0.001 (0.07)	−0.038 (0.029)	0.36*** (0.062)	0.24 (0.041)
N	96	96	96	96	96	96	96	96
R.Sq W	0.049	0.03	0.474	0.52	0.09	0.08	0.55	0.51
R.Sq B	0.003	0.027	0.001	0.18	0.008	0.06	0.004	0.14
R.sq	0.005	0.027	0.015	0.26	0.01	0.07	0.027	0.22
Hausman	2.75 (p = 0.43)		11.58 (p = 0.009)		2.42 (p = 0.49)		12.75***(p = 0.005)	

Source Author's estimation, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, standard error within the parenthesis

Table 5 Global Moran's Index (CIL)

Variables	GMI	Z-value	P-value
CIL 2000	0.21***	2.67	0.004
CIL 2005	0.26***	3.135	0.001
CIL 2010	0.31***	3.697	0.000
CIL 2015	0.354***	4.315	0.000

Source Author's estimation, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Global and Local Moran's Index for CIL: Basically Global Moran Index (GMI) has been formulated to capture the spatial autocorrelation impact on an aggregate level. In this case, it helps to understand whether there exists a neighbourhood effect between different states or not. It can be clearly observed from the following Table 5 that in case of CIL there exists a significant level of spatial autocorrelation between the different states for all time points. However, this fails to identify the states having spatial neighbourhood impact on or between each other. Therefore, a construction of Local Moran Index (LMI) is required to be formulated. In Table 6, the states are getting impacted or having an impact on other states can be clearly identified. For example, the states like Arunachal Pradesh (for first time point), Madhya Pradesh, Meghalaya (for last two time points), Mizoram, Nagaland, Orissa (for first two time points), Rajasthan, Sikkim (for last time point), Tripura (for last time point) and Uttar Pradesh are getting impacted by their neighbouring states. Negative sign of this index shows the outlier effect, that means this particular state is behaving in a opposite direction than its neighbouring states; whereas positive sign shows that the state is moving in the same direction as its neighbouring states or it can be said that high-high and low-low CIL states are clustering together. Therefore other than Arunachal Pradesh, all other states that are discussed above are influenced by their neighbouring states in a same direction. Here, it can be observed that northern states and northeastern states are influenced by their neighbouring states.

Global and Local Moran's Index for DSL: In Tables 7 and 8, applying altogether a different method of capturing an inequality in literacy that is DSL method gives the same significant result like CIL in case of global as well as for Local Moran Index. However, these two indices only capture the neighbourhood impact on each other. The explanatory factors contributing towards variations in CIL and DSL cannot be captured by these GMI or LMI. This is why we have developed spatial lag as well as spatial error models. Therefore, in Table 1.9 SAR and SLM model have been formulated and results are been reported in the next section. Here in appendix 2, we have tried to capture the clustering pattern of different states in and around its neighbor. Here we have only considered the gender inequality measurement (Coefficient of inequality and Sopher's Disparity Index) for literacy. In the first period, Sopher's Dispaity of literacy (DSL1), 11 states are having high-high (7 states) and low-low (4 states) association. Similarly, for DSL2, DSL3 and DSL4 number states are in negative-negative quadrant is 8 states, 8 states and 8 states, respectively. In case of DSL2, DSL3 and DSL4 6 states, 6 states and 5 states are in positive quadrant. In case coefficient of inequality in literacy CIL for four time periods, CIL1, CIL2, CIL3 and

Table 6 Local Moran's Index (CIL)

State	LMI2000(Z)	LMI2005(Z)	LMI2010(Z)	LMI2015(Z)
AP	−0.87 (−0.33)	−1.15 (−0.48)	−1.26 (−0.54)	−1.23 (−0.54)
Arunachal	−3.36* (−1.39)	−2.74(−1.11)	−1.74 (−0.66)	−0.51 (−0.1)
Assam	0.72 (0.47)	1.05 (1.05)	1.52 (0.83)	2.12 (1.11)
Bihar	2.25 (1.16)	1.03 (0.61)	−0.02 (0.12)	−0.79 (−0.23)
Goa	1.46 (0.86)	1.07 (0.66)	0.68 (0.47)	0.35 (0.308)
Gujarat	0.38 (0.36)	0.6 (0.52)	0.77 (0.66)	0.84 (0.74)
Haryana	0.37 (0.3)	0.8 (0.52)	1.27 (0.78)	1.77 (1.06)
Himachal	−1.1 (−0.52)	−0.93 (−0.42)	−0.58(−0.23)	−0.11 (0.03)
Karnataka	−0.01 (0.1)	−0.15 (0.03)	−0.21 (−0.001)	−0.21 (0.001)
Kerala	1.2 (0.77)	0.75 (0.52)	0.26 (0.25)	−0.18 (−0.004)
MP	6.26***(3.14)	7.47*** (3.72)	8.11***(4.09)	8.22*** (4.24)
Maharashtra	-0.17 (0.02)	−0.22 (−0.003)	−0.18 (0.019)	−0.08 (0.07)
Manipur	0.31 (0.29)	0.54 (0.39)	1 (0.6)	1.65 (0.9)
Meghalaya	0.9 (0.55)	2.45 (1.21)	3.9** (1.8)	5.09***(2.39)
Mizoram	4.48** (2.12)	5.49*** (2.56)	6.02*** (2.83)	5.85*** (2.8)
Nagaland	3.1* (1.55)	3.89** (1.92)	4.52** (2.23)	4.89*** (2.45)
Orissa	2.59**(1.72)	2.21* (1.48)	1.68 (1.17)	1.112 (0.82)
Punjab	−1.43 (−0.82)	−1.7 (−1)	−1.65 (−0.98)	−1.2 (−0.73)
Rajasthan	3.39** (1.76)	5.07*** (2.57)	6.71*** (3.4)	8.2*** (4.22)
Sikkim	0.64 (0.44)	1.29 (0.71)	1.98 (1.02)	2.65* (1.32)
TN	0.6 (0.43)	0.45 (0.35)	0.33 (0.29)	0.24 (0.24)
Tripura	0.71 (0.47)	1.63 (0.86)	2.82 (1.38)	4.16** (1.98)
UP	8.08*** (4.27)	7.74*** (4.09)	7.02*** (3.78)	5.99***(3.33)
WB	0.15 (0.22)	0.45 (0.35)	0.87 (0.54)	1.46 (0.82)

Source Author's estimation, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$, Values in parentheses represent Z values. Here distance matrix has been considered for spatial weight matrix

CIL4 in negative-negative quadrant there are 6 states, 7 states, 9 states and 9 states respectively are there. In positive-positive quadrant 6 states, 6 states, 8 states and 8 states respectively are there.

Table 7 Global Moran's Index (DSL)

Variables	GMI	Z-value	P-value
DSL 2000	0.24***	2.89	0.002
DSL 2005	0.29***	3.43	0.000
DSL 2010	0.35***	4.07	0.000
DSL 2015	0.4***	4.74	0.000

Source Author's estimation, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 8 Local Moran's Index (DSL)

State	LMI2000(Z)	LMI2005(Z)	LMI2010(Z)	LMI2015(Z)
AP	−0.84 (−0.31)	−0.96 (−0.38)	−1(−0.4)	−0.97 (−0.39)
Arunachal	−3.18* (−1.30)	−2.41 (−0.96)	−1.4 (−0.5)	−0.19 (0.04)
Assam	0.7 (0.45)	1.14 (0.65)	1.75 (0.92)	2.49 (1.26)
Bihar	1.91 (1)	0.85 (0.52)	−0.09 (0.09)	−0.88 (−0.26)
Goa	1.08 (0.66)	0.76 (0.5)	0.48 (0.36)	0.23 (0.23)
Gujarat	0.79 (0.66)	1.02 (0.84)	1.21 (0.99)	1.3 (1.08)
Haryana	0.94 (0.59)	1.44 (0.84)	2.03 (1.16)	2.69* (1.52)
Himachal	−0.54 (−0.2)	−0.26 (−0.04)	0.12 (0.17)	0.62 (0.45)
Karnataka	−0.26 (−0.02)	−0.32 (−0.05)	−0.32 (−0.05)	−0.29 (−0.04)
Kerala	0.79 (0.53)	0.34 (0.28)	−0.09 (0.04)	−0.51 (−0.19)
MP	6.86*** (3.4)	7.67*** (3.8)	8.18*** (4.07)	8.31*** (4.19)
Maharashtra	−0.07 (0.07)	0.006 (0.11)	0.11 (0.17)	0.22 (0.23)
Manipur	−0.41 (−0.03)	−0.13 (0.09)	0.43 (0.34)	1.29 (0.73)
Meghalaya	2.13 (1.07)	3.7** (1.7)	5.17*** (2.38)	6.42*** (2.93)
Mizoram	5.61*** (2.6)	6.6***1(3.04)	7.11***(3.28)	6.79*** (3.17w)
Nagaland	3.97** (1.94)	4.74** (2.29)	5.37*** (2.6)	5.77*** (2.81)
Orissa	2.65** (1.74)	2.26* (1.5)	1.77 (1.21)	1.23 (0.88)
Punjab	−1.78 (−1.03)	−1.91 (−1.12)	−1.76 (−1.04)	−1.28 (−0.74)
Rajasthan	4.29**(2.17)	5.83** (2.91)	7.46*** (3.73)	9.09*** (4.57)
Sikkim	0.94 (0.56)	1.48 (0.8)	2.09 (1)	2.72* (1.34)
TN	0.28 (0.25)	0.22 (0.22)	0.19 (0.2)	0.17 (0.2)
Tripura	0.94 (0.56)	1.89 (0.97)	3.19* (1.53)	4.82** (2.24)
UP	7.35*** (3.85)	7.19*** (3.79)	6.86*** (3.65)	6.29*** (3.4)
WB	0.19 (0.23)	0.47 (0.35)	0.94 (0.56)	1.63 (0.88)

Source Author's estimation, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$, Values in parentheses represent Z values. Here distance matrix has been considered for spatial weight matrix

Spatial Regression: In this section, there is an attempt towards capturing spatial causal effects of different socio-economic variables on CIL and DSL as given in Table 9. These models specially signify for finding out the spatial impact of not only its direct neighbour but also its neighbour's neighbour. Suppose, in case of measuring the variation in CIL and whether it is space-dependent or not, we have given a spatial weight to its explanatory variables. In case of Spatial Lag Model, CIL depends on its lag value and the lag value of its explanatory variables. Therefore, here the lags that we have incorporated are space that is the states and variation of CIL may not only depend on its exact neighbouring state but also the states that are the neighbours of its neighbour state. Surprisingly, for both CIL and DSL, the significance and directional impact of different explanatory variables' effects are more or less same. Here, it can be observed that urbanization significantly reduces the inequality in literacy and even

Table 9 Spatial Error (SER) and Spatial Lag (SLM) Model

Dependent variable	CIL		DSL	
Explanatory variable	Model 9(SEM)	Model 10(SLM)	Model 11(SEM)	Model 12(SLM)
URB	−0.003*** (0.001)	−0.003*** (0.001)	−0.0015*** (0.0005)	−0.0015** 0.0006)
PCNSDP	−1.80e-06 (1.10e-06)	−1.21e-06 (1.13e-06)	−5.02e-07(4.91e-07)	−3.09e-075.05e-07)
FWFPR	0.00004 (0.001)	0.0004 (0.001)	0.00015(0.0004)	0.00035(0.0005)
PCSE	−7.67e-06*** (3.59e-06)	−9.25e-06*** (3.78e-06)	−4.35e-06*** (1.60e-06)	−4.80e-06*** 1.68e-06)
Cons	0.621*** (0.073)	0.542*** (0.089)	0.3083*** (0.032)	0.287*** (0.039)
Lambda	−0.065*** (0.016)	–	−0.062*** (0.014)	
Sigma	0.12	0.12	0.82	0.05
Rho	–	−0.078*** (0.027)		−0.076*** (0.0279)
N	96	96	96	96

Source Author's estimation, * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$, standard error within the parenthesis

per capita social expenditure also helps to reduce the inequality. However, the per capita net state domestic product and female work-force participation rate seems to be insignificant in capturing the variations of both CIL and DSL.

4 Conclusion and Policy Implication

Gender disparity in net enrolment ratio is not space dependent. In case of Moran Index, it can be observed that northern states and northeastern states are influenced by their neighbouring states both for Coefficient of Inequality as well as for Sopher's Disparity index (of literacy rate). In case of disparity in literacy rate, urbanization and per capita social expenditure are found to be significant and there exists a direct as well as indirect impact of space. In case of total literacy still females are lagging behind male though over time disparity is found to be diminishing. Direct as well as indirect effect of space does matter here in case of urbanization and per capita social sector spending. This paper has successfully identified the way to reduce the gender disparity in literacy and it is space dependent. Therefore, government has to take initiatives to increase investment in social expenditure. Keeping in mind the space dependency of literacy rate, state-specific allocation of development grant may reduce gender disparity.

In India, equal achievement in literacy rate of male and female is still not witnessed (Kapur, 2019), whereas in case of enrolment ratio the gap over the year is being narrowed down (Virendra et al., 2013; Ghosh, 2018). It needs to be mentioned here that after 1991, more privileged section of our society prefers to move their children (irrespective of the sex of their children) to the private schools for improved infrastructure and functional quality. This results in more deterioration of the public school quality and this has a negative impact on girl child's education especially for the poor section of the society (Ramachandran, 2008). It is observed that sending younger girl child in rural private school is less likely compared to their male counterparts (Maitra et al., 2011). Therefore, more affirmative actions towards the improvement of gender equality is required to improve the position of female not only in upper primary level education but also in overall literacy.

Appendix 1: Graphical Representation of CIE, DSE, CIL and DSL (Mean Inequality of All States Has Been Considered as Overall Average)

See Figs. 1, 2, 3, and 4.

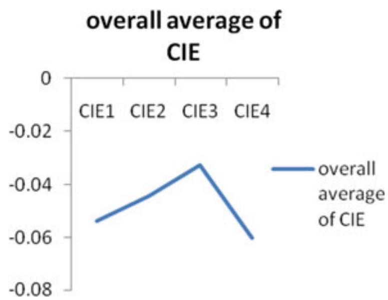


Fig. 1 Overall average of CIE

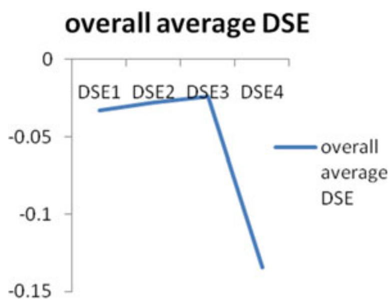


Fig. 2 Overall average of DSE

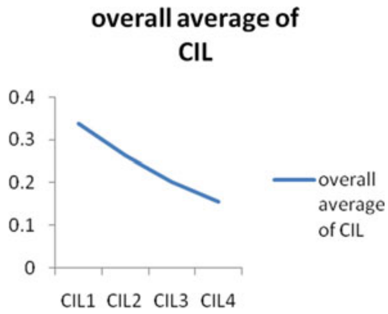


Fig. 3 Overall average of CIL

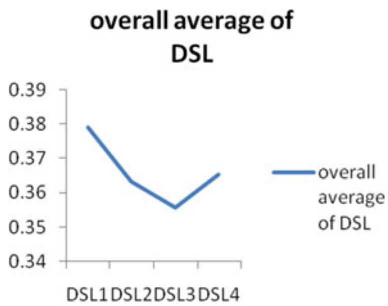


Fig. 4 Overall average of DSL

Appendix 2: Graphical Representation of LMI of DSL and CIL Over Four Time Points (2000, 2005, 2010, 2015)

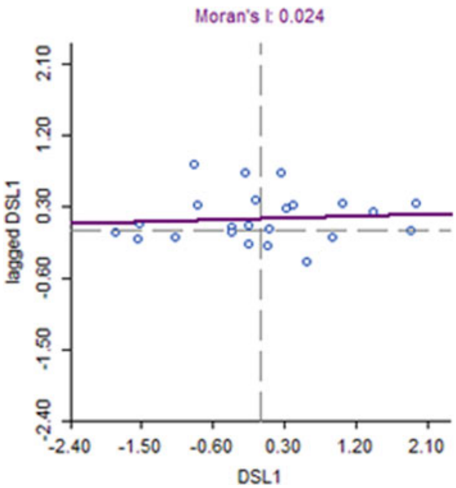


Fig. 5 LMI of DSL (2000)

Fig. 6 LMI of DSL (2005)

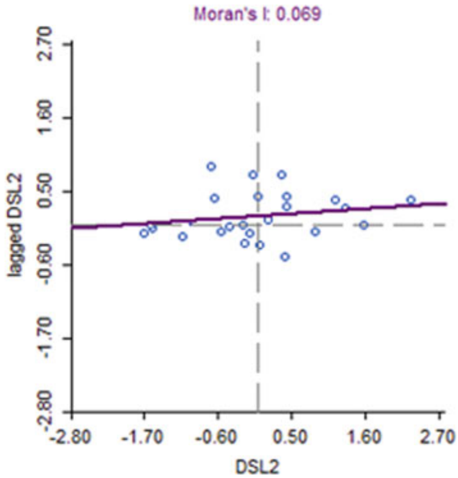


Fig. 7 LMI of DSL (2010)

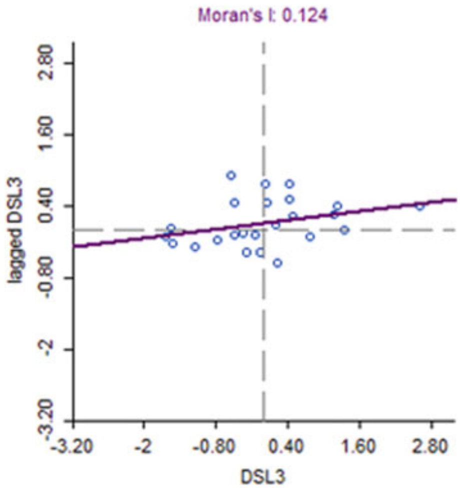


Fig. 8 LMI of DSL (2015)

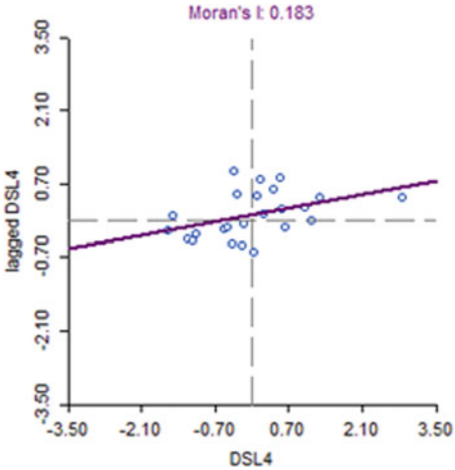


Fig. 9 LMI of CIL (2000)

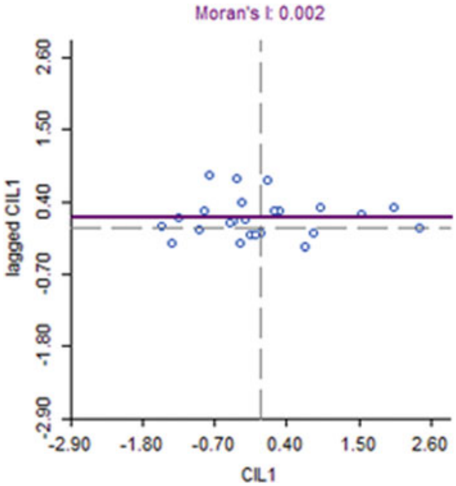


Fig. 10 LMI of CIL (2005)

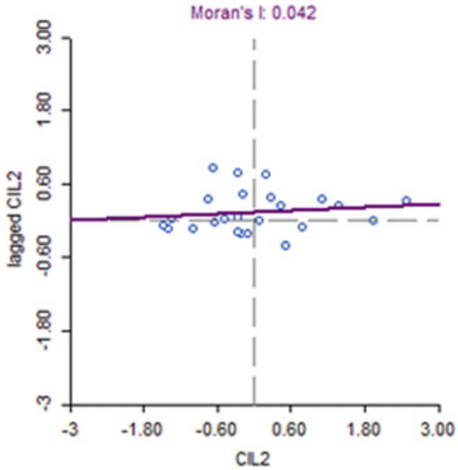


Fig. 11 LMI of CIL (2005)

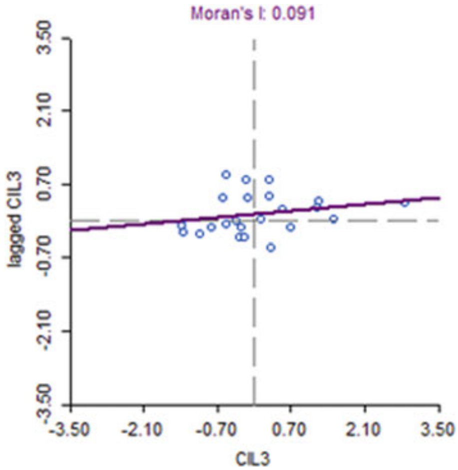
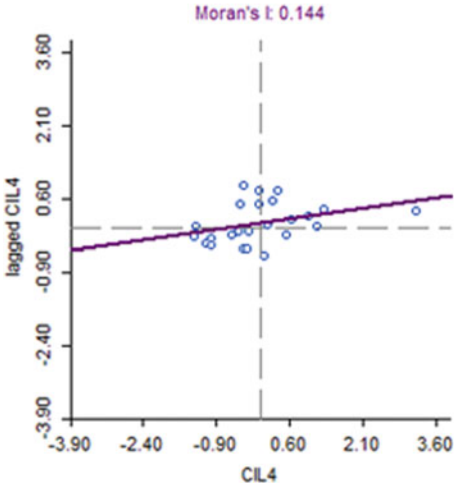


Fig. 12 LMI of CIL (2005)



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Inheritance of Educational Attainment: Instance of Caste Certificate in India

Rilina Basu, Poulomi Roy, and Shishir Roy

1 Introduction

The role of reservation policy for castes in India has always been much deliberated upon. As recent as 19th March 2021, a five-judge Constitution bench requestioned the justification behind reservation in higher education and employment. To understand the relevance of such "privileges" extended to the Scheduled castes and Scheduled Tribes, one needs to understand the issues of exclusion, discrimination and marginalization of these ethnic groups which have prevailed historically in India. While the Rights to Equality are an integral part of Fundamental Rights, Fundamental Duties and Directive Principles of the State Policy in the Constitution of India, the real picture is quite bleak. These subgroups remaining at the bottom of the social hierarchy have been socially excluded and exploited in spite of different policies at the national level.

Ever since the later Vedic ages in India, caste system emerged as an oppressor-oppressed class struggle. The caste system which had initially started on the basis of occupation, turned into a socio-economic and political vendetta where the lower "varnas" and "avarnas" were typically marginalized. Power and resources were mostly in the hands of the higher castes. Later in modern India, this system created the "minorities" who were categorized as Scheduled Castes and Scheduled Tribes. Starting with Jyotiba Phule, Rammohan Roy, the movement for inclusion of these "backward" castes into the general mainstream were carried forward by Mahatma Gandhi and B.

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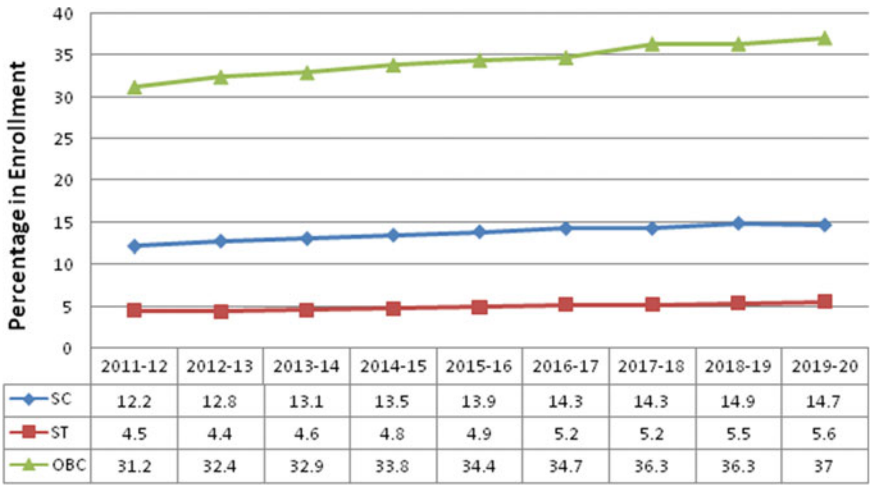
R. Ambedkar. This eventually found its way in the reservation policy which aimed at discrimination and inclusion of the excluded. The reservation policy is a legal mandate which requires seats to be reserved in education, employment and political representation at both the national and the state levels. The objective was to eradicate socio-economic marginalization of the classes at the bottom of the social hierarchy.

Reservation policy in India was first introduced in 1831 following the Dravidian movement in Tamil Nadu. Eventually, in 1932, reservation which was so far confined to local levels was first acknowledged at the national level. However, before independence, reservation in education and public sector jobs were extended only to the Scheduled castes. After independence in 1953, the Kaka Saheb Kelkar Commission proposed a quota system at the entry level for the Scheduled Castes and Scheduled Tribes. However, these recommendations were disregarded. Much later in 1982, following the Mandal Commission report, 15% and 7.5% of vacancies in the public sector and government-aided educational institution were reserved separately for the Scheduled Castes and Scheduled Tribes, respectively. Similarly, a total of 131 seats out of a total 543 seats in the parliament were reserved. In this analysis, we aim to investigate how far such reservation has been instrumental in increasing the incidence of higher education within the reserved sub-groups. In particular, we aim to analyze how far the possession of caste certificate has contributed to higher level of academic achievement among the reserved groups.

The implementation of reservation policy has led to a surge in the enrolment of the "lesser" castes into higher education, especially in elite educational institutions. Reservation policy requires the possession of a caste certificate. The question still remains how many can avail of this opportunity and how many of the enrolled can actually complete their degree. Moreover, how many of these groups have access to these certificates also needs to be explored. The absence of proper documentation necessary for this certificate is a major deterrent to apply for the same. The mechanism of scrutinee and legal verification for the certificate becomes extremely complicated in a country plagued by racism. There have been several instances where the certificate has been denied illegally by citing purely bureaucratic reasons. So irrespective of the egalitarian objective of the policy makers, the policy has failed to achieve the desired outcome.

How far reservation policy has been able to eliminate discrimination on the basis of caste needs to be investigated. While on one hand, the supply side is imperfect, on the other hand, the demand side also has its own tribulations. The presence of social, cultural and economic hierarchies within the Dalit[1] communities have restricted the lower sub-groups within these communities to access the perks coming with these policies. So like the anti-reservation policy lobbyists claim, the same families might continue to have access to these opportunities generation after generation. This would defeat the overall purpose of equality of opportunity. So it becomes imperative to trace whether these policies have attributed to intergenerational mobility, thus reducing

[1] A Dalit is considered to be a person outside the four main castes in the *varna* system; a member of the Scheduled Castes.



	2011-12	2012-13	2013-14	2014-15	2015-16	2016-17	2017-18	2018-19	2019-20
SC	12.2	12.8	13.1	13.5	13.9	14.3	14.3	14.9	14.7
ST	4.5	4.4	4.6	4.8	4.9	5.2	5.2	5.5	5.6
OBC	31.2	32.4	32.9	33.8	34.4	34.7	36.3	36.3	37

Fig. 1 Percentage distribution in enrollment in higher education by caste: from 2011–12 to 2019–20. *Data* https://www.education.gov.in/en/statistics and https://aishe.gov.in/aishe/home

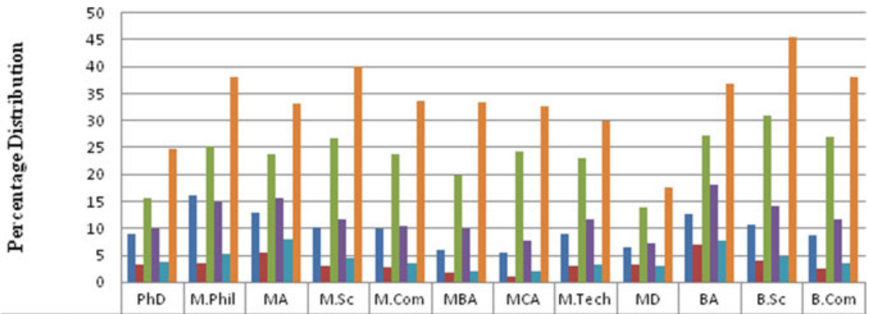
inequality even within these communities. This remains a major dilemma for policy makers as to how to make the benefits available to those who need it the most.

According to 2011 Census, Scheduled Castes and Tribes comprise of 16.6% and 8.6% of total population of India. Within the groups also, there are considerable diversities, both socially and economically. Data shows that 14% of SCs and 11% of STs fall in the "creamy layer" with an income range of above Rs. 80,000. While this implies that these subgroups have access to economic and social resources at their disposal and renders their caste identity irrelevant, the question still remains as to equality of opportunity for the remaining percentages of SCs and STs. In the context of higher education, the All India Survey on Higher Education shows that the gross enrolment ratio of the reserved categories, has increased from 19.40% in 2010–11 to 27.10% in 2019–20. In particular, it rose from 13.5 to 23.40% for SC and from 11.20 to 18% for ST over a ten-year period. Figure 1 shows the trend of percentage gross enrolment among the SC, ST and OBC.

Inspite of around 49.5% seats being reserved for the different caste categories in India,[2] it has been largely observed that seats remain vacant. The following figure illustrates the enrolment in the different higher education degree courses across the different castes (Fig. 2).

This questions the basic premises of the reservation policy. Do these vacancies imply that the backward castes do not have access to caste certificate or does it mean that inspite of having the caste certificate they are not eligible to enroll in higher education? There could well be other factors which could guide the choice of an individual to opt for higher education. In this chapter, we aim to understand the

[2] The proportion is variable across states. The reason being the proportion of other backward communities which are included are not uniform.



	PhD	M.Phil	MA	M.Sc	M.Com	MBA	MCA	M.Tech	MD	BA	B.Sc	B.Com
2010-11 SC	8.96	16.05	12.75	10.14	9.88	5.93	5.55	8.9	6.55	12.57	10.72	8.6
2010-11 ST	3.31	3.46	5.49	3.09	2.82	1.68	1.11	3.08	3.16	6.88	3.92	2.43
2010-11 OBC	15.71	25.31	23.71	26.72	23.66	19.84	24.2	22.93	13.94	27.28	30.91	27.03
2019-20 SC	9.83	14.8	15.57	11.55	10.28	9.99	7.64	11.62	7.11	18.19	14.06	11.72
2019-20 ST	3.59	5.12	7.88	4.36	3.5	1.88	1.99	3.13	3.05	7.62	4.78	3.48
2019-20 OBC	24.77	38	33.13	40.18	33.74	33.51	32.75	29.86	17.62	36.84	45.43	38.05

Fig. 2 Distribution of enrollment in different degree courses by castes from 2010–11 to 2019–20. *Data* https://aishe.gov.in/aishe/home

factors contributing toward higher educational attainment by the reserved categories in India.

The association between caste and higher education in India has been a relatively under-researched topic. While there have been some works looking into caste as a determinant on primary education like (Majumder, 2010; Mungekar, 2009; Nambissan, 2008; Ray & Majumder, 2013a, 2013b) higher education has been relatively ignored. There have been multidisciplinary papers that look into the exclusion of the "Dalits" in higher education (Neelakandan & Patil, 2012; Sukumar, 2008). Velaskar (1986) pointed out that for the economically backward castes; higher education is a luxury which resulted in lesser enrolment in higher education among the Dalits. Weisskopf (2004) obtained similar conclusion for higher drop-out rates. Previous studies like Henriques and Wankhede (1985) have shown that the reservation policy has typically backed the Dalit and Adivasis[3] coming from a higher socio-economic background. Higher education which is rarely funded completely by government aid, becomes accessible to a handful of these groups, who have been able to attain a higher income bracket. As a consequence, in spite of being eligible by virtue of having the caste certificate, higher education becomes a liability for majority of the reserved category. It has also been seen that the second generation of the groups who have shifted to a higher income regime, reaped the benefits of the positive discrimination (Patwardhan & Palshikar, 1992). The bias has also been toward the urban and male population. A few studies (Subramanian, 2015;

[3] Officially Adivasis are termed 'scheduled tribes', but this is a legal and constitutional term, which differs from state to state and area to area, and therefore excludes some groups which might be considered indigenous.

Thorat & Kumar, 2008) have provided empirical evidence of caste-based discrimination in higher education in India after getting enrolled. Kirpal and Gupta (1999) showed that the majority of the students enrolling in IIT between 1989 and 1992 were second generation beneficiaries. It is in this context, that we aim to look into the spillover effect of the previous generation's achievements onto the current generation. In particular we aim to trace the intergenerational mobility in higher education. If the educational achievement of the father has a significant bearing on the son's education level, then we would infer that mobility is absent. While there has been no dearth of literature on intergenerational mobility,[4] there has been substantial caveat when it comes to its association with reservation in higher education in India.[5] We have borrowed the methodology from papers on race-based discrimination in Europe and United States (Long & Ferrie, 2013) to understand caste-based discrimination in the Indian context. Our paper is also in line with Majumder and Ray (2016), where they have considered caste-based discrimination in education, occupation and income in India using NSSO data base. Though built on the same idea, we differ from their analysis in terms of (a) identification of exact father–son pairs (across three generations) since we have used IHDS data for 2011–12; (b) calculation of distance between two contingency tables using Long and Ferrie (2013), Altham and Ferrie (2007), and Lodh et al. (2021) methodology and (c) exploring the situation in higher education where the instance of reservation policy is more pronounced.

In this chapter, we have focused on two-fold empirical analysis following the literature.[6] One set of theories use transition matrix methodology while the other focuses on regression methodology. Here we have combined both these sets to make our result robust. In the first step we have calculated overall as well as vertical mobility and degree of association between father and son's education categories across generations within the reserved caste categories using the transition matrix methodology.[7] Furthermore, we have categorized educational achievement into four categories; Class X completed and below, class XII completed, Undergraduate Completed and Postgraduate completed. First, we have tried to understand the association for the whole sample and then we have divided the data further to analyse the effect of possessing caste certificate. This kind of technique helps in identifying "Structural mobility".[8] If there is a change in the position between two generations due to shift in socio-economic status between two generations then it is identified as structural

[4] See Cheng and Dai (1995), Checchi (1997), Bowles and Gintis (2002), Louw et al. (2006), Checchi et al. (2008), Brown et al. (2011).

[5] There have been some significant contribution by Kumar et al. (2002a, 2002b), Jalana and Murgai (2008), Maitra and Sharma (2009), Majumder (2010), Ray and Majumder (2013a, 2013b), Motriam and Singh (2021), Hnatkovska et al. (2013).

[6] See Leone (2021), Majumdar and Ray (2016), Long and Ferrie (2013), Azam and Bhatt (2015) etc.

[7] See Altham and Ferrie (2007).

[8] See Janicka and Furdyna (1977).

mobility.[9] Secondly, we have attempted to examine intergenerational vertical immobility based on multivariate Probit regression. Here higher education mobility is taken as a dependent variable while possession of caste certificate, place of residence (urban or rural and son's generation dummy (for G2 and G3) are taken as independent variables. Moreover, we have divided the data into groups depending upon the income strata[10] and level of father's educational achievement.[11] Compared to the transition matrix methodology, the advantage of this approach is that it controls for all the independent variables simultaneously.

For both the methodologies undertaken, we observe the incidence of vertical mobility and the effect being more prominent for third-generation sons. The possession of caste certificate has also been observed to be an important determinant for upward mobility. In particular for the first methodology, we obtain that there have been substantial change in the degree of association between father–son educational achievements if the household possesses caste certificate, but it is not so for the group which do not have caste certificate. In the regression analysis, we obtain that if the father's educational attainment is in category 2 and beyond, then caste certificate does not have a significant contribution toward upward mobility. While caste certificate is necessary to bring about vertical mobility, there may be other determining factors like income level, opportunity of acquiring higher education, government which can be instrumental on achieving the desirable outcome of egalitarian society.

The chapter is organized as follows. In Sect. 2, we provide a summary of the data and outline the methodology used for analysis. In Sect. 3 we present the empirical models and explore their outcomes. Section 4 concludes the paper with relevant policy implications and future scope of paper.

2 Data and Methodology

We compare the summary measures of mobility across three generations. Using new longitudinal data from Indian Human Development Survey (IHDS)[12] for the years 2011–12, we have identified mobility in higher education across different

[9] Intergenerational mobility is dependent on a host of factors. These factors could be micro like family background, income level of the family etc. or at a macro level like regional differences, policy parameters. A detailed study of these factors has been carried out by Kumar et al. (2002a, 2002b). In our paper we have restricted our study mostly to income and regional differences along with caste certificate as the instrument for reservation policy.

[10] Barooah (2005) have extensively looked into how income differences between the castes created a "discriminating effect" within the social classes. Thorat and Neuman (2012) have come down with similar conclusions.

[11] By this we mean if father's education is falling in category two and beyond and the remaining.

[12] A nationally representative, multi-topic panel survey of 42,152 households in 384 districts, 1042 urban and 1420 village neighborhoods across India was conducted by India Human Development Survey 2012. The researchers from the University of Maryland and the National Council of Applied Economic Research (NCAER), New Delhi jointly organized IHDS. Data source: https://www.icpsr.umich.edu/web/ICPSR/studies/36151/datadocumentation.

Table 1 Construction of father–son combination across G1, G2 and G3[14]

	Sample size
Total number of IHDS sample (2010–2011 data set)	204,569
Birth cohort of son (1940–1994)	136,771
Dropped general caste samples and samples with missing caste information	41,704
Total reserves category samples (Scheduled caste, scheduled tribe and other backward caste)	95,067
Dropped samples who are enrolled now	9151
Total number of reserved category samples who have completed education	85,916
Number of 2nd and 3rd generation sons[15]	38,638
Number of 2nd and 3rd generation sons dropping if caste certificate information is missing	38,348
Number of 2nd and 3rd generation reserved category sons after dropping observation with missing father's education information	34,622
Combinations of reserved category 1st generation fathers (G1) and 2nd generation sons (G2)	23,669
Combinations of 2nd generations father[16] (G2) and 3rd generation sons (G3)	10,953

generations' father and son combinations within the reserved category.[13] Table 1 explains how we have identified two groups of father and son combinations.

Our data set comprises of two groups of son and father combinations, namely: (i) Son (G3) and Father (G2) pair where father is head of the family and (ii) Son (G2) and father (G1) combination[17] where son is the head of the family. We have identified 23,669 pairs of G1 and G2 and 10,953 pairs of G2 and G3. The variables that we have used in our analysis are completed years of schooling, possession of caste certificate by the household, place of residence (rural/urban) and categories of monthly per capita family income: below median or above median. Completed years of schooling is further classified into four sub-categories; namely, secondary and below (henceforth reference group), higher secondary, graduate, postgraduate and above.

The following subsections elaborate on the methodologies undertaken.

[13] The reserved categories include Scheduled Castes, scheduled Tribes and Other backward classes.

[14] G1: generation one, G2: generation two, G3: generation three.

[15] Female family members and family members other than father and son are dropped.

[16] We refer them as second-generation sons or G2 in the chapter.

[17] Where G1 is first generation, G2 is second generation and G3 is the third.

2.1 Transition Matrix

We have analyzed intergenerational educational mobility using two dimensional matrices which contains father's education levels across one dimension and son's education levels across the other. Simply by comparing these two matrices (P and Q) we can comment on the mobility across two generations. Such a matrix will be represented by the form

$$P = \text{2nd Generation (Son)} \begin{array}{c} \\ \text{Secondary and below} \\ \text{Higher Secondary} \\ \text{Graduate} \\ \text{Post graduate and above} \end{array} \overset{\text{1st Generation (Father)}}{\left[\begin{array}{cccc} \text{Secondary and below} & \text{Higher Secondary} & \text{Graduate} & \text{Post graduate and above} \\ P_{11} & P_{21} & P_{31} & P_{41} \\ P_{12} & P_{22} & P_{32} & P_{42} \\ P_{13} & P_{23} & P_{33} & P_{43} \\ P_{14} & P_{24} & P_{34} & P_{44} \end{array} \right]}$$

$$Q = \text{3rd Generation Son} \begin{array}{c} \\ \text{Secondary and below} \\ \text{Higher Secondary} \\ \text{Graduate} \\ \text{Post graduate and above} \end{array} \overset{\text{2nd Generation (Father)}}{\left[\begin{array}{cccc} \text{Secondary and below} & \text{Higher Secondary} & \text{Graduate} & \text{Post graduate and above} \\ Q_{11} & Q_{21} & Q_{31} & Q_{41} \\ Q_{12} & Q_{22} & Q_{32} & Q_{42} \\ Q_{13} & Q_{23} & Q_{33} & Q_{43} \\ Q_{14} & Q_{24} & Q_{34} & Q_{44} \end{array} \right]}$$

where number of fathers in the different categories is plotted along the columns and those of the sons are in the rows. The off-diagonal elements like P_{ij} is the number of son–father combinations where i = education level of father and j = education level of son. Our analysis is based on four categories of higher education; namely, secondary and below, higher secondary, graduate, postgraduate and above. Vertical mobility is measured by taking the ratio of off-diagonal terms below the diagonal elements and number of overall sample observations. If son's educational attainment is higher than that of the father then vertical educational mobility takes place. Thus, the vertical mobility measurement is expressed as

$$M_v = \frac{\sum\limits_{j>i} P_{ij}}{\sum\limits_{i=1}^{4} \sum\limits_{j=1}^{4} P_{ij}}$$

We measure overall mobility as the fraction of sons who attained different levels of educational achievement than their fathers. It is measured as follows.

$$M_P = \frac{\sum\limits_{i \neq j} P_{ij}}{\sum\limits_{i=1}^{4} \sum\limits_{j=1}^{4} P_{ij}}$$

Mobility may arise due to change in distribution of education levels, that is, due to prevalence factor or because of change in row and column association in contingency tables (Altham & Ferrie, 2007; Hauser, 1980; Lodh et al., 2021; Long & Ferrie, 2013). Association can change as government takes up new policies that removes or reduces disparities in opportunities, such as seat reservation policy for backward caste groups and peer pressure, family inclination and preference toward higher studies. Thus, this mobility measure may be affected by the marginal frequencies. So, we have adjusted the marginal frequencies of one contingency table with another to accommodate for differences arising from other fundamental factors like socio-economic-regional background. Now using the marginal frequencies of matrix P for matrix Q we form the Q' matrix and measure $M_P - M_{Q'}$. Even after adjusting for the marginal frequencies the differences in mobility between P and Q may exist. Following Long and Ferrie (2013) and Lodh et al. (2021) we use the cross-product ratio from the mobility table as a pertinent measure of association between rows and columns. However, since we have a 4 × 4 matrix we adopt the Altham statistic (1970) to understand the extent of association for the full set. The Altham statistic is the sum of the squares of the differences between the logs of the cross-product ratios in the two tables (P and Q). It helps in measuring the distance between the row–column associations for the two tables each having r rows and s columns. The Altham statistic is defined as

$$d(P, Q) = \left[\sum_{i=1}^{r} \sum_{j=1}^{s} \sum_{l=1}^{r} \sum_{m=1}^{s} \left| \log\left(\frac{P_{ij} P_{lm} Q_{im} Q_{lj}}{P_{im} P_{lj} Q_{ij} Q_{lm}} \right) \right|^2 \right]^{\frac{1}{2}}$$

We have used the chi-square statistic G^2 to test for the independence between the row-column association of two matrices. Here, the null hypothesis is that the degree of row-column association between two matrices is identical. So, if we reject H_0 then it implies that mobility has occurred.

Next to identify which table has a stronger association we have calculated the distance between $d(P, I)$ and $d(Q, I)$ where I is the strict mobility matrix. Hence, we will observe higher mobility in Q if $d(P, Q) > 0$ and $d(P, I) > d(Q, I)$. If under some circumstances $d(P, Q) > 0$ but $d(P, I) \approx d(Q, I)$ then the row-column associations between the two matrices are equally distant.

In the contingency table, the diagonal terms represent the same education levels attained by both father and son whereas the off-diagonal terms indicate different education levels reached by father and son. We have also measured the row-column association of the off-diagonal terms only between the two matrices (P and Q). This new statistic $d_i(P, Q)$ has the likelihood ratio chi-square statistic G^2 with $[(r - 1)^2 - r]$ degrees of freedom (Agresti, 2002, p. 426; Lodh et al., 2021).

The steps that we have followed are as follows: (i) Simple mobility measures are obtained across generations in overall data and also sub-group data. (ii) Marginal frequencies in two contingency tables are adjusted and mobility estimates are obtained. (iii) Altham statistic measures such as $d(P, Q)$, $d(P, I)$, $d(Q, I)$ and $d^i(P, Q)$ and odd ratios for each component of the overall data are calculated .

a. **Regression Analysis**

Higher education is often a criterion for getting high-salaried jobs. Therefore, exploring intergenerational mobility in higher education becomes a crucial issue as this helps in creating opportunities to break the vicious circle of low education and low income. Caste reservation policy is one of the important policies that help the reserved category individuals in getting admission in higher education. In this chapter, we first examine the role of caste reservation policy and place of residence in higher educational mobility. The dependent variable is a binary variable that takes value 1 if son's education level is higher than father's education level and zero otherwise. The independent variables that we have considered are son's generation dummy (2nd or 3rd), caste certificate possession dummy (yes = 1, no = 0) and place of residence dummy (urban = 1 and rural = 0). Therefore, the econometric model used for estimation takes the following form:

$$\Pr(\text{Mobility} = 1) = \begin{pmatrix} \alpha\ \text{son's generation dummy} + \beta\ \text{caste certificate possession dummy} \\ + \gamma\ \text{place of urban residence dummy} \\ \end{pmatrix}$$

First, we try to gauge whether mobility has occurred in higher education. Then we have tried to identify the generations among G2 and G3 where the degree of mobility is higher. Next, we have controlled for variables like possession of caste certificate by the household, place of residence (rural/urban) and categories of monthly per capita family income: below median or above median to explain educational mobility. Possession of caste certificate coupled with the household level of income can affect the educational outcome of the child. We have also controlled for that.

3 Results

3.1 Observations from Transition Matrix

We have used the transition matrix method and estimated the Altham statistics to measure prevalence and association between father–son's educational attainments over three generations in India. In India second (G2) and third-generation (G3) father–son combinations have experienced higher and significant mobility compared to the first and second generations' father–son combinations. We have also identified the group; namely, possessing caste certificate have experienced higher and significant mobility but for households who do not possess caste certificate we could not find any significant difference in association across generations.

1. ***First- and Second-Generation Versus Second and Third Generation***

Simple measure of mobility (M) shows that second-third generations' father and son pairs are 6.8 percentage points more mobile compared to the first and second generation's father and son combinations (13.4 vs. 6.6). However, the observed mobility is primarily the result of the differences in marginal frequencies between the two contingency tables, known as prevalence (Altham & Ferrie, 2007; Lodh et al., 2021). We then adjust the marginal frequencies in order to isolate the impact of change in prevalence from the change in interaction or association. If total mobility is measured using the distribution of educational attainment of the second-third generation then we observe that the third generations sons are more mobile by 0.4 percentage points (13.4 vs. 13.0) more mobile than second generations sons. This difference is caused by difference in the underlying association, known as interaction. Now if we measure the total mobility by using the distribution in higher educational attainment by the first and second generation, then third-generation sons are only 6.6 percentage points more mobile than the second-generation sons and this difference is caused by difference in underlying association. However, we still do not know how different the father and son's educational attainment is over two different father–son combinations. Hence, we use the Altham statistic to measure the strength of association. The Altham statistics for first and second generations' and second and third generations' are $d(P, I) = 22.78$ and $d(Q, I) = 20.05$ respectively and both are significant at 1 percent level of significance. Thus, we reject the null hypothesis that the association between father and son's different levels higher educational attainment was same as that would have been under independence. Similar to simple mobility analysis, Altham statistics points out that intergenerational mobility in higher education is lower in first–second generation pairs over second-third generation pairs in overall data. The $d(P, Q)$ is 7.34 and significant at 1 percent level of significance. Thus, we have identified that no identical association between two tables (First–Second generation and Second–Third generation). Hence, we conclude mobility across the generations within the backward caste groups in India. We cannot reject the null hypothesis of the equal association in two contingency tables when we focus on only the off-diagonal terms; hence, we conclude that the significant difference in degree of association observed between the first and second generations father–son combinations and second and third generations father–son combinations is driven by the likelihood of sons inheriting father's educational attainment and not due to change in structure of association between father and son's educational attainment.

2. ***Second and First Generation Versus Second and Third Generation if Household Holds Caste Certificate***

In 1970 government of India introduced the policy of seat reservation for backward caste students in educational institutions. In our sample data we find that all the reserved category households do not hold the caste certificate but holding of caste certificate is necessary to get the benefits of seat reservation policy. Hence, we have examined intergenerational higher educational mobility within the groups with or without caste certificates. The simple mobility measure indicates that if households possess the caste certificate, then third-generation sons are 11.6 percentage points more mobile than the second-generation sons. Now to separate out the impact of change in prevalence from the change in interaction or association we first replace distribution of educational attainment of father and son of third and second generation for second and first generation and identify that third generation's sons are

1.4 percentage points more mobile than their fathers and this difference is result of change in degree of association between father and son's education levels. Similarly, if we replace the marginal frequencies of the second and third generation's table by first- and second-generation's distribution of education levels, we observe that third-generation sons are only 11.1 percentage points more mobile than second-generation's sons. Next, we used Altham statistic to test whether the degree of association between father and son's educational attainment is same in two contingency tables or not. We observe that $d(P, Q) = 6.51$ and it is significant at 1 percent level of significance. Thus, there is a change in degree of association between father and son's educational attainment across generations if caste certificate is present in a household. Mobility exercise further exhibited that though for P matrix degree of association between father and son's educational attainment is significantly different from that would have been under independence but for Q matrix that is, for second and third generation combinations no such significant difference in association between the table and the independent table is observed. Mobility is higher in third-generation sons compared to second-generation sons. Next, we focus on the off-diagonal terms and observe no significant difference in degree of association in both P and Q tables, we conclude that the difference in degree of association is driven by likelihood of son's inheriting father's education level within the households that possess the caste certificate. No significant difference in degree of association between second and third generation and first and second generation is observed if caste certificate is not present in the household. This emphasizes the role of caste certificate in achieving higher educational mobility in India (Table 2).

3.2 Results of Probit Regression

Next, we reran the same regression on different subgroups of individuals. The subgroups that we have considered are family income below median, family income above median, father's education level higher secondary and above and father's education level below higher secondary.

We observe that there has been vertical mobility in the context of higher education across generations. In particular the role of caste certificate and place of residence (urban) becomes significant for both the income groups as well as in entire sample. Moreover, for fathers having education level in the range of higher secondary and below the effect is more pronounced. One can interpret it as the policy of reservation having an effect where it is necessary. We also observe that 3rd generation sons are more mobile than 2nd generation sons. One of the important implications of this result is that caste certificate must be provided to the reserved category sons specially to those whose father's education level is below higher secondary level. The findings are consistent with the results of the previous analysis. The following table summarizes our findings (Table 3).

We obtain that the probability of higher education mobility is maximum for the groups having income above median and staying in urban region. This is logically

Table 2 Intergenerational higher educational mobility in India

	Mv	$M'v$	M	M'	$d(P, I)$	G^2	$d(Q, I)$	G^2	$d(P, Q)$	G^2	$di(P, Q)$	G^2
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
First and second generation (P) versus second and third generation (Q) (overall data)	0.066	0.130	0.075	0.148	22.78	1006.77***	20.05	829.79***	7.34	44.98***	4.61	5.764
	0.135	0.068	0.155	0.077								
First and second generation (P) versus second and third generation (Q) if caste certificate is present	0.134	0.236	0.145	0.259	18.53	597.6***	22.76	574.23***	10.55	44.84***	6.51	7.39
	0.250	0.139	0.285	0.155								
First and second generation (P) versus second and third generation (Q) if caste certificate is absent	0.097	0.182	0.107	0.202	22.87	404.36***	22.6	405.5***	7.3	13.704	1.829	0.514
	0.191	0.101	0.218	0.113								

Note G2 is given in the parentheses, Significance levels for the likelihood ratio Chi-squared statistic G2 (*df* 9 for $d(P, I)$, $d(Q, I)$ and $d(P, Q)$); and *df* is 5 for $di(P, Q)$

Source Author's own calculation

***Significant at 1 percent level

Table 3 Marginal effects

Higher educational mobility					
Sample	Full sample	Income above median	Income below median	Father's education higher secondary and above	Father's education below higher secondary
Generation 2 son dummy (Ref: Generation 1 son)	0.083*** (0.003)	0.112*** (0.011)	0.071*** (0.003)	0.053** (0.023)	0.084*** (0.004)
Caste certificate dummy (yes = 1, no = 0)	0.077*** (0.004)	0.097*** (0.011)	0.057*** (0.003)	0.036 (0.024)	0.078*** (0.004)
Urban dummy (yes = 1, no = 0)	0.085*** (0.005)	0.116*** (0.011)	0.041*** (0.004)	0.099** (0.024)	0.084*** (0.004)
Observation	34,622	6792	27,830	1174	33,448

Source Authors' calculations
***Significant at 1 percent level, **Significant at 5 percent level

consistent because higher education might be luxury for poor people and the opportunity set available to urban residents are substantially more. By opportunity set we refer to the educational infrastructure, information regarding future career scope and similar. Summing up we can conclude that while the possession of caste certificate is necessary at the entry level for the targeted reserved group (income level below median and father's education secondary and below), it is not sufficient to procure a higher education degree. One cannot ignore the role of government in providing subsidized or free education, offering substantial scholarships, initiating more professional courses etc. The inclusion of such variables is beyond the scope of the current chapter.

One can argue in this way that the opportunity set increases if either individual possesses caste certificate while controlling place of residence or other way round. Joint influence of possession of caste certificate and place of urban residence is not important in getting vertical higher educational mobility for poor individuals. Caste certificate variable is found to have significant impact on higher educational mobility if father's education level is higher secondary level and below but if father reaches at least higher secondary level of education then we observe no significant effect of caste certificate on higher educational mobility.

4 Conclusion

The relationship between higher education and caste in India has had myriad dimensions and complexities. To address these issues, there have been affirmative policies like “reservations” which would help the marginalized social classes to have an entry-level advantage in higher education among other benefits. This chapter has been an attempt to investigate the efficacy of such policies in attaining social equality as desired.

Using the Indian Human Development Survey (IHDS) 2011–12 database we have identified 2 pairs of “lower caste” father–son to trace intergenerational mobility in higher education. First, we have measured mobility using 4×4 matrices. Then we have used Altham statistic to check the marginal effects of socio-economic variables and policy parameters. In particular, we have tried to investigate the effect of reservation policy through the acquisition of caste certificate among the three generations. We observe that possession of caste certificate brings about a change in the degree of association between father and son’s educational attainment. Our analysis shows that third generation son is more mobile than second-generation son. So over time intergenerational higher educational mobility of backward castes is increasing. We have also undertaken Probit regression to substantiate our findings using the transition matrix technique. We have also taken two subgroups (i) with respect to father’s education level and (ii) with respect to income state. While the role of caste certificate has been significant for most of the cases, only with respect to highly educated fathers we find a different outcome. So while reservation policy still remains relevant today, it is not the sole determinant of higher education for the lesser castes. It has to be coupled with socioeconomic opportunities like expansion of income, provision of educational infrastructure at all levels among others to facilitate higher education.

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