Impact of Innovation on Firms Performance, Employment and Technology Spillovers: Evidence from Indian Manufacturing Firms

Doctoral Thesis

By

Pompi Chetia

(2018hsz0003)

DEPARTMENT OF HUMANITIES AND SOCIAL SCIENCES

INDIAN INSTITUTE OF TECHNOLOGY ROPAR

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Declaration of Originality

I hereby declare that the work which is being presented in the thesis entitled "**Impact of Innovation on Firms Performance, Employment and Technology Spillovers: Evidence from Indian Manufacturing Firms"** has been solely authored by me. It presents the result of my own independent investigation/research conducted during the time period from January, 2019 to September, 2024 under the supervision of Dr. Smruti Ranjan Behera, Associate Professor, Department of Humanities and Social Sciences, IIT Ropar. To the best of my knowledge, it is an original work, both in terms of research content and narrative, and has not been submitted or accepted elsewhere, in part or in full, for the award of any degree, diploma, fellowship, associateship, or similar title of any university or institution. Further, due credit has been attributed to the relevant state-of-the-art and collaborations (if any) with appropriate citations and acknowledgments, in line with established ethical norms and practices. I also declare that any idea/data/fact/source stated in my thesis has not been fabricated/ falsified/ misrepresented. All the principles of academic honesty and integrity have been followed. I fully understand that if the thesis is found to be unoriginal, fabricated, or plagiarised, the Institute reserves the right to withdraw the thesis from its archive and revoke the associated Degree conferred. Additionally, the Institute also reserves the right to appraise all concerned sections of society of the matter for their information and necessary action (if any). If accepted, I hereby consent for my thesis to be available online in the Institute's Open Access repository, inter-library loan, and the title & abstract to be made available to outside organisations.

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Certificate

This is to certify that the thesis entitled "**Impact of Innovation on Firms Performance, Employment and Technology Spillovers: Evidence from Indian Manufacturing Firms**", submitted by **Pompi Chetia (2018hsz0003)** for the award of the degree of "**Doctor of Philosophy"** of Indian Institute of Technology Ropar, is a record of bonafide research work carried out under my guidance and supervision. To the best of my knowledge and belief, the work presented in this thesis is original and has not been submitted, either in part or full, for the award of any other degree, diploma, fellowship, associateship or similar title of any university or institution.

In my opinion, the thesis has reached the standard of fulfilling the requirements of the regulations relating to the Degree.

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Lay Summary

As the global economy shifts towards innovation-driven growth, understanding the impact of innovation on firms' performance, employment, and technology spillover in emerging and developing markets like India is critical. Therefore, by using extensive data from Indian manufacturing firms, this doctoral research investigates the complementary relationship between innovation and firms performance, the impact of process and product innovation on employment and the influence of horizontal and vertical FDI spillovers on the innovation output of Indian manufacturing firms, with a special focus on the firms located in the major industrial clusters of the country.

The research outcomes from the thesis state that firms' productivity and innovation output are complementary in nature. However, the impact of productivity on innovation is found to be greater than the impact of innovation on firms' productivity. Based on this, the study suggests that policies aiming to promote innovation in Indian manufacturing firms should focus on productivity-enhancing measures. The research finds ample evidence that Indian manufacturing firms innovate through labour. In other words, Indian manufacturing firms prefer to employ additional labour to develop a new technology or a new production process. However, once the new technology or the production process is out in the market and is used in production, it significantly displaces labour. Nevertheless, this labour displacing impact of process and product innovation is limited only to domestic firms. Foreign firms are not associated with any significant displacement of labour. Stemming from this, we encourage foreign equity participation in Indian manufacturing firms. However, the research findings also provide robust evidence that foreign direct investment (FDI) spillovers are not significantly influencing the innovation output of Indian manufacturing firms, except for firms agglomerated in the major industrial clusters of the country that benefit from the entry of foreign firms in similar industries. Nevertheless, since foreign firms have been found to be significantly innovating more in Indian manufacturing firms than domestic firms after the 2014 FDI policy liberalisations of the government of India, we encourage foreign equity participation in Indian manufacturing firms.

Abstract

Using a comprehensive dataset of Indian manufacturing firms, this thesis investigates the impact of innovation, measured using granted patents, on firm-level productivity, employment and technology spillovers. The **first objective** of the thesis empirically examines the two-way relationship between innovation and firms' productivity. Results obtained from negative binomial and quantile regression estimates confirm the existence of a complementary relationship between innovation and firms' productivity. Further results from the propensity score matching method confirm that innovative Indian manufacturing firms are significantly more productive than their non-innovative counterparts. The empirical findings also show robust evidence that the impact of productivity on Indian manufacturing firms is way greater than the impact of innovation on productivity. Based on this, we suggest that policies aimed at promoting innovation should focus on productivity-enhancing measures. The **second objective** of the thesis investigates the impact of process and product innovation on employment. Econometric findings obtained using the generalised method of moments (GMM) confirm that process and product innovation significantly displace labour in Indian manufacturing firms. However, this labour-displacing impact of process and product innovation is limited only to domestic firms, and process and product innovation in foreign firms do not significantly influence the innovation output of Indian manufacturing firms. Based on this, we encourage foreign equity participation in Indian manufacturing firms. The **third objective** of the thesis investigates the impact of horizontal and vertical FDI (Foreign Direct Investment) spillovers on the innovation output of Indian manufacturing firms, with a special focus on the firms agglomerated in the major industrial clusters of India. Findings from negative binomial and GMM regression confirm that horizontal and vertical FDI spillovers do not significantly influence the innovation output of Indian manufacturing firms. This chapter identifies a lack of absorptive capacity as the key factor behind the inability of firms to leverage the benefits of FDI. Therefore, we suggest capacity building in firms through research and development expenditures. However, the results also show that firms located in the major industrial clusters of the country that capitalise on horizontal spillovers significantly innovate more. This highlights the crucial role of industrial clusters in generating innovation spillovers, reflecting the need for differentiated policies for firms in the industrially agglomerated clusters to nurture the benefits of industrial clustering. Further results from the difference-in-difference method confirm that foreign firms have been significantly innovating more in India after the 2014 FDI policy liberalisation. Based on this, we suggest encouraging FDI in Indian manufacturing firms to promote innovation.

Keywords: Innovation; manufacturing firms; productivity; employment; FDI-spillovers.

List of Publications from Thesis

1. Chetia, P. (2024). Do firms' performance act as a catalyst of innovation: Empirical evidence from innovative Indian manufacturing firms. ***Indian Growth and Development Review***, *17*(2),108-139. *Special Issue: A Note on the Productivity, Growth and Development: India and Beyond.* [with Behera, S. R.] (Emerald Insight). https://doi.org/10.1108/IGDR-07-2023-0091

Under Review

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Other Publications

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3. Do green innovation control environmental quality: Empirical evidence from the G-20 group of countries. ***European Journal of Innovation Management*** [with Behera, S. R.].
4. What determines intellectual property in less developed countries? Empirical evidence from Sub-Saharan Africa. ***International Journal of Social Economics*** [with Behera, S. R.].

Work in Progress

1. Does foreign direct investment spur the innovative performance of local firms? Evidence from Indian manufacturing firms?
2. Does location spur innovation? Evidence across Indian manufacturing industries?
3. Does agglomeration affect the innovation performance of firms? Empirical evidence from the Indian manufacturing firms.

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Notations and Abbreviations

ACF: Ackerberg-Caves-Frazer (2015)

CIS: Community Innovation Survey

CMIE: Centre for Monitoring Indian Economy

DID: Difference-in-Difference

EMDE: Emerging Markets and Developing Economies

FDI: Foreign Direct Investment

GDP: Gross Domestic Product

GMM: Generalised methods of moment

LP: Levinsohn and Petrin (2003)

MNE: Multinational Enterprises

OECD: Organisation of Economic Co-operation and Development

OLS: Ordinary Least Squares

OP: Olley and Pakes (1996)

PatSeer: Patent Search and Analysis Software

PSM: Propensity Score Matching

R&D: Research and Development

SD: Standard Deviation

TFP: Total Factor Productivity

TFP_{ACF}: Total Factor Productivity measured using Ackerberg-Caves-Frazer (2015) approach

TFP_{LP}: Total Factor Productivity measured using Levinsohn and Petrin (2003) approach.

TRIPS: Trade-Related Aspects of Intellectual Property Rights

WTO: World Trade Organisation

Chapter 1
Introduction

This chapter outlines the background (section 1.1) and context (section 1.2) of the research, and its purposes (section 1.3). Section 1.4 describes the significance and scope of this research. Finally, section 1.5 includes an outline of the remaining chapters of the thesis.

1.1 Background and Motivation of the Study

A major question that has arisen in the last few years is the impact of innovation in emerging markets and developing economies (EMDE). More specifically, is innovation leading to productivity growth of firms in the EMDEs? Or are only the productive firms in the EMDEs leading the innovation race? Is innovation displacing labour in the EMDEs and leading to 'technological unemployment' in these countries? Are the foreign multinationals generating more employment than domestic firms of the EMDEs? Has the innovation output of the firms in the EMDEs improved with the growing presence of foreign multinationals? While substantial evidence in the developed nations addresses these questions, the understanding of innovation and its economic impact is still limited in developing countries.

However, firms in the EMDEs differ in many technological dimensions from their peers in developed nations. The advanced developed economies' innovation regimes are structurally different from the EMDEs. Acemoglu et al. (2006) point out that countries at an early stage of development pursue an investment-based strategy for technological upgradation, relying on existing firms and managers to maximise investment. On the other hand, countries closer to the world technology frontier adopt a selection-based strategy with short-term relations, younger firms, fewer investments and better selection to gain technological advances. A segment of the existing studies has highlighted that innovation in the advanced economies is driven by research and development (R&D) investments and knowledge creation, while innovation in EMDEs is driven by non-R&D investments (e.g., investments in existing machinery and equipment) and knowledge use (Cirera and Maloney, 2017; RadoSevic, 2017; Stojčić et al., 2020). Therefore, innovation models focussing on R&D spending are not particularly relevant in the context of EMDEs (Radosevic and Yoruk, 2018; Stojˇci'c et al., 2020). From the above, we can fairly conclude that the technologically advanced developed economies and technologically distant EMDEs are different in terms of innovation. As such, we cannot infer the implications of one from the other.

Much of the lack of depth of research on the EMDEs could be attributed to the limited availability of detailed firm-level innovation data. In innovation literature, R&D is commonly used to measure innovation (Akcomak and Weel, 2009; Hassan and Tucci, 2010; Garcia-Manjon and Romero-Merino, 2012). However, R&D as an innovation measure is generally associated with three problems. First, R&D is only an input to the innovation process and says nothing about the "output" side of the innovation. Second, not all R&D expenditures translate into successful innovation. Third, literature has shown that firms in EMDEs usually generate technological advances outside the formal R&D process (Wadho and Chaudhry, 2018; Petelski et al., 2020). In such cases, formal R&D fails to capture the true extent of innovative efforts in such countries. Many studies have measured innovation using dichotomous variables that indicate the launch of a new product or process (Evangelista and Vezzani, 2012; Bianchini and Pellegrino, 2019; Dalgıç and Güven, 2023). However, using dichotomous variables to measure innovation makes it difficult to quantify the heterogeneous impact of innovation.

The literature on innovation suggests that patents are a "classic instrument for incentivising and measuring innovation" (Sweet and Eterovic, 2019). Patent data has certain advantages over R&D data. First, patents are unique and highly visible methods of technological progress or innovation (Furman et al., 2002). Second, as against R&D expenditures, patents are a confirmed source of disclosure of an invention, checked and verified by specialists. Third, as public documents, patent data are available for longer periods, richer, and more detailed than R&D data.[1]

A major criticism of using patent data to proxy innovation is that patents reflect inventions (development of new ideas) only, not innovations (development of commercially viable products or services from creative ideas). In this context, Artz et al. (2010) point out that since patents protect new products and many inventions eventually lead to marketable innovations, patents can be used to measure innovation. Their econometric evidences provide a positive and significant relationship between patents and product announcements, further justifying the use of patents for innovation.

With the growth of the patent literature around the turn of the century, an increasing effort has occurred to investigate the impact of innovation with specific stress at firm-level data. This widespread interest in micro-level studies, particularly within the context of innovation, is justified as firms are the decision-making units for innovation decisions. There has also been an aggravated dissatisfaction towards the aggregated analysis, which was perceived as unable to grasp the heterogeneity of firms' innovation behaviour and different technological sources

[1] Patents as an instrument of innovation is discussed in detail in chapter 2

of firms' competitiveness (Evangelista and Vezzani, 2010). Micro-level studies correct this bias by elaborately exploring firms' innovative inputs and outputs, thus giving us a clear picture.

Motivated by this, the present study uses the example of India, an emerging Asian economy where the ratio of patents granted to patents applied increased to 44 per cent in 2020-21 from 18 per cent in 2005-06 (Annual Report, Intellectual Property India). The country has moved up in the global innovation index from 81 in 2015 to 48 in 2020, followed by 46th in 2021 and 40th in 2022. The Global Innovation Index-2022 report claims India ranks 1st amongst 36 lower middle-income group economies. In terms of total patent filings, India ranks 4th amongst the Asian countries, behind China, Japan and South Korea, which are essentially upper-middle-income and high-income economies. India makes a fascinating case as although the country is growing in terms of intellectual property, its gross domestic expenditure on R&D (GERD) is much lower. For the year 2021-22, the GERD of the country stands at 0.64 per cent, much below other Asian countries like China (2.40%), Japan (3.26%), and Korea (4.79 %).[2]

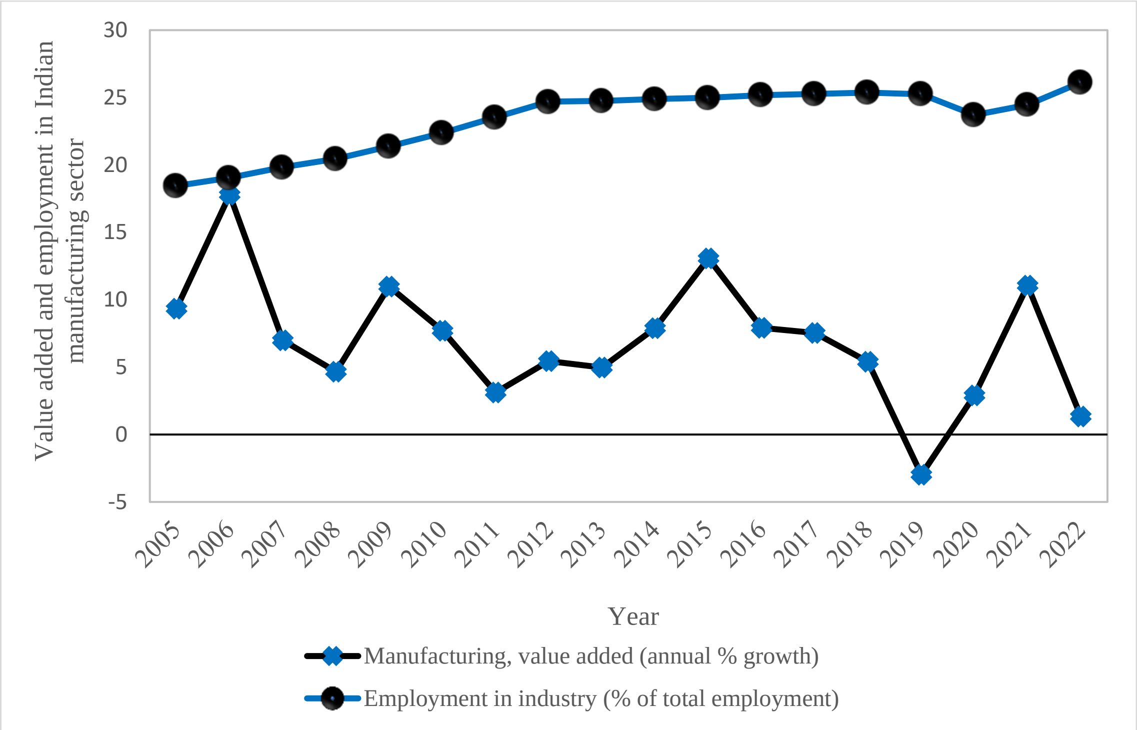
The empirical framework of the thesis uses patent information from Indian manufacturing firms. Two factors majorly influence the decision to consider the manufacturing sector. First, the use of patents as a measure of innovation makes the manufacturing sector more suitable to study the present research issue at hand than the services sector. The demarcation approach in the literature argues that innovation in the services industry is peculiar enough, and it requires a whole new framework, concept and instruments (Coombs & Miles, 2000; Gallouj and Savona, 2009). Services are more about doing useful things than making useful goods. Hence, patents are a more appropriate indicator of innovation for manufacturing than the services sector (Cainelli et al., 2006; Tether and Howells 2007). This restricts the dimension of the present thesis to the services sector only.

Second, economic theory considers the manufacturing sector as the engine of economic growth (Kaldor, 1968). No country has achieved and sustained high living standards without significant developments in its manufacturing sector, except for a few oil-rich countries (Chang et al., 2016). However, it has been argued that the importance of the manufacturing sector has diminished over the last two to three decades, resulting in premature deindustrialisation in developing countries (Haraguchi et al., 2017). Fig.1 makes it clear that India's annual growth rate in the manufacturing industry has stagnated. The employment generated by the manufacturing industry has been sluggish over the past two decades. This pragmatic scenario clarifies that India's manufacturing sector requires a much-needed policy thrust for a positive growth rate and employment creation. Can innovation be one such policy thrust? The present

[2] Data collected from the World Bank.

thesis provides an empirical analysis of these questions.

Figure 1.1: Trends of value-added and employment generated by the manufacturing sector in India



Source: World Development Indicators

1.2 Conceptual Framework

The present work draws inspiration from the Schumpeterian paradigm developed by Aghion et al. (1998) and Howitt (1999). Although the framework is best viewed in the context of developed economies, we try to draw comparative implications of the model for the EMDEs.

Aghion et al. (1998) and Howitt (1999) have presented their pretty standard model as follows:

$$Y_t = \int_0^{Q_t} A_{it} x_{it}^{\alpha} \qquad (1.1)$$

where Y_t is the gross output, Q_t is the measure of how many different intermediate products exist at time t, x_{it} is the flow of intermediate product i used throughout the economy, A_{it} is the productivity parameter attached to the latest version of intermediate product i.

In Aghion et al. (1998) and Howitt (1999), the next generation of an intermediate product i is developed by the research sector. The flow of innovation output φ_{it} is given as

$$\varphi_{it} = \lambda\varphi(\eta_{it}) = \lambda\varphi\left(\frac{R_{it}}{A_t^{max}}\right), \varphi^{/} > 0, \varphi^{//} < 0 \qquad (1.2)$$

Where φ_{it} is the flow of innovation output (rate of patenting), λ is the arrival rate of innovation, $\eta_{it} = \frac{R_{it}}{A_t^{max}}$ exhibits research intensity with R_{it} as the total amount of final output invested in

R&D at date t. A_t^{max} is the leading edge productivity parameter at date t.

Growth in the leading-edge parameter A_t^{max} occurs as a result of knowledge spillovers produced by innovations. Each innovation is implementable only in the intermediate industry in which it is used but increases the knowledge stock depending on innovation size σ, so that the next innovator in any intermediate industry can draw from an expanded pool of knowledge. Finally, the ratio of the average to leading-edge productivity is given as $A_t^{avg} = A_t^{max}/(1+\sigma)$, which with constant σ implies $\dot{A_t^{avg}}/ A_t^{avg} = \dot{A_t^{max}}/A_t^{max}$. Thus, productivity growth g_t , in Aghion et al. (1998) and Howitt (1999) equals the size of innovations (σ), and the arrival rate flow of innovation (φ_t) so that

$$g_t = \frac{\dot{A_t^{avg}}}{A_t^{avg}} = \sigma\varphi_t \tag{1.3}$$

Eq. (1.3) suggests a positive relationship between productivity growth and the rate of patenting. Furthermore, Aghion et al. (1998) and Howitt (1999) assert that in a steady state, output growth per worker depends solely on the growth of technological progress. The growth of output per worker indicates that either less labour is required to produce the same output or more output could be produced with the same labour inputs. Thus, innovation impacts the equilibrium in the labour market.

However, against the popular belief that innovation activities stem from R&D investments, recent literature draws that the EMDEs situated far from the innovation and technological frontier grow predominantly through expanding production capabilities (Radosevic, 2017; Radosevic and Yoruk, 2018). Such economies lack the scientific knowledge and resources required for cutting-edge R&D and invest far less in R&D than the countries closer to the technological frontier (Goñi and Maloney, 2017). Therefore, the innovation process in the EMDEs is based more on knowledge-intensive activities, such as technology adoption and incremental and cost-oriented innovation, such as acquiring machinery and equipment (Cirera and Maloney, 2017; RadoSevic, 2017; Stojčić et al., 2020). Given this, understanding the innovation mechanism in the EMDEs is of particular relevance.

Firms in EMDEs face greater challenges than their counterparts from advanced economies due to a lack of managerial and organisational competencies, low absorptive power and limited learning capabilities (Zhu et al., 2006; Bahl et al., 2021). Their domestic environment is oriented toward developing production competencies and capabilities (Radosevic and Yoruk, 2018) and does not provide sufficient incentives for firms to develop innovation capabilities (Stojˇci'c et al., 2020). This ignites the possibility that the frontier firms, who have a productivity advantage, would have a substantial advantage in conducting innovation activities over their counterparts in the EMDEs.

The existing literature has extensively documented the relevance of innovation in firms' productivity, especially in the context of developed economies (Evangelista and Vezzani, 2012; Bedford et al., 2022; Entezarkheir and Sen, 2023). However, the research agendas inspecting the linkages between innovation and firms' productivity in the EMDEs are quite scanty. In innovation and industrial organisation literature for the EMDEs, research has linked innovation with higher productivity growth (Chudnovsky et al., 2006, for Argentinian; Ambrammal and Sharma, 2016 for India; Aboal and Garda, 2016 for Uruguay; Santi and Santoleri, 2017 for Chile; Dalgıç et al., 2018 for Turkey; Wadho and Chaudhry, 2018 for Pakistan). Deviating from the majority of these findings, Fink et al. (2021) observed that patents had not played much role in Chile's rapid economic growth. However, they acknowledged that the small number of firms that had used patents had been amongst the fastest-growing firms. Similarly, Santi and Santoleri (2017) found that product innovation was insignificant for firm growth. Turning to the findings in the aggregate-level analysis, macroeconomists studying the interplay between innovation and productivity in the EMDEs mostly acknowledge innovation as a crucial aspect of firms' productivity (Dabla-Norris et al., 2012; Ramadani et al., 2019).

However, despite its importance for both firms and society, the prospect of firms' productivity affecting innovation output in EMDEs is missing in the micro econometric empirical works of innovation and industrial organisation. In fact, although the impact of innovation on productivity has been focused on some research, there is still a lacuna regarding the two-way relationship between innovation and firm productivity. Research is still needed to understand the interplay between innovation and firms' productivity, especially in EMDEs. To this end, the ***first objective (Chapter 3)*** of the present thesis aims to answer three questions using samples from Indian manufacturing firms. First, does innovation influence the productivity levels of Indian manufacturing firms? Second, do productivity levels serve as a foundation for successful innovation in Indian manufacturing firms? Third, are there any observed differences between the productivity levels of innovative firms vis-a-vis those of non-innovative firms?

While considering the observed structural differences between the developed nations and the EMDEs, gaining insights into the consequences of innovation on the labour market dynamics is particularly relevant for policymakers in the EMDEs to identify strategies for fostering gainful employment. The developed countries and EMDEs are completely different not only in terms of structural differences in technological advancements but also in terms of the composition of labour. The EMDEs mostly imitate or purchase technologies from the developed world (Helpman, 1993; Karaomerlioglu and Ansal, 2003). In this regard, two main points highlight the structural differences between developed and developing countries.

First, the EMDEs are essentially characterised by an excess labour supply, whereas developed countries face an acute labour shortage. Given this, developed countries' technological progress does not collide with the labour market. On the contrary, the EMDEs continuously face the trade-off between maximising growth through modernising the industrial sector vis-a-vis generating employment for the excess labour in the labour market. Second, the labour composition is also different in developed countries and EMDEs. The labourers in developed countries are prudent in skill, whereas EMDEs have unskilled labour in abundance. The abundance of skilled labourers leads the developed economies to devise skill-based capital-intensive technology. EMDEs require technological know-how and managerial and organisational proficiency to absorb the existing level of technology in the market. However, developing countries lack all of them.

In fact, the foreign firms operating in the EMDEs are also structurally different from the domestic firms.[3] Foreign firms possess superior technical and managerial assets and demand more skilled labour than domestic firms (Bellak, 2004; Griffith and Simpson, 2004). Additionally, both groups are different regarding market competitiveness and successful implementation of innovations in the market as well. Such differences can lead to significant differences in employment generation (or destruction) in the host country (Dachs and Peters, 2014).

The existing studies have meticulously distinguished between the employment effect of an increase in factor productivity viz. process innovation, and the introduction of a new stream of demand viz. product innovation. However, while studies focussing on the impact of process and product innovations on the labour market of developed economies are numerous, until recently, there has been very little empirical research on EMDEs. Most of these studies use a static framework, ignoring the path-dependent nature of the labour market, or measure innovation either with a dyadic variable, making it difficult to quantify innovation, or with an input variable, giving only a partial picture of the entire process. In addition, all the studies done for the EMDEs have assumed that the employment effect of innovation is the same for all firms, irrespective of their ownership structure (except Dachs and Peters, 2014). To this end, the ***second objective (4th chapter)*** of the thesis addresses the following questions using samples from Indian manufacturing firms. These are: being an EMDE with the vast majority of the workforce being essentially 'unskilled worker', is India facing 'technological unemployment'? Are foreign firms playing a crucial role in generating employment through innovation than

[3] For the purpose of the study, we have considered a firm as a foreign-owned/ foreign firm if the equity held by the foreign promoter in the firm is a minimum of 10 percent. This classification of foreign owned firm is consistent with the Report of the Dr Arvind Mayaram Committee on Rationalising the FDI/FII Definition, 2014.

domestic firms?

Finally, the theoretical underpinning of the Aghion et al. (1998) and Howitt (1999) model presents the idea that growth in the leading-edge technological parameter occurs due to knowledge spillovers generated through innovation. The theoretical foundation of the model states that individual firms invest in R&D activities to innovate. Once a firm successfully introduces an innovation into the market, the benefits are not confined to the individual firm alone but spill over to other firms, leading to widespread gains. However, firms in the EMDEs undertake little domestic R&D and hence have few domestic sources of new technology (Henry et al., 2009). Therefore, policymakers around the EMDEs are increasingly using foreign direct investment (FDI) as an instrument of technology diffusion. The underlying logic is that firms in the EMDEs may leverage the opportunity to access leading-edge technologies through innovation spillovers from foreign-owned or foreign firms.

Foreign multinationals often bring advanced technological know-how to the host countries when they invest in local subsidiaries. Based on this, most mainstream works assume that openness and easy access to FDI would generate positive innovation externalities or spillovers. However, the existing research provides mixed evidence. While Alazzawi (2012), Crescenzi et al. (2015), Li et al. (2017), Guo et al. (2022) and Chen et al. (2023) found that inward FDI generates positive innovation externalities, Qu et al. (2017), Ascani et al. (2020) and Ning et al. (2023) encountered negative effects of FDI spillover on innovation.

The literature on innovation spillover recognises two particular mechanisms through which innovation externalities occur. One such mechanism is within the industry, intra-industry, or horizontal spillovers where knowledge spills over from foreign firms to local firms operating within the same industry through channels such as labour mobility, imitation or reverse engineering and competition. The other mechanism is between industry or vertical linkages, which occurs if foreign firms establish contacts with domestic suppliers, creating opportunities for knowledge exchange and technology transfer across firms in related industries. However, empirical evidence regarding horizontal and vertical innovation spillovers from FDI in the EMDEs has been mixed and inconclusive. Empirical studies find that FDI can have positive (Khachoo and Sharma, 2016), negative (Vujanovic et al., 2022) and insignificant (Gorodnichenko et al., 2020) horizontal innovation spillovers. Compared to horizontal spillovers, empirical research quite unanimously agrees that vertical spillovers do not generate any significant innovation externalities (Gorodnichenko et al., 2020); Vujanovic et al., 2022), with the solitary exception of Khachoo and Sharma (2016) who found a positive vertical innovation spillover of FDI. Irrespective of the somewhat unanimous empirical findings of vertical innovation spillovers, the mixed empirical evidence in terms of horizontal innovation spillovers points to the need to understand better the mechanism of innovation spillovers from foreign to domestic firms.

Surprisingly, the existing studies mostly overlook the interplay between inward FDI and firms clustering and their consequent impact on innovation. The study done by Li et al. (2017) for China is one of the sparse literature that has investigated the spatial dimension of FDI spillovers on innovation spillovers. The seminal work of Marshall (1890) draws up channels (labour market pooling, input sharing and knowledge spillover) through which knowledge flows in industrial clusters. On the empirical front also, many studies found evidence for complementarity between innovation and geographical clusters (dos Santos and Dalcol, 2009; Mukim, 2012; Ruffner and Spescha, 2018; Tang and Cui, 2023). At the same time, many studies found the clustering of industries irrelevant to innovation outcomes (Beaudry and Breschi, 2003; Gordon and McCann, 2005). In fact, studies have even encountered a negative relationship between the two (Zhang, 2015; Niebuhr et al., 2020). Building on this set of work, we believe that the FDI spillovers in industrial clusters might have a differentiated impact on innovation compared to non-clustered firms. We extend this framework and study the interaction between the geographical location of the firm and the spillover variables. To this end, the ***third objective (5th chapter)*** of the thesis primarily answers the following questions. Does FDI generate any horizontal or vertical innovation spillovers in Indian manufacturing firms? Does FDI generate any horizontal or vertical innovation spillovers among the manufacturing firms clustered in the country's major industrial locations? This chapter of the thesis extends to empirically evaluate the impact of FDI policy liberalisations introduced in 2014 by the Government of India on the innovation output of manufacturing firms. To this end, the chapter addresses the question- are foreign firms filing for more patents in India post the 2014 FDI policy liberalisations compared to the pre-policy period?

1.3 Objectives of the Study

This thesis aims to study the impact of innovation on productivity, employment and the generation of technological externalities in Indian manufacturing firms. This section briefly discusses the broad objectives of the thesis.

The ***first objective*** of the thesis is to empirically evaluate the two-way dynamic nexus between the productivity of Indian manufacturing firms and their innovation productivity. Accordingly, three hypotheses have been formed. The first hypothesis explores whether or not firms' productivity is crucial in determining the innovation output of Indian manufacturing firms. The second hypothesis investigates whether or not innovation significantly improves the productivity of manufacturing firms in India. Finally, the third hypothesis investigates if innovation would make Indian manufacturing firms more productive than their non-innovative counterparts.

The ***second objective*** empirically investigates the employment effects of process and product innovation in the context of Indian manufacturing firms. Accordingly, the first hypothesis explores the employment effects of process innovation, and the second hypothesis explores the employment effects of product innovation. Further, the third and the fourth hypotheses investigate the employment effects of product and process innovation of foreign manufacturing firms in India.

Finally, the ***third objective*** explores whether FDI generates horizontal or vertical innovation spillovers in Indian manufacturing firms. For this purpose, the thesis frames three hypotheses. The first hypothesis explores the effect of horizontal FDI spillovers on the innovation output of Indian manufacturing firms. The second hypothesis explores the impact of vertical FDI on the innovation output of Indian manufacturing firms. Finally, the third hypothesis explores the effect of FDI spillovers on the firms clustered within the major industrial locations of the country.

1.4 Significance and Scope of the Study

Conceptually, this thesis aligns closely with the recent emerging micro-level patent literature in the EMDEs that links innovation with productivity, labour market and externality generation (Avenyo et al., 2019; Fink et al., 2021; Vujanovic et al., 2022). The general message from this literature is that innovation in the developed and the EMDEs is quintessentially different due to the unique challenges faced by the EMDEs. Therefore, the impact of innovation on EMDEs would also be different than that of developed nations.

While there is a growing body of research exploring the effects of innovation on firm-level productivity, employment and technological externalities in developed nations, more empirical studies are needed to deepen our understanding of these dynamics in the EMDEs for evidence-based policymaking. We identify this as a critical area of study, and the present thesis is an endeavour to provide a comprehensive picture of the impact of innovation on firm-level productivity, employment and technological spillovers. Given this, the scope of the present study extends to the fields of productivity economics, labour economics and industrial organisation economics, besides the economics of innovation. This section summarises the significance and the contribution of the present work.

One of the major contributions of the present work is that it adds to the thin literature on the EMDEs that has used actual patent count data. Patents explain the contribution of knowledge to productivity more efficiently than any other input measure, such as R&D expenditures (Lach, 1995). The existing literature also advances the understanding that firms in EMDEs usually generate technological advances outside the formal R&D process (Wadho and Chaudhry, 2018; Petelski et al., 2020). In such cases, formal R&D fails to capture the true extent of innovative efforts in the EMDEs. On the other hand, using dichotomous variables to measure innovation makes it difficult to quantify the heterogeneous impact of innovation. This makes patents the best available measure of innovation. However, studying the impact of innovation on firms' productivity, employment, and technological spillovers in the EMDEs using actual patent data has garnered increasing attention in recent years only and requires further exploration.

The ***first objective (Chapter 3)*** of the present thesis contributes to the economics of innovation by exploring the two-way link between innovation and firm-level productivity growth. While the relevance of innovation in firms' productivity growth is somewhat discussed for the EMDEs, the relevance of firm-level productivity in their innovation output is discussed for the first time for the EMDEs, to the best of our knowledge. This chapter also adds to the industrial organisational literature by studying the observed productivity differences between innovating and non-innovating Indian manufacturing firms. The empirical findings of this chapter broaden our knowledge of innovation and firm-level productivity in the EMDEs.

The ***second objective (chapter 4)*** of the thesis relates to the field of labour economics and concentrates on dissecting the impact of process and product innovation on employment generation. While research on the employment effects of process and product innovation is widely available for developed nations, few studies have empirically examined the same for EMDEs. In fact, even these few empirical studies available for the EMDEs further ignore the dynamic nature of the labour market. Our empirical and econometric framework considers these factors and evaluates the employment effects of process and product innovation in Indian manufacturing firms in a dynamic set-up. Our econometric framework also provides empirical estimates of the employment effects of domestic and foreign firms with differences in their process and product innovation behaviour. This contrasts with most studies that assume that employment growth is independent of the firm's ownership structure.

Finally, the ***third objective (chapter 5)*** of the thesis enriches the industrial organisation and innovation literature by decomposing the mechanisms of FDI innovation spillovers for Indian manufacturing firms. The empirical analysis in this chapter also contributes to the literature on the economics of geography by estimating cluster-specific innovation spillovers of FDI. Further, this chapter focuses on divulging the impact of FDI policy liberalisations on the innovation output of Indian manufacturing firms. The results obtained are, hence, crucial for policy formulation concerning FDI in the manufacturing sector.

1.5 Thesis Outline

In what follows, we discuss the outline of the thesis. The thesis is structured in six chapters. ***Chapter 1*** gives the background and motivation, conceptual framework, objectives, significance and scope of the study. This chapter includes a detailed discussion of the hypothesis of the study. It also outlines the major contributions of the work.

Chapter 2 includes a detailed literature review and identifies the literature gaps. The initial segment of this chapter provides a detailed outline of the various innovation instruments used in the existing studies. Based on the pros and cons of the instruments used to proxy innovation, it is apparent that patents are the most suitable and available innovation proxy for the present context. However, we notice a lack of patent literature in the EMDEs, which has focused exclusively on the impact of innovation on productivity, employment, and technological externalities. To this end, the chapter identifies three prominent research gaps. ***First,*** a comprehensive set of studies in developed nations has focused on studying the impact of innovation on firm-level productivity. However, patent literature devoted to this genre is quintessentially small for the EMDEs. In contrast, very few studies have empirically investigated the 'reverse' channel, i.e., the impact of productivity on firm-level innovation performance. This 'reverse' channel is notably understudied even for the developed nations. For the EMDEs, empirical research delving into this 'reverse' relationship is, in fact, largely absent. ***Second***, a thorough review of the literature shows that concerning the employment effects of process and product innovation, almost all the studies done in the context of EMDEs have ignored the dynamic nature of the labour market. Also, most of the studies for the EMDEs have used either an input variable of innovation, which gives only a partial outlook of the entire innovation process or dichotomous variables, making it difficult to quantify the heterogeneous impact of innovation. In addition, we could not find any study that reflected the differences in the employment behaviour of foreign firms vis-à-vis domestic firms. Our work addresses these gaps in the empirical estimation of the thesis. ***Third***, the existing empirical literature provides mixed evidence regarding the innovation spillover of foreign direct investment. Moreover, the number of studies investigating the channels of such spillover is quite limited.[4] This is

[4] The existing literature has mostly concentrated on the productivity spillovers of FDI, ignoring the innovation

particularly so for the EMDEs. Further, the existing studies mostly overlook the innovation spillovers of FDI for firms located in specified geographical clusters. This study is a sincere attempt to address these issues in the context of Indian manufacturing firms.

Chapter 3 examines the two-way relationship between innovation and the productivity of Indian manufacturing firms. Using data from 347 patenting Indian manufacturing firms for the period 2005-2020, this chapter examines (i) if firms' productivity significantly determines the innovation output of Indian manufacturing firms; (ii)if innovation significantly improves the productivity of the Indian manufacturing firms and (iii) if innovation would make the Indian manufacturing firms more productive than their non-innovative counterparts. The empirical framework of the chapter uses patent counts as the innovation indicator and measures productivity using the semi-parametric method developed by Ackerberg, Caves, and Frazer (ACF) (2015). The innovation equation with patent counts as the dependent variable is estimated using the negative-binomial estimation. On the other hand, the productivity equation is estimated using the quantile regression analysis. In order to empirically evaluate the observed differences between the innovative and non-innovative firms, we use the propensity score matching (PSM) method. Further, we use the generalised method of moment (GMM) estimation to verify the robustness of the empirical results obtained. The sensitivity of the empirical estimates is also verified by using the lags of the dependent and explanatory variables and re-calculating the productivity measure with the Levinsohn and Petrin (2003) method.
Key findings: The econometric results find a positive effect of firms' productivity on their innovation output. The representative sample also shows that innovation in individual firms improves their productivity. Furthermore, the empirical results confirm that innovative firms are significantly more productive than non-innovative ones. The estimated coefficients provide conclusive evidence that productivity has a greater impact on determining innovation output compared to the impact of innovation on determining productivity levels. This leverages the idea that India's innovation policy should first prioritise productivity-linked incentive schemes. Additionally, we find that R&D expenditures are not a significant driver of innovation in Indian manufacturing firms. Rather, older firms and firms recruiting more labourers are significantly innovating more. This finding re-establishes the notion discussed in the literature that R&D expenditures are not the primary driver of innovation output in the EMDEs. It also confirms that Indian manufacturing firms mostly rely on older and experienced firms for technological upgradation. The positive significance of the labour input reaffirms the labour-intensive nature of innovation in the context of India.

Chapter 4 investigates the impact of process and product innovation on the employment generation of Indian manufacturing firms under a dynamic empirical framework. To this end, the chapter delves into empirically estimating (i) the employment effects of process and product innovation on the Indian manufacturing firms and (ii) the employment effects of process and product innovation of the foreign firms vis-à-vis the domestic firms. Based on the availability of employment data, the econometric analysis of this chapter uses information from 169 Indian patenting manufacturing firms from 2005 to 2020. The empirical specification of this chapter uses the number of employees a firm hires each year as the dependent variable. The process and product innovation are proxied using the counts of process and product patents granted to the sampled firms. The empirical model is estimated using the OLS and GMM method. In an extension of the empirical results obtained, the trend analysis of manufacturing employment in India showed that the number of people employed in Indian manufacturing firms took an abrupt upward turn between 2011-12. We observe a corresponding substantial increase in the foreign equity inflow into the Indian manufacturing sector during the financial year ending 2011. This led to the obvious question of whether the abrupt rise in the employment generated by the Indian manufacturing sector during 2011-12 could be attributed to the infusion of foreign capital inflow during the financial year ending in 2011. To empirically evaluate this, we use a difference-in-difference estimation.

Key Findings: The empirical results reveal that the process and product innovations in Indian manufacturing firms significantly displace labour. The sub-sample analysis of the domestic and foreign firms validates that this labour displacement effect of process and product innovation is specific to domestic firms only, and foreign firms do not significantly impact the labour market owing to process and product innovation. Nevertheless, the results confirm that foreign firms, unlike domestic firms, at the least, do not significantly displace labour due to process and product innovation. This tailors the policy question of whether a heterogenous employment policy for domestic and foreign firms is necessary. However, the empirical results confirm that there is no significant difference in the employment generated by foreign firms compared to domestic firms, negating the requirement for heterogeneous policies for both types of firms.

Chapter 5 concentrates on the empirical estimation of the impact of horizontal and vertical FDI spillovers on the innovation output of Indian manufacturing firms, with a particular focus on the firms based in the major industrial clusters of the country. To this extent, this chapter investigates (i) the impact of FDI-generated horizontal and vertical innovation spillovers on the innovation output of Indian manufacturing firms (ii) the impact of FDI-generated horizontal and vertical spillovers on the innovation output of Indian manufacturing firms situated in the major industrial cluster of the country and (iii) the impact of 2014 FDI-liberalisations on the innovation output of foreign firms vis-à-vis the domestic firms. For this purpose, this chapter uses data from 347 Indian manufacturing firms from 2007 to 2020. We intend to conduct the study from 2005, based on the implementation of the Trade-Related Aspects of Intellectual Property Rights (TRIPS) norms. However, the input-output table for India is available only from 2007, limiting our study from 2007 to 2020. The empirical specification of this chapter uses patent counts as the dependent variable. However, for the econometric investigation of the 2014 FDI liberalisation policies on the innovation output, we have considered patents applied instead of patents granted. This decision is guided by the fact that granting a patent involves gestation periods (usually 3-6 years in India). This implies that the patents granted in 2015 or 2016 were actually applied a few years back, before the implementation of the policy liberalisation. Hence, using patents granted will not reflect the true impact of the decisions of the foreign firms. The key explanatory variables of the chapter are the spillover variables, which are calculated using the method described in Blalock and Gertler (2008). The variable geographical cluster enters the model as a dichotomous variable, taking the value of one if the firm is registered with a city that falls in one of the eight major industrial belts of the country and zero otherwise. This chapter focuses on an empirical investigation of the impact of FDI spillovers generated within these clusters on the innovation output of the sampled firms. For this purpose, we interact the location variable with the horizontal and vertical spillover variables. The econometric specification in this chapter uses a negative binomial regression model. Following prior empirical literature (Drakos & Gofas, 2006; Shkolnykova & Kudic, 2022), we include the lagged value of the dependent variable to verify the sensitivity of the analysis. The robustness of the results obtained from the negative binomial estimation is checked using the GMM method. Further, to estimate the policy impact of the FDI policy liberalisations, a difference-in-difference regression model is used.

Key findings: The econometric findings provide evidence that FDI-generated horizontal and vertical spillovers do not significantly impact the innovation output of Indian manufacturing firms. We identify firms' lack of absorptive capacity in the form of an insignificant R&D intensity as one of the key reasons for such insignificance. However, the analysis finds robust evidence that FDI-generated horizontal spillovers positively impact the innovation output of firms located in major industrial clusters. In this line, the empirical findings further show that firms located in the major industrial cluster of the country which engage in R&D are able to draw the benefits of horizontal spillovers. In other words, the results reveal that firms located in the major industrial cluster of the country and investing in R&D experience higher innovations through horizontal spillovers. This re-establishes the importance of R&D spending in absorbing foreign technology. In addition, empirical estimates of the control variables uniformly establish that exporting firms negatively influence the innovation output. Further empirical findings provide robust evidence that exporting firms negatively influence innovation output through vertical linkages. On the contrary, the entry of foreign firms in similar industries increases the innovation output of exporting firms through intra-industry linkages. In other words, firms that export intensely are likely to innovate more through horizontal linkages. Finally, the results from the control variable show that Indian manufacturing firms that employ more labour significantly innovate more. Finally, the result from the difference-in-difference analysis shows that foreign firms have been significantly innovating more than domestic firms in the post- FDI policy liberalisation period than in the pre-liberalisation period.

Chapter 6 is the last chapter of the thesis. It summarises the chapters' conclusions and draws the relevant policy implications based on these conclusions. Further, an emphasis is placed on the limitations of the thesis, and the future scope of the research is discussed.

Chapter 2

Literature Review

Schumpeter (1939, 1942) is credited with bringing innovation to the centre stage of studies in economics. The immediate theoretical works following Schumpeter considered "innovation" or "technological change" as exogenously determined (Solow and Swan, 1956; Cass-Koopmans- Ramsey, 1965). However, letting "technological change" be exogenously determined left the reality of economic growth unexplained. This issue is addressed by the endogenous growth models in the works of Lucas (1988) and Romer (1990), who theorised "technological progress" and "productivity growth" as endogenous. Aghion and Howitt (1992) provided further manifestations of this dynamics.

2.1 Instrumenting Innovation

On the empirical ground, with the growth of theories explaining innovation or technological change as exogenous, a parallel empirical literature was growing exploring a suitable proxy to measure innovation output (Pakes and Griliches, 1987; Freeman,1994; Griliches, 1998). Innovation is a subjective concept. Therefore, how to precisely measure innovation is an important empirical question.

An attempt to develop an innovation indicator has briefly resulted in three types of innovation proxies. First, research and development (R&D) expenditure is used as an instrument of innovation input. In this respect, the most commonly used proxies are R&D intensity (Akcomak and Weel, 2009; Hassan and Tucci, 2010; Garcia-Manjon and Romero-Merino, 2012) and R&D expenditures per researcher (Cainelli et al., 2006; Pradhan et al., 2016). However, the Jones Critique (1995) states that increasing R&D expenditures and increasing numbers of scientists and engineers are associated with constant total factor productivity (TFP) generation. In response, Aghion et al. (1998) and Howitt (1999) advocated using R&D intensity (R&D as a fraction of GDP or sales) while discussing Schumpeterian growth models. Second, patent counts are used as an intermediate measure of innovation output. In the literature, patent applications have commonly been used as a proxy for innovation (Crosby, 2000; Di Mauro et al., 2020; Damioli et al., 2021). However, an inherent limitation of patent applications is that they may capture spurious and contrived applications (Garcia et al., 2013).Therefore, many studies use counts of patent grants to measure innovation (Hu et al., 2017; Fink et al., 2021; Lo et al.,2023). Third, new product sales are a direct output measure of innovation (Hou et al., 2019; Guo et al., 2022; Chen and Zhou, 2023). However, these data are limited. This information is available only for the European countries and China.[5]

2.1.1 R&D as an input measure of innovation

The understanding of the economy during the 1950s and 1960s advanced R&D expenditure as a proxy for innovation (Mansfield, 1980; Acs et al., 2002). In fact, some recent studies also use R&D to proxy innovation (Audretschet al., 2014; Pellegrino et al., 2019; Barbieri et al., 2019). However, during the 1970s, advances were made to use patent data as a proxy for innovation output. It brought the appropriateness of R&D as a proxy for innovation increasingly under fire.

R&D expenditure as a proxy for innovation has certain limitations. First, the literature treats R&D expenditure only as an input to the innovation process. R&D says nothing about the "output" side of the innovation, i.e. the real introduction of new products, services and processes into commercial use. Second, not all R&D expenditures translate into successful innovation. R&D expenditures measure only the budgeted resources allocated towards trying to produce innovative activity. R&D is rather a surrogate measure reflecting the importance of many activities contributing to innovative success and growth (Freeman, 1994). According to Freeman (1994), success with innovation depends on many other factors besides R&D, such as external relationships, training and design, development, production and marketing functions within the firm, general management quality, etc. Third, many firms do not report R&D expenditure (Bound et al., 1987).

Using R&D as a measure of innovation poses special issues while studying a developing country like India. Wadho and Chaudhry (2018) point out that in developing countries, firms generally generate technological advances outside the formal R&D process, such as by acquiring embedded technology through the purchase of machinery, hardware, licensing, payment of royalty, etc. In such cases, formal R&D fails to capture the true extent of innovative efforts in such countries.

2.1.2 Patents as an intermediate output measure of innovation

The literature on innovation suggests that patents are a "classic instrument for incentivizing and measuring innovation" (Sweet and Eterovic, 2019). Patent data has certain advantages over R&D data as a proxy for innovation. First, patents provide a fairly good, although not perfect representation of (intermediate) innovation output (Acs et al., 2002). They are unique and

[5] For details, see Kleinknecht et al., 2002

highly visible methods of technological progress or innovation (Furman et al., 2002). Patents are considered a quantitative indicator of innovation, showing only minor disturbances due to occasional changes in patent laws (Kleinknecht et al., 2002). Second, as against R&D expenditures, patents are a confirmed source of disclosure of an invention, checked and verified by specialists. In fact, the criteria behind the patentability of any invention are its utility (industrial application), novelty and non-obviousness (inventive step) (Encaoua et al., 2006). Third, as public documents, patent data are available for a longer period, richer and more detailed than R&D data. The literature recognises patent data as the most easily accessible indicator of the number of inventions made by a firm (Pakes and Griliches, 1987). Lach (1995), in his work, found that R&D explains only 9 per cent of the contribution of knowledge to productivity changes at the industry level. As against this, patents explain the contribution of knowledge to productivity changes by 30 per cent.

Patents appear to be a better instrument of innovation from the perspective of policy formulation as well. The evolutionary school of economics (Nelson and Winter, 1982) argues that innovation amounts to knowledge creation, which is a public good. As public goods, knowledge creation or innovation is non-rival and non-excludable in nature and is susceptible to market failure. According to Encaoua et al. (2006), measuring innovation using R&D may create a market failure-like situation for public goods. They maintain that under the condition of perfect competition in the product market, innovators fail to recover their costs in terms of R&D investments. Moreover, these R&D-backed goods and services can be produced and distributed at a lower marginal cost if not protected. This would create a market failure-like situation for public goods, reducing the investment incentive. Further, Encaoua et al. (2006) put forward that patents have generally been considered a valid policy instrument to overcome such market failure. Patents impose a legal exclusivity on the use of knowledge, making it rival and giving the innovator the right to make it excludable. Thus, by providing some temporary exclusionary rights to the innovator, the government passes on R&D decisions and makes the inventor responsible for recovering his R&D investments.

Nevertheless, patents are also not a perfect measure of innovation output. The major point of criticism with patent data is that not all inventions are patentable and that not all inventions are patented. It has also been pointed out that not all patented inventions are actually implemented in market applications. Hence, it may not reflect the actual value of innovation. Pakes and Griliches (1987) have drawn significant conclusions to this extent. Using US patent information for 121 firms for eight years (1968-75), they have established that patents are more related to innovation output than R&D. Hence, it would be safe to say that despite being a noisy and imperfect measure of innovation, patents have been established as accepted for studying innovation and are closely related to essential inventions (Griliches, 1998; Aghion et al., 2009; Luo et al., 2022). Considering this, we treat R&D expenditure as a partial innovation measure and use patent counts to capture innovation behaviour.

A major point of criticism with using patent data to proxy innovation is that patents reflect inventions only and not innovations. Invention necessarily reflects the development of new ideas, whereas innovation reflects the development of commercially viable products or services from creative ideas. Invention is measured by the number of patents granted, and innovation is assessed by the number of new product announcements. However, Artz et al. (2010) point out that patents can be used to measure innovation as many inventions ultimately result in marketable innovations, and patents provide protection for new products. Their econometric evidences provide a positive and significant relationship between patents and product announcements, justifying the use of patents for innovation.

Another question that persists with using patent information to measure innovation is whether patent-based indicators could still be a reliable measure of innovativeness in the event of changes in the field of intellectual property protection and regulatory reforms. Santarelli and Lotti (2008) have taken up this question using a sample from Italian biotechnology firms. They conclude that patents represent an outcome of the production process, and their number could be taken as a measure of a firm's ability to improve its productivity growth and profitability.

No doubt, a direct measure of innovation, such as the market introduction of a new product or service as provided by the Community Innovation Survey (CIS) in the European countries, would have been a better measure. However, this data is not available for India. Therefore, patents appear to be the second-best solution to the issue of instrumenting innovation for empirical research, especially in India, where direct sales data from new products launched is not available.

2.2 The Case of Emerging Markets and Developing Economies in the Innovation Literature

While developed countries have been extensively discussed in the innovation literature in the context of patenting, emerging markets and developing economies (EMDE) remain broadly unexplored. The emerging economies differ in different dimensions with respect to their peers in developed nations. Acemoglu et al. (2006) point out that countries at an early stage of development pursue an investment-based strategy, relying on existing firms and managers to maximise investment. On the other hand, countries closer to the world technology frontier adopt a selection-based strategy with short-term relations, younger firms, fewer investments and better selection. Hence, we can safely say that the implication of innovation in technologically advanced developed economies cannot be drawn to technologically distant developing economies.

However, an analysis of the existing patent literature reveals a heavily skewed emphasis on the developed economies, grossly ignoring the EMDEs. The present work tries to fill this gap in the research on EMDEs with characteristics fundamentally different from those of heavily studied advanced economies. For a deeper understanding of the impact of innovation on firm performance, employment generation, and externality generation, we present an overview of the existing literature in this chapter.

2.3 Innovation and Firm Performance

This section of the study quintessentially draws from two strands of literature. The first is the neo-classical and endogenous growth models, which believe that innovation improves firms' performance (Aghion and Howitt, 1992; Aghion et al., 1998). The second one arises from the idea that innovation is essentially a costly, risky and uncertain venture. Hence, firms' innovative behaviour may be skewed towards firms with a competitive edge (Schumpeter, 1942). This view supports the findings of Schmookler (1966), who finds that output cycles precede innovation.

2.3.1 Innovation as a determining factor of firms' performance

Empirical exploration into the literature that uses patent data to measure innovation and treats innovation as the determinant factor of firms' performance gives us a number of macro studies such as Park and Giarthe (1997), Akcomak and Weel (2009), Hassan and Tucci (2010), Hu and Png (2013), Pradhan et al. (2016), Damioli et al. (2021), Gonzales (2023) and Parteka and Kordalska (2023).

Park and Giarthe (1997) constructed an intellectual property rights (IPR) protection index for 60 countries. They found that IPRs affect economic growth indirectly by stimulating the accumulation of factor inputs like R&D and physical capital. Akcomak and Weel (2009) used both R&D intensity and patent applications per million inhabitants to measure innovation in their sample of 102 European regions. They found that higher innovation performance was conducive to per capita income growth and social capital affected this growth indirectly by fostering innovation. Hassan and Tucci (2010) also used both R&D intensity and patent counts to measure innovation. Their findings revealed that countries hosting firms of higher quality achieved higher economic growth. Further, their empirical estimation provided evidence that countries with increasing levels of patenting activities had been experiencing concomitant increases in economic growth. Hu and Png (2013) studied the impact of changes in effective patent rights of 54 manufacturing industries in up to 72 countries. They constructed an effective patent rights index based on the Park and Giarthe (1997) index and interacted with patent intensity to obtain their innovation index. Their study discovered that faster industrial growth was associated with stronger patent rights. Similarly, Pradhan et al. (2016) used a sample of 18 European countries and used both patents and R&D information to measure innovation. They concluded that the development of the financial sector and enhanced innovative capacity in the Eurozone had contributed to long-term economic growth. Damioli et al. (2021) used patent application data and found that both AI and non-AI patent applications generated an extra-positive effect on companies' labour productivity across the globe. In the same line, Gonzales (2023), in his cross-country study, found that AI patents positively impacted economic growth. This influence was more robust for the developed countries. Similarly, Parteka and Kordalska (2023) used AI (Artificial Intelligence) patent applications as an innovation indicator for the OECD countries. However, their empirical findings indicated a lack of a strong relationship between AI patents and macroeconomic productivity growth in the OECD (Organisation of Economic Co-operation and Development) countries.

Nevertheless, the relationship between innovation and economic growth is complex, and country-specific characteristics play an important role in fostering innovation and productivity (Mtar and Belazreg, 2021). Micro studies establishing innovation as a determinant factor of firm performance or growth using patent data are predominantly researched in developed high-income countries only. At a micro level, firm-level panel studies have been conducted by Bloom and Van Reenen (2002) for UK, Gu and Tang (2004) for Canada, Cainelli et al. (2006) for Italy, Coad and Rao (2008) for US, Chen and Yang (2005) for Taiwan, Santarelli and Lotti (2008) for Italy, Evangelista and Vezzani (2012) for Italy, Bedford et al. (2022) for Australia and Entezarkheir and Sen (2023) for US. Besides, a series of work has been done by Hu et al. (2017), Di Mauro et al. (2020), Fang et al. (2020), Luo et al. (2022), Xu and Guan (2023), Lo et al. (2023) and Du et al. (2023) for China and.[6] These findings are complemented by the time series studies of Crosby (2000) for Australia, Goel and Ram (2008) for the US, and the industry-level study of Zachariadis (2003) for the US.

Using patent stocks and citation-weighted patent stocks as indicators of innovation, Bloom and Van Reenen (2002) found that patents have an economically and statistically significant impact on the productivity of UK firms. For a study of 15 manufacturing industries

[6] Although China is considered a developing economy, we are placing China in the group of developed economies as it is the second largest patents producing country after US

in Canada, Gu and Tang (2004) constructed an innovation index using R&D, patents, technology adoption and skills information data. They found that their measure of innovation had a positive and significant impact on labour productivity. Cainelli et al. (2006)used CIS data for the services firms in Italy. Their empirical work provided evidence that innovation positively impacted the performance of Italian service firms. Chen and Yang (2005) used patents as an output measure of innovation for 279 listed manufacturing firms in Taiwan. They found a positive and significant relationship between patents and productivity. In another study, Coad and Rao (2008) constructed their own innovation index by using patent applications and R&D data for US high-technology firms. They observed that innovation is of great importance for the fastest-growing firms as compared to the average firms. Santarelli and Lotti (2008) used patent information for Italian biotechnology firms. They found a statistically significant relationship between patents with the European Patent Office and both productivity growth and, in particular, profitability. Another study with respect to Italy was done by Evangelista and Vezzani (2012), who used dichotomous indicators from the CIS to measure innovation. They concluded that firm innovations are strongly associated with growth turnovers in the Italian manufacturing and services sectors. Bedford et al. (2022) used both stock of patent applications and patents granted to measure innovation and concluded that patented inventions were vital in driving sales performance among Australian firms. In a recent study, Entezarkheir and Sen (2023) used citation-weighted patent stocks and found that patent stocks positively and significantly affected the labour productivity of US publicly traded manufacturing firms.

Among the works done for China, Hu et al. (2017) used legally active patent counts as an innovation indicator and found that invention patents are positively related to labour productivity. However, the magnitude of this effect is very small. Their econometric evidence showed no significant impact of utility patents on labour productivity. In the same strand, Di Mauro et al. (2020) found that innovation, measured in terms of patents applied, is very weakly correlated with the productivity growth of Chinese manufacturing firms. They also found evidence that competitors' innovation negatively affects the growth of Chinese firms. Fang et al. (2020) found that higher levels of patenting increased firms' productivity. They also noticed strong persistence in the patent behaviour of the Chinese firms. In a recent study done in the context of Chinese manufacturing firms, Lo et al. (2023) found the total factor productivity of Chinese manufacturing firms with digital technology patents to be significantly higher than that of firms without digital technology patents. In another latest contribution to this strand of literature, Xu and Guan (2023) used counts of patents applied as the innovation indicator and found that blockchain innovation activities could improve the total factor productivity of Chinese manufacturing enterprises and leasing and business service enterprises.

In a different type of study, Luo et al. (2022) used invention patents, utility patents and design patent information to study the impact of heterogenous inventions on the green productivity of Chinese cities. They found that invention and design patents significantly promoted urban green productivity in China over the study period, while utility patents negatively affected it. Similarly, Du et al. (2023) used energy patent stock data for 30 provinces of China and found energy technology to be of great importance to total factor energy efficiency.

2.3.2 Firms' performance as a determining factor of innovation

In his seminal contribution, Schumpeter (1942) raises the issue that the increasing scientific base of economic activities leads to an equilibrium attained by 'an extremely costly method' with 'cutthroat competition or simply by struggles for control in the financial sphere'. There is no denying the centrifugal role that exogenously determined scientific discoveries and advances play in technological innovation and growth at the firm level. But these scientific discoveries are pretty prolonged, indivisible and expensive. Funding such risky projects requires ex-ante capital and efficient, productive inputs. Based on this, a meagre strand of literature has emerged that depicts firms' performance as a determining factor for innovation (Crepon et al., 1998; Li and Lin, 2016; Fang, 2020).

Crepon et al. (1998) used patent applications and innovative sales data to measure innovation. They found that firms correlate positively with a high innovation output. Cainelli et al. (2006) used CIS data for Italy and concluded that better-performing firms are more likely to innovate. Li and Lin (2016) used granted patent applications to measure innovation in 30 Chinese provinces. They found economic growth and R&D activities to be the driving force of energy patents. Similarly, Fang (2020) used patent data for Chinese firms and concluded that past firm performances significantly affect the current levels of patenting activity.

2.3.3 Studies in emerging market and developing economies

However, all these studies are done in the context of developed economies with a well-developed financial, managerial and technological infrastructure. However, EMDEs like India differ in various characteristics from those of the heavily studied advanced economies (Burhan et al., 2017). Developing countries are further away from the world's technological frontier than developed economies. Therefore, the implication of innovation in technologically advanced developed economies cannot be drawn to technologically distant developing economies.

However, we encounter very few EMDEs that are studied with respect to innovation and firms' performance using patent data (Ambrammal and Sharma (2016) for India; Fink et al. (2021) for Chile). This is surprising as the impact of innovation on productivity is found to be larger in developing countries as compared to developed countries (Dabla-Norris et al., 2012).

Amongst the studies investigating the link between innovation and firms' performance in the EMDEs economies, Chudnovsky et al. (2006) was one of the earliest ones done for Argentinian firms. However, they used input measures of innovation in the form of R&D, Technology acquisition and total innovation expenditure and concluded that innovators attained higher productivity levels than non-innovators. Aboal and Garda (2016) used both innovation input (Innovation expenditures, R&D, Machinery acquisition, Other innovation activities) and innovation output (turnover from product innovations, turnover from new-to-market product innovations) indicators and concluded that both technological and non-technological innovations were positively associated to productivity gains in services firms in Uruguay. However, whereas non-technological innovations were found to have a more important role for service firms, technological innovations were found to be more relevant to the productivity of manufacturing firms. Similarly, Santi and Santoleri (2017) used dichotomous indicators for process and product innovation in formal business enterprises in Chile. They found that process innovation positively affected firms' growth in the upper quantile. They found product innovation to be insignificant for firm growth.

Azad et al. (2018) found that the gains in productivity of Bangladeshi pharmaceutical firms with process patents were entirely due to technological advancements. In a study done for firms in Turkey, Dalgıç et al. (2018) used binary indicator variables for innovation output. They found that all types of innovation activity positively affected firms' productivity compared with non-innovating firms. Wadho and Chaudhry (2018) were probably the only studies that used a direct indicator to measure innovation in the form of innovation sales by collecting data from 377 textile and wearing apparel manufacturers from Pakistan. They found that product innovation led to increased labour productivity and higher productivity growth.

At the macro level, Dabla-Norris et al. (2012) used binary indicators for new products or new technology to measure innovation in both developed and developing countries. They found that innovation is crucial for firm performance in both developed and developing countries. However, their econometric pieces of evidence led to the conclusion that the impact of innovation on productivity was larger in developing countries. Similarly, Ramadani et al. (2019) studied the innovation behaviour of the transition economies using binary indicator variables for product, marketing, organisational, R&D investment and patents/trademarks applied. They found that product innovation had a positive impact on firm performance in the transition economies.

However, none of these studies has used patent counts to measure innovation. They have either used input measures or binary indicators to capture innovation. The limitations associated with using input measures of innovation are already described in the previous section. On the other hand, the use of binary indicators to describe innovation i.e. whether innovation takes place or not, makes it difficult to quantify the effect of heterogenous innovation intensity. This type of binary indicator fails to provide the actual number of innovations the firm achieves. They confirm only the existence of at least one innovation, which is likely to encompass a size bias.

To the best of our knowledge, Ambrammal and Sharma (2016) for India and Fink et al. (2021) for Chile are the only studies using patent data in the context of innovation and firms' performance. Ambrammal and Sharma (2016) took a sample from Indian high-tech and medium high-tech firms and found that patenting positively affected the productivity of the firms. Fink et al. (2021) argued that patents had not played much role in Chile's rapid economic growth. However, they acknowledged the fact that the small number of firms that had used patents had been amongst the fastest-growing firms.

2.3.4 Gaps identified

A brief discussion of the existing literature demonstrates serious gaps which need to be addressed. Firms in developing countries are experiencing a constantly changing landscape in the event of increasing global competitiveness. In such a situation, firms need to invest in technology and introduce improved products in the market. However, the understanding of innovation and its interlinkages with firms' performance is still limited when it comes to the EMDEs. Also, most of these researches have employed input data of innovation or used binary indicators for innovation, which have more limitations than patent data (see section 2.1.2).

Further, an in-depth analysis of the existing mainstream literature also clarifies that, whereas the impact of innovation on firms' performance is somewhat verified empirically, the literature unacceptably ignores the fact that the performance of individual firms may also determine innovation in them. This is especially so in the case of EMDEs, where firms are constrained by limited resources along with institutional and knowledge barriers, which may pull down any innovation efforts. Under such circumstances, it is pertinent for policymakers to address whether improving firms' productivity is something that needs to be addressed to infuse innovation in the firms of EMDEs. However, to the best of our knowledge, this question still remains unanswered with respect to the EMDEs.

This study adds to the existing literature by utilizing a holistic empirical model to study the nexus between innovation and firms' performance in Indian manufacturing firms. This study is closely related to the study done by Ambrammal and Sharma (2016) for Indian manufacturing firms. However, their empirical strategy concentrates solely on determining the role of innovation on firms' performance and not the other way around. Moreover, their sample uses only high- and medium-high-technology firms, giving a rather partial overview. As against this, the present study takes into account the complementary nature of innovation and firms' performance, using a sample of all the manufacturing firms in India.

2.4 Innovation and Employment

This section of the study draws from the compensation mechanism, which states the diversified impact of process and product innovation on the labour market. Process innovation refers to producing the same output with fewer factors of production via enhanced productivity. It leads the firms to produce the same amount of goods at lower costs. If this cost advantage is translated into the product's price, process innovation would positively affect employment (Hall et al., 2008; Lachenmaier and Rottman, 2011). If not, firms would produce the same output with less labour inputs (Dachs et al., 2014; Dosi and Yu, 2019).

On the other hand, product innovation refers to the diffusion of new technology. Product innovation creates a new stream of demand, opening avenues for additional labour absorption (Hou et al., 2019; Woltjer et al., 2021). However, it may also happen that introducing a new product takes away the market from an existing product, leading to labour displacement (Zhu et al., 2021).

On the basis of the approaches adopted to look into the synergism of innovation and employment, we can categorise the existing literature under three heads. The first one, initiated by Jaumandreu (2003) and further developed by Harrison et al. (2014), looks into innovation in output terms and considers new product sales or significantly improved production processes as an innovation proxy. The second approach frames a static model to capture the impact of innovation on the labour market. The third approach, initiated by Van Reenen (1997), uses a dynamic model to study the interaction between innovation and employment. However, he did not distinguish between process and product innovation. Later, Rottmann and Ruschinski (1998) used the dynamic approach and clearly distinguished process and product innovation using dyadic indicators.

2.4.1 The Harrison model

Literature has extensively used the model proposed by Harrison et al. (2014). They used a dichotomous instrument for process innovations and observed sales growth rate due to new products as a proxy for product innovation in their study for the firms in France, Germany, Spain and UK. Their results showed that process innovation had a labour displacement effect. However, this displacement effect tended to be compensated by the growth of old products via the price reduction mechanism. Product innovation, on the other hand, had a strong positive impact on employment growth. This framework was followed by studies such as Peters (2004) for Germany, Hall et al. (2008) for Italy, Dachs et al. (2014) for Europe, Hou et al. (2019) for France, Germany, Netherlands and China and Zhu et al. (2021) for China. These studies somehow corroborated the findings of Harrison et al. (2014) and found a labour-friendly effect of product innovation (Peter, 2004; Hall et al., 2008; Dachs et al., 2014; Hou et al., 2019) with the only exception of Zhu et al. (2021) who encountered a labour displacement effect of product innovation for China. However, the existing studies differ substantially in delineating the effect of process innovation on employment. Hall et al. (2008) and Hou et al. (2019) find that process innovation rarely impacts the labour market equilibrium. On the other hand, Hall et al. (2008) and Dachs et al. (2014) encountered labour displacement effects of process innovation, whereas Zhu et al. (2021) found labour-friendly effects of process innovation.

2.4.2 The static model

The second strata of literature can be diffused into three segments. All these segments use a static model. However, while the first segment uses R&D and related input expenditures to denote innovation, the second uses binary indicator variables, and the third uses patents to measure innovation without distinguishing between product and process innovation.

To the best of our knowledge, Brouwer et al. (1993) was one of the earliest to conduct the type of study relating to the first segment, using shares of product and process-related R&D from survey data from the Netherlands. They found that while R&D intensity exerted a labour-saving impact on the whole, product-related R&D entailed some labour-friendly impact. In recent times, Cirillo et al. (2017) and Barbieri et al. (2019) were some of the studies that followed this approach. Cirillo et al. (2017) used new product share and expenditure on new machinery to measure product and process innovation, respectively. This study found that while product innovation mainly benefitted the managers and technicians, process innovation negatively affected professional groups such as clerks, craft workers and manual workers. In a recent study, Barbieri et al. (2019) concluded that total innovation, measured through R&D and embodied technological expenditure, drove employment up in Italy.

Studies relating to the second segment of this approach used binary indicator variables, mostly from the CIS or through questionnaires. Some of the recent studies in this segment were done by Evangelista and Vezzani (2012) for five European countries and Herstad (2020) for Norway. Evangelista and Vezzani (2012) found a labour-friendly effect of product innovation. For process innovation, Evangelista and Vezzani (2012) encountered an insignificant association between the two. Herstad (2020), on the other hand, found that the combined effect of product and process innovation positively impacted employment growth.

Hall et al. (2013), Van Stel (2014) and Yang (2022) considered the patenting behaviour of firms to denote innovation. However, these studies did not distinguish between product and process innovation and, thus, gave a partial overview of the entire technology and labour market dynamism. Nevertheless, whereas Van Stel (2014) and Yang (2022) found a positive association of patents with employment, Hall et al. (2013) concluded that the patenting activity of firms had no impact on their employment growth.

2.4.3 The dynamic model

Both the aforementioned approaches, i.e., the model proposed by Harrison et al. (2014) and the static model ignore the dynamic aspect of innovation and labour market mechanism. On the other hand, employment adjustment is a dynamic process with high costs associated with hiring and firing labour along with other adjustment costs. Additionally, innovation is a dynamic process that lasts a long and persistent effect[7].

Van Reenen (1997) has long back dived into these issues and pioneered a dynamic analysis of the impact of innovation on employment. However, he did not distinguish between product and process innovation and found overall technological progress, measured in patents, to be instrumental in job creation. Following the study of Van Reenen (1997), Rottmann and Ruschinski (1998) presented their study from a dynamic angle by using dichotomous variables from German manufacturing firms as indicators of product and process innovation. They confirmed a positive impact of product innovation on the labour market, with process innovation having no influence on employment generation.

[7] For details, see Van Reenen (1997)

However, the studies that have considered the dynamic nature of the labour market have used either innovation inputs or binary indicators as proxies of innovation. Accordingly, we categorise them into three segments based on the type of innovation proxy used.

The first segment used R&D and other input variables to measure innovation in a dynamic set-up without distinguishing between product and process innovation. Some of the latest studies done in this line are Bogliacino et al. (2012) and Piva and Vivarelli (2017) for Europe, Pellegrino et al. (2019) for Spain and Aldieri et al. (2021) for Finland. A close look into this literature showed that studies undertaken using input variables as a proxy for innovation generally found a labour-friendly effect of R&D (Bogliacino et al., 2012; Pellegrino et al., 2019; Aldieri et al., 2020). This job-creating effect is more specific to high-skilled employees (Aldieri et al.,2020) and high-tech industries (Bogliacino et al., 2012; Pellegrino et al., 2019).

The second segment used dichotomous variables to measure product and process innovation in a dynamic setting. Followed by Rottmann and Ruschinski (1998), Garcia et al. (2004) for Spain and Bianchini and Pellegrino (2019) for Spain adopted this approach. Whereas Garcia et al. (2004) found that both product and process innovation generated employment, Bianchini and Pellegrino (2019) found only product innovation to be effective for sustainable employment generation and process innovation to be irrelevant.

Finally, the third segment went beyond the input variables of innovation and measured innovation using intermediate innovation output in the form of patents. However, these studies did not bifurcate the effects of product and process innovation, giving a partial picture of the entire dynamism. Amongst them, Coad and Rao (2011) for US, Piva and Vivarelli (2017) for Europe, and Pellegrino et al. (2019) for Spain concluded patenting to be labour-friendly, particularly for high-tech employment. On the other hand, Dosi and Yu (2019) found that patenting activities generated employment only in selected manufacturing sectors and not all. Contrary to this, Van Roy et al. (2018) found that innovation did not impact overall manufacturing employment.

Another variant of this study used patent data and distinguished between product and process innovation. However, they used binary variables, which captured merely the existence of a patent and not their actual counts. To the best of our knowledge, Lachenmaier and Rottmann (2011) for Germany is the only study that has bifurcated product and process innovation based on binary patent data. They used three indicators for product and process innovation from the Ifo innovation survey. The first measure was a dichotomous variable for any product and process innovations being introduced, the second was a dichotomous variable for any patents being filed for product and process innovations, and the third was innovation expenditure (expenditure on R&D, licenses, patenting and other costs). Their empirical framework showed that both product and process innovation created jobs in the German manufacturing sector.

2.4.4 Innovation and employment growth in foreign-owned vs. domestically-owned firms

The foreign-owned and domestically-owned firms differ substantially regarding successful product and process innovation. The foreign-owned firms possess superior technology and management (Aitken and Harrison, 1999; Crespo and Fontoura, 2007; Anwar and Sun, 2014). They have better distribution networks and access to wider markets than domestically-owned firms. These firms also benefit from the learning experiences of the parent company and intra-firm networking with the subsidiaries of the parent multinational company in other countries (Guo et al.,2022; Chen and Zhou, 2023). When it comes to attenuating risks, foreign-owned firms can spread it over larger projects via multinational collaborations. Multinational collaborations also facilitate access to external funds for risky ventures and a higher degree of specialisation of skilled workers. Thus, clearly, foreign-owned firms have an edge in terms of the adoption of knowledge and technology compared to domestic-owned firms.

The above also makes it clear that foreign-owned firms enjoy more market power than their domestic counterparts. Differences in market power are reflected in the differences in the price-setting behaviour between the two groups of firms, which would eventually impact the employment generation capability of the firms. Studies reflecting the impact of the ownership structure of firms on their employment capabilities are quite sparse and rare. To this end, Dachs and Peters (2014) is the only study that has systematically evaluated the impact of process and product innovation on the employment growth of 16 European countries using the Harrison et al. (2014) model. They found that process innovation displaced more labour in foreign-owned than domestically-owned firms. In contrast, product innovation created more jobs in foreign-owned firms. However, they found the net employment growth to be smaller for foreign-owned firms.

2.4.5 Studies in emerging markets and developing countries

An extensive review of the existing literature makes it clear that the studies integrating technology with the labour market are highly skewed towards the developed nations. This is surprising as the developing countries are the ones which have been facing the dilemma of absorbing their surplus labour into the workforce while upgrading their traditional industrial sector to keep up at the global frontier. Even after that, studies linking technology with the labour market in the EMDEs started capturing the attention of empirical economists only recently.

Following the Harrison et al. (2014) model, the labour-friendly impact of product innovation had been confirmed by Monge-González (2011) for Costa Rica, Elejalde et al. (2015) for the Sub Saharan African countries, Crespi et al. (2019) for Argentina, Chile, Costa Rica and Uruguay, Avenyo et al. (2019) for the Sub Saharan African countries and Cirera and Sabetti (2019) for a global sample of developing countries. On the other hand, Monge-González (2011) and Crespi et al. (2019) (only for Costa Rica) found that process innovation created more jobs. In contrast, Crespi et al. (2019) found that process innovation displaced labour in Uruguay. Further, Elejalde et al. (2015), Crespi et al. (2019) (for Argentina and Chili), and Cirera and Sabetti (2019) concluded that process innovation did not significantly impact the labour market.

Using the static framework, Alvarez et al. (2011) for Chile, Aboal et al. (2015) for Uruguay, and Baffour et al. (2020) for Ghana found a labour-friendly impact of product innovation on employment generation. Merikull (2010) found that process innovation created jobs in Estonian firms. Contrarily, Aboal et al. (2015) found that process innovation displaced unskilled labour. Alvarez et al. (2011) and Baffour et al. (2020) found process innovation to be insignificant for employment generation.

With reference to the differentiated impact of foreign-owned and domestically-owned firms on employment generation due to differentiated innovation capabilities, no systematic study could be found for the EMDEs. The only research that exists in this regard, viz. Dachs and Peters (2014) have used a static framework, ignoring the sticky nature of the labour market. Thus, a comprehensive review of the existing literature integrating process and product innovation with the labour market of EMDEs clearly points out that almost all the studies have ignored the dynamic nature of innovation and the labour market. Also, innovation is instrumented in these studies either with a dyadic variable, making it difficult to quantify innovation, or with an input variable, giving only a partial picture of the entire process. We append to this set of studies by introducing the dynamic aspect of innovation while considering the heterogeneous quantity of innovation in the context of an EMDE by drawing samples from Indian manufacturing firms.

2.4.6 Gaps identified

Thus, careful due diligence makes it clear that EMDE countries have scarce empirical evidence linking technology and the labour market. Additionally, none of the existing studies in the EMDEs consider the dynamic nature of this nexus. The innovation indicators used are also either dichotomous, making it difficult to quantify innovation, or an input variable, giving only a partial picture of the entire process. We contribute to this set of studies by introducing the dynamic aspect of product and process innovation while considering the heterogeneous quantity of innovation across firms. We also use a more reliable instrument of innovation in the form of actual patent counts while carefully categorising them as product and process patents.

Our work is closely related to the works of Lachenmaier and Rottmann (2011). However, we use actual patent counts instead of binary indicators measuring the mere existence of a patent. The use of binary indicators makes it difficult to quantify the effects of heterogeneous innovation intensity. We segregate the product and process patents based on their standard definition. Accordingly, patents directed to creating a new product are categorised as product patents and patents directed towards significant improvement in the production process are categorised as process innovation.[8] Further, drawing inspiration from the works of Dachs and Peters (2014), we address the question of whether foreign-owned firms are generating more employment than domestically-owned firms due to innovations. However, our work differs from the one done by Dachs and Peters (2014) as we use a dynamic framework in our study. Also, we make use of actual patent counts instead of dyadic variables, making it empirically possible to quantify innovation in the empirical model.

2.5 Innovation and Foreign Direct Investment Spillover

The literature on FDI and its spillover emanates from the belief that foreign multinationals possess superior technology and management than domestic incumbents (Aitken and Harrison, 1999; Crespo and Fontoura, 2007; Anwar and Sun, 2014). Once the multinationals cross their domestic border and invest in other countries, some of their technical and managerial know-how spills over to the local firms in the same industry and across the supplying industries. In economic literature, the former is known as intra-industry spillover or horizontal spillover, and the latter is known as inter-industry spillover.

[8] We are thankful to Mr. Pranjal Nath, patent analyst for helping us in segregating the patent data into product and process patents

The extant literature in the field of FDI spillover has explored the impact of inward FDI on local firms' productivity (Aitken and Harrison, 1999; Javorcik and Spatareanu, 2008; Goldar and Banga, 2020). Recent practice in this field has diverted this channel to investigate the impact of FDI spillover upon innovation. Although nascent, this set of literature has clearly identified that FDI spillovers have significantly different effects on firms' productivity and innovation output (Vahter, 2011; Alazzawi, 2012). Thus, while productivity spillovers stem from significant improvements in the factor inputs, innovation spillovers stem from investments in research and technology (Girma et al., 2009).

2.5.1 Inward FDI and innovation spillover

The present-day economies are knowledge-based economies. Technology plays an integral part in the policy-making of countries. With globalisation and the governments in emerging nations vigorously liberating their economy to attract foreign investments, empirical studies have tried to investigate the impact of inward FDI on the host country's innovation output. However, most of these studies are done in the context of developed countries.

Amongst the studies done taking samples from high-income developed nations, Kinoshita (2001) used firm-level R&D data from the Czech manufacturing sector. The study found that FDI would generate positive spillovers only when firms perform R&D. Crescenzi (2015) used binary indicators to measure innovation and found that the domestic firms in the UK which were active in sectors with greater investment by multinationals showed stronger innovative performance than the ones without investments by multinationals.

A series of studies have been done in this context for Chinese firms using new product sales as the innovation indicator (Liu and Buck, 2007; Girma et al., 2008; Girma et al., 2009; Guo et al., 2022; Chen and Zhou, 2023). In their empirical model, Liu and Buck (2007) showed that foreign R&D activities were an effective spillover channel for innovation only when indigenous Chinese firms had sufficient scientists and technicians who could learn from foreign firms. Similarly, Girma et al. (2008) found that FDI entry could augment the innovation of indigenous firms only when they have access to finance and are engaged in R&D activity. In another study, Girma et al. (2008) showed that state-owned enterprises with some foreign capital participation would innovate more subject to their own absorptive capacity. Similar conclusions had been drawn by Guo et al. (2022), who showed that local Chinese firms were required to build up their capabilities effectively to absorb FDI knowledge. On the other hand, Chen and Zhou (2023) concluded that FDI would encourage the entry of innovative entrepreneurs within a region.

A further important stream of literature related to inward FDI and innovation spillovers using patent data has been done by Aghion et al. (2009), Alazzawi (2012), Ascani and Gagliardi (2015) and Li et al. (2017). Drawing on a large longitudinal dataset of UK firms, Aghion et al. (2009) showed that the entry of technologically advanced firms would encourage innovation only in sectors close to the technological frontier. In contrast, Alazzawi (2012) found that both inward and outward FDI strongly and positively affected domestic innovation for technological followers in their cross-country analysis. In similar lines, the econometric results of Ascani and Gagliardi (2015), using firm-level data from Italy provided evidence that foreign investments would augment innovativeness in domestic firms and foreign disinvestments would negatively affect the innovative behaviour of domestic firms. Using Chinese firm-level data, Li et al. (2017) supported the preceding findings and concluded that FDI would generate positive spillovers in an industrially diverse setting.

However, the policy concern lies in the fact that the extant literature is quite ambiguous with respect to the impact of foreign entry on local firms. Whereas the preceding discussion focuses exclusively on the research which has reported a positive impact of foreign entry on local firms innovativeness, Aghion et al. (2009), Alazzawi (2012), Garcia et al. (2013), Li et al. (2017), Qu et al. (2017), Ascani et al. (2020) and Ning et al. (2023) have showed that FDI may also generate negative spillovers under specific circumstances. All of these studies use patent data except Qu et al. (2017), who have used binary indicators to measure innovation.

It is mentioned earlier that Aghion et al. (2009) discovered a positive innovation effect of entry of technologically advanced firms in sectors that were close to the technological frontier. As opposed to this, they found that entry of technologically advanced firms would discourage innovation in sectors which were behind the technological frontier. This might have serious implications for the EMDEs as they are structurally situated further away from the technological frontier. This is contrary to the findings of Alazzawi (2012), who encountered a negative impact of FDI on the domestic innovative capacity of technological leaders in their cross-country sample. Further, Garcia et al. (2013) found that FDI inflows would negatively impact the innovativeness of domestic firms and industries in Italy. Li et al. (2017), who found that FDI would generate positive spillovers in an industrially diverse setting, also showed that in an industrially specialised setting, FDI would generate negative spillovers for Chinese firms. In another study done in the context of China, Qu et al. (2017) found that FDI generated a crowding-out effect in Chinese manufacturing firms. However, their empirical results showed that this crowding-out effect could be averted by investing in R&D. On a slightly different note, Ascani et al. (2020) found that FDI did not generate innovation externalities except for science-based sectors and specialised supplier activities in Italy. Ning et al. (2023) added to this finding in their study of Chinese firms. Their econometric results provided robust evidence that the presence of FDI would exert a negative effect only below a certain threshold level, after which FDI would start generating positive externalities.

Thus, it is not possible to come to a conclusion as to the impact of inward FDI on the innovation performance of local firms. Preceding works in this field provide mixed results. However, almost all the studies have highlighted the importance of local firms' R&D in absorbing foreign technology. Therefore, detailed insight into this relationship highlights the role of individual firms' R&D investments in benefiting from the entry of any advanced technology and countering any negative effects of the same.

2.5.2 Channels of FDI spillover

The understanding of the channels through which FDI facilitate or inhibits innovation spillovers is a topic of particular relevance. While studies of the channels of FDI spillovers are numerous in the productivity literature (Aitken and Harrison, 1999; Javorcik and Spatareanu, 2008; Goldar and Banga, 2020), there are few empirical studies on the channels of innovation spillovers of FDI (Girma et al., 2009; Crescenzi et al., 2015; Khachoo and Sharma, 2016; Gorodnichenko et al., 2020; Vujanovic et al., 2022).

Foreign firms may generate horizontal or intra-industry innovation spillovers through the competition effect, demonstration or imitation effect and labour turnover. The competition effect would generate positive horizontal spillovers if the increasing level of competition (with the entry of foreign multinationals) pushes the domestically-owned firms to upgrade their technology. However, given their traditional technological set-up, the competition effect may generate negative innovation spillovers if the local firms fail to upgrade their technology. Local firms may also gain if they are able to imitate foreign technology successfully. However, imitation requires an existing pool of knowledge, failing to which may render the local firms with no benefit from foreign technology. Finally, local firms may gain via labour turnover from foreign-owned to domestically-owned firms. However, given the foreign firms' affluent position and cutting-edge marketing and managerial skills, they may attract the best of the workers available in the domestic market by offering them handsome packages, leaving the local firms with no benefits from labour turnover.

The empirical literature witnesses both positive and negative horizontal innovation spillovers. Girma et al. (2009), using new product sales as the innovation indicator, found a positive but moderate horizontal innovation spillover for Chinese firms. This positive horizontal innovation spillover for Chinese firms was confirmed by Ito et al. (2010) using patent applications as the proxy for innovation. In another study done for the firms situated in the developed economy of the UK, Crescenzi et al. (2015) encountered a positive horizontal innovation spillover using binary indicators for innovation.

FDI spillovers may also occur via inter-industry or vertical channels, through buyer-supplier linkages, by means of backward spillovers. Such spillovers occur when a domestic firm in an upstream sector gains through supplying inputs to a foreign firm in the downstream sector. In an effort to ensure a finer quality of products, at a greater quantity and in less time, the foreign firms in the downstream sector may provide technical support to the local suppliers for improving the quality of the product via assisting innovation efforts and providing organisational and management support. Local firms are also likely to make an effort to increase their efficiency as they are expected to compete for supplier contracts with foreign firms in the downstream sector. On the other hand, upgrading production quality may increase the cost of the products, reducing the demand for these products. Foreign firms may also decide to source materials from their parent country, ripping local suppliers off their customers and harming their efforts to climb the technological ladder. However, on the empirical front, both Girma et al. (2009) and Ito et al. (2010) encountered an insignificant effect of FDI on innovation through the backward or vertical or inter-industry linkages.

The studies done by Khachoo and Sharma (2016), Gorodnichenko et al. (2020) and Vujanovic et al. (2022) are done in the context of EMDE economies and hence are discussed in the subsequent section.

2.5.3 FDI spillover within an industrial clusters

It is surprising to see that the existing literature has mostly overlooked the impact of FDI spillover on the innovation output of firms located in industrial clusters. On the empirical front, many studies found evidence for complementarity between innovation and industrial clusters (dos Santos and Dalcol, 2009; Mukim, 2012; Ruffner and Spescha, 2018; Tang and Cui, 2023). At the same time, many studies found the clustering of industries irrelevant to innovation outcomes (Beaudry and Breschi, 2003; Gordon and McCann, 2005). In fact, studies have even encountered a negative relationship between the two (Zhang, 2015; Niebuhr et al., 2020). The seminal work of Marshall (1890) draws up channels (labour market pooling, input sharing and knowledge spillover) through which knowledge flows in industrial clusters. Following this, preceding works in the field of innovation and geographical clustering of industries shed light on the fact that the likelihood of knowledge transmission in clusters is stronger than in isolated firms (dos Santos and Dalcol, 2009; Gordon and McCann, 2005; Niebuhr et al., 2020). Building on this set of work, we believe that the FDI spillovers in industrial clusters might have a differentiated impact on innovation compared to non-clustered firms.

The study done by Li et al. (2017) for China is one of the few studies that have investigated the contagious role of FDI spillovers on innovation. They find that FDI generates negative spillovers in an industrially specialised setting. However, they have not specified the channels through which FDI generates innovation spillovers.

2.5.4 Studies in emerging market and developing economies

In view of the opening up of the EMDEs, a major question that the policymakers need to address is whether the firms in the EMDEs have achieved the desired technological progress with the growing presence of FDI within their borders. However, our understanding of FDI and innovation spillovers is limited when it comes to EMDEs due to the paucity of research done in such economies. Many studies have highlighted the difference between the innovation regimes of firms in advanced economies and the EMDEs. Whereas the former is driven by R&D investment or knowledge creation, the latter is mainly driven by investment in machinery and equipment (i.e., non-R&D investment) or knowledge use (Cirera and Maloney, 2017; RadoSevic, 2017).

The works which are done by Vahter (2011) for Estonia, Khachoo and Sharma (2016) for India, Konstandina and Gachino (2020) for Albania, Gorodnichenko et al. (2020) for a panel of 18 developing countries and Vujanovic et al. (2022) for Serbia are some of the studies which have particularly focussed on EMDEs in terms of knowledge and technology spillovers from foreign investments. Vahter (2011) confirmed that FDI would augment the level of innovation of Estonian firms using CIS data. Khachoo and Sharma (2016) used patent information to measure the innovation of manufacturing firms in the Indian subcontinent. They confirmed that FDI has a significant impact on the innovation performance of domestic manufacturing firms. Their econometric evidence showed the presence of positive horizontal and vertical linkages for the selected sample. Konstandina and Gachino (2020) constructed a technology transfer index for Albania and found that FDI played an important role in technology transfer. Gorodnichenko et al. (2020) used binary indicators reflecting the introduction of new products and the adoption of new technology as innovation indicators. They found no significant horizontal or vertical linkages through FDI in their sample of developing economies. Vujanovic et al. (2022) used both input (R&D and investments in machinery, equipment, purchase of know-how and training) and output (innovation sales) measures of innovation. They found that FDI generates negative innovation spillovers for the firms in Serbia. On the other hand, the econometric analysis in their study did not find any significant vertical innovation spillovers emanating from foreign participation.

In what follows from the above is the lack of conclusive results on the innovation spillovers generated by FDI. The results differ widely in terms of the horizontal spillovers generated by FDI in the EMDEs. The existing literature finds that FDI can have positive (Khachoo and Sharma, 2016), negative (Vujanovic et al., 2022) and insignificant (Gorodnichenko et al., 2020) impact on the innovation performance of firms belonging to similar industries. In terms of vertical innovation spillovers, the results are somewhat similar with Gorodnichenko et al. (2020) and Vujanovic et al. (2022) finding an insignificant effect of FDI on the local firms' innovation performance, except Khachoo and Sharma (2016) who have found it to be positive. Such lack of conclusive evidence, particularly regarding the horizontal (and somewhat vertical) case, calls for further research.

2.5.5 Gaps identified

A bird's eye view of the existing literature makes it clear that the number of studies investigating the channels of FDI spillovers on the innovation output of firms is quite paltry and requires special attention. This is particularly so in the case of EMDEs. Further, the existing studies mostly overlook the interplay between inward FDI and firms clustering and their consequent impact on innovation. This study addresses these issues in the context of Indian patenting manufacturing firms.

The present study is closely related to the study of Khachoo and Sharma (2016). They uncover positive and significant horizontal and vertical spillovers of foreign participation in the Indian patenting manufacturing firms. However, their framework grossly ignores the spatial aspect of innovation activities. At the same time, contemporary economic geography provides systematic evidence of the spatial distribution of firms' innovation-related activities (Chen and Zhou, 2023; Gordon and McCann, 2005). It has been argued that the transmission of technological knowledge is subject to spatial boundaries because knowledge has a tacit and uncodified nature and thus flows through networks of interpersonal communication (Audretsch, 1998). The most important extension of the present study relates to the inclusion of the spatial dynamics of the Indian patenting manufacturing firms by considering the major industrial locations of the country. We extend this framework and study the interaction between the geographical location of the firm and the spillover variables. In another extension, the present study investigates the interaction effects of the spillover variables with the international orientation of the firms and the R&D expenditures of the firms to capture differential spillovers, if any. Finally, the econometric findings of the study lead us to investigate the impact of FDI policy liberalisations on the innovation output of Indian manufacturing firms. Thus, we claim the uniqueness of our study in detailed and convincing documentation of the impact of FDI on the innovation output of Indian manufacturing firms.

2.6 Conclusion

By drawing on the discussions above, we can conveniently conclude that there is very little micro evidence-based literature on the impact of innovation on firms' performance, employment and technology spillovers for the EMDEs. To this end, we draw special attention to the type of proxy used for innovation. Based on well-documented literature, we take the stance that patents are the best-available instrument for intermediate innovation output in the absence of a direct measure of innovation output, such as sales generated from new products launched. Even with limitations, patents certainly qualify as a better instrument of innovation for empirical studies than any other input measures and binary indicators. The preceding discussion has shown that the understanding of the innovation process in the EMDEs is predominantly confined to innovation inputs and binary innovation indicators only. The present study addresses this gap in the literature and broadens the knowledge of the innovation behaviour of firms in the EMDEs using actual patent counts.

The present study contributes to the field of industrial innovation literature by bringing together the complementarity between innovation and firms' performance within the same framework using actual patent counts. Our discussion has shown that while most mainstream economics researchers have empirically investigated innovation as a catalyst for firms' performance, they tend to overlook the reverse relationship. This study takes a holistic approach and aims to establish the two-way nature of this relationship. To the best of our knowledge, this is the first study done in the context of a developing economy which has empirically investigated firms' performance as a determining factor of innovation output. This is somewhat surprising as the firms in developing economies are limited by the availability of resources for new knowledge creation. Therefore, the empirical findings of this study hold greater policy implications for policymakers.

We also add to the field of labour economics by providing much larger comparative evidence on the impact of process and product innovations on the labour market of India. The labour markets of the EMDEs are characterised by the presence of an excess supply of labour. At the same time, they are being constantly challenged by the presence of a traditional industrial sector that needs to be upgraded. Our analysis covers the heterogeneous impact of process and product innovation on India's labour market using actual patent counts. The existing studies done for the EMDEs mostly ignore the heterogenous impact and use either input or binary measures to proxy innovation. We also contribute to the literature by empirically segregating the heterogenous effect of process and product innovations in foreign-owned and domestically-owned firms on employment generation for Indian manufacturing firms.

Finally, the present study contributes to the economics of industrial organisation and innovation by estimating the FDI spillover channels. It further extends the functioning of these channels within geographical clusters, contributing to the literature on the economics of geography. The mainstream economics theory assumes that openness and access to foreign technology facilitate imitation and knowledge creation in the EMDEs. However, a detailed discussion of FDI as the external source of knowledge and technology makes it clear that the relationship between FDI and innovation spillovers is not straightforward and depends greatly on the host economy's absorption capacity. The EMDEs are characteristically situated far from the technological frontier and lack the scientific knowledge and resources required for engaging in cutting-edge technology. Moreover, geographical proximity may also have a role to play in determining the spillovers generated by the entry of foreign multinationals. Empirical findings do not have a concrete answer to these questions with respect to the EMDEs. We bring together these aspects under our empirical framework. This study also provides a bridge between FDI liberalisation policies by India's government and their impact on generating innovation output.

Chapter 3

The Two-way Dynamic Relationship between Innovation and Productivity

3.1 Introduction

3.1.1 Contexualisation and motivation

Macroeconomic literature has long acknowledged the role of innovation in improving firm performance. Building on the pioneering work of Schumpeter (1939), the relevance of innovation in firms' productivity is well-established in the literature, especially in the context of advanced and developed economies (Evangelista and Vezzani, 2012; Bedford et al., 2022; Entezarkheir and Sen, 2023). However, recent literature has distinctly shaped the differences between the innovation regimes of firms in developed economies and the emerging market and developing economies (EMDE) (Dabla-Norris et al., 2012; Burhan et al., 2017). Researches in this dimension reveal that innovation in firms in advanced countries is driven by research and development (R&D) and knowledge creation, whereas the innovation in firms in EMDEs is driven by investment in non-R&D activities (such as machinery and equipment) and knowledge use (Cirera and Maloney, 2017; Vujanovic et al., 2022). This points to the need to understand the mechanism of innovation in the EMDEs separately from the firms in developed economies. However, our knowledge of innovation and its impact is still limited in the case of EMDEs.

While it is widely acknowledged that innovation is at the heart of the competitive process, most mainstream macroeconomists tend to overlook the 'reverse' relationship, that is, the extent to which firms' competitive productivity levels spur innovation. This 'reverse' relationship stems from the fact that innovation projects are highly risky, costly and uncertain, which requires long-term investments (Schumpeter, 1942). Therefore, only productive firms with *ex-ante* resources are able to take up such innovation projects (Cainelli et al., 2006; Li and Lin, 2016; Fang et al., 2020). Building on this, understanding the 'reverse' relationship becomes particularly important for policymakers in EMDEs as firms in these economies face greater challenges than their counterparts from advanced economies. The domestic environment of the EMDEs renders the firms with inadequate technical and scientific knowledge, distressed financial resources and incompetent managerial and organisational framework. Such domestic orientation does not provide firms with the incentive to innovate. Against this backdrop, the prospect of only productive firms with *ex-ante* resources being able to take up innovative projects gains more prominence. However, despite its relevance to policymakers, the impact of firms' productivity on their innovation output is rarely studied for an EMDE like India.

Micro studies establishing innovation as a determinant of firm's total factor productivity or labour productivity using patent data are predominantly researched in developed high-income countries only (Bloom and Van Reenen (2002) for UK, Gu and Tang (2004) for Canada, Chen and Yang (2005) for Taiwan, Cainelli et al. (2006) for Italy, Coad and Rao (2008) for US, Santarelli and Lotti (2008) for Italy, Evangelista and Vezzani (2012) for Italy, Hu et al. (2017) for China, Di Mauro et al. (2020) for China Fang et al. (2020) for China, Bedford et al. (2022) for Australia and Entezarkheir and Sen (2023) for US).[9] Further, in his seminal contribution, Schumpeter (1942) brings up the fact that the scientific discoveries associated with innovation are pretty prolonged, indivisible, expensive, and highly risky. Funding such risky projects requires *ex-ante* capital and efficient, productive inputs. However, very few studies have empirically investigated this channel, all based on the developed nations (Crepon et al., (1998) for France, Cainelli et al., (2006) for Italy, Li and Lin (2016) for China and Fang (2020) for China).

EMDEs, like India, differ in many characteristics from those of the heavily studied advanced economies (Burhan et al., 2017). EMDEs are further away from the world's technological frontier than developed economies. Therefore, the implication of innovation in technologically advanced developed economies cannot be drawn to technologically distant EMDEs. Despite this, research linking firm innovation and productivity growth in the EMDEs is limited (Chudnovsky et al., 2006, for Argentinian; Ambrammal and Sharma, 2016 for India; Aboal and Garda, 2016 for Uruguay; Santi and Santoleri, 2017 for Chile; Dalgıç et al., 2018 for Turkey; Wadho and Chaudhry, 2018 for Pakistan). Moreover, most of these studies measure innovation with either an input variable such as R&D expenditures or technology acquisition expenditures (Chudnovsky et al., 2006; Aboal and Garda, 2016) or dichotomous innovation indicators (Santi and Santoleri, 2017; Dalgıç et al., 2018). We encounter few empirical models that quantify innovation with patent data while documenting the two-way relationship between firm-level innovation and productivity growth in the EMDEs (Ambrammal and Sharma, 2016 for India; Fink et al., 2021 for Chile). In fact, all these studies have projected innovation as a catalyst of firms' productivity growth, ignoring the reverse relationship.

Moreover, the existing studies for EMDEs also provide mixed evidence. While Chudnovsky et al. (2006), Ambrammal and Sharma (2016), Aboal and Garda (2016), Santi and Santoleri (2017), and Dalgıç et al. (2018) have linked innovation with higher productivity, Fink et al. (2021) observed that patents had not played much role in Chile's rapid economic

[9] Although China is considered a developing economy, we are placing China in the group of developed economies as it is the second largest patents producing country after US

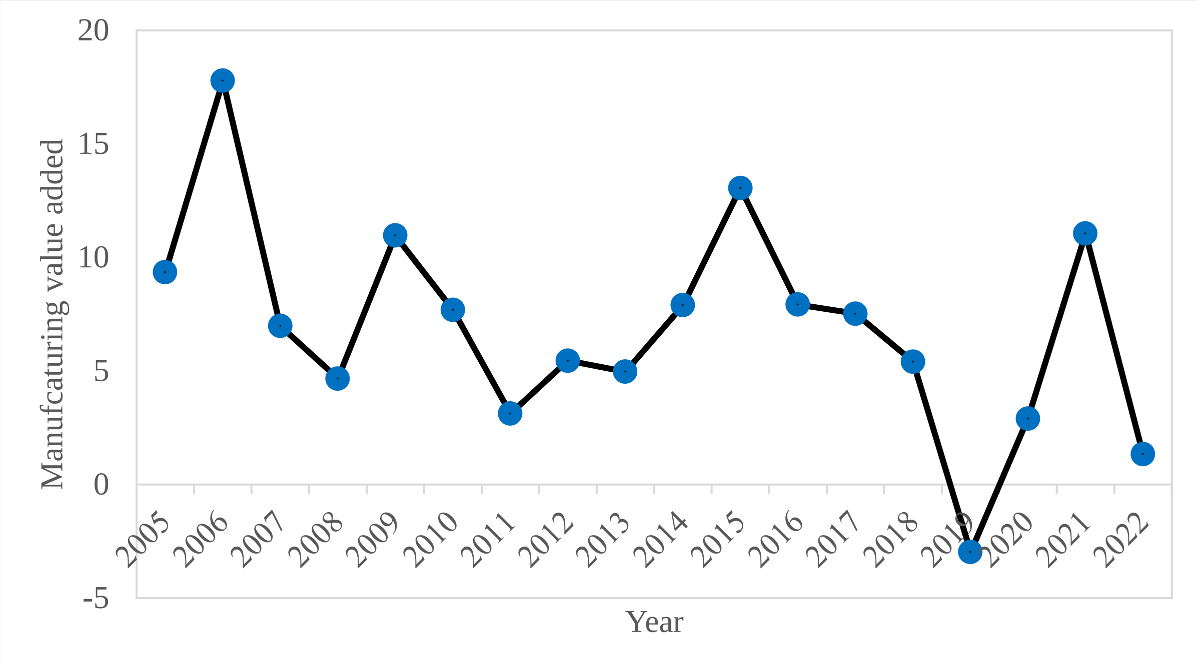
growth. Similarly, Santi and Santoleri (2017) found product innovation insignificant for firm growth.

However, despite its importance for both firms and society, the prospect of firms' productivity affecting innovation output in EMDEs is missing in the micro econometric empirical works of innovation and industrial organisation literature. In fact, although the impact of innovation on productivity has been focused in some research, there is still a lacuna regarding the two-way relationship between innovation and firm productivity. Research is still needed to understand the interplay between innovation and firms' productivity, especially in EMDEs like India.

Motivated by this, the present chapter aims to examine the dynamic nexus between innovation and productivity by taking samples from one of the fastest-growing EMDE, India. India serves as an ideal focus for the present research, given its remarkable progress in terms of innovation outputs amongst the EMDEs. To this end, the ratio of patents granted to patents applied in the country has increased to 44 per cent in 2020-21 from 18 per cent in 2005-06 (Annual Report, Intellectual Property India). The country has moved up in the global innovation index from 81 in 2015 to 48 in 2020, followed by 46th in 2021 and 40th in 2022. India is ranked one amongst 36 lower middle-income group economies in the Global Innovation Index-2022. In terms of total patent filings by Asian countries, India follows China, Japan and South Korea, which are essentially high-income economies.

However, a look at the country's manufacturing sector shows a very pessimistic picture. As seen from Figure 3.1, the value added by the manufacturing sector has fluctuated considerably over the years. Moreover, the manufacturing growth rate has decreased overall in the last one-and-a-half decades. However, given the crucial role of the manufacturing sector in the growth of any economy, policymakers in India need to find ways to revive the manufacturing sector. Can innovation be one such way? The present study tries to address this question empirically. Stemming from this, this research takes samples from Indian manufacturing firms.

Figure 3. 1: Value added by the manufacturing sector (annual percentage growth)



Source: World Development Indicator

It is mention-worthy here that the present work is not the first to specifically focus on the innovation and productivity dynamics of Indian manufacturing firms. Studies have considered the same relationship using Research and Development (R&D) information (Raut, 1995;Goldar and Banga, 2020). However, while these studies have focussed on the input side of innovation using R&D data, this study focuses on the output side of innovation using patent information.[10] Ambrammal and Sharma (2014; 2016), whose study perhaps most closely matches the theme of the present work, have documented the impact of innovation output (measured with patents) on the productivity of Indian high-tech and medium-high-tech manufacturing firms. However, each of these works forwards their empirical inference that shows only a one-way relation by projecting innovation as a catalyst of firms' productivity while grossly ignoring the 'reverse' relationship. The present work, of course, shares an apparent common thread with this body of works. It departs in that the present study not only projects innovation as a catalyst of firms' productivity growth but also brings together the two-way dynamic relationship between innovation and firms' productivity. The direct examination of the impact of productivity on firms' innovation output is desirable and relevant for policymakers, particularly in EMDEs like India.

[10] Kindly refer to the section "Description of variables" for a detailed discussion of the measures of innovation input and innovation output.

Contribution

The present work contributes to three strands of literature that broaden the knowledge of innovation and firm-level productivity in the EMDEs. First, the present study contributes to the economics of innovation by exploring the two-way link between innovation and firm-level productivity growth. While the relevance of innovation in firms' productivity growth is somewhat discussed for the EMDEs, the relevance of firm-level productivity in their innovation output is discussed for the first time for the EMDEs, to the best of our knowledge. Second, the present study adds to the industrial organisational literature by studying the observed differences between innovating and non-innovating firms in terms of fostering productivity in India. Third, the present study adds to the thin developing country literature, which focuses on the output side of innovation, departing from the conventional works in the economics of innovation, which focuses on the input side of innovation.

To this end, our work aims to answer three questions. First, do the productivity levels of the manufacturing firms in India influence their innovation outputs? Second, does the innovation output of the Indian manufacturing firms influence their productivity levels? Third, are there any observed differences between the productivity levels of innovative Indian manufacturing firms vis-a-vis those of non-innovative firms?

The empirical results validate the existence of a two-way relationship between innovation and firms' productivity. Interestingly, we note that the impact of productivity on innovation output is greater than the impact of innovation on productivity. However, the results show robust evidence that innovative Indian manufacturing firms are significantly more productive than non-innovative firms. Taken together, the empirical findings imply that although innovation has a relatively weak impact on the productivity growth of Indian manufacturing firms, policymakers should focus on promoting innovation in them as innovative Indian manufacturing firms are more productive than non-innovative ones. To this end, policymakers should devise productivity-enhancing policies to infuse innovation in Indian manufacturing firms.

3.2 Conceptual Framework and Hypothesis Development

The conceptual framework of this chapter is linked to the works of Aghion et al. (1998), Howitt (1999) and Aghion et al. (2014). Although the framework is best viewed in the context of developed economies, we try to draw comparative implications of the mode for the EMDEs.

Aghion et al. (2014) proposed that the closer an economy is to the productivity frontier, the more growth is driven by innovation-enhancing policies or institutions. Following Aghion et al. (2014), we presume and argue that at the micro level, the higher the firm's productivity, the greater the chances for the firm to innovate, which is specified in the following equation:

$$\theta_{ijt}=f(\rho_{ijt}z_{it}) \tag{3.1}$$

We believe that the innovation output θ of any firm i that belongs to industry j in any time period t depends on its productivity level ρ_{ijt}. ρ_{ijt} is the productivity level of firm i that belongs to industry j at time period t. Thus, a firm's innovation is a direct function of its productivity. z_{it} depicts the set of all other variables that affect θ_{ijt} but not ρ_{ijt}.

We assume that innovation output is measured by patents granted to an individual firm and present the patent equation as a heterogenous count data process with an expectation ϑ_{it}^{*} conditional on firms' performance or productivity and other explanatory variables.

$$\vartheta_{it}^{*} = E(\vartheta_{it}|g_{it}^{*}, x_{2it}, e_{2it};\ a_g, b_2)= Exp(a_g g_{it}^{*} + b_2 x_{2it} + e_{1it}) \tag{3.2}$$

where g_{it}^{*} is the productivity measure, x_{2i} is the vector of explanatory variables, $e_{1i}$is the error term and a_g and b_2 are associated parameters attached. We assume that patenting activities are positively associated with g_{it}^{*}. $g_{it}^{*} \equiv \hat{g}_{it}$ is the productivity indicator calculated using the Ackerberg-Caves-Frazer (ACF) (2015) method.

In a seminal contribution, Schumpeter (1942) suggests that the increasing scientific base of economic activities leads to an equilibrium attained by 'an extremely costly method' with 'cutthroat competition or simply by struggles for control in the financial sphere.' There is no denying the centrifugal role that exogenously determined scientific discoveries and advances play in technological innovation and productivity growth at the firm level. But these scientific discoveries are pretty prolonged, indivisible, and expensive. Funding such risky projects requires *ex-ante* capital and efficient, productive inputs. In EMDEs like India, a lack of appropriate structure may hinder innovation in firms further away from the productivity frontier. This might project firms' productivity as an important driver of innovation in these economies. Building on this, we hypothesise that firms' productivity plays a crucial role in determining the innovation output of firms in the EMDEs.

Hypothesis 3.1 *Firms' productivity is crucial in determining the innovation output of Indian manufacturing firms.*

The economic literature has well-scripted innovation as a major driver of firms' productivity growth. The Schumpeterian Paradigm developed by Aghion et al. (1998) and

Howitt (1999) have shown that any innovation raises the technology parameter constantly and buys the firm a temporary monopoly. It vanishes when the next firm makes an innovation. Thus, each innovation supersedes the previous one. The quality of each innovation is a fixed increase over the previous one, and knowledge spills inter-temporarily from one innovator to the next. Hence, even though production functions at the micro-level are governed by constant returns to scale, spillovers that flow from one firm to the rest of the economy imply increasing returns to scale at the macro level. Aghion et al. (1998) and Howitt (1999) have presented their model as follows:

$$Y_t = \int_0^{Q_t} A_{it} x_{it}^{\alpha} \tag{3.3}$$

where Y_t is the gross output, Q_t is the measure of how many different intermediate products exist at time t, x_{it} is the flow of intermediate product i used throughout the economy, A_{it} is the productivity parameter attached to the latest version of intermediate product i. In their model, innovation occurs due to research investments for either creating a new intermediate product or improving the quality of the existing intermediate product. Accordingly, innovations would trigger either the creation of a new product or quality improvements of the existing products. A successful innovation by frim i improves the parameter A_{it} and is thus able to displace the previous product until the next innovator displaces it.[11] Based on this, modern industrial organisation theories specify that long-term productivity growth depends on firms' innovation. Building on this, we frame the following two hypotheses:

Hypothesis 3.2 *Innovation significantly improves the productivity of Indian manufacturing firms.*

Hypothesis 3.3 *Innovative Indian manufacturing firms are significantly more productive than their non-innovative counterparts.*

3.3 Data and Variables

3.3.1. Sample selection

This study spans the period from 2005 to 2020. The starting year corresponds to India's full-fledged implementation of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS). Our initial dataset comprises 10,316 firms established on or before 2005,

[11] For details, see Aghion et al. (1998) and Howitt (1999)

spread across 23 manufacturing industries. Out of these firms, only 1798 firms have consistent data available throughout the sample period. The firm-level data are collected from the Centre for Monitoring Indian Economy (CMIE) database Prowess. These firms are mapped following the 2-digit NIC-2008 code into 23 manufacturing industries. The firm-level patent information is collected from the PatSeer (Patent Search and Analysis Software) database. Out of the 1798 firms, 347 firms have at least one patent to their credit during the study period. We refer to these firms as innovative firms. Thus, our final sample consists of 347 innovative and 1451 non-innovative firms.

3.3.2 Description of variables

This section discusses the innovation and productivity measures along with the firm-specific, market-specific and technology-specific control variables used in this chapter.

Innovation Variable

The present study measures innovation using the number of patents granted. In innovation literature, the three most commonly used innovation proxies are R&D intensity, which is an input indicator of innovation (Akcomak and Weel, 2009; Hassan and Tucci, 2010; Garcia-Manjon and Romero-Merino, 2012); patent counts, which is an intermediate measure of innovation output (Hu et al., 2017; Fink et al., 2021; Lo et al.,2023) and new product sales which is a direct measure of innovation output (Hou et al., 2019; Guo et al., 2022; Chen and Zhou, 2023).

A common practice prevalent in innovation literature was to measure innovation using R&D expenditures (Akcomak and Weel, 2009; Hassan and Tucci, 2010; Garcia-Manjon and Romero-Merino, 2012). However, the development of innovation literature over the years has pointed out the limitations of using R&D as an innovation measure. First, R&D is only an input to the innovation process and says nothing about the "output" side of the innovation. Second, not all R&D expenditures translate into successful innovation. Third, existing works have shown that firms in EMDEs often achieve technological advances through channels other than the formal R&D activities of the firms (Wadho and Chaudhry, 2018; Petelski et al., 2020). Such channels could include importing technologies, paying royalty or license fees to use certain technologies developed by others, etc. In such cases, formal R&D fails to capture the true extent of innovative efforts in such countries.

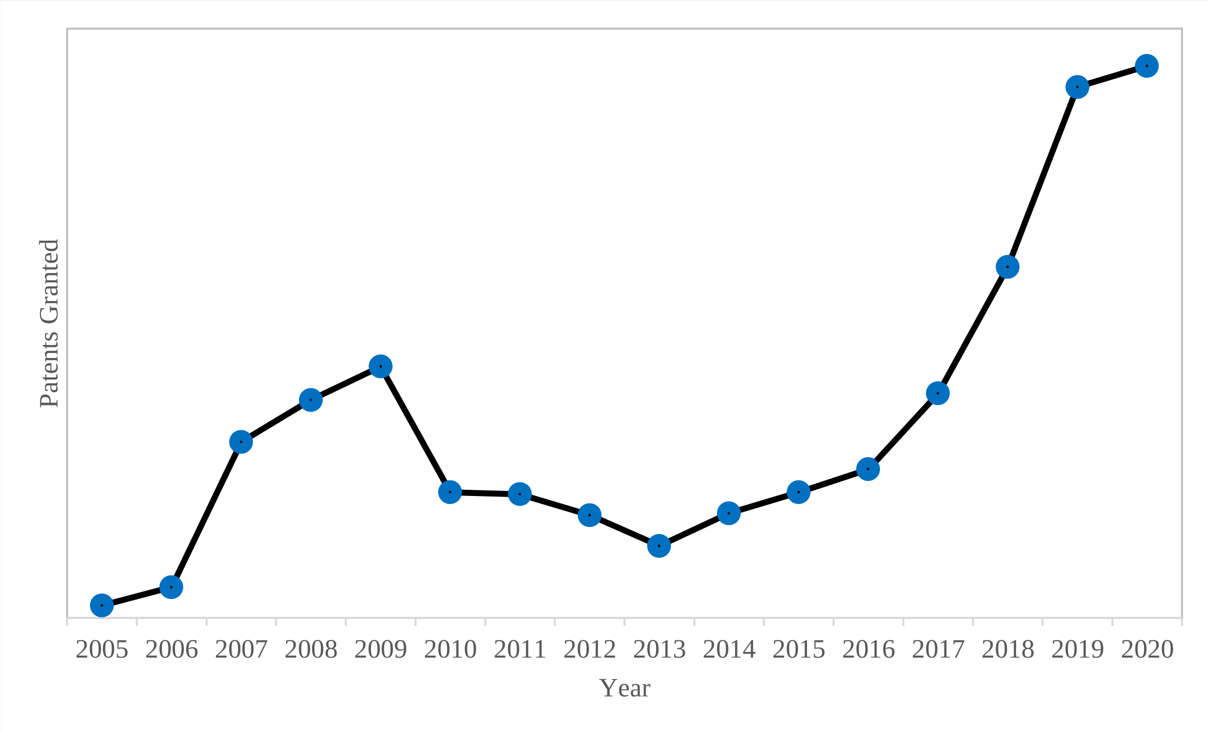
In order to overcome the limitations of R&D in empirical works, the literature on innovation suggests patents as a "classic instrument for incentivizing and measuring innovation" (Sweet and Eterovic, 2019). Patent data has certain advantages over R&D data. First, patents are unique and highly visible methods of technological progress or innovation (Furman et al., 2002). Second, as against R&D expenditures, patents are a confirmed source of disclosure of an invention, checked and verified by specialists. Third, as public documents, patent data are available for more extended periods, are richer, and are more detailed than R&D data. Empirical studies also confirm that patent data shows only minor disturbances by occasional changes in patent laws (Kleinknecht et al., 2002; Santarelli and Lotti, 2008). Further, Lach (1995) shows that whereas R&D explains only 9 per cent of the contribution of knowledge to productivity changes, patents explain the same by 30 per cent. Pakes and Griliches (1987) have also established the superiority of patents as an innovation indicator compared to R&D data. Using US patent information for 121 firms for eight years (1968-75), they have established that patents are more related to innovation output than R&D.

A major criticism of using patent data to proxy innovation is that patents reflect inventions (development of new ideas) only, not innovations (development of commercially viable products or services from creative ideas). However, Artz et al. (2010) point out that patents can be used to measure innovation as many inventions ultimately result in marketable innovations, and patents provide protection for new products. Their econometric evidence gives a positive and significant relationship between patents and product announcements, justifying the use of patents for innovation.

In the literature, both the number of patent applications and the number of patents granted have been used as innovation instruments. An inherent limitation of patent applications is that they may capture spurious and contrived applications (Garcia et al., 2013).Therefore, we use counts of patent grants to measure innovation output.

Figure 3.2 shows the trend in patents granted to manufacturing firms in India from 2005 to 2020. We see an upward trend in the patenting activities of Indian manufacturing firms during the period. The patents granted to the manufacturing firms rose until 2009, followed by a downswing till 2013. This downswing could be attributed to a decline in patent filings during the global financial crisis of 2008-09. As par the Annual Report of Intellectual Property, India, the patents applied during 2008 was 36812, which fell to 34287 in 2009. Since the granting of patents in India usually has a lag of 2-3 years, the fall in the patents granted till 2013 could be attributed to a decline in the patent filings. However, as the economy started recovering, measures were taken to improve the intellectual property ecosystem in the country, such as reductions in the processing fee of patent applications and government initiatives like Make in India (IPR newsletter, 2021). Following this, the patent applications, and subsequently the granting of patents started showing an increasing trend.

Figure 3. 2: Trends of patents granted in India (2005-2020)



Source: Data collected from Patseer and Indian Patent Office

Productivity Variable

The existing productivity literature suggests that an increase in output over time is not accounted for by the rise in labour and capital inputs but is deemed linked to innovation and technology change (Greenhalgh and Rogers, 2010). Therefore, this chapter uses Total Factor Productivity (TFP_{ACF}) as the productivity measure.

The TFP is calculated using the Ackerberg-Caves-Frazer (ACF) (2015) approach. The empirical literature specific to industrial productivity has enormously used parametric methods like OLS and semi-parametric methods like Olley and Pakes (1996), Levinsohn and Petrin (2003) and more recently Ackerberg-Caves-Frazer (2015) method to calculate TFP. All these methods have their advantages and disadvantages.

The OLS estimation presents unbiased coefficients only in the assumption of strict exogeneity. However, Griliches and Mairesse (1998) point out that profit-maximising firms immediately adjust their inputs, especially capital, in case of any productivity shock, ensuring that the input levels are correlated with the shocks. In a positive productivity shock, a profit-maximising firm would expand output by employing additional inputs. Similarly, the firm would contract output in a negative productivity shock by decreasing its input uses. However, these productivity shocks are unobserved. Hence, they enter into the regression's error term, making the inputs correlate with the error term. Ordinary least square estimates, under these circumstances, lead to biased estimates of productivity.

This issue was further addressed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) in their semi-parametric approaches. Olley and Pakes (1996) (OP) have developed an estimator using investments as a proxy for unobservable shocks. However, investment as a proxy has certain limitations. As Levinsohn and Petrin (2003) (LP) have pointed out, investment as a proxy is very lumpy and is valid for firms reporting only nonzero investments. Therefore, they have suggested using intermediate inputs as a proxy instead of investment. Another advantage of using intermediate inputs is that firms usually report inputs, making accessing the required information easy.

Ackerberg-Caves-Frazer (2015) claims that the OP and LP methods may suffer from identification issues unless additional assumptions are made regarding the labour input. The OP and LP method correctly identifies the labour coefficient only if there is an optimal level of labour input and if labour is considered a state variable. However, firms always choose the optimal level plus exogenous noise in the desired input levels (Kane and Lopez, 2023). Also, labour is a dynamic variable with significant hiring and firing costs and long-term contracts. To overcome this issue, Ackerberg-Caves-Frazer (2015) allows for unobserved firm-specific adjustment costs to labour input, enabling labour input to have a dynamic effect. Therefore, following recent studies (Singh and Sharma, 2020; Kane and Lopez, 2023), we have calculated the TFP using the ACF method.

The starting point of the ACF method is the same as the LP method, and both approaches introduce a Cobb-Douglas production function in logarithm form, which is as follows:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_m m_{it} + \beta_l l_{it} + w_{it} + \varepsilon_{it} \tag{3.4}$$

where Y_{it} is the logarithm of the firm's output, k_{it}, m_{it} and l_{it} is the logarithm of the capital, materials and labour. The error term in Eq. (3.4) has two distinctive parts, i.e., the transmitted productivity component w_{it} and the error term that is uncorrelated with the input choices ε_{it}. Firms' decisions depend on their productivity, leading to the endogeneity issue in estimating a production function. In this regard, the ACF method makes the same strict monotonicity assumption as LP. Thus, Eq. (3.4) could be rewritten as

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_m m_{it} + \beta_l l_{it} + f_t^{-1}(k_{it}, l_{it}, m_{it}) + \varepsilon_{it} \tag{3.5}$$

where $w_{it} = f_t^{-1}(k_{it}, l_{it}, m_{it})$ is the productivity level. Here, ACF uses the first stage of the procedure to eliminate the untransmitted error and thus to obtain an estimate of the composite term, which is as follows:

$$\Phi_t\,(k_{it}, l_{it}, m_{it}) = \beta_0 + \beta_k k_{it} + \beta_m m_{it} + \beta_l l_{it} + f_t^{-1}(k_{it}, l_{it}, m_{it}) \tag{3.6}$$

Using the first stage moment conditions, the ACF method obtains as,

$$E[\varepsilon_{it}|I_{it}] = E[y_{it} - \Phi_t\,(k_{it}, l_{it}, m_{it})|I_{it}]=0 \qquad (3.7)$$

where I_{it} represents a set of information. To estimate all the parameters of interest, the ACF method uses the second stage of the estimation procedure following the second stage moment conditions,

$$\mathrm{E}[\xi_{it} + \varepsilon_{it}|I_{it-1}] = E\big[y_{it} - \beta_0 - \beta_l l_{it} - \beta_k k_{it} - \beta_m m_{it} - \hat{b}(\Phi_{t-1}\big(k_{it-1,} l_{it-1}, m_{it-1}\big) - \beta_0 - \beta_k k_{it-1} - \beta_l l_{it-1} - \beta_m m_{it-1})|I_{it-1}\big] = 0 \qquad (3.8)$$

where $\Phi_{t-1}$is replaced by the estimate from the first stage.

The estimated values obtained by TFP following the ACF method are further regressed with our innovation indicator.

Control Variables

The relationship between firms' productivity and innovation cannot be discussed in isolation. Apart from the key variables in the form of firm's productivity and innovation, we control for the firm's age, $location$, $size$, $R\&D\ intensity$, $capital$ and $profit$ of in the innovation equation and the firms' age, $salary$, $R\&D\ intensity$, $market\ competition$, $export\ intensity$ and $import\ intensity$ in the productivity equation.

3.4 Empirical Framework and Methodology

Following the conceptual framework and hypotheses developed, the empirical models of the present study illustrate the two-way relationship between innovation and firms' productivity. For this purpose, based on existing works (Crepon et al., 1998; Zachariadis, 2003; Cainelli et al., 2006), we frame Eqs. (3.9) and (3.10). As shown below, while Eq. (3.9) estimates the impact of productivity on innovation output, Eq. (3.10) estimates the impact of innovation on productivity. Further, to estimate Eqs. (3.9) and (3.10), we limit the regression samples to firms that report innovation during the reference period to ensure that, in principle, all firms face a decision on how to protect their innovation (Hall et al., 2013).

$$Innovation_{it} = \beta_0 + \beta_1 Productivity_{it} + \sum \beta_k\, Z^k_{1it} + \beta_j + \beta_t + \varepsilon_{1it} \qquad (3.9)$$

$$Productivity_{it} = \gamma_0 + \gamma_1 Innovation_{it} + \sum \gamma_n\, Z^n_{2it} + \gamma_j + \gamma_t + \varepsilon_{2it} \qquad (3.10)$$

Where the $innovation$ variable is measured using the counts of patents, and the $productivity$ is measured using the ACF method. Z_{1it}, and Z_{2it} represent the set of control variables. β_j, and γ_j are firm-specific dummies, and β_t, and γ_t are time-specific dummies. Our empirical setup uses $innovation$ and firms $productivity$ as dependent variables. These variables are not normally distributed, preventing us from using traditional linear methods in our analysis.

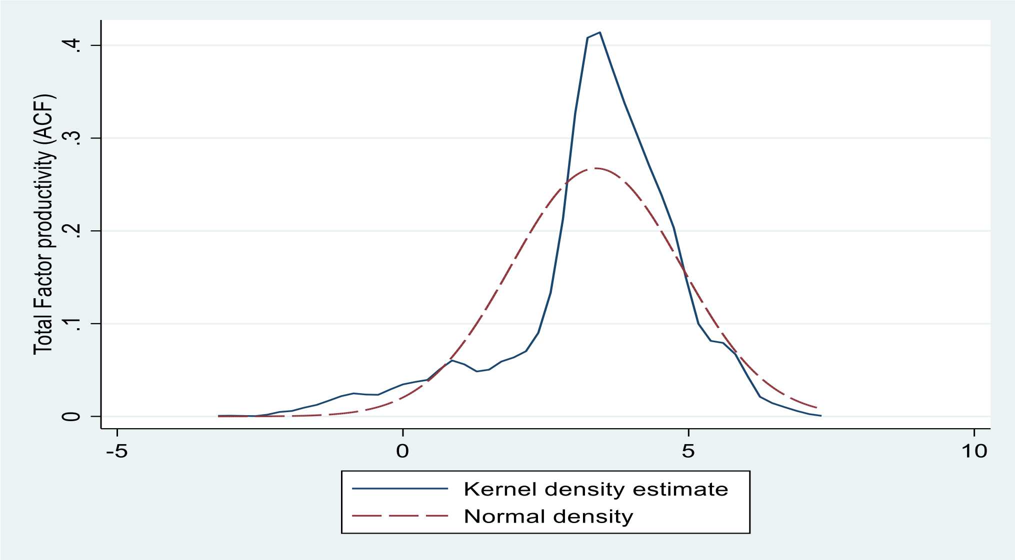
In Eq. (3.9), the response indicator is $innovation$. The empirical model discussed in Eq. (3.9) indicates $innovation$ as a function of firms' $productivity$ and tests for hypothesis 1. The response indicator here, $innovation,$ takes non-negative integer values, with many observations being zero. This type of data can be estimated using count data models. The most prominent count models are the Poisson regression and negative binomial models. However, the Poisson model has the limited property of equidispersion, referring to the equality of mean and variance. This somewhat restrictive property often fails to hold good in practice. Using the Poisson regression model in overdispersed distributions causes misspecified likelihood functions, yielding erroneous results. The negative binomial model has proven the most effective in such instances of overdispersion (Hausman et al., 1984; Cameron and Trivedi, 1998). Unlike the Poisson model, the negative binomial model has less restrictive properties and does not require the variance to be equal to the mean (μ), i.e.,

$$\text{Var } (y|x) = \mu+\alpha\mu^2 \tag{3.11}$$

The negative binomial model estimates the overdispersion parameter α. If $\alpha = 0$, then the use of Poisson regression suffices. However, if $\alpha > 0$, it is suggested to go for negative binomial regression. In this study, α is significantly different from zero without fail. Therefore, we form a negative binomial model to estimate Eq. (3.9).

Further, the empirical model discussed in Eq. (3.10) indicates firms' productivity as a function of $innovation$ and provides empirical building to our second hypothesis. Our dependent variable $Productivity$ shows a greater presence of extreme values. The skewness in our data is -1.01. Figure 3.3, which shows the kernel density of the TFP(ACF) vis-à-vis the normal density plot, makes it further clear. The JB test also rejects the hypothesis of normality. This calls for special attention to the treatment of the variable. While the properties of the standard mean regression are not robust to modest departures from normality, the quantile regression results are robust to the presence of outliers and heavy-tailed distributions. Therefore, following the prior literature (Koenker, 2004; Powell, 2022), Eq. (3.10) is estimated using the panel quantile regression.

Figure 3. 3: Kernel density of Total Factor Productivity (ACF)



Source: Authors' computation

The conventional OLS estimates describe the explanatory variables' effect on the indicator variable's conditional mean. Conversely, the quantile regression estimates detect the influence of the explanatory variables throughout the conditional distribution of the dependent variable. Quantile regression is, hence, more informative. In addition, the quantile regression approach avoids the assumption that the error terms are identically distributed at all points of the conditional distribution. It allows us to consider firm heterogeneity, opening the possibility that the estimated parameter slopes can vary at different quantile distributions of the response indicator. Quantile regression was initially introduced by Koenker and Bassett (1978) as a cross-sectional estimator. In a linear regression framework, it can be represented as follows:

$$Y_i = x_i^{/}\beta + u_i \tag{3.12}$$

where x_i is a vector of the explanatory variables. The ordinary least square estimate of β minimises the sum of the square of the residuals, i.e., $min \sum_{i=1}^{N}\left(y_i - x_i^{/}\beta\right)^2$. By contrast, the quantile regression estimation minimises an asymmetric linear penalty function given by

$$\hat{\beta}(\tau) = arg_{\beta \epsilon R^p} min \sum_{i=1}^{N} \rho_\tau \left(y_i - x_i^{/}\beta\right) \tag{3.13}$$

where $\hat{\beta}(\tau)$ is the τ^{th} regression quantile and $\rho_\tau(.)$ is the check function. Thus, the quantile function is a weighted sum of the absolute value of the residuals. By varying the parameter τ on 0 to 1 interval, we generate all the regression quantiles and obtain the conditional distribution of y_i given x_i in the following form.

$$Q_{y_i}(\tau|x_{ik}) = x_{ik}^{/}\beta(\tau) \tag{3.14}$$

The coefficient on the k^{th} explanatory variable can be interpreted as the marginal change in the dependent variable due to marginal changes in the k^{th} explanatory variable on the τ^{th} quantile. Since this estimator provides one β for each τ, it allows identifying the effects of the covariates on the dependent variable at different points in the distribution. Hence, these are robust to outliers and distribution with heavy tails. However, these estimators do not consider the unobserved firm-specific heterogeneity. Koenker (2004) later developed this model for longitudinal or panel data settings, including firm-specific heterogeneity. Koenker (2004) evaluated the model with the following specification:

$$Q_{y_{it}}\left(\tau|\alpha_i, x_{it}^{/}\beta\right) = a_i + x_{it}^{/}\beta(\tau) \tag{3.15}$$

Here a_i controls for the firm-specific omitted factors that are relatively stable over time. Later Powell (2022) developed a quantile regression model with nonadditive fixed effects for panel data. We follow this method for our empirical estimation.

Finally, Hypothesis 3.3 is estimated using the Propensity Score Matching (PSM) method. The PSM method is based on constructing a counterfactual group of non-treated firms by quasi-experimental matching methodology. It is used to obtain accurate estimates of the treatment effects associated with binary variables, which is 1 for the innovative firms and 0 for the non-innovative firms in our study. The validity of the PSM estimates depends on the selection of observables and the overlap condition. The selection of observables requires that all systematic differences between the 'treatment' and the 'control' groups are removed by including observed control variables as covariates. The overlap condition requires that the 'treatment' and the 'control' groups are comparable in terms of their characteristics.

The matches under the PSM approach are done based on the probability of receiving the benefits (the propensity scores) considering the observable characteristics of firms (Rubin, 1977; Rosenbaum and Rubin, 1983). In the context of the present study, it ensures that the samples of innovative and non-innovative firms are, on average, statistically not different in terms of their observable characteristics.

The PSM method is a two-stage procedure. In the first stage, a probit model estimates the propensity scores, ensuring that firms in the control group (non-innovative firms) are comparable to firms in the treatment group (innovative firms). This stage uses the binary variable D_i, which is usually1 for the treated group and 0 for the control group as the dependent variable and a vector of x_{it}s as the independent variables.

$$p(x) = prob(D - 1|x) = E(D|x) \tag{3.16}$$

Thus,

$$Y_i = \begin{cases} Y_1 \; if \; D = 1 \\ Y_0 \; if \; D = 0 \end{cases} \tag{3.17}$$

Once it has been verified that the treatment and control groups have similar propensity scores, the differences between the treatment and the control groups are calculated in the second stage to estimate the average treatment effects on the treated (ATT). The ATT will be given by

$$E(\propto_T) = E[(Y_1 - Y_0)/D = 1] = E[(Y_1/D = 1) - (Y_0/D = 1)] \quad (3.18)$$

Here $\propto_T$ is the average impact of D on Y.

3.5 Empirical Results

3.5.1 Does firm productivity significantly impact innovation? Firms' productivity as a catalyst of innovation

The estimated results of Eq. (3.9), presenting firms' productivity as a function of innovation, are reported in Table 3.1. The negative binomial regression results (see Column 1, Table 3.1) confirm that firms' productivity positively influences innovation outcomes, validating Hypothesis 1. The empirical results of the study support the findings of Aboal and Garda (2016), Santi and Santoleri (2017), and Dalgıç et al. (2018) and establish that the firms with productivity advantages have a competitive edge in innovation. To put it differently, the findings of the study suggest that complexities associated with innovation, as discussed in the preceding sections, give productive firms an edge and firms' productivity positively and significantly affects their innovation output. More specifically, firms' productivity and patenting behaviour coexist in Indian manufacturing firms.

Turning to the control variables, in line with much of the literature suggesting that R&D is not the primary driver of innovation in the EMDEs (Cirera and Maloney, 2017; Fernández-Sastre and Montalvo-Quizhpi, 2019), our empirical analysis finds an insignificant impact of R&D intensity on the innovation output of the Indian manufacturing firms (see column I, Table 3.1). This finding also aligns with the National Manufacturing Innovation Survey 2021-22 report, which states that 59.89 per cent of innovative manufacturing firms in India are engaged in non-technological innovations that do not require rigorous R&D activities.

Furthermore, we investigate whether Indian manufacturing firms that invest in R&D and are clustered geographically in the major industrial agglomerations of the country innovate significantly or not.[12] For this purpose, we interact R&D intensity with location (column III, Table 3.1). Firms located in industrial clusters draw positive externalities on input markets,

[12] These industrial belts include the Mumbai-Pune industrial region, the Hugli industrial region, the Bangalore-Chennai industrial region, the Gujarat industrial region, the Chotanagpur industrial region, the Vishakhapatnam-Guntur industrial region, the Gurgaon- Delhi- Meerut industrial region, the Kollam-Thiruvanthapuram industrial region. This classification is demarcated by Singh (1971).

labour markets and knowledge exchange, which results in significant innovation convergence (Magrini and Galliano, 2012; Tang and Cui, 2023). Based on this, we capitalise on the possibility that firms located in the major industrial clusters may leverage the benefits of R&D. However, the estimated coefficient is statistically not different from zero. Thus, in line with Radicic and Balavac (2018) and Petelski et al. (2020), our findings re-establish that innovations in EMDEs such as India are not driven by R&D investments. Low levels of R&D investments could be a possible reason behind this. Low R&D investments have long been a matter of concern for policymakers in India. This is also highlighted in the Research and Development Statistics 2022-23. As per the report, India's gross domestic expenditure on R&D (GERD) for the year 2021-22 stands at 0.64 per cent, much below other BRICS countries like Brazil (1.3%), Russia (1.1%), and China (2.4%). This is even below the GERD of 0.8 per cent during the 2020 pandemic (Statista, 2022).

Next, turning to the other control variables, the estimated coefficients show that firms' age, location, and labour input significantly influence the innovation output of the Indian manufacturing firms. The positive and significant coefficient of the variable age reflects that experienced firms are significantly more innovative than younger ones, thus confirming the role of learning effects in driving up the innovation output of the Indian manufacturing firms (see Table 3.1, columns I, II and III).

The economics of geography establishes two competing hypotheses. The first one conjectures that firms located in geographical clusters benefit from easier access to markets, better buyer-supplier linkages, and other tertiary services such as legal advisory, training, demonstration, better networking among firms, etc. (Ruffner and Spescha, 2018; Tang and Cui, 2023). Alternatively, the second hypothesis speculates that the geographical clustering of firms would trigger congestion and heated competition, which would outweigh the possible benefits derived from networking and other tertiary services (Zhang, 2015; Niebuhr et al., 2020). In this chapter, the estimated coefficient of the variable $location$, which takes the values of 1 if the firm is located in the major industrial belt of the country and zero otherwise, is negative and significant across all the model specifications, lending support to the latter stand of literature (see Table 3.1, columns I and II).

Finally, the positive and significant nature of the estimated coefficient of the variable $labour$, confirms the labour-intensive nature of innovation in India (see Table 3.1, columns I, II and III). This demonstrates that innovation in Indian manufacturing firms is rooted in employing more workers, far more than investments in R&D, which is consistent with the previous literature that has emphasised that innovation in EMDEs is not necessarily R&D driven (Cirera and Maloney, 2017; Stojčić et al., 2020). A larger pool of human capital facilitates greater degrees of specialisation in labour, which enables efficient teamwork and greater knowledge sharing. The involvement of more human capital also allows the firms to handle multiple projects simultaneously, allowing for risk diversification across the projects, nurturing an innovation-friendly ecosystem.

Table 3. 1: Firms' productivity and innovation, dependent variable: Patents granted

Variables	I	II	III
$Productivity_{ACF}$	0.380**		
	(0.16)		
Age	1.288**	1.506**	1.471**
	(0.56)	(0.60)	(0.58)
$Location$	-1.701*	-2.197**	
	(0.93)	(1.04)	
$Labour$	0.238*	0.428***	0.429***
	(0.13)	(0.11)	(0.11)
$R\&D$		-1.447	
		(1.91)	
$Capital$	0.056	-0.009	-0.005
	(0.05)	(0.05)	(0.05)
$Profit_{t-1}$	0.001	0.001	0.001
	(0.01)	(0.01)	(0.01)
$Location \times R\&D$			-2.064
			(2.20)
$Constant$	-7.976***	-8.047***	-10.146***
	(1.58)	(1.61)	(2.39)
Time Dummy	Yes	Yes	Yes
Cross-Section Dummy	Yes	Yes	Yes
Log Likelihood	-1730.53	-1716.50	-1716.35
Pseudo R^2	0.317	0.307	0.307
Obs.			

Notes: *** p<0.01, ** p<0.05, * p<0.10, standard error in parenthesis;
Columns I to III are estimated using Negative binomial model estimators.

3.5.2 Does innovation significantly impact firms' productivity? Innovation as a catalyst of firms' productivity

The empirical specification discussed in alternative models in Eq. (3.10) presents innovation as a competing source of firms' productivity. Table 3.2 presents the estimation results of the quantile regression that uses $productivity$ as the dependent variable.

Empirical results reveal that the influence of innovation is not uniform across the productivity distributions of firms. Innovation does not significantly affect firms' productivity in the extreme lower tail of the quantile (Column I, Table 3.2). This can be justified as firms in the lower quantiles of productivity often face structural barriers, such as organisational and managerial bottlenecks, coupled with limited financial resources. They also have limited access to physical infrastructures, like an efficient digital network and state-of-the-art machinery. Drawing benefits from innovation requires integrating new technology into the existing system effectively. However, such institutional voids limit the ability of the firms in the lower quantiles of productivity distribution to generate significant returns from innovation. The inclusion of firms in the higher quantiles of the productivity distribution changes the firm dynamics. Firms with better organisational, managerial and infrastructural inclination are able to scale their innovation to draw productivity benefits. Therefore, as we move ahead to the upper quantiles in Table 3.2 viz., $\tau = 50$ in Column II, $\tau = 75$ in Column III and $\tau = 90$ in Column IV, the significance of the innovation parameter changes and innovation becomes positive and significant.

Here, we want to draw attention to the magnitude of the estimated coefficient of the innovation parameter in Table 3.2. It indicates that a one-unit increase in innovation, on average, increases the firm's productivity in the range of 0.002 to 0.054. This is much lower than the estimated coefficients of the productivity parameter in Table 3.1, which shows that, on average, a one-unit increase in firms' productivity is associated with an increase in the innovation parameter in the range of 0.380. To restate, it reflects that firms' productivity has a larger impact on innovation output than innovation has on productivity growth. This finding leads to important policy implications. Based on the empirical findings, policy should be oriented towards productivity-linked incentives to infuse innovation in Indian manufacturing firms.

The estimated coefficients of the control variables also provide concluding evidence. The negative and significant nature of the variable age across all the models in Table 3.2 reflects that new firms are significantly more productive than old ones.

The variable $salary$ is positively significant across all the quantiles in Table 3.2. It corroborates the expectation that higher compensation would attract skilled labour, improving firm-level productivity.

Surprisingly, the estimated coefficient of the R&D intensity shows a negative and significant relationship with firm-level productivity in the higher quantiles (see Table 3.2, columns II and III). The results reflect that research investments by Indian manufacturing firms are dragging down productivity levels. This result is consistent with the findings of Kancs and Siliverstovs (2016) and Guo et al. (2022), who find a negative effect of R&D intensity on productivity growth when R&D intensity is too low. They find that a certain critical amount of R&D capacity is required before achieving significant productivity growth from R&D investments.

As discussed in the previous section, India's investment in R&D is quintessentially low, standing only at a mere 0.64 per cent for 2021-22, much below the world average of 3 per cent (Statista, 2022). The average level of R&D intensity in our sample is only 0.44 per cent. This reflects that without sufficient existing knowledge, Indian manufacturing firms are unable to absorb and use new knowledge effectively. Further, effective channelisation of R&D expenditures to gear up productivity growth requires efficient management, organisational practices, and a skilled workforce. In the Indian context, the National Manufacturing Innovation Survey 2021-22 reports that 53% of innovative firms have no scientists or engineers. Also, 88% of the innovating firms declare access to skilled human resources a vital constraint. Given this, we can only expect that the existing workforce in these innovative firms cannot generate returns on the R&D expenditures incurred by the firm.

Next, the industry $competition$ negatively and significantly affects productivity across all quantiles in Table 3.2. This supports the findings of Girma et al. (2009) and Garcia et al. (2013) that firms can control the market under monopolistic and oligopolistic situations.

The estimated coefficient of the variable $import\ intensity$ is negatively and significantly related to the productivity variable at the median quantile (see Column II, Table 3.2). In line with Lu et al. (2021), this negative effect of $import\ intensity$ on firm productivity may be attributed to the increasing prices of imported goods. Also, Doan et al. (2016) show that importing embodied and disembodied products adversely affects domestic firms' productivity for EMDE with lower absorptive capacity and resources.

The $export\ intensity$ parameter is also negative and significant (see columns I and IV, Table 3.2), reflecting that intense exporting activities have an adverse effect on firms' productivity. Exporting firms face intense competition in the international market, requiring them to maintain specific international standards in order to remain competitive. This often leads to the diversification of resources to deal with operational complexities such as international regulations, currency fluctuations, transportation and logistic costs etc. This distracts resources from core operations, adversely affecting their productivity. Moreover, exporting firms often become vulnerable to fluctuations in the international landscape, such as geopolitical disturbances, global market tensions, etc. Such disturbances lead to instability in their operations, causing supply chain disruptions, increased costs, and market inaccessibility. These create uncertainty and hinder productivity improvements.

Table 3. 2: Firms' innovation and productivity, dependent variable: TFP_{ACF}

Variables	I	II	III	IV
	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
$Innovation$	0.004	0.002**	0.004*	0.054***
	(0.00)	(0.00)	(0.00)	(0.01)
Age	-0.915***	-0.203***	-0.352***	-0.630***
	(0.10)	(0.02)	(0.09)	(0.05)
$Salary$	0.168***	0.448***	0.436***	0.291***
	(0.05)	(0.01)	(0.03)	(0.05)
$R\&D$	-0.042	-1.009***	-2.210**	0.602
	(0.47)	(0.34)	(1.04)	(0.53)
$Competition$	-0.590***	-0.335***	-0.658***	-0.673***
	(0.18)	(0.03)	(0.08)	(0.11)
$Import$	-0.615	-1.000***	-0.464	-0.180
	(0.40)	(0.16)	(0.84)	(0.45)
$Export$	-0.695***	-0.120	0.130	-0.507***
	(0.06)	(0.09)	(0.09)	(0.10)
Cross Section Dummy	Yes	Yes	Yes	Yes
Time Dummy	Yes	Yes	Yes	Yes
Observations	1,695	1,695	1,695	1,695
Number of groups	154	154	154	154

Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis
Columns I to III are estimated using quantile regression.

3.5.3 Are innovative firms more productive than non-innovative firms? Results from Propensity Score Matching

Finally, using the PSM regression analysis, we address whether innovative Indian manufacturing firms are more productive than non-innovative firms.

The first stage of the PSM regression involves estimating the selection equation through Probit regression. The results are summarised in Table 3.3. The Likelihood Ratio (LR) Chi2 test indicates that at least one of the regression coefficients in the model is not equal to zero. The estimated coefficient of the R&D intensity variable in Table 3.3 shows that the probability of spending on $R\&D$ activities is higher for innovative firms than non-innovative firms. In terms of $location$, the positive and significant nature of the variable indicates that innovative firms are more likely to cluster around the major industrial locations of the country. The results also show that $competition$ amongst firms is likely to hurt their innovation output, as the variable competition is negative and significant. Finally, the significance of the variable $labour$ indicates that having a larger pool of labourers increases the probability of innovation amongst firms, once again confirming the labour-intensive nature of innovation in Indian manufacturing firms.

Table 3. 3: First step of PSM estimate: Probit model

Variables	F=Pr(Innovation=1)
$R\&D$	0.695***
	(0.17)
$Location$	0.205***
	(0.03)
$Competition$	-0.038***
	(0.02)
$Labour$	0.356***
	(0.01)
$Constant$	-3.596***
	(0.11)
Observations	11,260
Pseudo R^2	0.13
Chi^2	1554.66
Log Likelihood	-5286.694

Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis

Our sample includes 347 innovative and 1451 non-innovative firms. Table A3 in the Appendix presents the PSM balance test showing the matching between these two groups of firms using the kernel matching and the nearest neighbor N(3) method. The PSM balance test provides evidence of a good fit, as it has been observed that the innovative and non-innovative firms are, on average, statistically not different in terms of observable characteristics included in the selection equation.

Table 3.4 summarises the results of the impact evaluation of innovation on the TFP of the Indian manufacturing firms. Based on the matching through Kernel and N(3) method, it is possible to say that the innovative firms are significantly more productive than their non-innovative counterparts, verifying Hypothesis 3.3. The estimated coefficients in Table 3.4 show that the sample of innovative firms has productivity in the range of 38 to 39 per cent, while the same for the sample of non-innovative firms ranges between 26 to 28 per cent. The magnitude of the mean comparison test shows a difference of 10 to 11 per cent between the innovative and the non-innovative firms. This reflects that the innovative firms are, on average, 10 to 11 times more productive than the non-innovative firms. The low magnitude of this difference further validates the low impact of innovation on firm productivity in the EMDEs.

Table 3. 4: Average treatment effect on the treated (ATT): Impact of innovative and non-innovative firms on TFP

Outcome Variable	Sample	Methodology	Treated	Controls	Difference	SE	T-stat
TFP	ATT	Kernel	0.38044734	0.268936	0.116109	0.011835	9.81***
		Nearest neighbor	0.38504473	0.284487	0.100558	0.013777	7.3***

*Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis*
Outcome variable: TFP_{ACF}
Treatment variable: Binary variable for innovative and non-innovative firms (innovative firms=1)

3.6 Robustness Checks

In order to deal with the evident endogeneity issue, certain alternative specifications are conducted. This section discusses the results of the alternate specifications.

5.6.1 Firms' productivity as a determining factor of innovation

We follow three alternative approaches summarised below to check the robustness of the results obtained following the empirical model discussed in Eq. (3.9). First, we lag the dependent variable to check the endogeneity in the model (see Columns I to V, Table 3.5). The empirical literature on the negative binomial model suggests using the dependent variable's lagged values to control the endogeneity (Drakos & Gofas, 2006; Shkolnykova & Kudic, 2022). Using the lagged dependent variable allows the current dependent variable to temporarily co-vary with past instantiations of the dependent variable (Garcia, 2013). Second, the lagged value of the explanatory variable is introduced in the empirical model (see Columns I and III, Table 3.5). Using lagged explanatory variables moves the channel through which endogeneity biases causal estimates (Bellemare et al., 2017). This is because Y_t cannot possibly cause X_{t-1}. Third, we use productivity measured by the Levinsohn and Petrin (2003) (LP) (TFP_{LP}) method to calculate productivity (see Columns II to V, Table 3.5).[13] The LP method considers the correlation between unobservable productivity shocks and input levels in firm-level observations. The existing productivity literature has widely used the LP method to calculate firm-level productivity (Choudhry, 2021; Wang et al., 2022). Fourth, we use the Generalised Method of Moments (GMM) to address the endogeneity issues in the estimation (see Table 3.6).

[13] For details, readers can refer to Levinsohn and Petrin (2003).

The negative binomial results presented in Table 3.5 and the GMM results in Table 3.6 are consistent with the empirical findings reported in Table 3.1. Hence, the econometric evidence of this chapter establishes that firms' productivity significantly affects firms' innovation. The estimated value of the lagged innovation term is positive and significant across all the models, reflecting that Indian manufacturing firms innovate in a loop, with the previous innovation significantly affecting the current innovations (see columns I to V, Table 3.5 and I to IV of Table 3.6). This supports the empirical findings of Girma et al. (2009) and Garcia et al. (2013), who showed that the manufacturing firms which had applied for patents in the previous years are more likely to apply for patents in the current year. This also aligns with the "success-breeds-success" process (Nelson and Winter, 1982), whereby innovation success breeds further innovations. To put the results into perspective, the persistency in the innovation behaviour shows that knowledge previously used to produce innovations can be used to produce current and further innovations.

Turning to the productivity variable, column I of Table 3.5 uses the lagged value of TFP calculated through the ACF method (TFP_{ACF}) as the explanatory variable. Columns II to V of Table 3.5 use the TFP calculated using the LP method (TFP_{LP}) and its lagged values as the explanatory variable. Results in columns I and V of Table 3.5 show that the estimated coefficient of the lagged productivity parameter is positive and significantly different from zero, reflecting persistency in the productivity behaviour of the firms. Based on the empirical findings, we infer that firms' past productivity performances significantly influence their innovation output. To be more precise, higher past productivity leads to more innovation outputs. Thus, the results provide evidence that innovation is systematically related to firms' past productivity performances and innovation cycles.

Further, we turn to a quasi-differenced GMM estimation. The results, presented in Table 3.6, further establish the robustness of the empirical findings of the study. Columns I of Table 3.6 use TFP_{ACF} as the explanatory variable, and Column IV of Table 3.6 use TFP_{LP} as the explanatory variable. The estimated coefficients of the lagged innovation variables are positive and significant across all the specifications, re-establishing the persistency in innovation behaviour. The productivity indicator, calculated using both the ACF and the LP method, is again positive and significant, supporting the empirical findings from Table 3.1 and Table 3.5. Thus, the econometric results provide concluding evidence that firms' productivity significantly determines the innovation output of Indian manufacturing firms.

Table 3. 5: Firms productivity as a determining factor of firms' innovation: Negative binomial estimation

Variables	I	II	III	IV	V
$Innovation_{t-1}$	0.034***	0.0357***	0.035***	0.036***	0.036***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
$Productivity_{ACF(t-1)}$	0.261*				
	(0.14)				
$Productivity_{LP}$		0.236*			0.227*
		(0.14)			(0.14)
$Productivity_{LP(t-1)}$			0.248*		
			(0.14)		
Age	1.491**	1.584***	1.666***	1.621***	1.608***
	(0.59)	(0.57)	(0.59)	(0.57)	(0.56)
$Location$	-1.869*	-2.550**	-2.643***	-2.305**	
	(1.02)	(0.99)	(1.02)	(0.99)	
$Labour$	0.326***	0.347***	0.329***	0.396***	0.350***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
$R\&D$	0.943	0.045	-0.028		
	(1.93)	(1.86)	(1.85)		
$Capital$	0.003	0.008	-0.001	-0.002	0.008
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
$Profit_{t-1}$	-0.002	0.000	-0.003	0.002	-.0003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
$Productivity_{LP} \times RD$				-0.097	
				(0.28)	
$Location \times RD$					-0.752
					(2.10)
$Constant$	-8.568***	-9.463***	-9.477***	-8.299***	-12.067***
	(1.62)	(1.70)	(1.72)	(1.54)	(2.48)
Time Dummy	Yes	Yes	Yes	Yes	Yes
Cross-Section Dummy	Yes	Yes	Yes	Yes	Yes
Log Likelihood	-1566.507	-1672.675	-1629.680	-1674.073	-1672.611
Pseudo R^2	0.326	0.322	0.325	0.321	0.322

Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis.
Columns I to V are estimated using negative binomial estimation.

Table 3. 6: Firms performance as a determining factor of firms' innovation: GMM estimation

Variables	I	II	III	IV	V	VI
$Innovation_{t-1}$	1.007***	0.853***	0.876***	0.845***	0.936***	0.850***
	(0.07)	(0.01)	(0.01)	(0.01)	(0.06)	(0.01)
$Productivity_{ACF}$	0.198*		0.792***			
	(0.10)		(0.11)			
$Productivity_{LP}$				0.724**		0.592***
				(0.31)		(0.21)
Age	-0.008	-0.082	0.223	-0.125	0.005	-0.064
	(0.19)	(0.25)	(0.24)	(0.41)	(0.15)	(0.32)
$Location$	0.133	-0.057		-0.021	0.47	
	(0.36)	(0.38)		(0.53)	(0.35)	
$Labour$	0.467**	0.484***	0.361**	0.196	0.787***	0.366**
	(0.20)	(0.15)	(0.16)	(0.25)	(0.16)	(0.17)
$R\&D$	-0.081			0.164		
	(0.10)			(0.12)		
$Capital$	0.053	0.084	0.127***	0.042	0.144*	0.005
	(0.09)	(0.08)	(0.03)	(0.11)	(0.08)	(0.08)
$Profit_{t-1}$	-0.038	-0.003	-0.029***	-0.121***	-0.047*	-0.049***
	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)
$Productivity_{ACF} \times RD$		0.482				
		(0.83)				
$Productivity_{LP} \times RD$					-0.407	
					(0.33)	
$Location \times RD$			0.093			0.099
			(0.06)			(0.07)
AR2	0.57	0.40	0.39	0.13	0.40	0.20
AR2(p)	0.570	0.689	0.693	0.897	0.687	0.840
Hansen	23.99	34.72	75.24	33.70	34.80	47.78
Hansen(p)	0.773	0.178	0.406	0.251	0.250	0.285

Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis
Columns I to VI are estimated using GMM estimation.

3.6.2 innovation as a determining factor of firms' productivity

The empirical findings of the quantile regression (see Table 3.2) show that the innovation output of Indian manufacturing firms significantly influences their productivity. In this section, we re-investigate whether this result is sensitive to a particular specification or robust across all specifications. To this end, first, we use TFP_{LP} as the productivity indicator instead of the TFP_{ACF} (Columns I to IV and VI, Table 3.7). Second, we use GMM to deal with the endogeneity issue (Columns V and VI, Table 3.7).

The empirical findings presented in Table 3.7 are consistent with the earlier findings in Table 3.2. More specifically, the results indicate that innovation does not significantly affect firms' productivity (TFP_{LP}) at the lower quantile distribution. However, innovation significantly affects firms' productivity (TFP_{LP}) at higher quantiles. These results are consistent with prior empirical findings reported in Table 3.2 (using TFP_{ACF} as the dependent variable). The estimated coefficients from GMM estimation, shown in column V (with TFP_{ACF} as the dependent variable) and VI (with TFP_{LP} as the dependent variable) of Table 3.7 further confirms that innovation in individual firms positively influences firms' productivity.

Thus, the results provide robust evidence that innovation in Indian manufacturing firms significantly improves their productivity, irrespective of any alternative indicator used to denote firms' productivity and methodology used to estimate the regression models. Nevertheless, the impact of innovation output on firm productivity is again found to be much lower than the impact of productivity on innovation output. More specifically, the results reported in Tables 3.5 and 3.6 indicate that a one-unit increase in firms' productivity increases their innovation output, on average, in the range of 0.198 units to 0.289 units. On the other hand, results reported in Table 3.7 show that a one-unit increase in innovation output increases firms' productivity, on average, by 0.001 units to a maximum of 0.010 units.

As an EMDE, India is necessarily a technological follower (Helpman, 1993). Hence, the technology frontier of Indian manufacturing firms is quite far away from the optimal technological frontier. Given this, any technological progress, represented by the innovation parameter, has a smaller impact on the firm growth (Howitt and Mayer-Foulkes, 2005). By the same logic, these manufacturing firms require a bigger push to take up innovation activities. Productivity improvement gives this much-needed push, resulting in a greater impact of firm productivity on innovation.

Table 3.7: Innovation as a determining factor of firms' productivity: Sensitivity and robustness checks

Variable	I	II	III	IV	V
	$\tau = .25$	$\tau = .50$	$\tau = .75$		
$TFP_{ACF(t-1)}$				0.419***	
				(0.05)	
$TFP_{LP(t-1)}$					0.775***
					(0.05)
$Innovation$	0.001	0.004***	0.010**	0.005***	0.002*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Age	0.039	0.056	-0.032	-0.403***	-0.06
	(0.03)	(0.04)	(0.04)	(0.12)	(0.07)
$Salary$	0.498***	0.546***	0.621***	0.312***	0.166***
	(0.02)	(0.03)	(0.01)	(0.05)	(0.04)
$R\&D$	-1.900***	-1.979***	-2.621***	0.01	0.015
	(0.33)	(0.15)	(0.34)	(0.06)	(0.03)
$Competition$	0.035	0.132***	0.349***	-0.878***	-0.216
	(0.09)	(0.04)	(0.03)	(0.23)	(0.14)
$Import$	-1.598***	-1.300***	-1.565***	-1.687***	-1.099***
	(0.27)	(0.44)	(0.17)	(0.50)	(0.31)
$Export$	-0.724***	-0.344***	0.034	0.157	0.072
	(0.07)	(0.11)	(0.05)	(0.44)	(0.34)
$AR2$				1.01	0.38
$AR2(p)$				0.311	0.706
$Hansen$				23.18	28.46
$Hansen(p)$				0.623	0.387
Observations	1735	1735	1735		
Number of groups	155	155	155		

Notes: *** p<0.01, ** p<0.05, * p<0.10, standard errors in parenthesis. Columns I to IV report the results of quantile regression, and columns V and VI report the results of GMM estimators. The dependent variable for columns I to IV and VI is the TFP_{LP}. The dependent variable for column V is TFP_{ACF}

5.*6.3 Are innovative firms more productive than non-innovative firms?*

Table 3.4 shows that the innovative firms are more productive than their non-innovative counterparts. To assess the sensitivity of the findings of Table 3.4, we re-run the PSM estimation using TFP_{LP} as the productivity indicator. The results of the first stage of the PSM method, the probit estimation, are reported in Table 3.8. The estimated coefficients of the probit estimation show that innovative firms are more likely to spend on $R\&D$ than non-innovative firms. The findings reveal that firms located in the major industrial $locations$ of the country and firms in the monopolistic or oligopolistic markets have a higher probability of patenting. Further, the innovation probability is higher for firms with a greater pool of $labour$. These results align with the empirical findings of Table 3.3. Table A4 in the Appendix reports the results of the balance test. The PSM balance test indicates a good fit using the kernel and nearest neighbor (N3) method.

Table 3. 8: First step of PSM estimate: Probit model

Variables	F=Pr(Innovation=1)
R&D	0.666***
	(0.17)
Location	0.207***
	(0.03)
Competition	-0.038***
	(0.02)
Labour	0.356***
	(0.01)
Constant	-3.598***
	(0.11)
Observations	11,285
Pseudo R^2	0.1291
Chi^2	1566.03
Log Likelihood	-5283.87

Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis
Productivity is measured using the Levinsohn and Petrin (2003) method

Table 3.9 reports the impact evaluation of innovation on the productivity of the manufacturing firms in India. The results fully confirm the main findings of Table 3.4, and we can conveniently conclude that the innovative firms are more productive than the non-innovative firms.

Table 3. 9: Average treatment effect on the treated (ATT): Impact of innovative and non-innovative firms on TFP

Outcome Variable	Sample	Methodology	Treated	Controls	Difference	SE	T-stat
TFP	ATT	Kernel	6.762821	6.079745	0.683076	0.345569	19.77***
		Nearest neighbor	6.762821	6.182436	0.580385	0.40292	14.40***

Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis
Outcome variable: TFP_{LP}
Treatment variable: Binary variable for innovative and non-innovative firms (innovative firms=1)

3.7. Conclusion, Limitations, and Policy Implications

This chapter investigates the dynamic nexus between innovation and firms' productivity in the context of EMDEs by taking a sample of Indian manufacturing firms from 2005 to 2020. Based on the conceptual framework drawn and prior evidence, we frame three hypotheses. The first hypothesis explores whether or not firms' productivity is crucial in determining the innovation output of Indian manufacturing firms. The results of our analysis provide robust evidence supporting the first hypothesis. In fact, the empirical findings reveal that productivity has a greater impact on generating more innovation output than innovation has on stimulating productivity increases. The second hypothesis investigates whether or not innovation significantly improves the productivity of Indian manufacturing firms. Our analysis provides robust evidence that innovation substantially improves the productivity of Indian manufacturing firms. Finally, the third hypothesis investigates if innovation would make Indian manufacturing firms more productive than their non-innovative counterparts. The empirical findings of the chapter confirm that innovative firms are significantly more productive than non-innovative firms. However, the observed productivity difference between the two groups of firms is found to be very low, in the range of 10 to 12 per cent only.

The findings of the chapter are informative for policymakers in EMDEs. Our empirical analysis yields robust evidence that firms' productivity has a more powerful impact on innovation output than the impact of innovation on productivity growth. Based on this, we suggest that policymakers direct future policies towards productivity-diffusing measures to infuse innovation in Indian manufacturing firms. Further, our analysis also finds that innovation improves firms' productivity and that innovative firms are more productive than non-innovative firms, even though the productivity difference between the two groups is small. Given the crucial role of innovation, policies should be channelled towards incentivising innovation in individual firms.

We wind up this study by stressing the complementary nature of innovation with firm productivity and the need for an all-inclusive and meticulous analysis of this relationship, especially in the context of EMDEs like India. Also, the relationship between innovation and productivity is influenced not only by the quantity of innovation but also by the quality of innovation. The present study ignores this. Future research could well be directed towards an all-inclusive empirical analysis of this aspect for a comprehensive understanding of the two-way synergistic of innovation at the micro-level. In fact, the synergistic of innovation and firm productivity may also differ for foreign and domestic firms, which is not incorporated in the present study, leaving a scope for future research. Further, there is a great degree of discrepancy in the funding of R&D in India, where the public sector accounts for the majority of the funding while the private sector’s contribution is grossly minimal. A detailed analysis of such discrepancies may add major insights into the theme under discussion. Future research could look into it.

Appendix A

Table A 1: Computation of variables and sources of data

Variable Name	Variable Description	Source
	Innovation Indicator	
Innovation	Counts of patents granted to a firm i during period t	IPO/Patseer
	Firm Performance Indicator	
Productivity	Calculated using the ACF method	Prowess
	Firm-Specific Factors	
Age	difference between the current year t and the firm $i's$ establishment year	Prowess
Salary	Wages and compensation paid to the employees of firm i during period t	
Location	dummy variable, which takes the value of 1 if the firm is located in one of the cities falling in the major industrial cluster and 0 otherwise	Prowess
Labour	Number of labor inputs of firm i during period t	Prowess
	Market Specific Factors	
Export Intensity	Export of goods and services of firm i as a ratio of sales of the firm during period t	Prowess
Import Intensity	import of capital goods and royalty, licensing and technical fees paid by firm i as a ratio of sales of the firm during period t.	Prowess
Competition	Measured using Herfindahl Hirschman Index	Prowess
Profit	Profit before tax of a firm i during period t.	Prowess
	Technology Specific Factors	
R&D	Research and development expenditure as of firm i a ratio of sales of the firm during period t.	Prowess
Capital	Addition to the physical assets of a firm i during period t.	Prowess

Table A 2: Descriptive Statistics and correlation matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1.Innovation	1											
2.Productivity	0.192***	1										
3.Age	0.078**	0.001	1									
4.Salary	0.314***	0.637***	0.283***	1								
5.Location	0.072**	0.016	0.072**	0.149***	1							
6.Labour	0.310***	0.576***	0.237***	0.904***	0.105***	1						
7.Export	-0.023	-0.008	-0.231***	-0.084***	-0.093***	-0.056*	1					
8.Import	0.001	-0.167***	0.018	-0.156***	-0.073**	-0.109***	0.233***	1				
9.Competition	0.009	-0.292***	-0.058*	0.011	-0.071**	0.003	-0.249***	-0.058*	1			
10.Profit	0.034	0.291***	0.117***	0.399***	0.121***	0.353***	-0.192***	-0.188***	0.036	1		
11.R&D	0.013	0.055*	-0.029	-0.048	-0.114***	-0.007	0.188***	-0.007	-0.001	-0.064*	1	
12.Capital	0.262***	0.497***	0.167***	0.823***	0.051*	0.778***	-0.091***	-0.094***	0.064*	0.433***	-0.001	1
Mean	0.87	3.38	3.37	6.22	0.86	7.89	0.26	0.06	-4.37	5.32	0.04	5.63
SD.	4.9	1.49	0.64	1.82	0.35	1.41	1.97	1.62	0.76	4.93	0.99	2.35

Note: *** p<0.01, ** p<0.05, * p<0.10

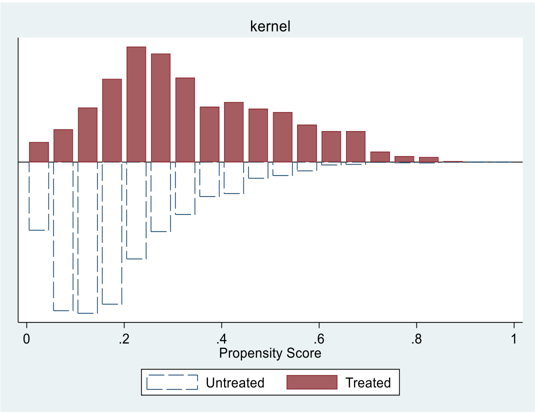
Table A 3: PSM balance test after matching (Dependent variable- TFP_{ACF})

Variables	Kernel					N(3)				
	Mean			t-test		Mean			t-test	
	Treated	Control	% Bias	t	p>|t|	Treated	Control	% Bias	t	p>|t|
RD	0.015	0.010	9.2	3.85	0.000	0.015	0.013	4.8	1.85	0.07
Location	0.754	0.744	2.1	0.79	0.429	0.754	0.740	3.1	1.16	0.25
Competition	-4.972	-4.997	2.8	1.03	0.302	-4.972	-4.984	1.3	0.48	0.63
Labour	7.778	7.756	1.5	0.53	0.595	7.778	7.810	-2.2	-0.77	0.44

Table A 4: PSM balance test after matching (Dependent variable- TFP_{LP})

Variables	Kernel					N(3)				
	Mean			t-test		Mean			t-test	
	Treated	Control	% Bias	t	p>|t|	Treated	Control	% Bias	t	p>|t|
RD	0.015	0.011	8.0	2.97	0.003	0.015	0.013	4.5	1.54	0.12
Location	0.753	0.743	2.2	0.83	0.405	0.753	0.743	2.4	0.90	0.37
Competition	-4.971	-4.996	2.9	1.05	0.292	-4.971	-4.984	1.5	0.54	0.59
Labour	7.777	7.754	1.6	0.56	0.578	7.777	7.808	-2.2	-0.75	0.45

Figure A 1: Propensity score by treatment (Dependent variable- TFP_{ACF})



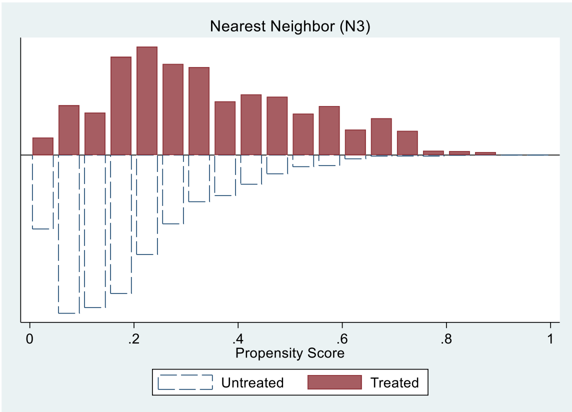
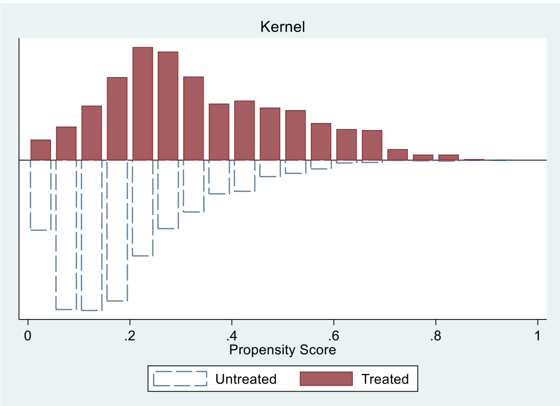
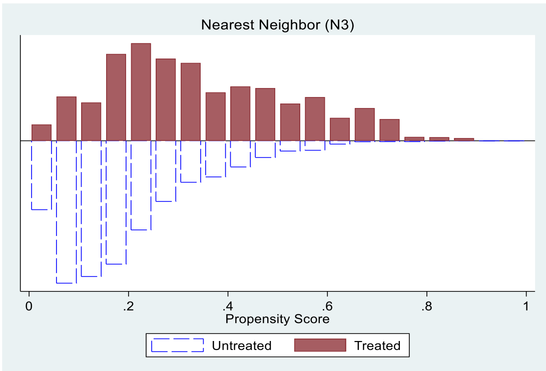


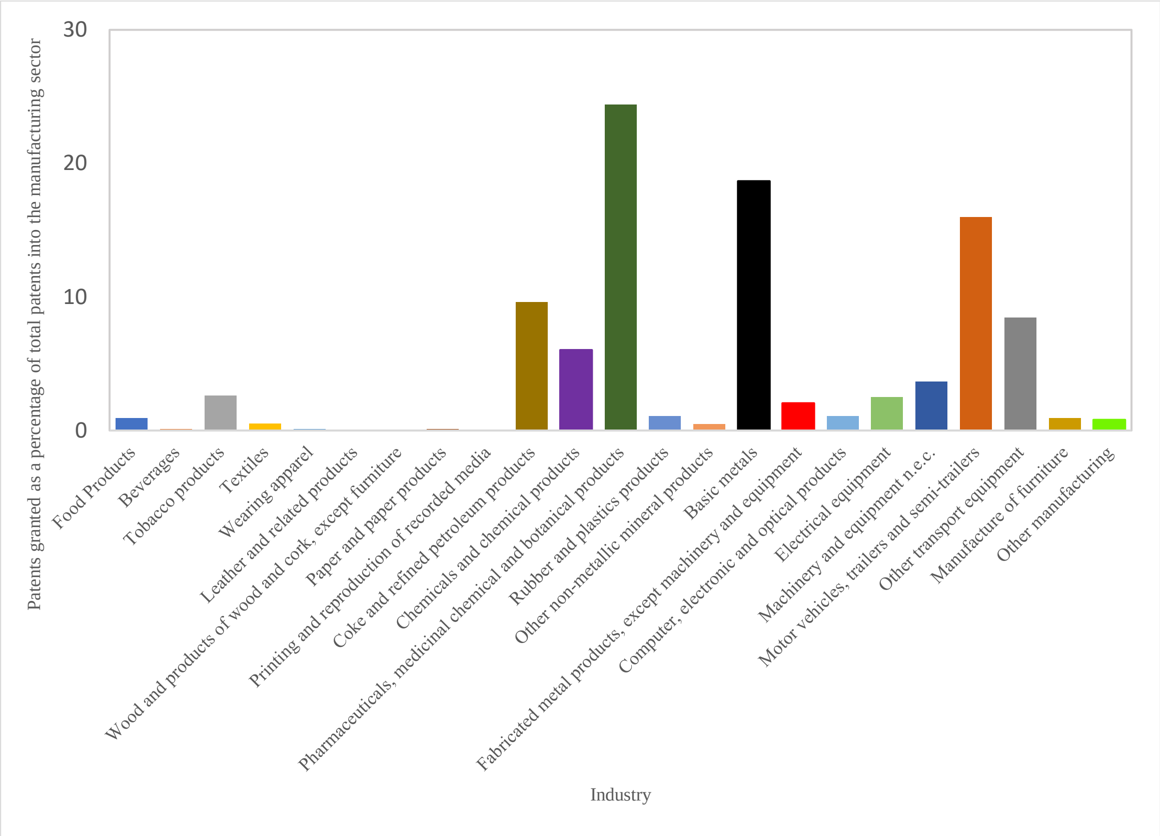
Figure A 2: Propensity score by treatment (Dependent variable- TFP_{LP})





Source: Authors' computation

Figure A 3: Industry-wise distribution of patents granted (as a percent of total patents in the manufacturing sector)



Source: The authors’ computation based on data collected from Patseer.

Chapter 4

Employment Effects of Process and Product Innovation in India and the Role of Foreign-Ownership

4.1 Introduction

4.1.1 Contextualisation and motivation

Technologies are introduced to save labour. Any new technology increases the total productivity of the economic agents, raising the possibility of jobless growth and technological unemployment. Historically, Ricardo's popular "working class opinion" is sketched by the fear of being wiped out by technology (Sraffa, 1951). Even during the industrial revolution of the late eighteenth century and early nineteenth century, the immediate response of the English workforce was the destruction of machines. Two and a half centuries later, in this era of industrial revolution-IV, with the blurring of the boundary between the physical, digital and biological world, some questions still persist. Are machines taking up human jobs? Is technology replacing labour? The present chapter takes up this issue and tries to find out whether technological augmentations in the form of process and product innovations substitute or complement job creation by taking a sample from India.

The existing studies on the impact of technology on the labour market have distinguished between the effect of an increase in factor productivity and the introduction of a new stream of demand. Schumpeter (1934) defines 'the introduction of a new method of production or a new way of handling a commodity commercially' as process innovation and 'the introduction of a new good or a new quality of a good' as product innovation.

By and large, process innovation essentially refers to producing the same output with lesser factors of production via enhanced productivity. Textbooks present process innovation as a downward movement of the isoquant. It leads the firms to produce the same amount of goods at lower costs. If this cost advantage is translated into the product's price, process innovation would positively influence employment (Hall et al., 2008; Lachenmaier and Rottman, 2011). If not, firms would produce the same output with less labour inputs (Dachs et al., 2014; Dosi and Yu, 2019).

On the other hand, product innovation, i.e., diffusion of new technology, can create new jobs by initiating new demand. A buoyant product market would shift the aggregate demand, opening avenues for additional labour absorption (Hou et al., 2019; Woltjer et al., 2021). However, introducing a new product may also take away the market of an existing product

(Zhu et al., 2021). We have seen such instances in the course of history with computers taking over typewriters, cell phone technology taking over landline technology, or even the Uber and Ola markets pushing the traditional taxi market to the backseat in India. Under such circumstances, the effect of product diffusion in the labour market would depend upon the relative size of the displacement effect in the old market vis-a-vis the labour supplementary effect in the new market.

In the economics literature, assessing the effect of innovation upon employment is a vintage practice. It dates back to the classical compensation mechanism, later adopted by neo-classical economists. However, the compensation mechanism was severely criticised by David Ricardo and Karl Marx for lacking practicality. Economic theory fails to provide a distinct picture of the relationship between technology and employment. Inconsistency in the theoretical framework has led empirical economists to translate the dual dynamics of technological progress and employment from theories to the empirical world.

Moving ahead, the labour market in any economy is dynamic in nature as it is inherently characterised by continuous change and adaptability. This profoundly affects the relationship between process and product innovation and employment generation in any firm. Firms will always take into account the previous labour market situation before recruiting additional employees. However, most of the empirical researches investigating the impact of process and product innovation on employment in advanced economies ignore the dynamic nature of the labour market (Peters, 2004; Hall et al., 2008; Harrison et al., 2014; Dachs et al., 2017; Hou et al., 2019; Lim and Lee, 2019; Zhu et al., 2021; Woltjer et al., 2021). There are, of course, some researches which have acknowledged the dynamic nature of the labour market in the context of advanced economies (Van Reenen, 1997; Garcia et al., 2004; Lachenmaier and Rottmann, 2011; Piva and Vivarelli, 2017; Van Roy et al., 2018; Pellegrino et al., 2019; Bianchini and Pellegrino, 2019; Dosi and Yu, 2019; Aldieri et al., 2021). However, these studies have either used an input measure of innovation (Bogliacino, 2012; Piva and Vivarelli, 2017; Pellegrino et al., 2019; Dosi and Yu, 2019; Aldieri et al., 2021), or a dichotomous measure of innovation (Rottmann and Ruschinski, 1998; Garcia et al., 2004; Lachenmaier and Rottmann, 2011; Bianchini and Pellegrino, 2019), or have failed to distinguish between process and product innovation while using an output measure of innovation (Van Reenen, 1997; Coad and Rao, 2011; Van Roy et al., 2018). In addition, the output measure used by the existing works is also in the form of dichotomous variables and not in the form of actual innovation counts, which makes it difficult to quantify the heterogeneous impact of innovation. The only study that uses actual innovation counts while studying the link between innovation and the labour market (Van Reenen, 1997) fails to distinguish between process and product innovation.

However, the relationship between innovation and the labour market differs vividly between advanced countries and emerging market and developing economies (EMDE). Whereas the advanced countries possess skilled labour, the EMDEs are mostly flooded with unskilled labour. Given this, technological progress or innovation in developed economies does not collide with the labour market in the advanced developed countries. On the contrary, developing countries continuously face the trade-off between modernising the industrial sector vis-a-vis generating employment for the excess labour in the labour market. This underscores the importance of research specifically focusing on the impact of process and product innovation in EMDEs.

Some researchers have tried to bridge the gap between labour economics and economics of innovation in EMDEs by discussing the impact of process and product innovation on employment generation (Alvarez et al., 2011; Monge-González, 2011; Aboal et al., 2015; Elejalde et al., 2015; Cirera and Sabetti, 2019; Avenyo et al., 2019; Crespi et al., 2019; Lim and Lee, 2019; Baffour et al., 2020; Naidoo et al., 2024). However, all these studies have used a static framework and a binary variable to measure process innovation. While using the binary variable makes it difficult to quantify the heterogeneous impact of process innovation, failing to address the dynamic nature of the labour market gives rise to serious misspecification issues in the empirical framework. The study done by Merikull (2010) for Estonia improves upon the misspecification issue, as they acknowledge the dynamic nature of the labour market in their empirical estimation. However, they use the share of firms with process and product innovations to measure innovation, which leaves out the scope to adequately estimate the impact of the actual quantity of innovation on the labour market.

Contribution

Our study enriches this literature as we use actual counts of process and product innovation using patent data. To the best of our knowledge, this is the first study, both in the context of advanced countries and EMDEs, which has segregated the actual patent counts of the firms into process and product innovation and empirically investigated their impact on the labour market. This study also acknowledges the dynamic nature of the labour market in the empirical specification, which again is a unique addition to the literature in this field, especially in the context of EMDEs. Moreover, while discussing the link between process and product innovation with employment, most of the studies grossly ignore the synergies of globalisation, technological upgradation and employment generation. Foreign-owned firms (hereafter referred to as foreign firms), the affiliates of foreign multinational corporations, possess superior technical, managerial and organisational capabilities and demand more skilled labour than domestic firms (Bellak, 2004; Griffith and Simpson, 2004) as against local domestic firms. Both groups also differ quintessentially in terms of successfully introducing innovations into the market and market competitiveness. Such differences can lead to significant differences in employment expansion or contraction in the host country (Dachs and Peters, 2014). However, empirical research evaluating these differences is surprisingly scarce. We find only one research conducted in the context of Europe (Dachs and Peters, 2014), which measures innovation using binary variables while estimating the model in a static framework. This chapter makes a significant contribution to this end, as we use actual innovation counts and a dynamic framework. Besides, this study is concerned with the trade-off between innovation and employment in the context of EMDE, which gives significant weightage to the study's findings.

It is quite interesting that hardly any study has investigated the link between technological progress and the labour market in the country with the world's largest labour force, India. Incidentally, the workforce participation in the country has decreased from 63.70 per cent in 2005 to 45.90 per cent in the second quarter of 2020 (Trading Economics, 2022). On the flipside, India holds the highest position in central and southern Asia in terms of innovation (Intellectual property statistical country profile 2021). This gives rise to certain interesting questions. Being a developing country where the majority of the workforce is essentially "unskilled worker", is India facing what the critiques of the compensation theory called "technological unemployment"? If yes, what must the government do to rectify the situation? Because halting technological progress is not a solution. It would simply mean arresting growth. Also, are the foreign firms generating more employment than the domestically-owned firms (hereafter referred to as domestic firms) due to innovations[14]? These questions require concrete and fact-ridden answers. Sadly, the existing literature hardly assists us in this respect. We consider this fact and take our sample from the Indian manufacturing firms.

Our findings support the Ricardian and Marxian views that process and product innovation displace labour in the Indian manufacturing sector. The econometric findings confirm that the labour-displacing effect of process and product innovation is specific only to domestic firms and not to foreign firms. Further, a detailed insight into the relationship nullifies the requirement of heterogeneous policies for foreign and domestic firms, as we do not find any evidence of foreign firms significantly generating more employment than domestic firms.

[14] For the purpose of the study, we have considered a firm as a foreign-owned/ foreign firm if the equity held by the foreign promoter in the firm is a minimum of 10 percent. This classification of foreign owned firm is consistent with the Report of the Dr Arvind Mayaram Committee on Rationalising the FDI/FII Definition, 2014.

4.2. Conceptual Framework and Hypothesis Development

The relationship of process and product innovation with the labour market could be better understood with the help of the classical compensation mechanism. The introduction of process innovation involves increasing input productivity and thus disrupts the equilibrium in the labour market. The supporters of the compensation mechanism adhere to four channels through which economic agents would operate in a way that would restore market equilibria. First, process innovation would reduce the unit cost of production. This would translate into reduced prices in a competitive market, stimulating a new line of product demand, subsuming the displaced labour. This is referred to as 'compensation via decrease in prices' (Steuart, 1767). Second, the labourers displaced in the consumer market via the introduction of new machines can be compensated in the capital sector by producing the new machines (Say, 1836). Third, the classical assumption of J. B. Say states that in a competitive market, there always exists a lag between cost reduction due to technical progress and a subsequent fall in prices. The entrepreneurs can earn extra profit during this period. These profits are always invested immediately and entirely, opening new demand and employment channels. This is referred to as the 'compensation via new investment'. Fourth, on the basis of the neo-classical assumption of perfect substitutability of labour and capital, the compensation theory states that the direct effects of labour-saving technology can be compensated in the labour market via decreases in wages.

However, many neo-classical economists refuted these channels of compensation. According to J. S. Mill, dismissal of labour would lead to a decreased demand for labour, leading to a downward shift in the labour demand curve and displacing more labour than before. Moreover, in the case of a developing country, a price decrease does not necessarily create any demand in downstream industries as there hardly exists user and buyer sectors in an industry (Karaomerlioglu and Ansal, 2003). Also, developing countries face slow or negative growth, hindering employment growth even in case of unsatisfied demand. Karl Marx adherently criticised the idea that displaced labourers in the consumer market could be accommodated in the capital goods sector. The capital goods sector is extensively characterised by labour-saving technology rather than labour-friendly technology, leaving no room for any additional employment in this sector, even with an increase in demand. The critiques of the compensation theory refute the idea of 'compensation via new investment' on the grounds of Keynes' 'animal spirit' and argue that the additional profit may not necessarily be always invested. Also, even though invested, if the new investment is labour saving, it would rather retrench employment. Finally, the notion of 'compensation via a decrease in wages' has been refuted on many grounds. First, a decrease in wages would also mean a decrease in demand, ultimately terminating additional employment opportunities. Second, in the presence of trade unions and collective bargaining, wage decrease is only a theoretical possibility. Third, in the case of ‘localised’ or ‘locked in’ technical change, the hypothesis of perfect substitutability between labour and capital collapses (Freeman and Soete, 1987; Stiglitz, 1987). Especially in the context of a developing economy, which is already characterised by the predominance of cheap labour, lowering wages is unlikely an option. Given this, we hypothesise that process innovation is labour-saving in nature.

Hypothesis 4.1 *Process innovation is associated with significant displacement of labour in Indian manufacturing firms.*

Product innovation involves creating new products and opening avenues for a completely new demand sector. The direct impact of product innovation would involve an upward shift in the labour demand curve owing to entirely new branches of production. However, if the new product launched is capital intensive, it may reduce labour demand, leading to a downward shift in the demand curve. Product innovation may reduce jobs by replacing old products as well.

The EMDEs are highly dependent on foreign technology. Innovation in such economies is essentially in the form of imitation or purchase of technology from the developed world. Developed economies are capital-intensive and labour-scarce. Hence, their technology is also directed towards skill-intensive labour-saving activities. Imitating foreign technology under these circumstances would adversely impact employment generation in EMDEs. Nevertheless, we hypothesise that product innovation would augment a new stream of demand in the Indian labour market, leading to an upward shift in the labour demand curve.

Hypothesis 4.2 *Product innovation is associated with a significant generation of employment in Indian manufacturing firms.*

The ownership structure of firms may affect their labour market outcomes. Foreign firms enjoy greater market power than domestic firms as they have access to a wider range of markets as a part of the multinational group. Such firms also have a better distribution network. Thus, with process innovation and the consequent increase in productivity, foreign firms are more likely to expand their market by lowering their prices. This should generate more demand for the firms’ products, increasing labour demand. However, process innovation by advanced foreign firms often involves adopting advanced machinery and artificial intelligence tools that were previously handled with human resources. Many process innovations require highly skilled labour, which the EMDEs essentially lack. As a result, foreign firms may outsource certain functions to their parent country, adversely influencing the labour market in the host country. Thus, there exists ambiguity in divulging the employment effects of process innovation. Nevertheless, we hypothesise that process innovation in foreign firms would significantly displace labour in the host country.

Hypothesis 4.3 *Process innovation leads to significant displacement of labour in foreign firms.*

Foreign firms cater to larger demand sizes by virtue of greater market power and wider market range. As a result, product innovation, which essentially creates new avenues for demand for the firms' products, should increase the labour demand of the innovating firm. However, product innovation also renders the old product obsolete. Under this scenario, if the new product replaces the old product with reduced demand or if the new product completely wipes out the old product from the market, labour demand may be reduced. Moreover, the labour demand of firms producing the old product may also see a downward trend, or in the worst case possible, the firms producing the old products may experience a closure, leading to mass labour displacement. However, even though there is substantial ambiguity regarding the employment effect of product innovation of foreign firms, given the fact that the direct impact of any product innovation is an increase in labour demand, we frame the following hypothesis.

Hypothesis 4.4 *Product innovation leads to significant employment generation in foreign firms.*

4.3. Data and Variables

4.3.1 Sample selection

The present study spans the period from 2005 to 2020. The year 2005 marks India's full-fledged implementation of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS). Our initial dataset comprises 10,316 firms established on or before 2005, spread across 23 manufacturing industries. The firm-level data are collected from the CMIE Prowess database. These firms are mapped as par 2-digit NIC-2008 code. These data are complemented with PatSeer (Patent Search and Analysis Software) data for patent information. We dropped the firms without a single patent to their credit during our entire study period from the sample. It left us with 347 innovative firms, i.e., firms that were granted at least a single patent during our study period. Amongst these 347 firms, only 169 firms reported employment information consistently. This consists of our final sample. We limit the regression samples to firms that report innovation during the reference period to ensure that, in principle, all firms face a decision on how to protect their innovation (Hall et al., 2013; Igna and Venturini, 2023). Moreover, since the present study investigates the impact of process and product innovation on the labour market, including the non-innovative firms may create noise in the analysis.

Further, the firms are categorised as foreign and domestic firms. A foreign firm is an affiliate of a foreign multinational. Based on the Dr Arvind Mayaram Committee on Rationalising the FDI/FII Definition, 2014, a firm is categorised as a foreign firm if the equity held by the foreign promoter in the firm is a minimum of 10 per cent.

4.3.2 Description of variables

This section gives details of the dependent variable, the product and process innovation variables and the set of control variables.

Employment Variable

The dependent variable of the present chapter is $Employment$. This variable is constructed as the number of people employed by a firm in a year. The variable is introduced in a logarithmic scale.

Innovation Variable

Empirical works in innovation economics have acknowledged that patents are a "classic instrument for incentivising and measuring innovation" (Sweet and Eterovic, 2019).[15] Building on this, the present study instruments $innovatio$n with patent counts. For the purpose of the study, patent counts have been bifurcated as process and product patents.[16] Process patents are granted for a particular manufacturing process and not for the product. Thus, any other person can produce

[15] For details, see, Pakes and Griliches 1980; Griliches, 1998.

[16] To segregate the patents into product and process patents, we have considered the independent and dependent claims of the patents granted. Accordingly, if the independent claims categorise the patent as a process, we take the patent as process patent and vice versa. We are thankful to patent analyst Mr. Pranjal Nath for helping us with this segregation process

the same product through some other process, and hence, there can be more than one producer for the same product, given the possibility of different manufacturing processes. Product patents, conversely, are exclusive rights given to the original inventor of the product, entrusting him with the monopoly power to produce it.

Control Variables

The present work considers some additional explanatory variables that might influence the firm's job creation decisions. In order to assess the impact of firm's experience on its job creation capability, this study considers the age of the firm.

The economics of geography has documented that firms' geographical $location$ influences the employment generation capacity of the firms (Puga, 2010; Artz et al., 2016). The present study captures this impact by introducing the location variable, which enters the model as a binary variable, with the value being one for a firm situated in the major industrial belt of the country and zero otherwise.[17]

In order to empirically evaluate the "compensation via reduction in wages" argument, the empirical specification of the model includes the variable $salary\ per\ worker$ in the model. This variable is constructed as a ratio of the number of labourers to the compensation paid to the firm's employees.

The financial condition of a firm is considered by incorporating the $debt\ to\ equity\ ratio$ of a firm. Following Zhu et al. (2021) and Fukuda (2022), we believe that leveraged firms would not create long-term jobs.

The market demand of the firms is captured with their net $sales$. Higher demand is expected to augment jobs in the market (Greenhalgh et al., 2001; Bogliacino et al., 2012; Van Roy et al., 2018).

To account for the import of technology and license fees paid by the firms, we construct the $import\ intensity$ variable. This variable is the sum of the import of capital goods and fees paid for licensing and technological know-how expressed as a percentage of the firm's sales.

Finally, the level of internal technological expenditure is measured with the help of the $R\&D\ intensity$ of the firm. It is calculated as the ratio of the R&D expenditures of a firm to the sale of the firm.

[17] These industrial belts include the Mumbai-Pune industrial region, the Hugli industrial region, the Bangalore-Chennai industrial region, the Gujarat industrial region, the Chotanagpur industrial region, the Vishakhapatnam-Guntur industrial region, the Gurgaon- Delhi- Meerut industrial region, the Kollam-Thiruvanthapuram industrial region. This classification is demarcated by Singh (1971).

Table B1 in Appendix B presents the details of the variables, followed by the descriptive statistics and correlation matrix of the variables in Table B2.

4.3.3 Process and product patents by the Indian manufacturing firms: A general overview

This section overviews the process and product patents granted to manufacturing firms registered with India.

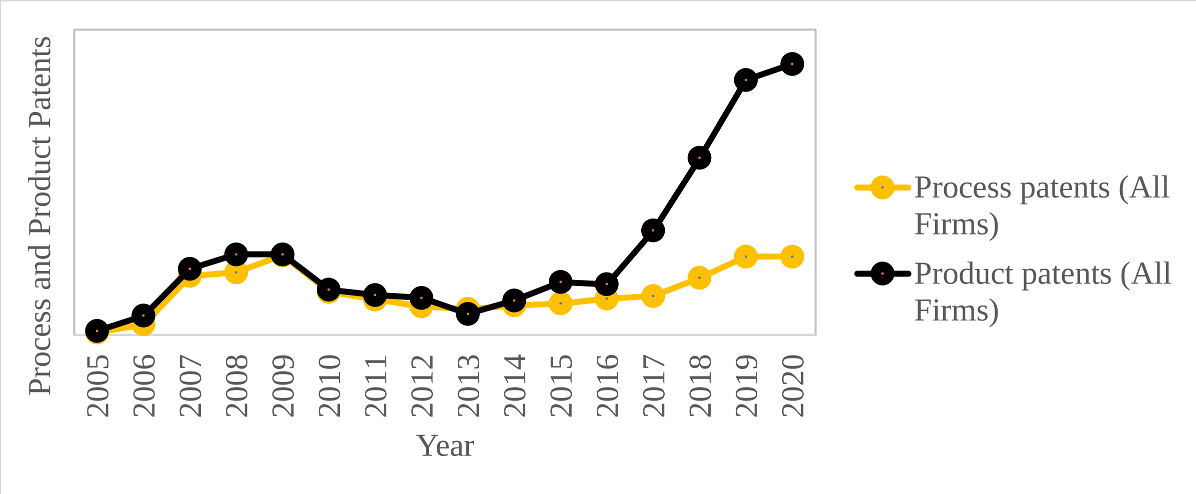
Fig. 4.1 shows the patents granted to all the manufacturing firms irrespective of their ownership. The figure provides a diverging picture of the number of product patents granted from 2014 onwards. During 2005-2013, the number of process and product patents both grew simultaneously. However, from 2013 onwards, the number of product patents granted started outgrowing the number of process patents.

Prior to TRIPS, developing countries such as India allowed only 'weak' protection to patents comprising solely process patents but not product patents. Implementation of TRIPS required India to allow product patents in sectors such as pharmaceuticals where product patents were not allowed previously. As a member of the WTO, India was given a ten-year transition period from 1995-2005 to become TRIPS compliant. Thus, TRIPS became effective in India only on 1 January 2005. Full compliance with TRIPS norms increased the number of product patents filed in the immediate years following the fuller adoption of the TRIPS. Thus, the surge in product patents granted by the patent offices in India from 2013 onwards could be explained in terms of the gestation period of 3-6 years involved with the grant of a patent application.

Further, Fig. 4.3 and Fig. 4.4 uncover the process and product patents granted to the domestic firms vis-à-vis the foreign firms. Both figures exhibit that domestic firms patent more intensely than foreign firms. This may be due to the lower numbers of foreign firms (only 24 per cent of firms in our sample are foreign firms). However, it may also happen that foreign firms are shifting their innovation base to the parent country, resulting in low patenting activity in India. Also, the figures do not reflect any quintessential divergence between domestic and foreign firms in terms of process and product patents granted. It indicates that the likelihood of engaging in process or product innovation does not substantially differ by ownership type. However, the figures show a steeper increase in the intensity of product patent behaviour of foreign firms from 2016 onwards as compared to the process patents.[18]

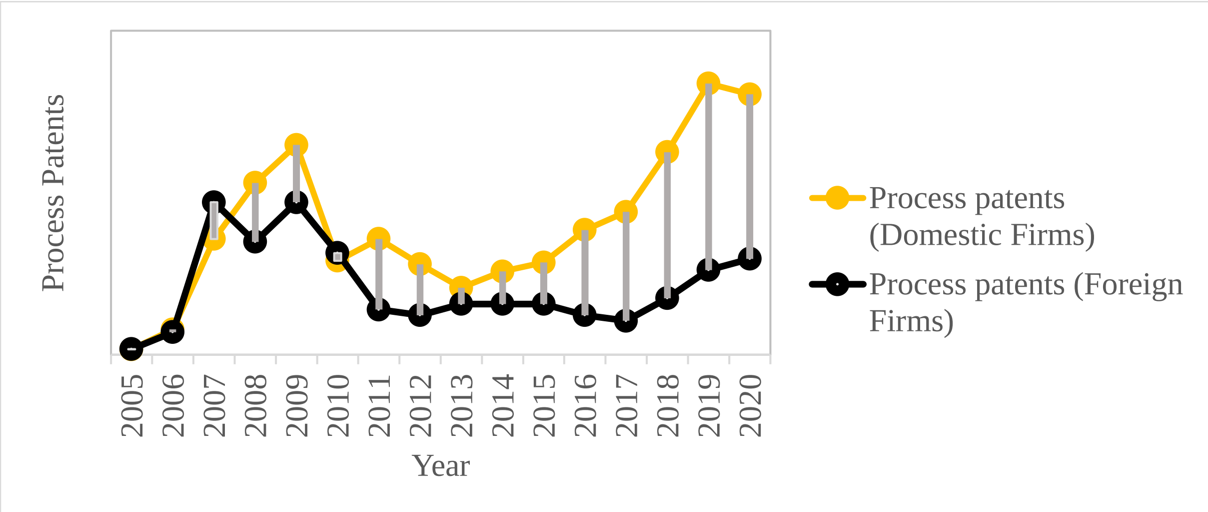
[18] Kindly refer to the Appendix B for the kernel density plots of the domestic and foreign product and process patents

Figure 4. 1: Patents granted to all the manufacturing firms



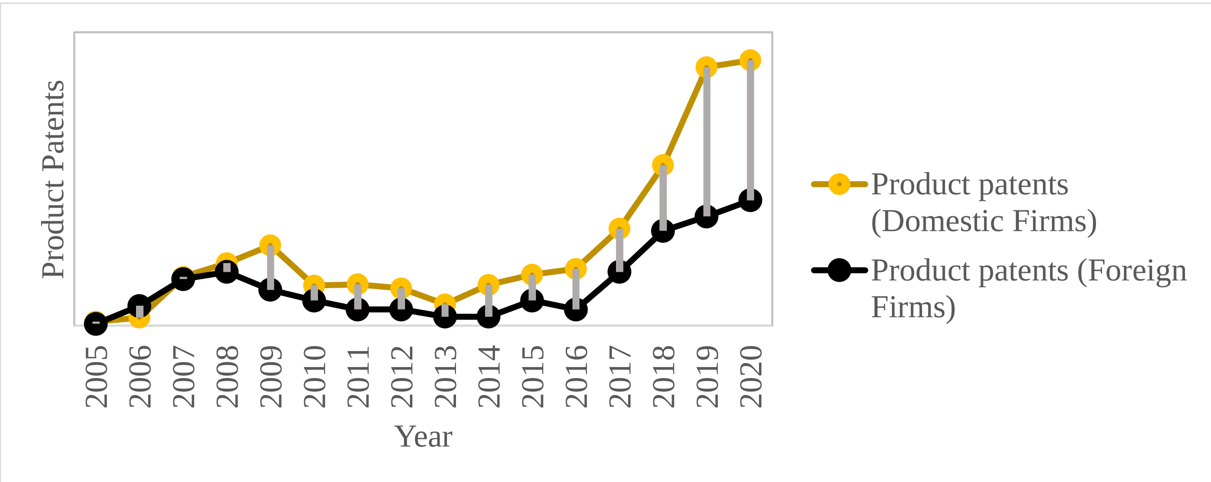
Source: Data collected from Patseer

Figure 4. 2: Process patents granted to domestic firms vis-à-vis foreign firms



Source: Data collected from Patseer

Figure 4. 3: Product patents granted to domestic firms vis-à-vis foreign firms



Source: Data collected from Patseer

4.4 Empirical Model and Methodology

Based on the literature (Van Reenen, 1997), the present work's empirical framework considers the viscosity of labour demand. Thus, to test the competing hypothesis, the econometric analysis in this chapter moves from static specification to dynamic specification based on the works of Lachenmaier and Rottmann (2011) and Bianchini and Pellegrino (2019) and frames the following panel equation:

$$Employment_{it} = \propto_1 + \beta_1 Employment_{t-l} + \beta_2 Innovation_{i,t-l} + \sum \beta_k Z_{it}^k + \gamma_i + \gamma_t + \varepsilon_{it} \tag{4.1}$$

Here, i denotes firms, t denotes the time and l denotes the lag lengths. The response indicator $Employment_{it}$ gives the number of people employed by a firm in a year. The innovation indicator $Innovation_{i,t-l}$ represents the total counts of process and product patents granted to a firm i during any time t. Z includes the set of control variables, γ_i is the firm-specific dummy and $\gamma_t$is the time dummy.

Turning attention to the adopted methodology, Eq. (4.1) takes into account the sticky and path-dependent nature of labour demand. This gives rise to the apparent endogeneity issue in the empirical specification. Endogeneity issues may also arise due to contemporaneous correlation among other variables in the equation (e.g., wage and employment decisions may very well be jointly adopted; the decision to invest internally through R&D and import technologies may also be affected by the same decision procedures). Such endogeneity biases can lead to inconsistent estimates and incorrect inferences, resulting in misleading conclusions. Conventional panel regressions fail to provide efficient estimates in the presence of endogeneity. Arellano and Bond (1991) introduced the difference-GMM estimator as a suitable tool to deal with endogenous regressors. Blundell and Bond (1998) further improved upon the difference GMM estimator and developed a more appropriate system GMM approach in case of high persistency of the lagged dependent variable. The present chapter uses this system-GMM approach with robust standard errors to estimate Eq. (4.1).

As far as the diagnostic tests are concerned, the validity of the instruments created by the GMM procedure is tested using the Hansen test of overidentifying restrictions. The Hansen test is robust to heteroscedasticity and autocorrelation.The hypothesis that the error term is not serially correlated in the regression is measured using the AR test. By construction, the differenced error term is allowed to be first-order serially correlated. This assumption is relaxed for the second-order error term.

4.5. Empirical Results

The econometric analysis proceeds in two steps. First, we separately estimate Eq. (4.1) for process and product innovation regardless of their ownership structure. Here, we assume that the firm's innovation output is independent of their ownership structure and the consequent employment decisions. In the second step, we relax this assumption and examine the linkage between innovation and employment by running separate regressions for domestic and foreign firms.

4.5.1 The impact of process and product innovation on employment growth (full-sample, all manufacturing firms)

Building on Eq. (4.1), Table 4.1 presents the empirical results of the two-step-system-GMM regression estimating the impact of process and product innovation on employment generation of the innovative manufacturing firms registered in India, irrespective of their ownership structure (see columns V-VIII, Table 4.1). The panel-pooled regression estimates are displayed in the first four columns for comparison (see columns I-IV, Table 4.1). The estimated coefficient of the lagged dependent variable is positive and highly significant across all the models. This confirms the path dependency and persistency in labour, justifying the use of dynamic specifications for the purpose.

Columns I, II, V and VI of Table 4.1 report the results of process innovation on employment generation of the Indian manufacturing firms. The estimated coefficients are negative and significant, reflecting that productivity gains through process innovation significantly displace labourers. The results corroborate the findings of Dosi and Yu (2019) and Dalgıç et al. (2023). Following Van Roy et al. (2018), we lag our process innovation indicator to take into account the potential delay in the possible impact of process innovation on employment. The estimated value of the lagged process innovation is also negative and statistically different from zero, indicating persistency in the labour-displacing effect of process innovation (columns II and VI, Table 4.1).

Thus, the econometric findings of the present chapter refute the channels of compensation mechanisms for process innovation. The compensation mechanism believes that productivity increases translate into reduced costs and reduced prices in a competitive market, stimulating a new line of demand and employment opportunities. However, the econometric evidence presented in this chapter refutes this. For developing countries like India, price decreases do not necessarily create demand in downstream industries as there hardly exists any user and buyer sectors in an industry (Karaomerlioglu and Ansal, 2003*)*. Even if price decreases lead to additional demand, the EMDEs are characterised by the presence of unsatisfied demand. Therefore, additional demand does not necessarily translate into additional employment avenues in such economies. The supporters of the compensation mechanism also stated that the direct effects of labour-saving technology could be compensated in the labour market via decreased wages. However, such countries are already characterised by the predominance of cheap labour, and further lowering wages is only a theoretical possibility here.

Moving ahead, the statistical results confirm that product innovation also significantly displaces labour in Indian manufacturing firms (Columns VII and VIII, Table 4.1). The labour-displacing impact of product innovation is also consistent with previous literature (Zhu et al., 2021). Again, we lag the product innovation indicator to take into account the potential delay in the possible impact of product innovation on employment. The lagged value of the product innovation is significant and negative, indicating persistency in the labour-displacing effect of product innovation. The estimated coefficients of the pooled OLS presented in columns III and IV of Table 1 further support the GMM findings (Columns VII and VIII, Table 4.1).

Thus, the econometric findings reject the channels of compensation mechanism for product innovation also. EMDEs predominantly imitate foreign technologies or purchase technology from advanced countries (Helpman,1993; Sasidharan and Kathuria, 2011). However, given developed nations' technological intensity and demographic configuration, they introduce labour-saving technologies. As against this, the EMDEs have an abundance of unskilled labour. Therefore, direct replication of foreign technologies without modifying them to suit the labour market conditions in EMDEs would widen the gap between demand for and supply of labour.

To conclude, the econometric findings of the study confirm Hypothesis 4.1 of the chapter while presenting evidence against Hypothesis 4.2. The control variables in Table 4.1 also showed concluding evidence. The estimated coefficient of the salary per worker is negative and significant at conventional levels across all the specifications, supporting the notion that wage reduction would open up additional employment opportunities in the labour market (see Table 4.1). The negative significance of the estimated coefficient of the financial indicator variable, the debt-equity ratio, reflects that leveraged firms have low employment creation ability (see columns I-IV, Table 4.1). As expected, the coefficient of the revenues generated from the sales of the firms' products positively and significantly affects the job creation capability of the firms (see columns I-VIII, Table 4.1). This highlights the importance of the demand factors in the generation of employment. The estimated coefficient of the R&D intensity and import intensity of firms is positively and significantly related to the response indicator (see columns I-IV, Table 4.1). This reflects that firms' involvement in R&D activities and processing of imported technologies generates additional labour requirements, creating more employment avenues.

Table 4. 1: Impact of process and product innovation on employment (full-sample)

Variables	I	II	III	IV	V	VI	VII	VIII
$Employeemnt_{t-1}$	0.920***	0.920***	0.922***	0.922***	0.646***	0.629***	0.596***	0.596***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.07)	(0.09)	(0.09)
$Process\ Innovation$	-0.005**				-0.017**			
	(0.00)				(0.01)			
$Process\ Innovation_{t-1}$		-0.005**				-0.016**		
		(0.00)				(0.01)		
$Product\ Innovation$			-0.003***				-0.005**	
			(0.00)				(0.00)	
$Product\ Innovation_{t-1}$				-0.004**				-0.009**
				(0.00)				(0.00)
Age	-0.007	-0.007	-0.008	-0.008	0.038	0.039	0.04	0.043
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.06)	(0.06)
$Location$	0.008	0.008	0.006	0.006	0.012	0.011	-0.006	0.004
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.06)	(0.07)	(0.07)
$Par\ Capita\ Salary$	-0.004***	-0.004***	-0.003***	-0.003***	-0.015***	-0.016***	-0.018***	-0.018***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
$Debt\ to\ Equity\ Ratio$	-0.003***	-0.003***	-0.003***	-0.003***	0.004	0.004	0.007	0.006
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
$Demand$	0.068***	0.067***	0.067***	0.066***	0.328***	0.342***	0.369***	0.366***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.06)	(0.07)	(0.08)	(0.08)
$R\&D\ Intensity$	0.009**	0.009**	0.010**	0.010**	0.241	0.213	0.818	0.805
	(0.00)	(0.00)	(0.00)	(0.00)	(0.57)	(0.60)	(0.77)	(0.79)
$Import\ Intensity$	0.487**	0.487**	0.460**	0.463**	0.483	0.545	0.600	0.653
	(0.19)	(0.20)	(0.19)	(0.20)	(0.45)	(0.46)	(0.54)	(0.55)
Constant	0.163***	0.163***	0.160***	0.158***	-0.283	-0.293	-0.295	-0.285
	(0.06)	(0.06)	(0.06)	(0.06)	(0.21)	(0.23)	(0.27)	(0.27)
Cross-section dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR2(p)					0.11	0.13	0.14	0.12
Hansen (p)					0.18	0.21	0.11	0.11

Notes: *** p<0.01, ** p<0.05, * p<0.10, Robust Standard Errors are in parenthesis
Columns I to IV report the results of OLS estimation
Columns V to VIII report the results of GMM estimation

4.5.2 The impact of process and product innovation on employment growth for domestic firms vis-à-vis foreign firms

This section relaxes the assumption that the employment effect of process and product innovation is the same for both domestic and foreign firms. Thus, the econometric results in

Tables 4.2 and 4.3 present the observed differences in employment creation between domestic and foreign firms and their linkages with process and product innovation. Columns I-IV in both the Tables report the results of OLS regression, and columns V-VIII in both the Tables report the results of GMM estimation. For explanation purposes, we consider the GMM results for both the Tables.

Columns V and VI of Table 4.2 show the empirical estimates of the GMM model for the impact of process innovation on the employment generation of domestic firms. The estimated coefficient of the process innovation is negative and significant, reflecting that process innovation significantly displaces labour in Indian domestic manufacturing firms. This labour-displacing effect is persistent over time as the lagged value of the process innovation continues to be negatively significant (see column II, Table 3.2). However, the econometric findings from GMM estimation confirm that process innovation in foreign firms is not significantly displacing any labour, failing us to accept Hypothesis 4.3 (columns VI and VIII, Table 4.2). In fact, we do not even find evidence of any possible delayed displacement effect of process innovation in foreign firms as well (see column VIII, Table 4.2). The findings from the OLS estimation support the results presented (columns I-IV, Table 4.2).

As clarified in the previous section, the “compensation via decreases in price” mechanism does not hold good for developing countries as price decreases fail to create any demand across the associated industries in such countries (Karaomerlioglu and Ansal, 2003*)*. Also, developing countries are characterised by unsatisfied demand despite having excess capacity due to institutional bottlenecks. Thus, increases in productivity and the consequent generation of excess capacity brought about by process innovation fail to create additional employment opportunities for Indian manufacturing firms. Rather, the domestic firms engaging in process innovation prefer to benefit from increased productivity by releasing the excess workers.

However, the same is not true for foreign firms. The foreign firms are affiliates of multinationals with a strong grip on the global market. This creates new avenues of operation for foreign firms. First, exposure to the international market allows global interaction across all the associated industries. This opens up potential business opportunities in the event of a reduction in production costs via productivity gains through process innovation. Second, internationalisation leads to an expansion in the scale of firms’ operations. Thus, any excess capacity brought about by increases in productivity could be nurtured through the expansion of firms’ output and market share. International integration of manufacturing firms thus offset the labour-displacing effect of process innovation for foreign firms.

In terms of product innovation, the statistical findings confirm that while product innovation significantly displaces labour in Indian domestic manufacturing firms, foreign firms are not associated with, at least, any significant displacement of labour (columns V and VII, Table 4.3). We also find evidence that the labour-displacing impact of product innovation is persistent over time for domestic firms (column VI, Table 4.3), in contrast to the foreign firms (column VIII, Table 4.3). The findings of the OLS estimation presented across columns I-IV of Table 4.3 support these findings. Thus, the econometric results lead us to nullify Hypothesis 4.4.

The statistical results hinted at the possibility that direct replication of foreign technology from developed countries, without modifying it to suit the demographic attributes of the developing countries, adversely affects the labour market in the host country. The developed countries, which are essentially labour-scarce and capital-abundant, predominantly introduce labour-saving skill-intensive technologies. Processing these technologies requires highly skilled manpower and higher capital intensity to absorb the sophisticated technologies. Foreign firms, given their stronger bargaining power and global operations, may attract a more skilled labour force. These firms also operate with higher capital intensity and on a larger scale than the domestic firms. Moreover, the strategic objective of the multinationals in any host country is always to expand their existing market. These factors combined together dampen the labour-displacing effect of product innovation for foreign firms. In contrast, domestic firms that may have failed to avail themselves of the skilled labour force given their low bargaining power might innovate either only to survive the competition or may innovate with the primary goal of reducing production costs. Both of these lead to cost-cutting measures, which are often met by replacing labour.

Table 4. 2: Impact of process innovation on employment (domestic vs foreign firms)

Variables	Domestic Firms		Foreign Firms		Domestic Firms		Foreign Firms	
	I	II	III	IV	V	VI	VII	VIII
$Employemnt_{t-1}$	0.898***	0.898***	0.881***	0.882***	0.819***	0.821***	0.650***	0.311**
	(0.02)	(0.02)	(0.05)	(0.05)	(0.06)	(0.06)	(0.11)	(0.15)
$Process\ Innovation$	-0.006**		0.005		-0.011*		0.006	
	(0.00)		(0.01)		(0.01)		(0.01)	
$Process\ Innovation_{t-1}$		-0.006**		0.004		-0.012**		0.015
		(0.00)		(0.01)		(0.01)		(0.02)
Age	0.003	0.003	0.011	0.011	0.003	-0.013	0.097**	0.206**
	(0.02)	(0.02)	(0.02)	(0.03)	(0.05)	(0.05)	(0.05)	(0.08)
$Location$	0.005	0.005	0.033	0.033	0.012	0.009	0.142	0.257
	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.03)	(0.10)	(0.19)
$Par\ Capita\ Salary$	-0.005***	-0.005***	-0.157***	-0.157***	-0.009***	-0.009***	-0.315***	-0.463***
	(0.00)	(0.00)	(0.06)	(0.06)	(0.00)	(0.00)	(0.11)	(0.14)
$Debt\ to\ Equity\ Ratio$	-0.003***	-0.003***	-0.001	-0.001	0.00	0.0000	-0.001**	-0.002**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	0.00	(0.00)
$Demand$	0.085***	0.085***	0.092***	0.093***	0.162***	0.162***	0.222***	0.409***
	(0.01)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)	(0.07)	(0.09)
$R\&D\ Intensity$	0.016***	0.016***	0.013	0.013	0.013	0.014	1.246	3.426
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(1.01)	(2.25)
$Import\ Intensity$	0.665***	0.665***	-0.18	-0.181	0.460	0.518	0.122	-0.729
	(0.22)	(0.22)	(0.30)	(0.30)	(0.35)	(0.39)	(0.83)	(2.71)
Constant	0.198**	0.200**	0.134	0.134	-0.071	-0.027	0.297	0.664
	(0.08)	(0.08)	(0.10)	(0.10)	(0.18)	(0.22)	(0.23)	(0.66)
Cross-section dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR2(p)					0.343	0.385	0.144	0.395
Hansen (p)					0.396	0.441	0.998	0.994

Notes: *** p<0.01, ** p<0.05, * p<0.10, Robust Standard Errors are in parenthesis
Columns I to IV report the results of OLS estimation
Columns V to VIII report the results of GMM estimation

Table 4. 3: Impact of product innovation on employment (domestic vs foreign firms)

Variables	Domestic Firms		Foreign Firms		Domestic Firms		Foreign Firms	
	I	II	III	IV	V	VI	VII	VIII
$Employeemnt_{t-1}$	0.900***	0.901***	0.882***	0.883***	0.759***	0.759***	0.654***	0.306*
	(0.02)	(0.02)	(0.05)	(0.05)	(0.11)	(0.12)	(0.11)	(0.17)
$Product\ Innovation$	-0.003***	-0.002			-0.003**		0.007	
	(0.00)		(0.00)		(0.00)		(0.01)	
$Product\ Innovation_{t-1}$		-0.004**		-0.003		-0.006**		0.015
		(0.00)		(0.00)		(0.00)		(0.01)
Age	-0.00004	-0.0002	0.013	0.013	0.034	0.03	0.091	0.220**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.06)	(0.06)	(0.10)
$Location$	0.002	0.002	0.033	0.034	-0.01	-0.014	0.118	0.233
	(0.02)	(0.02)	(0.05)	(0.05)	(0.04)	(0.04)	(0.10)	(0.18)
$Salary\ per\ Worker$	-0.004***	-0.004***	-0.158***	-0.158***	-0.012*	-0.012*	-0.323***	-0.516***
	(0.00)	(0.00)	(0.06)	(0.06)	(0.01)	(0.01)	(0.11)	(0.16)
$Debt\ to\ Equity\ Ratio$	-0.003***	-0.003***	-0.001	-0.001	0.0001	0.0002	-0.001**	-0.002***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	0.00	(0.00)
$Sales$	0.084***	0.083***	0.093***	0.093***	0.184**	0.185**	0.223***	0.425***
	(0.01)	(0.01)	(0.03)	(0.03)	(0.08)	(0.08)	(0.08)	(0.11)
$R\&D\ Intensity$	0.017***	0.017***	0.013	0.013	0.051**	0.050**	1.111	3.56
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(1.31)	(2.29)
$Import\ Intensity$	0.625***	0.630***	-0.178	-0.178	0.414	0.334	-0.382	-1.209
	(0.22)	(0.22)	(0.29)	(0.29)	(0.46)	(0.46)	(0.58)	(1.91)
Constant	0.202**	0.201**	0.128	0.125	0.274	0.284	0.299	0.548
	(0.08)	(0.08)	(0.11)	(0.11)	(0.21)	(0.22)	(0.21)	(0.67)
Cross-section dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
AR2(p)					0.432	0.371	0.144	0.452
Hansen (p)					0.191	0.186	0.996	0.993

Notes: *** p<0.01, ** p<0.05, * p<0.10, Robust Standard Errors are in parenthesis
Columns I to IV report the results of OLS estimation
Columns V to VIII report the results of GMM estimation

4.5.2 Does employment generation in Indian manufacturing firms depend on the ownership type? Robustness checks

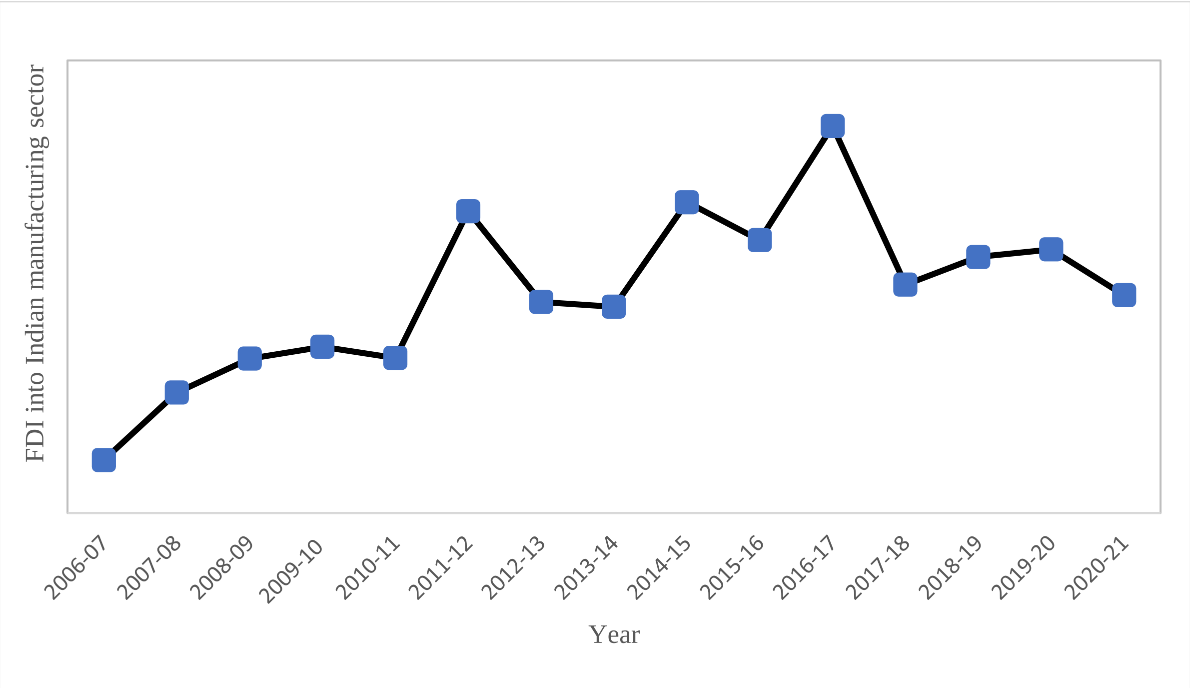
The above raises some serious policy questions. If technology is indeed significantly replacing labour in domestic firms but not in foreign firms, have foreign firms been significantly employing more people in the Indian labour market than domestic firms? If so, do policymakers need to implement heterogeneous policies to create more employment opportunities? These are important questions that need to be addressed, especially when unemployment in the country hit the highest point of 10 per cent in 2020, followed by 7.8 per cent in 2021 and 7.3 per cent in 2022.[19]

The trend in foreign equity inflow into Indian manufacturing firms and the consequent trend in the employment numbers generated by these firms reveal some interesting things. Fig.

[19] Unemployment rate as a percentage of total labour force, modelled ILO estimate. Data collected from World Development Indicators.

4.4 shows that the foreign equity shares in the country's manufacturing sector saw a sharp upturn in the financial year ending in 2011. This is followed by an abrupt upswing in the employment generated by Indian manufacturing firms after 2011, as shown in Fig. 4.5.[20] This further validates the questions addressed in this section. The abrupt increase in employment post-2011 could be due to the specific objectives of the National Manufacturing Policy, 2011. This policy aimed to create an additional 100 million jobs in the manufacturing sector by 2022. To achieve this, the policymakers decided to welcome foreign investments and technologies by encouraging joint ventures between foreign companies and Indian partners. Nevertheless, in order to empirically estimate whether the abrupt increase in manufacturing employment post-2011 could be attributed to an increase in foreign equity inflow in the previous financial year, we use a difference-in-difference (DID) model.

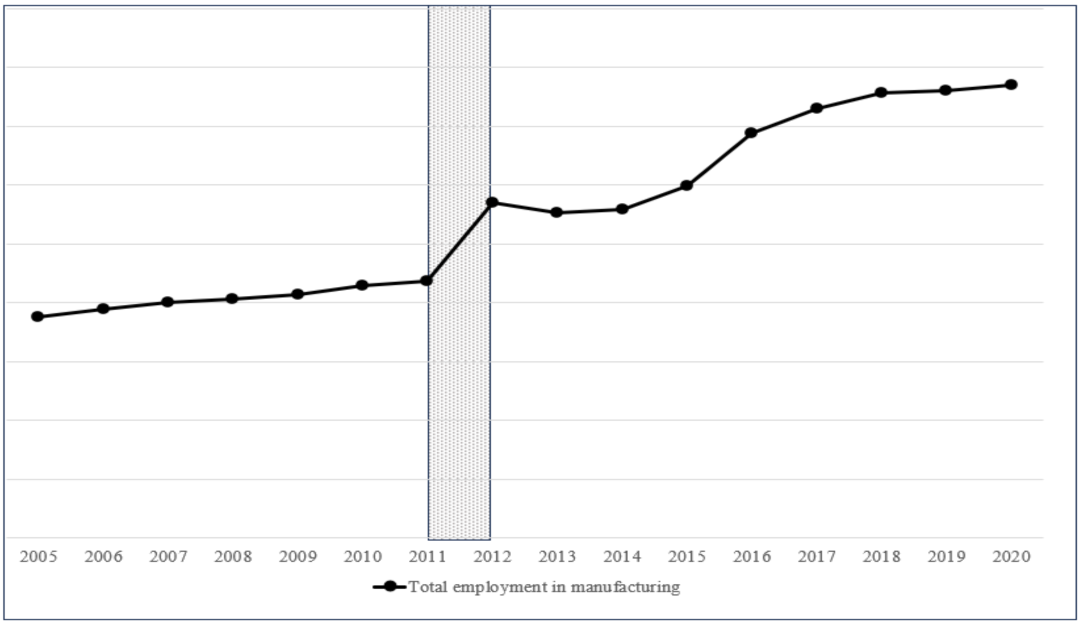
Figure 4. 4: Trend in foreign equity investment inflows to the Indian manufacturing sector



Source: Reserve Bank of India

[20] Kindly refer to the Appendix B for the kernel density plots for the number of people employed by the domestic and foreign firms

Figure 4. 5: Trend in employment generated by the Indian manufacturing firms



Source: Reserve Bank of India

The DID method is based on quasi-natural experiments that can prevent the problem of endogeneity. The method compares the development between two groups based on their treatment. In the present chapter, the classification of the groups is based on the ownership of the firm, viz., whether or not the firms have foreign equity participation of a minimum of ten per cent during the study period. The firms with foreign equity participation of at least ten per cent during the study period are considered foreign firms and represent the treatment group. In contrast, the control group involves the firms with less than ten per cent foreign equity participation during the study period and are considered domestically owned firms. Accordingly, we construct a dummy variable $Ownership_{ij}$ which takes the value one if the firm is foreign and 0 otherwise. The DID model can be represented as

$$Employment_{it} = \alpha_0 + \alpha_1 Ownership_{ij} \times Time_t + \sum \alpha_k Z_{it}^k + \delta_i + \gamma_t + \varepsilon_{it} \qquad (4.2)$$

In this section of the study, $time = 1$ covers the periods from 2012 to 2020, and $time = 0$ covers the periods from 2005 to 2011. In Eq. (4.2), $Employment_{it}$ stands for the number of people employed by a manufacturing firm i during the time period t. The interaction term between the dummy of foreign ownership $Ownership_{ij}$ and the time variable $Time_t$ is added to compare the development in employment generation between the two groups, viz., the foreign and domestic firms before and after 2011. Z_{it}^k represents the set of control variables, which includes the process innovation, product innovation, age, salary per worker, debt-to-equity ratio, sales, R&D intensity and import intensity of the firms. δ_i controls for the time-invariant characteristics of a certain firm i such as the production models, distance from the border etc., and γ_t represents the firm invariant features in a certain time period t such as political instability, GDP etc.

Table 4.4 reports the results of the difference-in-difference estimator. The estimation results of columns I and III of the Table do not consider any time or firm-specific factors amongst the Indian manufacturing firms. The empirical estimates in columns II and IV of the Table consider the time-specific and firm-specific heterogeneity across the sample. In columns III and IV of Table 4.4, we introduce the lagged value of the dependent variable. The values and significance level of the variables across all four models are similar, with little variation in the coefficient value. However, we consider specifications II and IV of Table 4.4 for explanation purposes.

The estimated difference-in-difference coefficient in Table 4.4 across all the specifications is not significant at the conventional levels, reflecting that there is not enough statistical evidence to suggest that the observed changes between the treated (foreign firms) and the control groups (domestic firms), before and after the treatment year of 2012, are large enough to be considered different from random variation. To be more precise, the results did not provide sufficient evidence to conclude that foreign firms, as a whole, had a different impact on employment relative to domestic firms post-2012. Therefore, based on the econometric analysis of the difference-in-difference approach, we do not have enough evidence to conclude that the presence of foreign firms leads to significant employment generation as compared to domestic firms for the years under consideration.

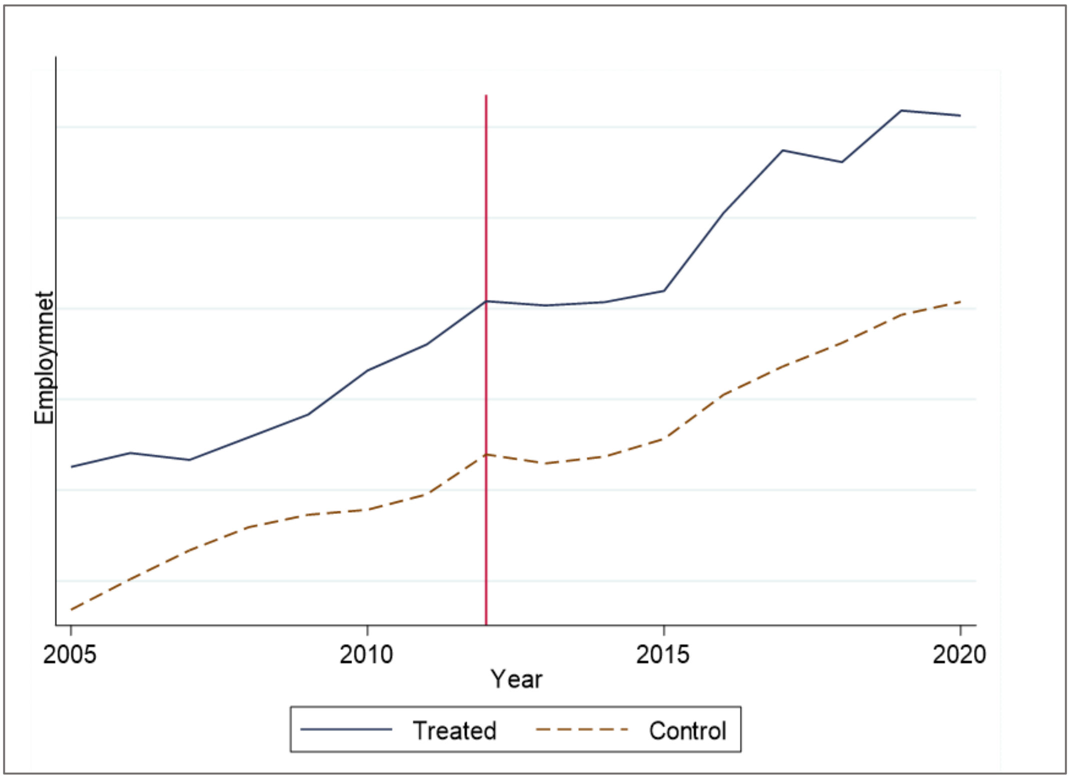
Table 4. 4: Firm-ownership and employment generation: Difference-in-Difference estimation

Variable	I	II	III	IV
$Ownership \times Time$	0.053	0.052	0.031	0.031
	(0.02)	(0.01)	(0.01)	(0.01)
$Employment_{t-1}$			0.694**	0.683**
			(0.02)	(0.03)
$Product\ Innovation$	0.003	0.001	-0.001	-0.001*
	(0.00)	(0.00)	(0.00)	(0.00)
$Process\ Innovation$	-0.009	-0.01	-0.004	-0.005
	(0.00)	(0.00)	(0.00)	(0.00)
Age	0.337	0.261	0.056	0.015
	(0.25)	(0.32)	(0.05)	(0.01)
$Salary\ per\ Worker$	-0.057	-0.054	-0.033	-0.031
	(0.02)	(0.02)	(0.02)	(0.02)
$Debt\ to\ Equity\ Ratio$	-0.005	-0.004	-0.002	-0.002
	(0.01)	(0.01)	(0.00)	(0.00)
$Sales$	0.503**	0.539**	0.185*	0.201*
	(0.03)	(0.02)	(0.03)	(0.02)
$R\&D\ Intensity$	0.053*	0.051***	0.015	0.015
	(0.01)	(0.00)	(0.01)	(0.00)
$Import\ Intensity$	1.444***	1.227***	0.774	0.683
	(0.01)	(0.02)	(0.17)	(0.14)
$Constant$	2.099	2.119	0.55	0.653**
	(0.64)	(0.94)	(0.19)	(0.03)
$Cross - section\ dummy$	No	Yes	No	Yes
$Time\ dummy$	No	Yes	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.10, Robust Standard Errors are in parenthesis

A visual inspection of the estimated difference-in-difference coefficients in Figure 4.6 re-establishes the insignificance of the parameter. The figure shows a common upward trend, irrespective of the treatment year 2012. We do not see any significant divergence between the control and the treated group before and after 2012. Thus, we can conclude that there is no significant difference in the employment generation of foreign firms as compared to domestic firms before and after the spike in employment in the year 2012.

Figure 4. 6: Results of difference-in-difference estimation for firm ownership and employment generation: pre and post-period analysis



Source: Authors' computation

4.6. Conclusion, Limitations and Policy Implications

The present chapter takes up the protracted debate of technology vs. employment in the Indian context. Even after being such a long-lasting debate core to the economic literature, to our surprise, we find very few studies probing into the issue thoroughly and orderly for the EMDEs. This is particularly surprising as developing nations continuously face the challenge of absorbing the excess labour supply while modernising their industrial sector.

The empirical results of the present chapter do not find evidence of the neo-classical compensation mechanism. Rather, the econometric evidence finds evidence of technology substituting labour. The empirical estimation of the present research confirms that both process and product innovation significantly displace labour in Indian manufacturing firms. Disentangling manufacturing firms by ownership type reveals that the labour-displacing impact of process and product innovation is limited to the domestic firms only, and the foreign firms are not significantly influencing the labour market of the Indian manufacturing firms through process or product innovation. However, further segregated analysis could not furnish enough evidence to conclude that the presence of foreign firms would lead to significant employment generation compared to domestic firms.

The empirical results are quite expected as India, being a developing country, primarily imports technology from developed parts of the world. The technology used in these developed nations, on the other hand, is designed to suit their demographic set up of thrifty labour and hence is characteristically capital intensive. Therefore, we suggest that policymakers make necessary refinements before amalgaming these techniques into practice to suit the demographic portfolio of the country rather than imitating foreign technology recklessly. Another way to subsume the released labour from the manufacturing sector would be to absorb them in the service or any other sector. However, we do not have the necessary data to look into this channel. Further research could be devoted to this direction.

Allowing for the structural differences in the ownership of the firms reveals that, while process and product innovation in domestic firms displace labour, process and product innovations in foreign firms do not significantly influence the employment structure of the Indian manufacturing firms. Since the findings reflect that unlike domestic firms, foreign firms are, at least, not significantly displacing labour, we suggest that policymakers may encourage foreign equity participation in the country's manufacturing. The foreign firms are also major drivers of technology spillovers in the developing countries. A more comprehensive study linking the knowledge spillovers from foreign firms to domestic firms and the consequent effect on job creation would provide a more panoramic overview of the entities under investigation. Further studies could take this up.

The results also show that process and product innovation in domestic firms significantly displaces labour in the Indian manufacturing industry. Based on this, we suggest that policymakers may advance the domestic firms with incentives such as tax concessions, special grants or subsidies for manoeuvring technologies that create more jobs.

Halting technology is never an option. It would simply push the economy to the abyss of obsoleteness. Advanced economies have already seen large numbers of manual workers being displaced by automation. Between 2012 and 2013, UK telecom firm O2 replaced 150 workers with a single piece of software. However, unlike developed economies, developing economies do not have the luxury of replacing labour with technology, given their demographic configuration. Human capital is key to understanding innovation in developing economies. Therefore, it rests with the policymakers to ensure the transition of the traditional manufacturing sector of these countries to grow hand in hand with the developed nations while accommodating the excess labour supply in the labour market. For that to happen, more research must be done linking technology and the labour market in these income-thrift countries. Given the irregularity in economic theory, we expect further research into this arena to understand better the dynamic relationship between innovation and job creation.

Appendix B

List of Tables

Table B 1: Description of Variables

Variable	Description	Source
	Dependent Variable	
Employment	Number of employees employed by a firm in a year	Prowess
	Independent Variables	
Process Innovation	Total number of process patents granted to a firm during the study period	Patseer
Product Innovation	Total number of product patents granted to a firm during the study period	Patseer
	Control Variables	
Age	The current year t subtracted by the incorporation year of the firm	Prowess
Location	Dummy variable equal to one if the firm is located in the major industrial location of the country, 0 otherwise	Prowess
Par Capita Salary	Salaries and wages paid by the firm during year t as a ratio of the number of labourers of the firm	Prowess
Debt-Equity ratio	Firm's debt as a ratio to the firm's equity	Prowess
Sales	Revenues generated from the sales of the firm's products	Prowess
R&D intensity	Expenditure on domestic research and development as a ratio to the sales of the firm	Prowess
Import intensity	Expenditure on import of capital goods and royalty and license payment as a ratio to the sales of the firm	Prowess

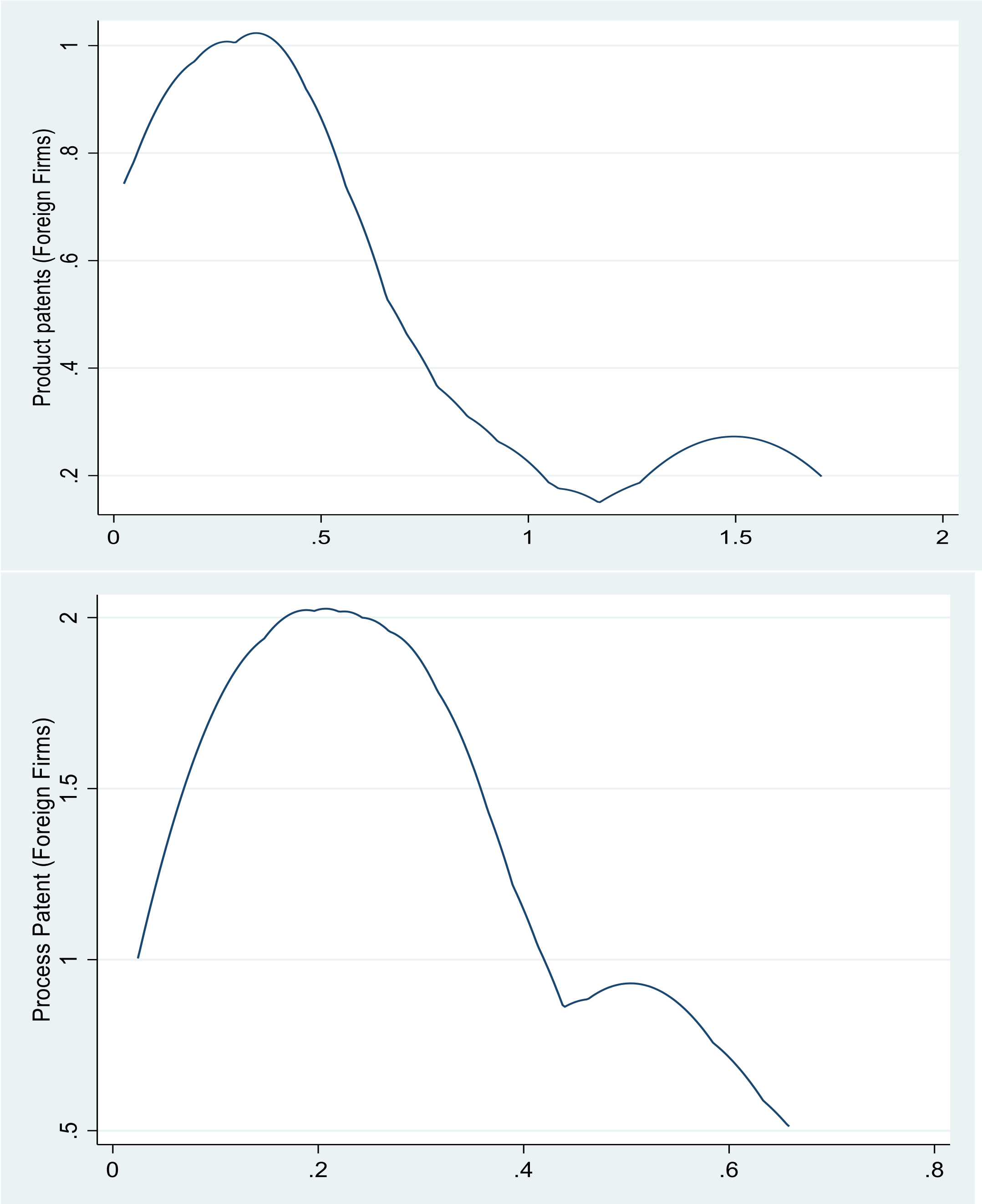
Table B 2: Descriptive statistics and correlation matrix

Variables	1	2	3	4	5	6	7	8	9	10	11
1. $Employemnt$	1										
2. $Employment_{t-1}$	0.986***	1									
3. $Process\ Innovation$	0.302***	0.309***	1								
4. $Product\ Innovation$	0.254***	0.264***	0.482***	1							
5. Age	0.243***	0.252***	0.0915***	0.0830***	1						
6. $Location$	0.072**	0.070**	0.074***	0.067**	0.103***	1					
7. $Salary\ per\ Worker$	-0.206***	-0.210***	-0.009	-0.007	0.057*	0.038	1				
8. $Debt\ to\ Equity\ Ratio$	-0.0525*	-0.034	-0.027	-0.010	-0.011	-0.119***	-0.018	1			
9. $Sales$	0.793***	0.782***	0.262***	0.244***	0.238***	0.045*	0.058**	-0.114***	1		
10. $R\&D\ Intensity$	-0.002	-0.001	0.112***	0.076***	-0.080***	0.185***	0.011	-0.022	-0.251***	1	
11. $Import\ Intensity$	0.087***	0.080***	0.111***	0.039	-0.039	-0.057**	-0.031	-0.013	0.049*	-0.014	1
Mean	7.8	7.7	0.5	1	3.6	0.8	0.9	1.4	9.6	-5.6	0
S.D.	1.5	1.5	2.2	5.6	0.6	0.4	6.9	6.3	1.9	1.9	0

Notes: *** p<0.01, ** p<0.05, * p<0.10

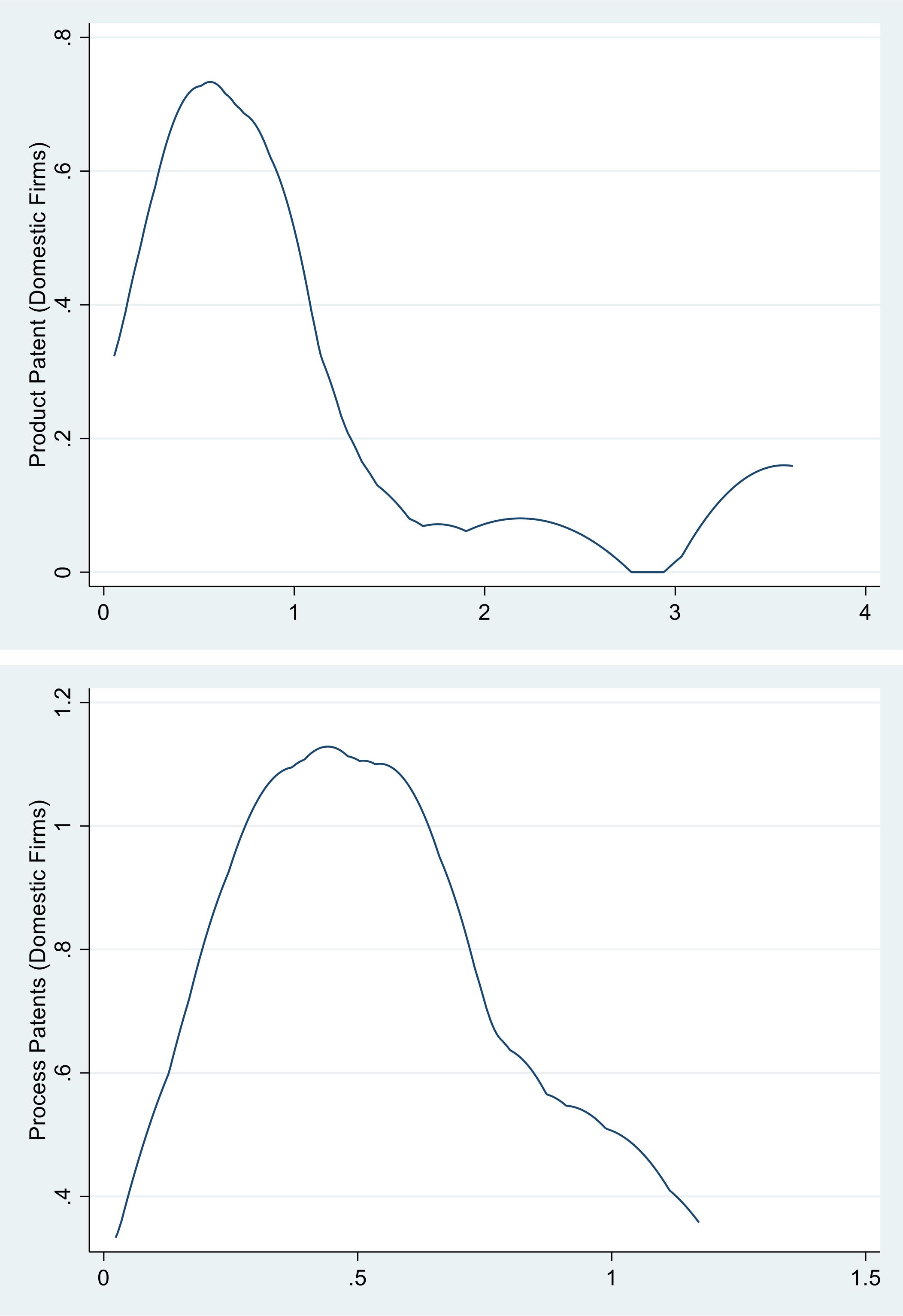
List of Figures

Figure B 1: Kernel density plot of product and process patents granted to foreign firms



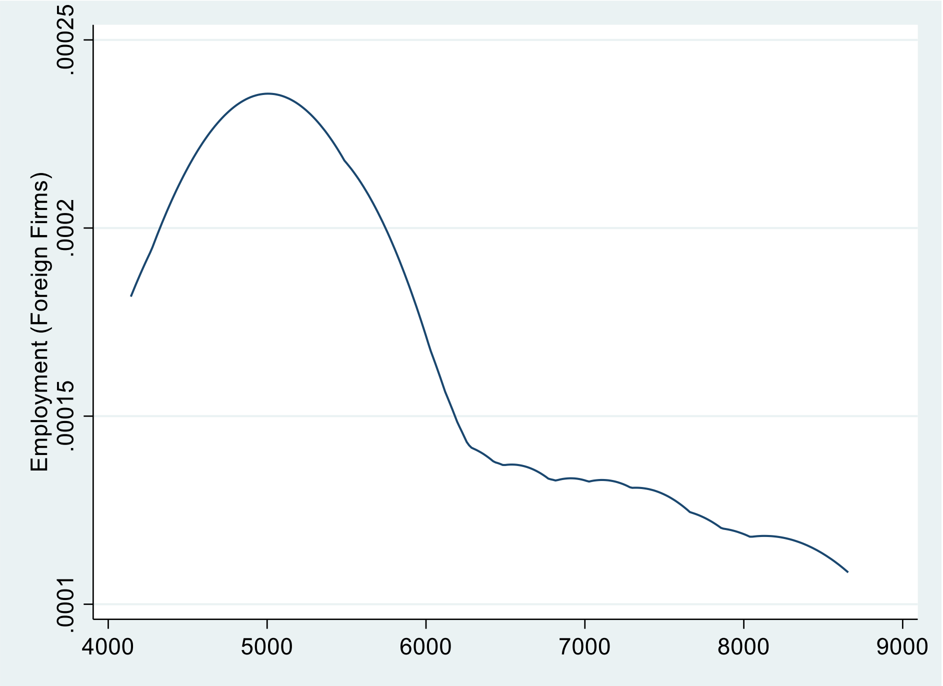
Source: Authors' computations

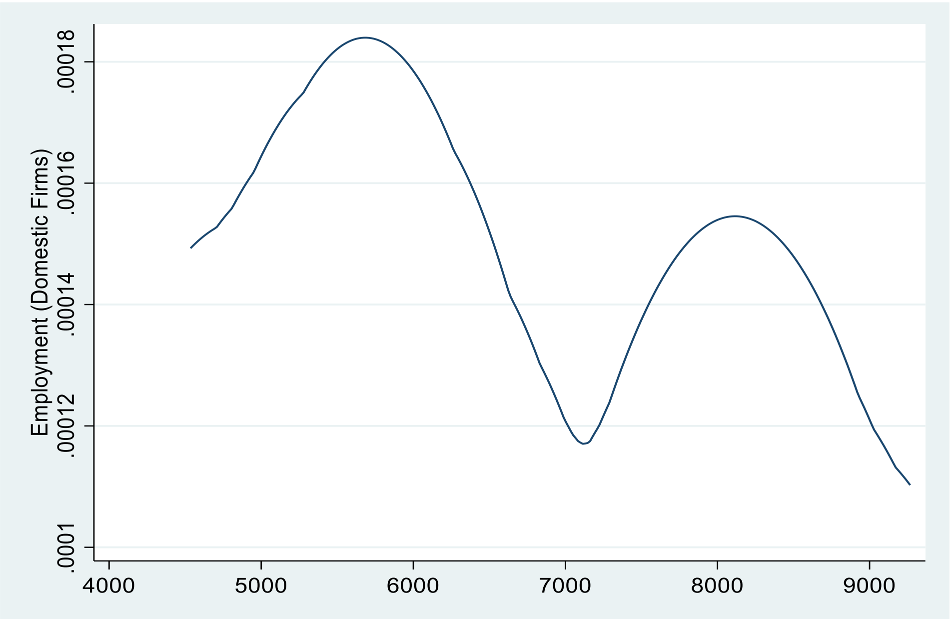
Figure B 2:Kernel density plot of product and process patents granted to domestic firms



Source: Authors' computations

Figure B 3: Kernel density plot of the number of people employed by the foreign and domestic firms





Source: Authors' computations

Chapter 5

FDI Spillovers, Innovation and the Role of Industrial Cluster: Examining the Impact of FDI Policy Liberalisation on Innovation

5.1 Introduction

5.1.1 Contexualisation and motivation

Technology diffusion is an integral part of firms' competitive advancement. In the present day, worldwide integration has opened up technological followers (i.e., countries far away from the global technology frontier) to technological leaders (i.e., countries closer to the technology frontier) (Grossman and Helpman, 1993). While the technological leaders are well endowed with state-of-the-art technology and highly skilled human capital, the technological followers primarily rely on traditional technology methods and unskilled labour. In such a structure, the mainstream economic theory argues that international trade between technological leaders and followers may lead to technology spillovers via foreign direct investments (FDI) (Vernon, 1966; Grossman and Helpman, 1993). Following this, the emerging markets and developing economies (EMDE) worldwide have increasingly been using FDI as a policy instrument to promote innovation.

However, the existing research provides mixed evidence in terms of FDI-augmented innovation spillovers. While one body of research finds that FDI generates positive innovation spillovers (Crescenzi et al., 2015; Li et al., 2017; Guo et al., 2021; Chen et al., 2023), a parallel branch of the literature shows that FDI generates negative innovation spillovers (Qu et al., 2017; Ascani et al., 2020; Ning et al., 2023). The extant literature identifies two mechanisms of such spillovers- horizontal or intra-industry spillovers and vertical or backward or inter-industry spillovers. Horizontal spillovers are spillovers from foreign firms to domestic firms operating within the same industry, and vertical spillovers are spillovers across different industries emanating from foreign firms establishing contacts with domestic suppliers. While empirical works investigating the impact of horizontal and vertical spillovers on productivity are extensive (Javorcik and Spatareanu, 2008; Xu and Sheng, 2012; Goldar and Banga, 2020), empirical works investigating the impact of horizontal and vertical spillovers on innovation are scarce and largely sparse. At the same time, empirical research confirms that FDI productivity spillovers differ significantly from FDI innovation spillovers (Ito et al., 2012; Garcia et al., 2013). This underscores the need to study FDI-generated innovation spillovers separately from FDI-generated productivity spillovers.

The limited empirical evidence investigating the channels of FDI-generated innovation spillover is largely inconclusive. The existing empirical studies find that horizontal FDI spillovers can have positive (Khachoo and Sharma, 2016), negative (Vujanovic et al., 2022) and insignificant (Gorodnichenko et al., 2020) impact on innovation. Compared to horizontal spillovers, empirical research quite unanimously agrees that vertical or inter-industry spillovers do not generate any significant innovation spillovers (Gorodnichenko et al., 2020); Vujanovic et al., 2022), with the solitary exception of Khachoo and Sharma (2016) whose study found a positive vertical innovation spillover of FDI in Indian manufacturing industries. Irrespective of the somewhat unanimous empirical findings of vertical innovation spillovers, the mixed empirical evidence in terms of horizontal innovation spillovers leverages the need to understand the channels of FDI-augmented innovation spillovers better.

Furthermore, building upon the work of Marshall (1890), empirical studies have investigated the impact of firms' location on innovation. This stems from the fact that firms located in industrially agglomerated clusters get easy access to a thick labour market, third-party services and knowledge-sharing platforms, which positively influences their innovation (Fornahl and Brenner, 2009; Dos Santos and Dalcol, 2009; Zhang, 2015; Tang and Cui, 2023; Chen and Zhou, 2023). However, being located in an industrially agglomerated cluster also increases the likelihood of congestion, which may negatively affect the firms' innovative ventures. (De Propris et al.,2009; Shearmur, 2011; Grillitsch et al., 2015; Fitjar and Rodriguez-Pose, 2017). Stemming from this, recent studies have integrated the literature on industrial agglomeration with the FDI spillover literature (Ning et al., 2016; Li et al., 2017). The limited literature available in this context shows that industrial clusters play a moderating role in FDI-augmented innovation spillovers (Ning et al., 2016; Li et al., 2017). However, these studies do not specify the channels of such FDI spillover, leaving out critical gaps to be filled.

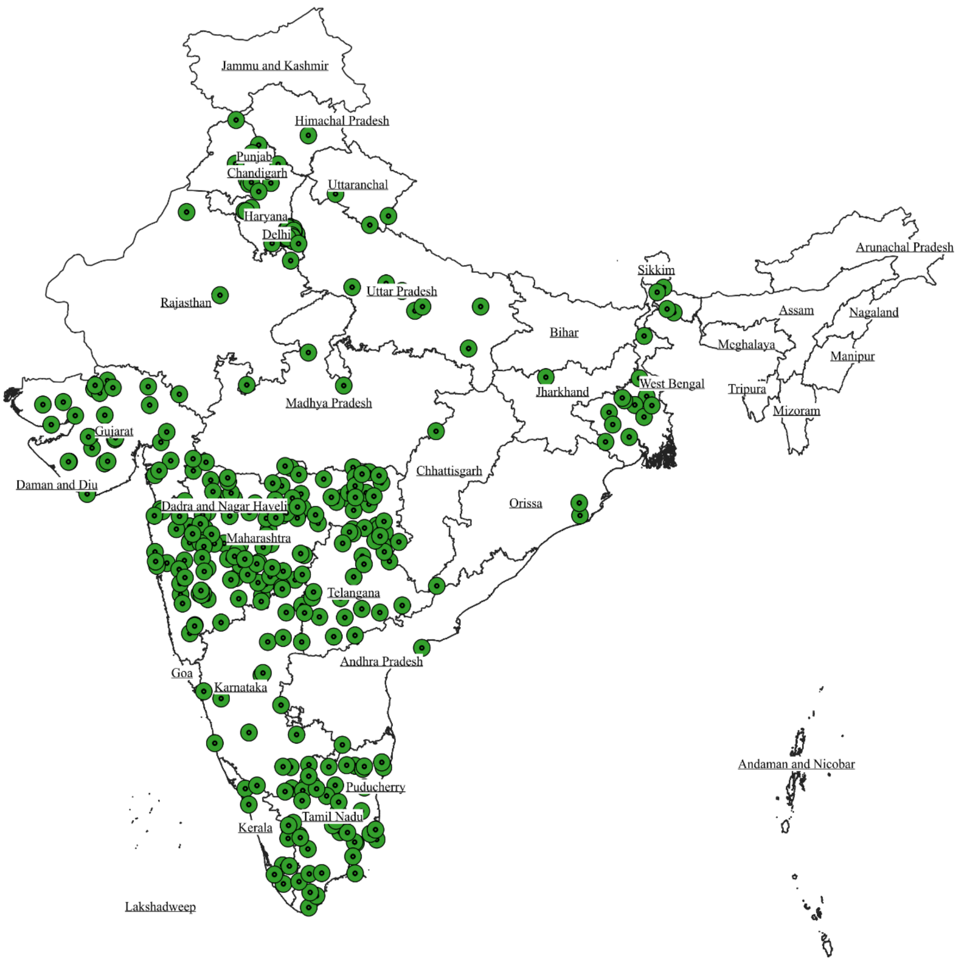
The relevance of industrial clusters on firms' innovation could be better understood with the help of Figure 5.1. Figure 5.1 shows the spatial distribution of innovative (patenting) Indian manufacturing firms across different locations in the country.[21] A visual representation of the data indicates the regional disparity in the location of the innovative Indian manufacturing firms. Most of the innovative firms are concentrated in the southwestern and northern regions of the country. On the eastern side of the country, innovative firms are located only in the region surrounding the Hoogly industrial belt or Kolkata industrial belt. The entire northeastern part of the country, along with the states of Jammu and Kashmir, Himachal

[21] Based on existing works (Hall et al., 2013; Igna and Venturini, 2023), the present study considers a firm as an innovative firm if it has at least a single patent to its credit during the study period. For details, kindly refer to section 5.4.

Pradesh, and Bihar, do not have any innovative firms. Interestingly, the areas with a dense population of innovative firms mostly surround the regions marked as the country's "major industrial cluster". This underscores the importance of firms' location in studying innovation.

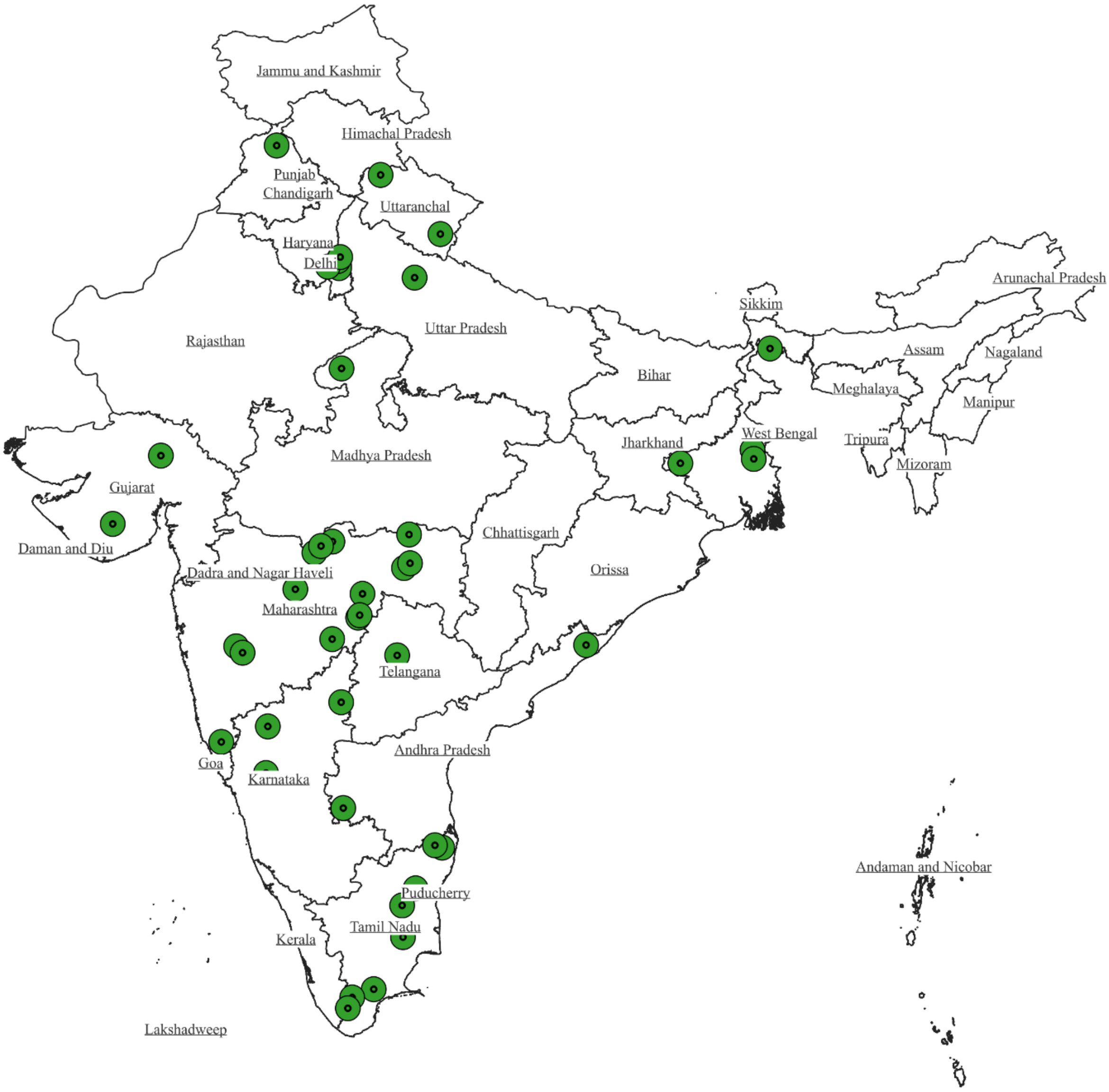
However, innovation is not exclusively confined to the boundaries of the firms. Innovation is an open process which generates externalities or spillovers (Vujanovic et al., 2022; Ning et al., 2023). To this end, drawing from existing works (Ning et al., 2016; Li et al., 2017), we extend our study by examining the influence of FDI spillovers on the innovation output of Indian manufacturing firms located in the country's major industrial clusters. While doing so, the present study makes a critical contribution to the literature as we explore the channels of such FDI spillovers, viz., horizontal and vertical spillovers, which the existing works highlighting the FDI-augmented innovation spillovers in industrial clusters have overlooked.

Figure 5. 1: Spatial distribution of innovative firms in India



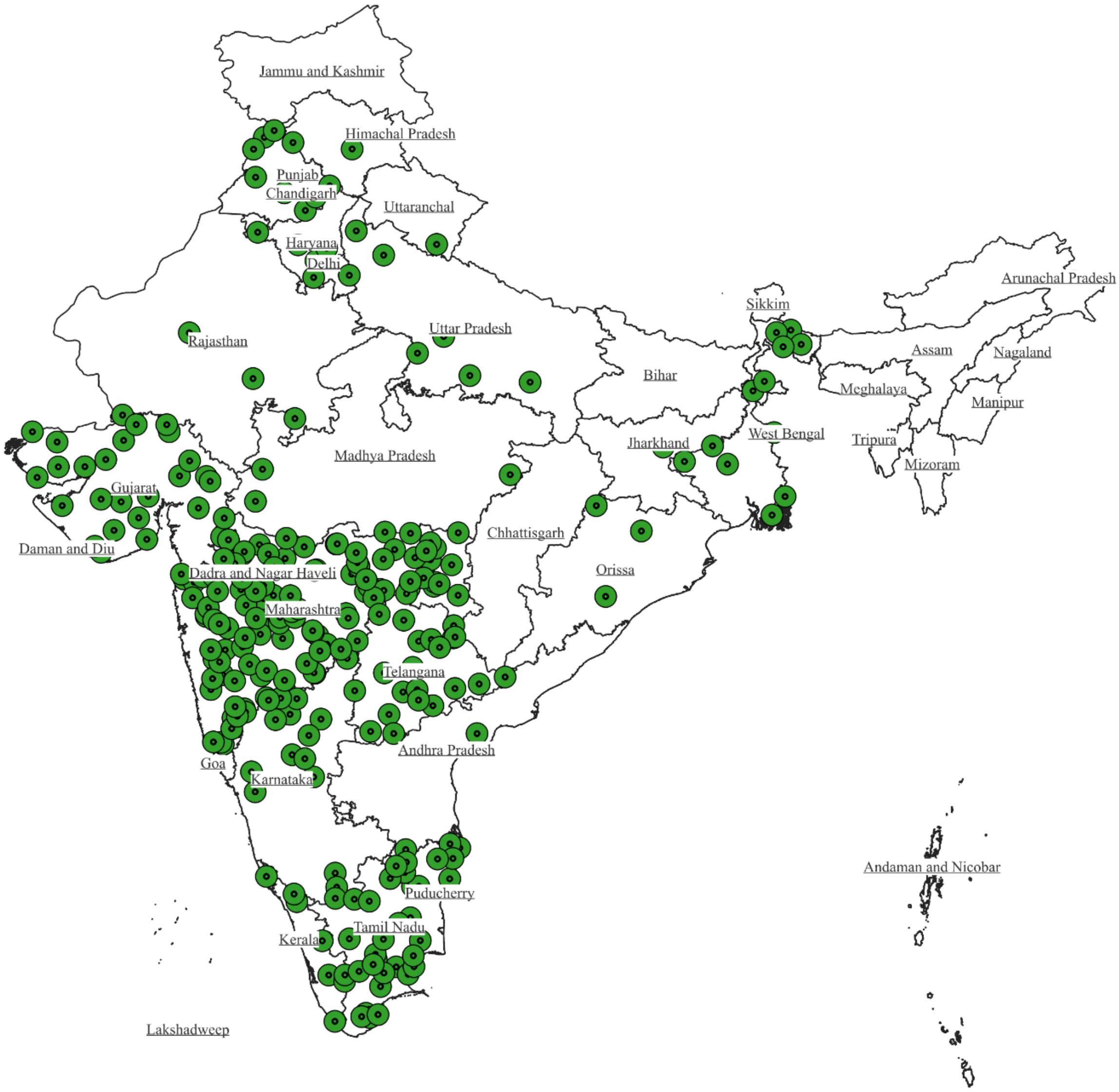
Source: Authors' computation

Figure 5.1: (Contd.) Spatial distribution of innovative foreign firms in India



Source: Authors' computation

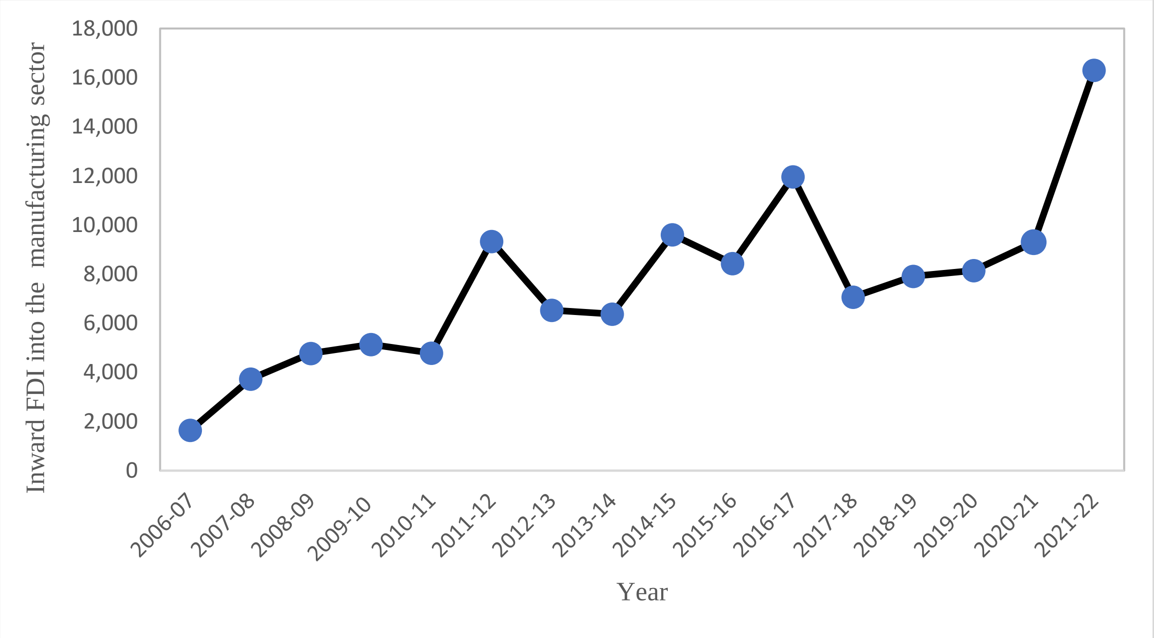
Figure 5.1: (Contd.) Spatial distribution of innovative domestic firms in India



Source: Authors' computation

Motivated by these factors, this chapter empirically investigates the impact of FDI spillovers on the innovation output of Indian manufacturing firms, with a special focus on the firms located in the major industrial cluster of the country. India serves as an ideal research setting to assess the link between innovation and FDI spillovers. As per the Indian Ministry of Commerce and Industry reports, FDI equity inflow in the manufacturing industry in the country has increased 76 per cent in the financial year 2021-22 compared to the previous year. India ranks seventh in FDI inflows amongst the top 20 host economies (World Investment Report, 2022). Figure 5.2 gives a visual representation of foreign equity inflow into the country's manufacturing sector. The figure reveals that FDI in the manufacturing sector of India has maintained an increasing trend from 2006-07 to 2021-22, with some upswings and downswings. In fact, during 2021-22, FDI inflows were received from 101 countries, while it was received from 97 countries during the previous financial year.

Figure 5. 2: Trend of inward FDI in the manufacturing sector of India



Source: Reserve Bank of India

The above clearly highlights India's growing prominence as a favourable FDI destination. The government of the country is also taking several transformative measures to attract foreign investments into the country and undertaken major policy liberalisations in September 2014 (such as allowing FDI up to 100 per cent in non-critical sectors through the automatic route, nurturing international relations and improving business environments). To this end, an extension of the present study based on the empirical results obtained empirically investigates the impact of 2014 FDI policy liberalisations by the Government of India on the innovation output of Indian manufacturing firms.

This study is related to the small segment of literature that has investigated the channels of FDI-generated innovation spillover. To this end, our study is closely related to the study done by Khachoo and Sharma (2016), which has investigated the link between FDI spillover and innovation in Indian manufacturing firms. However, it departs from the work of Khachoo and Sharma (2016) and other empirical research in similar fields (Gorodhnichenko et al., 2020; Vujanovic et al., 2022) in terms of highlighting the impact of horizontal and vertical FDI spillovers on innovation across major industrial clusters of the country. The present study further departs from the existing works by providing concrete empirical evidence of the impact of 2014 FDI policy liberalisations on the innovation output of Indian manufacturing firms using patent data. To the best of our knowledge, this is the first attempt to empirically evaluate whether or not foreign firms are significantly innovating more than domestic firms in India post the 2014 FDI policy liberalisations than the pre-liberalisation period.

Contribution

The present study contributes to three strands of literature. First, this study enriches the literature in the field of industrial organisation and innovation by examining the impact of horizontal and vertical FDI spillovers on the innovation output of manufacturing firms in an EMDE like India, using patent counts as the innovation indicator. Second, the existing empirical work bridges the economics of geography with the economics of innovation by examining the moderating role of industrial clusters on FDI spillovers. While a few works highlight the spatial linkage between innovation and FDI spillovers (Ning et al., 2016; Li et al., 2017), they have not specified the channels of such spillovers, viz., the horizontal and vertical FDI linkages. This study makes a unique contribution to the extant literature as we specify the influence of horizontal and vertical FDI linkages on the innovation output of Indian manufacturing firms located in the major industrial clusters. Third, a significant contribution of the present work is empirically evaluating the impact of 2014 FDI policy liberalisations on the innovation output of Indian manufacturing firms. The 2014 FDI policy liberalisation took a significant shift in the FDI policy regimes, and to the best of our knowledge, this is the first empirical study investigating the impact of 2014 FDI policy liberalisation on the innovation output of foreign firms vis-à-vis domestic firms in the pre-and post-liberalisation era.

The empirical framework of the chapter uses a sample of 347 innovative Indian manufacturing firms from 2007 to 2020. The findings reveal that horizontal and vertical FDI spillovers do not significantly influence the innovation output of Indian manufacturing firms. However, the estimation results show robust evidence that firms located in the major industrial cluster of the country innovate substantially through horizontal linkages. This finding, in line with previous works (Ning et al., 2016; Li et al., 2017), highlights the crucial role of industrial clusters in moderating innovation through FDI spillovers. Further, the empirical evidence reveals that foreign firms are significantly innovating more than their domestic counterparts post-2014 FDI liberalisations than in the pre-2014 period.

5.2 Conceptual Framework and Hypothesis Development

Firms in EMDEs often face greater challenges than their counterparts from advanced nations. Lack of managerial and organisational capabilities, low absorptive capacity and limited learning capabilities are some of the challenges faced by firms in EMDEs (Zhu et al., 2006;

Bahl et al., 2021). Under such circumstances, firms in these economies do not get sufficient incentive to develop innovation capabilities. Against this backdrop, the existing empirical work suggests FDI is one of the primary sources through which innovation capability could be generated in firms of the recipient developing country (Ascani and Gagliardi, 2015; Konstandina and Gachino, 2019; Ascani et al., 2020). The theoretical backing for this could be found in the works of Grossman and Helpman (1993). The famous North and South model of Grossman and Helpman (1993) states that the firms in the developed (North) region have the exclusive ability to produce state-of-the-art products, while the developing (South) region imitates the technology invented in the developed North. Thus, building upon the works of Grossman and Helpman (1993) and the existing literature (Garcia et al., 2013; Ning et al., 2016; Li et al., 2017), the present study considers that technology transcends from developed nations to developing countries.

The perspective that FDI would benefit the firms in the host economies stems from the belief that knowledge is tacit and, hence, often spills to domestic firms (Antonelli and Scellato, 2013; Useche et al., 2020; Vujanovic et al., 2022). To this end, theoretical works in economics also state that while the firms in developed countries bring out new products (innovation), entrepreneurs in developing countries devote their resources to learning and imitating the technology (Grossman-Helpman, 1991, 1993). It is well understood that multinational enterprises (MNEs) exhibit technological advances, better organisational and managerial routines and access to broader markets over domestic firms (Aitken and Harrison, 1999; Crespo and Fontoura, 2007; Ascani et al., 2020). However, since foreign MNEs cannot confine the value of their technology within the boundaries of the originating firms, the entry of foreign multinationals into the markets of EMDEs through FDI would generate knowledge spillovers to firms that they interact with (Inkpen et al., 2019; Ning et al., 2023).

Existing works in related fields have discussed the channels through which such spillovers occur (Crescenzi et al., 2015; Grodhnichenko et al., 2020; Vujanovic et al., 2022). To this end, the entry of a foreign firm in similar industries may generate spillovers through the 'demonstration effect', whereby the local firms imitate the foreign technology through observation; the 'competition effect', whereby the domestic firms are forced to upgrade their technology in order to compete with the advanced foreign firms and 'labour turnover' whereby the domestic firms benefit from mobility of labour from MNEs to local firms (Ito et al., 2012; Crescenzi et al., 2015; Khachoo and Sharma, 2016). As mentioned in the earlier sections, spillovers generated through such channels within firms that belong to similar industries are known as horizontal (intra-industry) or within-industry spillovers.

Nevertheless, imitation is risky and requires a minimum level of research and development to absorb foreign technology (Grossman and Helpman, 1993). However, firms in EMDEs are far from the global technological frontier and lack scientific knowledge and resources for cutting-edge research (Radosevic and Yoruk, 2016; Vujanovic et al., 2022). Given their traditional technological setup, low absorptive capacity and technological incompetencies, the domestic firms in EMDEs may fail to internalise the sophisticated technology of the foreign MNEs (Qu et al., 2017; Ascani et al., 2019; Ning et al., 2023). Prior empirical works have drawn attention to these barriers and associated FDI with deteriorating innovation spillovers (Garcia et al., 2013; Jin et al., 2019).

Taken together, the above suggests that horizontal spillovers may influence the innovation capabilities of domestic firms in either of two ways- a positive influence through demonstration effect, competition effect and labour turnover effect, or a negative influence in case the domestic firms fail to internalise the foreign technologies vide low absorptive capacity. While the analysis in this field has extensively focussed on the impact of horizontal spillovers on productivity (Aitken et al., 1997; Newman et al., 2015; Mai Lan et al., 2024), the impact of horizontal spillovers on the innovation output of firms in EMDEs has gained little attention in the existing empirical works. Our understanding of the impact of horizontal spillover on innovation output is further limited by the mixed and inconclusive evidence presented in the scarce available literature. Stemming from this and considering the low absorptive capacity of firms in EMDEs such as India, we formulate the first hypothesis of this chapter:

Hypothesis 5.1 *Horizontal FDI spillovers would adversely affect the innovation output of the Indian manufacturing firms.*

FDI spillovers may also occur through buyer-supplier linkages when a domestic firm in an upstream industry gains through supplying inputs to a foreign firm in the downstream industry (Barge-Gil et al., 2020; Guo and Zhang, 2022; Hoekman and Sanfilippo, 2023). This is known as backward, vertical, or inter-industry spillover. Using materials from local suppliers is cost-effective for the firms. Therefore, as multinationals enter the market of an EMDE, they establish linkages with local suppliers. In an effort to ensure a finer quality of products, at a greater quantity and in less time, the foreign firms in the downstream sector may provide technical support to the local suppliers for improving the quality of the product via assisting innovation efforts and providing organisational and management support. The local firms are also likely to put an effort into increasing their efficiency as they are expected to compete for supplier contracts with foreign firms in the downstream sector. This enables inter-industry exposures and generates positive innovation spillovers (Khachoo and Sharma, 2016; Barge-Gil et al., 2020).

However, upgrading production quality may increase the cost of the products, reducing the demand for these products. Foreign firms may also decide to source materials from their parent country or use their established global supply chain to import materials, ignoring the local suppliers. This adversely affects the local suppliers' growth and may result in weaker domestic industries (Aitken and Harrison, 1999; Sari et al., 2016). To this end, previous literature has widely regarded that knowledge generation or positive FDI spillovers would take place only if sufficient levels of domestic absorptive capacity exist (Kosova, 2010; Damijan et al., 2013; Ben Hassine et al., 2017). In other words, the greater the gap between the technological levels of foreign and domestic firms, the less will be the spillover absorbed.

While a parallel stream of literature has extensively studied the effects of vertical FDI spillovers on firms' productivity (Malik, 2015; Bournakis et al., 2022; Mai Lan, 2024), evidence of the impact of vertical FDI spillovers on firms' innovation output is grossly scarce. Taking this into account and considering the low absorptive capacity of firms in EMDEs like India, we formulate our second hypothesis:

Hypothesis 5.2 *Vertical FDI spillovers would adversely affect the innovation output of the Indian manufacturing firms.*

Innovation also has a spatial specificity (Bottazzi and Peri, 2003; Ning et al., 2016; Hu et al., 2020). Building on the works of Marshall (1890), economic literature has extensively shown that firms located in industrially agglomerated clusters have a greater propensity to innovate (dos Santos and Dalcol, 2009; Zhang, 2015; Tang and Cui, 2023). Being located in a dense industrial cluster gives the firm access to a thick labour market, allowing a better match between the employer and the employee. It increases the likelihood of a firm finding employees with desired skills for specialised positions. Firms located in major industrial clusters also benefit through input sharing and various third-party specialised services such as financing, legal support, advertising, etc., which are more quickly accessible to firms in such industrial clusters than the ones located in sparsely populated clusters. Finally, firms in an industrial cluster may also benefit from interpersonal contacts and the sharing of ideas.

However, there might also be adverse effects of being located in major or dense industrial clusters, which may deter the firm from innovating (Zhang, 2015; Ruffner and Spescha, 2018; Niebuhr et al., 2020). The existence of a dense labour market can augment intense competition among the participating firms for specialised workers. As a consequence, some firms may struggle to recruit desired candidates, lacking the required skills and expertise to innovate. Further, locating in an industrial cluster would also mean higher demand for such intermediate services, driving up their prices and making it unaffordable for some firms to bear the costs. As a result, such firms are required to undertake these services independently, which would be time-consuming, and the result may not even be fruitful. In all likelihood, these firms may not necessarily get access to experienced and qualified third-party contracts, which would place these firms behind the ones getting easy and experienced third-party services.

While the existing research has focussed on the innovation behaviour of firms located in industrially agglomerated clusters, a fundamental issue that has received scant attention despite its academic and policy relevance is the moderating role of horizontal and vertical FDI spillovers on the innovation output of firms located in industrially agglomerated clusters. Limited analysis of this relationship provides mixed results (Positive in Ning et al., 2016, and negative in Li et al., 2017). Moreover, the existing studies do not specify how the horizontal and vertical channels of FDI spillover influence the innovation output of firms in industrial clusters. This gap needs to be filled, given the emphasis laid down by policymakers on using FDI as a vital tool of innovation in EMDEs like India. This leads us to formulate our third hypothesis:

Hypothesis 5.3 *Horizontal and vertical FDI spillovers would positively influence the innovation output of the Indian manufacturing firms located in the major industrial clusters of the country.*

5.3 Data and variables

5.3.1 Sample selection

We intend to conduct the study from 2005 onwards, as the year marks India's full-fledged implementation of the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS). However, the Input-Output Table for India, required to calculate the vertical spillover variable, one of the key variables of the study, is available only from 2007 onwards. This makes 2007-2020 the sample period for the present study. Our initial dataset comprises 10,316 firms spread across 23 broader two-digit level manufacturing industries. These data are further complemented with PatSeer (Patent Search and Analysis Software) data for patent information. The firm-level data are collected from the CMIE Prowess database. Following Hall et al. (2013) and Igna and Venturini (2023), we dropped the firms without a single patent to their credit during our entire study period from the sample. This decision is consistent with the literature as it ensures that all firms face a decision on how to protect their innovation. This process left us with 347 innovative firms, which constitute the final sample for the empirical analysis.

5.3.2 Description of variables

The empirical specification of the present work uses patent counts as the innovation indicator. The spillover variables are calculated using the method described in standard literature such as Javorcik (2004), Blalock and Gertler (2008) and Javorcik and Spatareanu (2008). This section discusses the construction of these variables and the firm-specific, market-specific and technology-specific control variables used in this chapter. A more detailed description of the variables is presented in Table C1 in Appendix C.

Innovation Variable

A fundamental issue discussed extensively in the economics of innovation is the quantification of innovation. Two strands of literature follow in this respect. One strand of literature measures innovation using input variables such as research and development (R&D) expenditures (Kinoshita, 2000; Vujanovic et al., 2022). However, recent studies have raised the issue that EMDEs usually generate technological advances outside the formal R&D process (Wadho and Chaudhry, 2018; Petelski et al., 2020). Also, R&D is only an input to the innovation process and says nothing about the 'output' side of the innovation. In view of such limitations, the other strand of the literature proposes using patent counts as a measure of intermediate innovation output (Garcia et al., 2013; Ascani and Gagliardi, 2015). The existing research on empirical works of innovation economics underscores patents as a 'classic instrument for incentivising and measuring innovation' (Sweet and Eterovic, 2019). However, a major criticism of using patent data to proxy innovation is that patents reflect inventions (development of new ideas) only and not innovations (development of commercially viable products or services from creative ideas). To this end, Artz et al. (2010) offer econometric evidence establishing a positive and significant relationship between patents and product announcements, justifying the use of patents for innovation. Drawing on this, our work aligns with the second strand of literature and uses patent counts as a proxy for innovation.

In the literature, both the number of patent applications and the number of patents granted have been used as innovation instruments. An inherent limitation of patent applications is that they may capture spurious and contrived applications (Garcia et al., 2013).Therefore, we use counts of patent grants to measure innovation output. However, in section 5.7 of the chapter, we use patents applied to instrument innovation, given the requisites of the empirical analysis. This is discussed in detail in section 5.7.

Spillover Variables

This chapter uses two spillover variables- the horizontal spillover and the backward spillover. Horizontal spillover refers to within-industry or intra-industry spillovers from foreign firms to domestic firms operating within the same industry. In contrast, backward spillovers refer to the inter-industry spillovers between the local upstream suppliers and the foreign downstream customers.

Following Javorcik (2004) and Blalock and Gertler (2008), we measure horizontal spillover as the share of an industry's output that foreign-owned firms produce. Specifically,

$$Horizontal_{jt} = \frac{\sum_{i \in j} Foreign\_Output_{it}}{\sum_{i \in j} Output_{it}} \tag{5.1}$$

Where i indicates firm, j indicates industry and t indicates the time period. $Foreign\_Output_{it}$ refers to the output of firm i, if the equity held by the foreign promoter in the firm is a minimum of 10 percent.[22] $Output_{it}$ refers to the output of firm i in time period t. Output here is proxied by the sales of the firm.

Following prior literature (Blalock and Gertler, 2008; Javorcik and Spatareanu, 2008), the vertical or backward or inter-industry FDI spillovers are calculated as the share of the total output of an industry that is sold to downstream foreign buyers across all industries, which can be measured as follows:

$$Vertical_{jt} = \sum_k \alpha_{jkt} Horizontal_{kt} \tag{5.2}$$

Where α_{jkt} is the proportion of industry j output consumed by industry k. $Horizontal$ is the measure of intra-industry spillover calculated by Eq. (5.1). The values of α_{jkt} is taken from the India Input-Output table.

Cluster-specific-spillover Variable

The study measures location in the form of a binary indicator, which takes the value of one if the firm is registered with a city that falls in one of the eight major industrially agglomerated clusters of the country and zero otherwise[23]. The firms located in these areas may benefit from

[22] Based on the Report of the Dr Arvind Mayaram Committee on Rationalising the FDI/FII Definition, 2014

[23] These industrial belts include the Mumbai-Pune industrial region, the Hugli industrial region, the Bangalore-

easy access to the required inputs and other intermediate services. At the same time, they may also face congestion, which would hamper their innovative efforts. This chapter focuses on an empirical investigation of the impact of horizontal and vertical FDI spillovers on the innovation output of firms located in the major industrial clusters of the country. For this purpose, we interact the location variable with the horizontal and vertical spillover variables.

Control Variables

We use the age of a firm to account for their learning experience. Due to accumulated learning, older firms are better at making technology-diffusing decisions. At the same time, younger firms have higher expected growth rates and can adapt to the latest technology more conveniently (Fang et al., 2020; Bertrand and Murro, 2022). Based on existing works, we measure the $size$ of the firm using the number of employees of a firm (Wadho and Chaudhry, 2018; Bertrand and Murro, 2022; Yang, 2022). In innovation literature, researchers have encountered both positive (Fang et al., 2020; Cecere et al., 2020) and negative (Shefer and Frenkel, 2005; Santi and Santoleri, 2017) associations between labour size and innovation output. To capture the international orientation of the firm, we include the $export$ and i$mport\ intensity$ of the firm in our group of control variables (D'Souza and Kulkarni, 2015; Yang, 2018). Following prior work (Sasidharan and Kathuria, 2011; Ambrammal and Sharma, 2014), the export intensity of the firms is calculated as a ratio of the sum of exports of goods and services to the sales of the firm. Based on existing literature (Kathuria, 2002; Sasidharan and Kathuria, 2011), the import intensity of the firms is calculated as the ratio of the sum of import of capital goods, royalty, licensing and technical fees paid by a firm to the sales of the firm. Firms involved in intense export and import activities have access to international contacts and superior technical know-how. Therefore, they are expected to be better at internalising sophisticated technology in the market (Yang and Chen, 2012; Yang, 2018). However, close contact with the international counterpart may also trigger shifting of the innovation base to a foreign country, given the favourable conditions prevailing in the developed markets (Ambrammal and Sharma, 2014; Anwar and Sun, 2014). Following existing literature (D'Souza and Kulkarni, 2015; Giovannetti and Piga, 2017; Eapen et al., 2019), the absorptive capacity of the firm is captured by the $R\&D\ intensity$ of the firm.[24] R&D investment is essential not only

Chennai industrial region, the Gujarat industrial region, the Chotanagpur industrial region, the Vishakhapatnam-Guntur industrial region, the Gurgaon- Delhi- Meerut industrial region, the Kollam-Thiruvanthapuram industrial region. This classification is demarcated by Singh (1971).

[24] Absorptive capacity refers to the ability of the firms in the host economy to internalize knowledge created by others and modify it to fit their specific applications (Narula and Marin, 2003).

for new knowledge development but also to internalise the existing level of knowledge prevalent in the market. Hence, higher levels of R&D intensity are expected to correspond positively to innovation output (Link and van Hasselt, 2020; Xu and Liu, 2021).

5.4 Empirical Framework and Methodology

Based on the conceptual framework drawn and hypotheses formed, the empirical model of the present chapter follows the works of Crescenzi et al. (2015) and Gorodnichenko et al. (2020) and specifies the following empirical model:

$$Innovation_{it} = \beta_0 + \beta_1 Horizontal_{ijt} + \beta_2 Vertical_{ijt} + \beta_3 Location_{ijr} \times Horizontal_{ijt} + \beta_4 Location_{ijr} \times Vertical_{ijt} + \sum \beta_k Z_{it}^{k} + \beta_i + \beta_t + \varepsilon_{it} \tag{5.3}$$

Where the $innovation$ variable measures the counts of patents. Z_{it} is the set of control variables. β_i and β_t are cross-section (firm-specific) and time dummies, respectively. The variable $Horizontal_{ijt}$ captures the intra-industry and $Vertical_{ijt}$ captures inter-industry FDI spillovers of a firm i, that belongs to industry j, during time-period t. These two spillover variables vary between industry and time. The interaction term $Location_{ijr} \times Horizontal_{ijt}$ captures the intra-industry FDI spillovers within an industrial cluster (r), and the interaction term $Location_{ijr} \times Vertical_{ijt}$ captures the inter-industry spillovers within an industrial cluster (r).

The response indicator here, $innovation,$ takes non-negative integer values, with many observations being zero. This restricts us from using traditional measures of analysis. Figure C1 in the Appendix shows the Kdensity plots of the patents granted to the manufacturing firms in India. It clearly shows the high degree of skewness in the data. The literature treats these kinds of data with count data panel models. The most prominent count models are the poisson regression and negative binomial models. However, the Poisson model has the limited property of equidispersion, referring to the equality of mean and variance. This rather restrictive property often fails to hold good in practice. Using the Poisson regression model in overdispersed distributions causes misspecified likelihood functions, yielding erroneous results. The negative binomial model has proven the most effective in such instances of overdispersion (Hausman et al., 1984; Cameron and Trivedi, 1998). Unlike the Poisson model, the negative binomial model has less restrictive properties and does not require the variance to be equal to the mean (μ), i.e.,

$$\text{Var}\ (y/x) = \mu + \alpha\mu^2 \tag{5.4}$$

The negative binomial model estimates the overdispersion parameter α. If $\alpha = 0$, then the use of Poisson regression suffices. However, if $\alpha > 0$, we need to go for negative binomial regression. In our patent data, α turns out to be significantly different from zero without fail. Therefore, we form a negative binomial model with fixed effects to study Eq. (5.3).

Table C2 in Appendix C presents the descriptive statistics of the variables used.

5.5. Empirical Results

5.5.1 Do horizontal and vertical FDI spillovers influence the innovation output of Indian manufacturing firms? Baseline findings

Table 5.1 presents the negative binomial regression results using patent counts as the dependent variable. The estimated coefficients of the horizontal and vertical spillover variables in column I of Table 5.1 are not significantly different from zero. However, this result could be affected by omitted variable bias as the current level of innovation also depends on past innovation levels and R&D intensity. Therefore, we include the lagged values of R&D intensity and innovation in columns II and III of Table 5.1, respectively.[25] However, the results are similar to those reported in column I of Table 5.2. Based on this, we conclude that horizontal and vertical FDI spillovers do not significantly influence the innovation output of Indian manufacturing firms. While the insignificant impact of horizontal FDI spillovers on innovation corresponds with the findings of Gorodhnichenko et al. (2020), the insignificant vertical FDI spillover is consistent with much of the related literature (Girma et al., 2009; Crescenzi et al., 2015; Vujanovic et al., 2022) that reports an insignificant inter-industry FDI spillover on innovation.

The existing studies in similar fields have broadly shown that domestic firms' capacity to benefit from FDI spillovers is subject to the absorptive capacity of the local firms (Girma et al., 2008; Guo et al., 2021; Xu and Hu, 2024). In our empirical specification, the R&D intensity (and lagged R&D intensity), which measures the firm's absorptive capacity, is uniformly insignificant across all the specifications in Table 5.1 (see all columns). This justifies the insignificance of the spillover variables and supports the view that firms' absorptive capacity plays a crucial role in mediating the relationship between FDI spillovers and innovation.

Further, we extend the model and introduce interactions between horizontal spillovers and location, as well as vertical spillovers and location (see columns IV and V, Table 5.1). This allows us to empirically evaluate whether horizontal and vertical FDI spillovers impact the

[25] Using the lagged dependent variable addresses the possible endogeneity issue. It also allows the current dependent variable to temporarily co-vary with past instantiations of the dependent variable (Garcia, 2013). Further, using lagged explanatory variables moves the channel through which endogeneity biases causal estimates (Bellemare et al., 2017)

innovation output of firms located in the major industrial clusters of the country. The estimated coefficient of the interaction term between horizontal spillover and location is positive and significant (see column IV of Table 5.1), reflecting that FDI spillovers positively influence the innovation output of industrially clustered firms through horizontal channels. This is consistent with the findings of other empirical studies (Rosenthal and Strange, 2003; Arzaghi and Henderson, 2008), which suggest that knowledge spills over more fluidly within geographical clusters. Thus, our results demonstrate that spatially concentrated firms benefit from FDI in similar industries through interpersonal contacts, sharing of ideas and the probable mobility of labour from foreign to domestic firms. However, these benefits are limited to intra-firm contacts only as the estimated coefficient of the interaction between vertical spillover and location is not significantly different from zero (see column V, Table 5.1). Thus, the empirical findings suggest that FDI spillovers positively influence the innovation output of firms located in the major industrial clusters of the country through horizontal linkages.

Moving further, dwelling upon the role of R&D intensity in generating technological spillovers, we introduce two more interaction terms in columns VI and VII of Table 5.1. To estimate the innovation impact of firms in the major industrial cluster that capitalise on horizontal spillover and invest in R&D, we include the interaction between horizontal spillover, location and lagged R&D intensity (see column VI, Table 5.1). The estimated coefficient is positive and significant, indicating that firms located in the major industrial clusters of the country which intensely spend on R&D are able to draw the benefits of horizontal spillovers and innovate significantly. This, again, highlights the role of the absorptive capacity of firms in internalising technology.

On the contrary, the absorptive capacity of supplying firms in the major industrial clusters of the country is inefficient, as reflected by the negative and significant estimated coefficient of the interaction term between vertical spillovers, location and lagged R&D intensity (see column VII, Table 5.1). This further explains the insignificant vertical linkages for industrially clustered firms in column IV of Table 5.1. Thus, our empirical findings again reaffirm the role of R&D intensity in internalising foreign technology.

Moving to the control variables, the estimated coefficient of the variable size, measured as the firm's number of employees, is uniformly positive and statistically significant across all the models in Table 5.1. This reflects the labour-intensive nature of the Indian manufacturing market. This demonstrates that innovation in Indian manufacturing firms is rooted in employing more workers, far more than investments in R&D. This is consistent with the previous literature that has emphasised that innovation in EMDEs is not necessarily R&D driven (Cirera and Maloney, 2017; Stojčić et al., 2020). A larger pool of human capital facilitates greater degrees of specialisation in labour, which enables efficient teamwork and greater knowledge sharing. The involvement of more human capital also allows the firms to handle multiple projects simultaneously, allowing for risk diversification across the projects, which allows the firms to nurture an innovation-friendly ecosystem.

Further, the estimated coefficients of export intensity are also negative and significantly different from zero across all specified models in Table 5.1, reflecting that Indian manufacturing firms that export intensely tend to innovate less. This is consistent with previous literature (Anwar and Sun, 2014; Yang, 2018), and specifically previous works in the context of Indian manufacturing firms (Ambrammal and Sharma, 2014). Exporting firms face intense competition in the international market, requiring them to maintain specific international standards in order to remain competitive. This often leads the firms to adopt a risk-averse approach to ensure consistency in the volatile global market. Moreover, such firms also have a more potent global network, making it easier to patent abroad. If firms perceive greater strategic value in patenting globally, they would capitalise on their international networks to obtain global patents rather than going for Indian patents. However, while the negative impact of export intensity on innovation output is consistent with some of the previous works (Anwar and Sun, 2014; Ambrammal and Sharma, 2014; Yang, 2018), these findings contradict the findings of some other works as well (Aboal and Garda, 2016; Dalgıç et al., 2023). Therefore, in the following section, we further investigate the relationship between export intensity and innovation behaviour of Indian manufacturing firms.

Table 5. 1: FDI spillovers and innovation. Negative binomial regressions

Variables	I	II	III	IV	V	VI	VII
$Innovation_{t-1}$			0.012**	0.012***	0.011**	0.011**	0.011**
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Horizontal\ Spillover$	-0.287	0.059	0.142		-0.386		0.035
	(0.45)	(0.43)	(0.42)		(0.27)		(0.13)
$Vertical\ Spillover$	0.189	-0.066	-0.146	-0.449*		-0.047	
	(0.36)	(0.35)	(0.35)	(0.23)		(0.11)	
$Location$	-1.239	-1.492	-1.628				
	(1.19)	(1.26)	(1.24)				
Age	0.604	0.433	0.490	0.497	0.416	0.563	0.700
	(0.61)	(0.64)	(0.63)	(0.63)	(0.63)	(0.63)	(0.63)
$Labour$	0.362***	0.418***	0.413***	0.431***	0.388***	0.422***	0.410***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
$Export\ Intensity$	-0.989**	-1.102**	-1.043**	-1.063**	-1.039**	-1.018**	-1.013**
	(0.44)	(0.43)	(0.42)	(0.42)	(0.42)	(0.42)	(0.42)
$Import\ Intensity$	-1.434	-0.358	-0.407	-0.368	-0.45	-0.368	-0.377
	(1.92)	(1.76)	(1.77)	(1.77)	(1.79)	(1.75)	(1.75)
$R\&D\ Intensity$	-0.146						
	(1.98)						
$R\&D\ Intensity_{t-1}$		-0.003	0.001	-0.004	0.007		
		(0.08)	(0.08)	(0.08)	(0.08)		
$Horizontal\ Spillover \times Location$				0.598**			
				(0.29)			
$Vertical\ Spillover \times Location$					0.358		
					(0.23)		
$Horizontal\ spillover \times Location \times R\&D\ Intensity_{t-1}$						2.105*	
						(1.24)	
$Vertical\ spillover \times Location \times R\&D\ Intensity_{t-1}$							-0.797***
							(0.24)
Constant	-4.929	-1.836	-1.120	0.170	-7.098**	-4.151	-4.985*
	(4.05)	(4.01)	(3.93)	(3.28)	(3.34)	(2.58)	(2.58)
Cross-Section Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.2993	0.3114	0.3131	0.3142	0.3136	0.3142	0.3159
Log-likelihood	-1529.71	-1417.8	-1414.2	-1412.03	-1413.1	-1412.59	-1409.08
Observations	1,491	1,384	1,384	1,384	1,384	1,386	1,386

Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis

5.5.2 Robustness checks

In order to further validate the findings of the previous section, we apply the two-step system GMM (Generalized Method of Moments) estimation to Eq. (5.3). The validity of the instruments created by the GMM procedure is tested using the Hansen test of overidentifying restrictions as it is robust to heteroscedasticity and autocorrelation.The hypothesis that the error term is not serially correlated in the regression is measured using the AR test.

The empirical results reported in Table 5.2 are analogous to the findings reported in Table 5.1. The estimated coefficients of the horizontal and vertical spillovers in column I of Table 5.2 are not significantly different from zero. Based on this, we infer that in general, horizontal and vertical FDI spillovers do not substantially affect the innovation output of Indian manufacturing firms. Further, the estimated values of the interaction terms presented in column II of Table 5.2 provide robust evidence that horizontal FDI spillovers positively influence the innovation output of manufacturing firms located in the major industrial clusters of the country, supporting the empirical findings in column IV, Table 5.1. Analogous to the results of column V, Table 5.1, the estimated coefficients in column III of Table 5.2 show that vertical FDI linkages do not significantly influence the innovation output of firms in the major industrial clusters.

Similar to the findings shown in Table 5.1, the estimated coefficients of the R&D intensity variable across all the models in Table 5.2 are statistically insignificant. Following columns VI and VII of Table 5.1, columns IV and V of Table 5.2 introduce interactions between horizontal and vertical spillovers with location and lagged R&D intensity variables. The estimated coefficients provide robust evidence that while the industrially clustered firms that benefit from horizontal linkages efficiently convert their R&D expenditures into innovation output, the industrially clustered firms in the supplying industries are inefficient in doing the same. This again establishes that the lack of absorptive capacity of Indian manufacturing firms is a major obstacle in assimilating foreign technology.

The estimated coefficients of the control variables in Table 5.2 also present results similar to those in Table 5.1. Much like the findings of Table 5.1, the variable labour size is positive and significant across most of the specifications in Table 5.2, confirming the labour-intensive nature of innovation in India. The variable export intensity is also negative and significant across some specifications in Table 5.2, confirming the results presented in Table 5.1. Additionally, the import intensity of the patenting firms turns out to be negative and significant across some of the specifications. This is in line with the findings of Goel (2022), who conclude that certain high-tech imports directly replace scientific products and thus make scientific discoveries or innovation less desirable.

Table 5. 2: FDI-spillovers and innovation: Results from GMM estimation

Variables	I	II	III	IV	V
$Innovation_{t-1}$	0.874***	0.925***	0.869***	0.820***	0.868***
	(0.00)	(0.01)	(0.01)	(0.08)	(0.00)
$Horizontal\ Spillover$	-0.088		0.073		0.047
	(0.15)		(0.06)		(0.07)
$Vertical\ Spillover$	0.087	-0.043		0.062	
	(0.11)	(0.05)		(0.05)	
$Location$	0.065				
	(0.20)				
Age	0.067	-0.021	0.002	-0.145	0.078
	(0.10)	(0.08)	(0.10)	(0.21)	(0.13)
$Labour$	0.197	0.247***	0.225***	0.423***	0.277**
	(0.12)	(0.04)	(0.05)	(0.13)	(0.12)
$Export\ Intensity$	-0.289	-0.199	-0.212	-0.481*	0.029
	(0.20)	(0.27)	(0.22)	(0.25)	(0.22)
$Import\ Intensity$	-0.056*	-0.0004	0.006	-0.111**	-0.222
	(0.03)	(0.03)	(0.04)	(0.05)	(0.77)
$R\&D\ Intensity_{t-1}$	0.011	-0.007	-0.005		
	(0.03)	(0.02)	(0.03)		
$Horizontal\ Spillover$		0.152*			
$\times\ Location$		(0.08)			
$Vertical\ Spillover$			0.013		
$\times\ Location$			(0.02)		
$Horizontal \times Location$				2.409***	
$\times\ R\&D\ Intensity_{t-1}$				(0.45)	
$Vertical \times Location$					-0.773***
$\times\ R\&D\ Intensity_{t-1}$					(0.18)
Cross-section Dummy	Yes	Yes	Yes	Yes	Yes
Time Dummy	Yes	Yes	Yes	Yes	Yes
AR2	1.16	1.18	1.15	1.08	1.15
AR2 (P)	0.247	0.239	0.248	0.282	0.25
Hansen	48.39	63.42	31.64	12.52	43.36
Hansen (P)	0.12	0.133	0.169	0.326	0.218
Observations	1,356	1,356	1,356	1,358	1,386

Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis

The firms that operate internationally are well acquainted with the contemporary technological levels prevailing in those markets. Therefore, we anticipate that internationally oriented firms may have an advantage in assimilating foreign technology. Based on this and as mentioned in the previous section, we extend our empirical analysis to evaluate whether the spillovers generated within and across the exporting firms impact the innovation output of Indian manufacturing firms. For these purposes, we introduce the interaction of horizontal spillovers and export intensity, as well as vertical spillovers and export intensity in Tables 5.3 and 5.4 (columns I and II). Further, even though the import intensity of firms is found to be mostly insignificant in influencing the innovation output of Indian manufacturing firms, the importing firms, much like their exporting counterparts, are also exposed to international markets. Taking this into account, we further look into the possibility of whether the horizontal and vertical spillovers in importing firms have any significant influence on the innovation output of the Indian manufacturing firms. Therefore, we also introduce the interaction of horizontal spillovers and import intensity, as well as vertical spillovers and import intensity, in Tables 5.3 and 5.4 (columns III and IV).

True to our expectations, the empirical estimates of the negative binomial model, presented in Table 5.3, provide evidence that exporting firms that capitalise on horizontal spillovers achieve higher innovation levels (see column I). The results from GMM estimates presented in Table 5.4 support this finding (see column I). Horizontal spillover, which captures knowledge spillovers within the same industry, gives the firm access to modern technologies and best practices in the same industry. Exporting firms, which are already exposed to the insights of the diverse international markets, are able to integrate these practices through their learning in the global markets. Moreover, exporting firms, on the one hand, are exposed to broader competitive pressure and opportunities in the international market, and horizontal linkages, on the other hand, allow them access to updated industry trends. The dual effect of both leads the exporting firms to innovate more through horizontal linkages.

However, firms that intensely export innovate less in the presence of vertical spillovers (column II, Tables 5.3 and 5.4). This negative linkage across supplying industries could be explained in terms of the superior bargaining power of foreign firms. By virtue of their superior position, foreign firms enjoy greater bargaining power, especially in an EMDE country like India (Graham and Thorpe, 1999). Hence, while these firms may teach their local suppliers to be more efficient, they may demand lower prices for the intermediate products in return. The exporting firms, therefore, prefer to operate in the international market where they would avail better returns for their supplies. However, the global markets are highly competitive and price-sensitive. Therefore, the supplying exporting firms prefer to devote resources to fulfilling the demands and requirements of international buyers, limiting the scope for innovation.

Columns III and IV of Tables 5.3 and 5.4 show the estimated results of the interaction of the horizontal and vertical spillover variables with the import intensity of the firms using the negative binomial model and GMM, respectively. Both the interaction terms are statistically insignificant, reflecting that the importing firms are not innovating substantially through horizontal or vertical linkages.

Amongst the control variables, similar to the findings presented in Tables 5.1 and 5.2, the size of the labour retains its positive significance across all the specifications, reaffirming the labour-intensive nature of innovation in the country. The export intensity variable also maintains its negative and significant nature across most specifications, providing robust evidence that the exporting firms do not prefer to patent in the domestic market.

Table 5. 3: FDI innovation spillovers and the role of firms' R&D intensity and international orientation: Results from negative binomial regressions (Additional Evidence)

Variables	I	II	III	IV
$Innovation_{t-1}$	0.012***	0.011**	0.012**	0.012**
	(0.00)	(0.00)	(0.00)	(0.00)
$Horizontal\ Spillover$		-0.007		-0.026
		(0.13)		(0.13)
$Vertical\ Spillover$	-0.085		-0.046	
	(0.11)		(0.11)	
$Location$	-1.073	-1.535	-1.49	-1.423
	(1.13)	(1.15)	(1.16)	(1.13)
Age	0.340	0.498	0.477	0.463
	(0.62)	(0.63)	(0.63)	(0.63)
$Labour$	0.437***	0.406***	0.411***	0.408***
	(0.12)	(0.12)	(0.12)	(0.12)
$Export\ Intensity$			-1.033**	-1.052**
			(0.41)	(0.43)
$Import\ Intensity$	-1.193	-0.320		
	(1.85)	(1.75)		
$R\&D\ Intensity_{t-1}$	0.005	0.001	0.004	0.002
	(0.08)	(0.08)	(0.08)	(0.08)
$Horizontal\ Spillover \times Export\ Intensity$	0.426*			
	(0.26)			
$Vertical\ Spillover \times Export\ Intensity$		-0.112***		
		(0.04)		
$Horizontal\ Spillover \times Import\ Intensity$			0.499	
			(0.97)	
$VerticalSpillover \times Import\ Intensity$				-0.027
				(0.20)
Constant	-1.963	-2.619	-2.184	-2.614
	(1.88)	(1.76)	(1.89)	(1.76)
Cross-section Dummy	Yes	Yes	Yes	Yes
Time Dummy	Yes	Yes	Yes	Yes
Pseudo R^2	0.3123	0.3133	0.3131	0.3131
Log-likelihood	-1415.94	-1414.00	-1414.14	-1414.31
Observations	1,384	1,384	1,384	1,384

Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis

Table 5. 4: FDI innovation spillovers and the role of firms' R&D intensity and international orientation: Results from GMM estimation (Additional Evidence)

Variables	I	II	III	IV
$Innovation_{t-1}$	0.872***	0.900***	0.856***	0.868***
	(0.00)	(0.09)	(0.01)	(0.01)
$Horizontal\ Spillover$		0.024		0.045
		(0.07)		(0.06)
$Vertical\ Spillover$	0.028		0.045	
	(0.04)		(0.12)	
$Location$	0.100	0.136	0.059	0.056
	(0.13)	(0.11)	(0.36)	(0.15)
Age	-0.048	0.062	-0.117	0.031
	(0.05)	(0.17)	(0.18)	(0.10)
$Size$	0.287***	0.314**	0.498***	0.225***
	(0.04)	(0.15)	(0.19)	(0.05)
$Export\ Intensity$			-0.215	-0.191
			(0.42)	(0.22)
$Import\ Intensity$	0.029	0.886		
	(0.58)	(0.72)		
$R\&D\ Intensity_{t-1}$	0.0004	0.016	0.011	-1.218
	(0.02)	(0.05)	(0.05)	(0.84)
$Horizontal\ Spillover \times Export\ Intensity$	0.274**			
	(0.12)			
$Vertical\ Spillover \times Export\ Intensity$		-0.054*		
		(0.03)		
$Horizontal\ Spillover \times Import\ Intensity$			0.305	
			(0.90)	
$Vertical\ Spillover \times Import\ Intensity$				-0.001
				(0.09)
Cross-section Dummy	Yes	Yes	Yes	Yes
Time Dummy	Yes	Yes	Yes	Yes
AR2	1.15	1.15	1.14	1.16
AR2 (P)	0.25	0.249	0.254	0.247
Hansen	48.63	12.13	35.44	17.39
Hansen (P)	0.116	0.436	0.542	0.136
Observations	1,384	1,384	1,384	1,384

Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis

5.5.3 FDI policy liberalisation and innovation in foreign firms: A Difference-in-Difference analysis

The findings from the preceding sections show that FDI spillovers are not significantly affecting the country's innovation output. This gives rise to profound policy questions as the government is taking major steps to ease the FDI inflows while focusing on fostering innovation in the country. In September 2014, the government of India announced important FDI reforms under the "Make in India" initiative and promoted the country's manufacturing sector as the magnet for foreign investments. Accordingly, the government of India allowed 100 per cent FDI via the automatic route in agriculture, plantation, mining, exploration of petroleum and natural gas, contract manufacturing, broadcasting, aviation, construction, telecom, trading, railway infrastructure, insurance intermediaries, other financial services and NBFCs and greenfield pharmaceuticals. Besides, FDI through the automatic route was allowed up to 49 per cent in the defence sector, 74 per cent in brownfield pharmaceuticals, 49 per cent in the insurance and pension sector, and 74 per cent in private-sector banking. Consequently, the FDI inflow into the country has increased to US $ 286 billion during the period 2014-15 to 2018-19 as compared to US $ 189 billion in the five years prior to that, i.e. 2009-10 to 2013-14 (Cabinet Approves Proposal for Review of FDI Policy on Various Sectors, 2019). The government intends to supplement domestic capital, technology and skills for accelerated economic growth 'via promoting foreign direct investments'.

Under circumstances where FDI is insignificant in generating innovation spillovers, the opening up of the manufacturing industry would make sense only if the foreign firms are innovating significantly in India after the policy liberalisation. To test the competing speculation, this section analyses whether or not foreign firms have innovated significantly post the 2014 FDI policy liberalisations.

For this purpose, this chapter relies on the difference-in-difference (DID) method to measure the impact of FDI liberalisation policies on the innovation behaviour of foreign firms. The empirical studies in economics have established DID as an efficient way to analyse the influence of policies and regulations (Pippel and Seefeld, 2016; Zhuge et al., 2020). The DID method is based on quasi-natural experiments that can prevent the problem of endogeneity. The method compares the development between two groups based on their treatment. In the present chapter, the classification of the groups is determined by whether the firm is foreign (having at least ten per cent foreign equity participation) or domestic (firms with less than ten per cent foreign equity participation). The foreign firms represent the treatment group, and the domestic firms represent the control group. The DID model can be represented as:

$$Innovation_{it} = \alpha_0 + \alpha_1 Ownership_{ij} \times Time_t + \sum \alpha_k Z_{it}^k + \delta_i + \gamma_t + \varepsilon_{it} \qquad (5.4)$$

In this section of the chapter, Time=1 refers to the post-policy era and covers the periods from 2015 to 2020, and time=0 refers to the pre-policy era and covers the periods from 2007 to

2014.[26]

In Eq. (5.4), $Innovation_{it}$ stands for the counts of patents filed by any manufacturing firm i during the study period in any of the patent offices in India. For the econometric investigation of the FDI liberalisation policies on the innovation output, we have considered patents applied instead of patents granted. This decision is guided by the fact that granting a patent involves gestation periods (usually 3-6 years in India). This implies that the patents granted in 2015 or 2016 were actually applied a few years back, before the implementation of the policy liberalisation. Hence, using patents granted will not reflect the true impact of the decisions of the foreign firms. Moreover, the innovation literature extensively uses patent applications as an indicator of innovation, justifying the use of the variable (Crepon et al., 1998; Akcomak and Weel, 2009).

In Eq. (5.4), the interaction term between the dummy of foreign ownership $Ownership_{ij}$ and policy $Time_t$ is added to test the moderating effect of FDI policy liberalisation on the innovation output of foreign firms. Z_{it}^{k} represents the set of control variables, which includes the horizontal spillovers, the backward spillovers, the size of labour, the export intensity, the import intensity and the R&D intensity of the firms. δ_i controls for the time-invariant characteristics of a certain firm i such as the production models, distance from the border etc. and γ_t represents the firm invariant features in a certain time period t such as political instability, GDP etc.

Table 5.5 reports the results of the DID estimation. The estimation results of column I of Table 5.5 do not consider any time or firm-specific effects. Column II of Table 5.5 considers the time-specific shocks that are the same across all the sampled firms without controlling for any firm-specific unobserved heterogeneity. On the other hand, column III of Table 5.5 considers the firm-specific unobserved heterogeneity across the sample without controlling for time-specific shocks. Finally, the empirical estimates in column IV of Table 5.5 consider both the time-specific and firm-specific heterogeneity across the sample. The values and significance level of the variables across all four models are precisely similar, with slight variations in the magnitude of the coefficient. However, for explanation purposes, we consider specification IV of Table 5.5.

The estimated DID coefficients in Table 5.5 across all the specifications indicate a significant difference between the treatment and control groups at the 1 per cent level. The positive and significant coefficient of the interaction term $Ownership_{ij} \times Time_t$ indicates that

[26] The FDI policy liberalisation has been implemented on September 2014. Therefore, we have considered the effect of the policy from 2015 onwards

the increase in the innovation performance of the treatment group (foreign firms) is higher than that of the control group (domestic firms) in the post-policy era. In other words, foreign firms have significantly innovated more than domestic firms after the policy liberalisation. As has already been mentioned, the liberalisation policies adopted by the government of India aimed to relax various regulatory barriers and improve the country's investment climate. Such reforms encourage foreign firms to undertake innovation projects, which are essentially risky, uncertain and require long gestation periods. In the Indian context, following the FDI liberalisation policies of 2014, FDI inflow into the manufacturing sector increased vehemently from US $ 6381 million in the financial year ending 2014 to US $ 16300 million in the financial year ending 2022. This reflects an increase in joint ventures of foreign firms in the Indian manufacturing sector. Such collaborative joint venture often leads to a rise in the number of patent filings as both the parties engaged seek to protect their intellectual property. Foreign firms are also likely to secure patents in India as a strategic tool, as it would help them secure a competitive advantage in one of the world's fastest-growing emerging markets. As per the World Bank data, non-resident patent applications, which were about 30814 in 2014, reached about 35306 in 2021. This reflects the increasing interest of foreign firms in patenting in India.

In terms of the estimated coefficients of the control variables, similar to findings across Tables 5.1, 5.2, 5.3 and 5.4, the empirical results presented in Table 5.5 show that whereas labour size positively influences the innovation output of Indian manufacturing firms, exporting intensity of the firms has a negative influence on the innovation output. Further, the estimated coefficients of the control variables again confirm the insignificance of the spillover variables on the innovation output of the Indian manufacturing firms. Therefore, we conclude that even though the entry of foreign firms is not significantly improving the innovation output in the Indian manufacturing firms through horizontal and vertical linkages, the foreign firms are improving the innovation landscape of the country as they are significantly innovating more than their domestic counterparts, especially after 2014 FDI policy liberalisations.

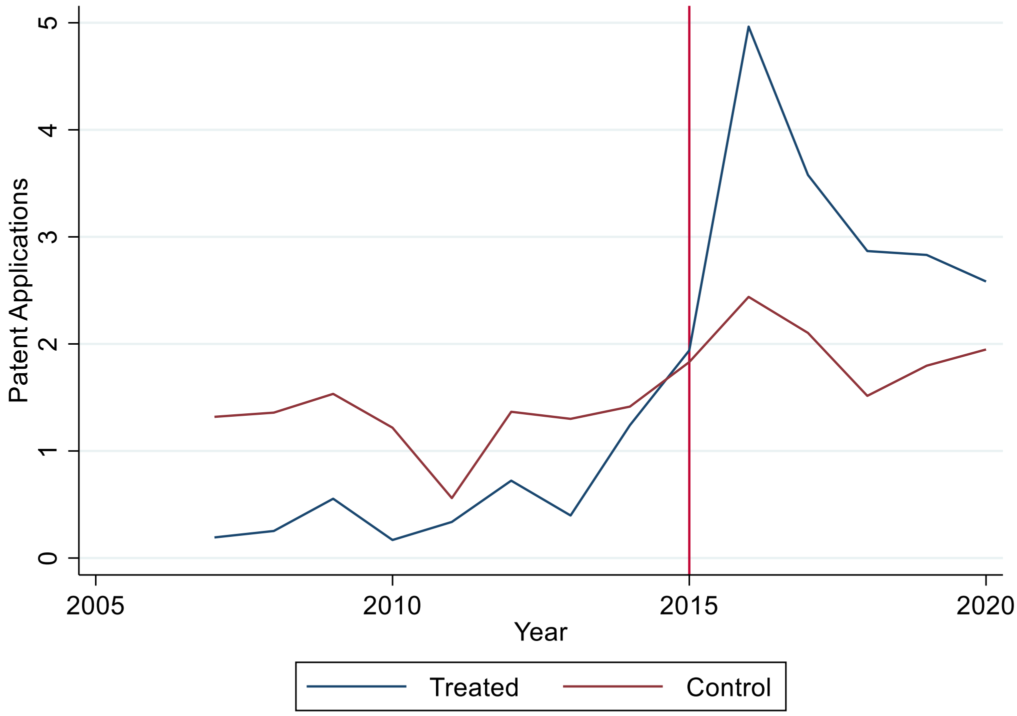
Table 5. 5: Difference-in-Difference estimation

Variables	I	II	III	IV
$Ownership_{ij} \times Time_t$	7.128***	7.128***	7.192***	7.192***
	(0.06)	(0.06)	(0.04)	(0.04)
$Horizontal\ Spillover$	-0.004	-0.004	-0.439	-0.439
	(1.45)	(1.45)	(0.72)	(0.72)
$Vertical\ Spillover$	0.286	0.286	0.614	0.614
	(1.21)	(1.21)	(1.18)	(1.18)
Age	-4.595	-4.595	-4.323	-4.323
	(2.22)	(2.22)	(6.73)	(6.73)
$Labour$	2.640*	2.640*	2.623	2.623
	(0.41)	(0.41)	(0.62)	(0.62)
$Export\ Intensity$	-6.367**	-6.367**	-6.259**	-6.259**
	(0.18)	(0.18)	(0.15)	(0.15)
$Import\ Intensity$	-0.166	-0.166	-0.123	-0.123
	(0.10)	(0.10)	(0.10)	(0.10)
$R\&D\ Intensity$	0.274	0.274	0.216	0.216
	(0.23)	(0.23)	(0.27)	(0.27)
Cross-section dummy	No	No	Yes	Yes
Time dummy	No	Yes	No	Yes
Observations	2,131	2,131	2,131	2,131

Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis

A visual inspection of the estimated difference-in-difference coefficients in Fig. 5.3 re-establishes this significance further. The figure shows till the FDI policy Liberalisation in September 2014, the control group, viz., the domestic firms, has been patenting significantly more than the treated group, viz. the foreign firms. However, after the liberalisation of the policy, foreign firms have significantly been applying for more patents in India than domestic firms. Thus, we can conclude that after the FDI policy liberalisation, the foreign firms have significantly been innovating more in India than the domestic firms.

Figure 5. 3: Patents Applied by domestic and foreign firms before and after FDI-policy liberalisation: Difference-in-Difference estimation



Source: Authors' computation

5.6 Conclusion, Limitations and Policy Implications

The empirical findings of the present chapter highlight that horizontal and vertical FDI spillovers are insignificant in influencing the innovation output of Indian manufacturing firms. In other words, having foreign firms in similar or across supplying industries does not influence the innovation output of the firms. We identify a lack of absorptive capacity restricting the domestic firms' ability to internalise contemporary technology as one of the key reasons for such insignificance.

One of the significant contributions of this chapter is documenting the potential impact of horizontal and vertical FDI spillovers on the innovation output of firms in the major industrial clusters of the country. Confirming the role of geographical proximity in anchoring FDI spillovers and innovation, the empirical results provide robust evidence that firms in the major industrial clusters which leverage the benefits of horizontal spillovers experience higher levels of innovation. However, vertical spillovers are not significantly influencing the innovation output across firms in supplying industries located in the major industrial clusters of the country.

Stepping ahead, this chapter provides robust evidence that the exporting firms adversely influence the innovation output of Indian manufacturing firms. Further empirical insights show that supplying firms which capitalise on vertical linkages and export intensely tend to innovate less. Contrary to this, exporting firms that capitalise on horizontal linkages generate greater innovation outputs.

One coherent finding of this study is the labour-intensive nature of innovation in India. Thus, the present study provides compelling evidence that innovation in Indian manufacturing firms is rooted in employing more workers. This sheds light on important aspects of policy formulation in the country.

Despite accounting for insignificant innovation spillovers, FDI is crucial for the country. The difference-in-difference estimates clearly suggest that foreign firms have significantly been innovating more in the country after the 2014 FDI liberalisation policy than domestic firms.

Policy Suggestions

Based on the results from the spillover variables, we suggest that FDI policies should foster the scope for learning and improving the technology of the local firms. Policymakers should try to stimulate strategies for integrating local suppliers in the upstream industries with downstream foreign firms, devise policies for local technology promotion under the umbrella of technologically advanced foreign firms, promote the organisation of symposiums and colloquiums for dissemination of managerial, organisational and other aspects learning and improving technology.

The empirical underpinning of the present study finds robust evidence that horizontal spillovers positively influence the innovation output of industrially clustered firms. Based on this, we advise heterogeneous policy designs to promote innovation. Such policies could be to develop appropriate infrastructure for better networking amongst firms, setting up single systems for end-to-end facilitation of tertiary activities, etc., so that firms in industrial clusters could mitigate the effects of any possible congestion that may exude from the spatial concentration of firms.

The present study identifies that lack of absorptive capacity as the major factor limiting domestic firms' ability to internalise contemporary technology. Therefore, we stress the importance of firms' capacity-building through R&D investments to sustain a competitive advantage.

The analysis in the present work showed that innovation in Indian manufacturing firms is labour-intensive. Based on this empirical finding, we suggest promoting labour-intensive techniques in manufacturing firms. The government could devise policies to set up a network of incubation centres to accelerate the growth of the labour-intensive manufacturing industries.

Finally, our study reveals that having exporting firms within the vicinity lowers the innovation output of the supplying industries. Therefore, policymakers should direct the exporting firms to source materials from local suppliers, at least to a certain extent. The empirical specification of the present study also hinted at the possibility of exporting firms shifting their innovation hub to the global market. To this extent, the government should encourage and incentivise exporting firms to innovate domestically. Such incentives may include access to credit facilities specifically for innovations at a local level, concession on tax to be paid on the royalty from patents, etc. The estimation results also confirm that exporting firms that capitalise on horizontal linkages generate greater innovation outcomes. Therefore, to mitigate the adverse effects of firms' intense exporting activities on their innovation output, we suggest policymakers establish formal collaborative platforms among firms within the same industry.

Limitations

This study makes a sincere attempt to empirically estimate the impact of horizontal and vertical FDI spillovers on the innovation output of Indian manufacturing firms, with a particular focus on the firms located in the major industrial clusters of the country. Although the work sheds light on vital issues relevant to the policymakers, certain related aspects of policy design could not be included in the study, leaving out the scope for future research. First, there could be horizontal and vertical linkages from one major industrial cluster to another major industrial cluster or a minor industrial cluster. There could also be horizontal and vertical linkages from one minor industrial cluster to another minor or major industrial cluster. The present study does not take this into account. Second, horizontal and vertical spillovers could also influence the innovation output of firms within each industrial cluster. This would amount to analysing the horizontal and vertical spillovers for all the major and minor industrial clusters individually. However, the scope of the present research excludes such detailed cluster-specific analysis. Future research could explore these channels and their effects on innovation output in the context of India.

Appendix C

Table C 1: Computation of variables and sources of data

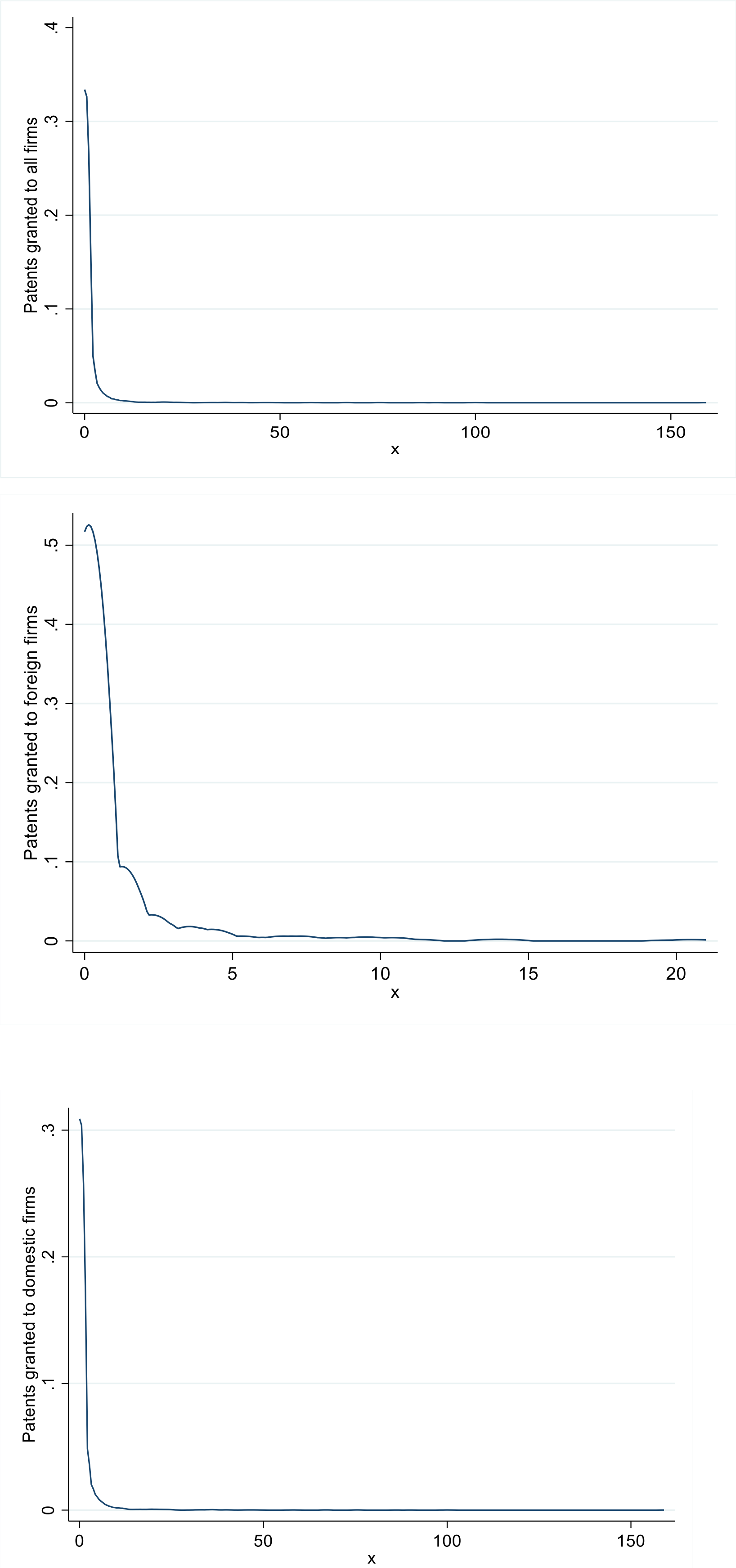
Variable Name	Variable Description	Source
	Innovation Indicator	
$Innovation$	Counts of patents granted to a firm i during period t	Patseer
	Spillover variables	
$Horizontal\ spillover$	Calculated using the method described in Javorcik (2004) and Blalock and Gertler (2008)	Authors' calculation
$Vertical\ spillover$	Calculated using the method described in Blalock and Gertler (2008) and Javorcik and Spatareanu (2008)	Authors' calculation
	Firm-Specific Factors	
$Location$	dummy variable, which takes the value of 1 if the firm is located in one of the cities falling in the major industrial cluster and 0 otherwise	Prowess
Age	Difference between firm i's establishment year and current year t.	Prowess
$Labour$	Number of labour inputs of firm i during period t	Prowess
	Market Specific Factors	
$Export\ Intensity$	Export of goods and services of firm i as a ratio of sales of the firm during period t	Prowess
$Import\ Intensity$	Import of capital goods and royalty, licensing and technical fees paid by firm i as a ratio of sales of the firm during period t.	Prowess
	Technology Specific Factors	
$R\&D$	Research and development expenditure as of firm i a ratio of sales of the firm during period t.	Prowess

Table C 2: Correlation matrix and descriptive statistics

Variables	1	2	3	4	5	6	7	8	9
1. $Innovation$	1								
2. $Horizontal\ Spillover$	-0.007	1							
3. $Vertical\ Spillover$	0.050	0.826***	1						
4. $Location$	0.0727**	0.155***	0.124***	1					
5. Age	0.0897***	-0.160***	-0.117***	0.0857***	1				
6. $Size$	0.322***	-0.114***	-0.003	0.132***	0.246***	1			
7. $Export\ Intesity$	-0.024	0.032	0.185***	-0.113***	-0.236***	-0.044	1		
8. $Import\ Intensity$	-0.002	-0.007	0.014	-0.0866***	0.037	-0.110***	0.214***	1	
9. $R\&D\ Intensity$	0.009	-0.143***	-0.244***	-0.111***	-0.048	0.011	0.205***	-0.011	1
$Mean$	1.00	-1.60	8.90	0.90	3.40	7.90	0.30	0.10	0.00
SD	5.20	1.10	1.40	0.40	0.60	1.40	2.10	1.70	1.10

Notes: *** p<0.01, ** p<0.05, * p<0.10, Standard Errors are in parenthesis

Figure C 1: Kernel density plots of patents granted to Indian manufacturing firms



Source: Authors' computation

Chapter 6

Conclusions, policy implications, limitations and future scope of research

6.1 Summary of the Contributions and Key Findings

The growing importance of innovation in EMDEs like India is driven primarily by its potential influence on productivity gains, employment generation and technology spillovers. While the literature is to some extent suggestive of the impact of innovation in developed economies, studies on the EMDEs are scanty and inconclusive. The purpose of this thesis is to take a wider perspective and analyse the impact of innovation on firm-level productivity growth, employment generation and technology spillover in the context of EMDEs. We address these aspects by taking a sample from Indian manufacturing firms.

The ***first objective (Chapter 3)*** of the present thesis explores the two-way link between innovation and productivity using the firm-level dataset of Indian manufacturing firms. The empirical estimates of the study presented in this chapter provide robust evidence for the existence of a complementary relationship between innovation and firm productivity. In other words, the results show that whereas firms' productivity is crucial in determining the innovation output of Indian manufacturing firms, firms' innovation output also significantly determines their productivity levels. The findings of the analysis confirm that innovative firms are significantly more productive than their non-innovative counterparts. However, the observed productivity difference between the two groups of firms is found to be very low, in the range of 10 to 12 per cent only. The most intriguing finding of the chapter, particularly pertinent for the policymakers, is that productivity has a larger impact on fostering innovation output than innovation has on spurring productivity increases. This amounts to infer that policymakers should prioritise policies aimed at enhancing firms' productivity to promote innovation in Indian manufacturing firms.

The empirical findings presented in the chapter further provide robust evidence that the R&D expenditures of Indian manufacturing firms are not significantly influencing their innovation outputs. Research expenditures are not effectively increasing the productivity of Indian patenting firms as well. This finding is consistent with recent literature, which argues that innovation in EMDEs is not R&D-driven (Cirera and Maloney, 2017; Vujanovic et al., 2022). This strand of literature suggests that developing countries are not spending enough on R&D and should consider increasing R&D investments (Goñi and Maloney, 2017). The findings presented in the chapter also confirm that innovation in Indian manufacturing firms is labour-intensive. Furthermore, the econometric evidence also showed that exporting firms are negatively affecting the innovation output of Indian manufacturing firms.

The ***second objective (chapter 4)*** of the thesis concentrates on dissecting the effects of process and product innovation on employment generation in Indian manufacturing firms. The findings from the first objective confirm that innovation in India is labour-intensive, i.e. increasing labour input increases the innovation output of Indian manufacturing firms. However, what happens once the new innovation output is out in the market and is used as input in other production processes? Does it reduce employment? Or does it create more employment? The second objective of the thesis answer these questions. The empirical estimates provide robust evidence that technology is substituting labour. The econometric evidence reveals that both process and product innovation significantly displace labour in Indian manufacturing firms. The results hold valid epistemologically as India, being a developing country, primarily imports technology from developed parts of the world. The technology used in these developed nations, on the other hand, is designed to suit their demographic set-up, which is inherently labour-scarce and capital-intensive. Therefore, technology introduced in developed countries is also labour-saving in nature. Imitation of such labour-saving technologies negatively affects the employment opportunities generated by Indian manufacturing firms. Disentangling manufacturing firms further by ownership type reveals that only domestic firms are associated with significant labour displacement due to process and product innovations. Process and product innovations by foreign firms do not significantly affect the employment generation of the manufacturing firms. However, further segregated analysis confirms that the foreign firms are not significantly generating more employment than the domestic firms, nullifying the requirement of heterogeneous policy for both types of firms.

Finally, the ***third objective (chapter 5)*** of the thesis primarily answers the question of whether or not FDI spillovers influence the innovation output of Indian manufacturing firms and whether such spillovers are cluster-specific. Using a panel of Indian manufacturing firms and measuring FDI spillovers following the method developed by Javorcik (2004), Blalock and Gertler (2008) and Javorcik and Spatareanu (2008), we find that the horizontal and vertical FDI spillovers are insignificant in influencing innovation output in Indian manufacturing firms. To sum up, the innovation output of domestic firms is largely unaffected by foreign presence in the same industry and across supplying industries. We identify a lack of absorptive capacity restricting the domestic firms' ability to internalise contemporary technology as one of the key reasons for such insignificance.

Furthermore, the empirical framework presented in the chapter explores the potential impact of horizontal and vertical FDI spillovers on the innovation output of firms clustered in the major industrial locations of the country. The findings suggest that horizontal FDI spillovers within firms in the major industrial cluster positively affect their innovation output. However, vertical spillovers amongst supplying firms in the major industrial cluster do not significantly shape their innovation output. Within this context, subsequent findings indicate that the R&D intensity of industrially clustered firms operating in industries similar to the foreign firms (i.e. generating horizontal spillovers) positively influences their innovation output. As against this, the R&D intensity of industrially clustered firms in the supplying industry (i.e. generating vertical spillovers) negatively influences their innovation output. This reaffirms the crucial role of internal R&D spending in absorbing foreign technology. Additionally, the findings presented in the chapter again establish the labour-intensive nature of innovation in Indian manufacturing firms. Furthermore, the findings in this chapter show that the firms that export intensely are likely to innovate more through horizontal spillovers. On the contrary, exporting firms negatively affect the innovation output of Indian manufacturing firms through vertical spillovers.

To conclude, besides the main objectives of the thesis, certain additional findings emerge from the findings of the chapters of the thesis. First, we find that R&D expenditure is not significantly influencing the innovation output in India. This is consistent with the existing literature on EMDEs, which states that R&D is not the primary source of innovation in these economies (Cirera and Maloney, 2017; Vujanovic et al., 2022). However, the econometric findings of the thesis also demonstrate that R&D is quintessential for absorbing foreign technology and benefiting from it. Therefore, we suggest more intensive R&D investments in the manufacturing sector. Second, the empirical findings of the study confirm that innovation in India is labour-intensive. Based on this, we can infer that introducing labour-intensive technologies would boost the innovation performance of the manufacturing sector. Finally, the empirical findings of the chapters provide coherent evidence that exporting firms are negatively affecting the innovation output of Indian manufacturing firms. This calls for strict policy action directing the exporting firms to innovate domestically to boost the innovation output of the Indian manufacturing sector. At the same time, we see evidence that exporting firms innovate more through horizontal FDI linkages. Based on this, we also suggest collaborative networks to facilitate knowledge sharing between foreign firms and firms that export intensely.

6.2 Policy Implications

The findings of the thesis are informative for policymakers. Based on the empirical evidence presented across the chapters, we forward the following policy suggestions.

The empirical findings for the ***first objective*** show robust evidence that firms' productivity has a larger impact on generating more innovation output than innovation has on stimulating productivity increases. Based on this, we suggest policymakers adopt productivity-strengthening measures to promote innovation in Indian manufacturing firms. The empirical findings presented in this chapter confirm that innovation improves firms' productivity and that innovative firms are more productive than non-innovative firms, even though the productivity difference between the two groups is small. Given the crucial role of innovation, policies should be channelled towards incentivising innovation in individual firms, which could be done by initiating productivity-augmenting measures.

The empirical results for the ***second objective*** show that both process and product innovations in Indian manufacturing firms are displacing labour. Further, allowing for the structural differences in the ownership of the firms, we see that this labour displacing effect is particular to the domestic firms only. Process and product innovations in foreign firms do not significantly influence the employment generated by these firms. This clarifies that foreign firms are, at least, not significantly displacing labour. In light of this, we suggest promoting reskilling and retraining programmes in collaboration with foreign firms to mitigate labour displacement in domestic firms. Further, policymakers should devise labour market policies that would support the displaced workers and help them relocate to labour-intensive industries. In this context, measures should also be taken to promote labour-intensive industries in the country.

The results for the ***third objective*** show that FDI spillovers are not significantly affecting the innovation output of Indian manufacturing firms. The inability of the local firms to absorb foreign technology is deemed one major factor behind this insignificance. Based on this, we suggest that FDI policies should foster the scope for learning and improving the technology of the local firms. For this purpose, policymakers should try to stimulate strategies for integrating local suppliers in the upstream industries with downstream foreign firms, devise policies for local technology promotion under the umbrella of technologically advanced foreign firms, promote the organisation of symposiums and colloquiums for dissemination of managerial, organisational and other aspects learning and improving technology. Furthermore, the empirical underpinning presented in the chapter finds robust evidence that horizontal spillovers positively influence innovation output within major industrial clusters of the Indian subcontinent. Based on the econometric evidence presented in the chapter, we advise heterogeneous policy designs for promoting the innovation of firms in the major industrial clusters.

The thesis also draws certain ***general policy insights*** that are common across all the issues discussed in different chapters. First, the econometric evidence presented across all chapters provides conclusive evidence that R&D investments are not significant enough to drive up the innovation output of Indian manufacturing firms. This, once again, reinforces the widespread view that while the innovation regime in the developed nations is driven by R&D investment or knowledge creation, the innovation regime in the EMDEs is mainly driven by non-R&D investments or knowledge use (Cirera and Maloney, 2017; RadoSevic, 2017). However, our findings also highlight the role of R&D expenditures in assimilating foreign technology. Low R&D investments have always been a topic of debate in the EMDEs such as India. Further inquiries based on the results reveal that the Indian manufacturing sector is also struggling with low R&D investments. Therefore, we suggest policymakers bend their industrial policies to facilitate the flow of R&D into Indian manufacturing firms. Proper strategies also need to be formed to ensure that the R&D investments are directed toward successful innovation outputs.

Second, the empirical findings across all the chapters provide robust evidence that innovation in Indian manufacturing firms is labour-intensive. Based on this, we suggest promoting labour-intensive industries in Indian manufacturing firms. The government could devise policies to set up a network of incubation centres to accelerate the growth of the labour-intensive manufacturing industries.

Finally, the findings across the chapters show that exporting lowers the innovation output, hinting at the possibility that the exporting firms prefer to shift their innovation hub to the global market. To this extent, the government should encourage and incentivise exporting firms to innovate domestically. Such incentives may include credit facilities specifically for innovations at a local level, concession on tax to be paid on the royalty from patents, etc. The empirical insights also show that exporting firms innovate more through horizontal linkages. Therefore, we suggest promoting collaborative networks to facilitate knowledge sharing between foreign and exporting firms. Further, the empirical findings of the third objective make it clear that the negative impact of exporting firms on innovation output is more prominent across the supplying industries. In light of this, we suggest policymakers direct the exporting firms to source materials from local markets, at least to a certain extent.

6.3 Limitations and Further Research Scope

This thesis sheds light on many key aspects of innovation and its probable impact by taking a sample from Indian manufacturing firms. However, the present work is not free from lacuna, and several topics of inquiry are left for future research.

The most important limitation of the work is inherent in the type of proxy used for measuring innovation. As discussed in Chapter 2, patents are an imperfect measure of innovation output and appear to be the second-best solution only to the issue of instrumenting innovation for empirical research in the absence of direct sales data from new products launched. Future research could take up primary surveys to collect new product sales data and provide a comparatively more concise picture of the various innovation dynamics.

The various impacts of innovation are affected not only by the quantity of innovation but also by the quality and value of the innovation. Accounting for the quality and value of innovation is out of the purview of the present work. Future research could be directed towards an all-inclusive empirical analysis for a comprehensive understanding.

One of the coherent findings of the thesis is that Indian manufacturing firms employ more labour inputs to produce higher innovation outputs. However, the empirical findings also show that labour is displaced once these innovation outputs are used in the production process as inputs. In other words, the findings show that technology is labour-intensive until the new updated technology is used to produce further goods and aid production processes. For policy purposes, a focussed comparative analysis between labourers engaged while producing the technology and labourers displaced after the technology produced is used in the production of further goods and services is required. Further research could explore this aspect.

The present work empirically investigates the impact of horizontal and vertical spillovers on the innovation output of Indian manufacturing firms with special reference to firms located in the major industrial clusters of the country. However, there could be horizontal and vertical spillovers from one major industrial cluster to another major industrial cluster, from one major industrial cluster to another minor industrial cluster, or from one minor industrial cluster to another minor industrial cluster. At the same time, there could be horizontal and vertical spillovers within each cluster as well. Further studies could take these into account.

The present work focuses exclusively on the manufacturing sector. However, the services industry in India is growing continuously, and systematic study is required to understand the innovation dynamics in the service sector. Further research could be devoted to this direction.

With respect to the two-way relationship between innovation and firm productivity, the same may be influenced by the ownership structure as well. However, the present study fails to account for it. Subsequent research could examine the observed differences in the two-way relationship between innovation and firms' productivity between domestic and foreign firms.

Further, a major concern that is ignored in the thesis is the apparent pronounced discrepancy in the R&D funding of India, where public sector R&D funding outweighs the private sector R&D funding. A thorough exploration of these disparities could yield critical insights relevant to the policymakers and could serve as a foundation for future research.

The R&D expenditures of the country vary not only by funding source but also by levels of R&D expenditures. Particularly, in EMDEs like India, where innovation often involves adaptative products and processes, a more refined study that systematically categorises firms based on their scale and type of R&D expenditures and then maps the patenting and non-patenting firms into these categories would add much value to the policymakers. Future research could look into it.

The patenting behaviour of different industries may have varied impacts on productivity, employment generation and technology spillovers. For example, the avenues of employment generation, or the effect of horizontal and vertical spillover on the innovation output of a firm that belongs to a high-technology sector, such as chemical or pharmaceutical, may differ from that of a firm that belongs to a low- technology industry, such as textile or food products. However, the scope of the present study does not take this into account. Future studies could explore this possibility.

Finally, Aghion and Howitt extend their model to capture the distinct impact of neck-and-neck and laggard firms on innovation (Aghion et al., 2009). However, the empirical investigation of the same lies outside the scope of the present study, leaving it as a potential future direction of the study.

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