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Patent Protection, Technical Efficiency and Productivity Growth in Indian Manufacturing Industries

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgment has been made. This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Tanusree Chakravarty Mukherjee

August 2021

This Thesis is dedicated to my beloved father Late R. M Mukherjee.

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List of Abbreviations

AE	Allocative Efficiency
ASI	Annual Survey of Industries
CAGR	Compound Annual Growth Rate
CD	Cobb-Douglas
CMIE	Centre for Monitoring Indian Economy
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DiD	Difference-in-Difference
DMU	Decision-Making Unit
EMR	Exclusive Marketing Rights
ERP	Effective Rate of Protection
FDI	Foreign Direct Investment
FEM	Fixed-Effects Model
GA	Growth Accounting
GATT	General Agreement on Tariffs and Trade
GDP	Gross Domestic Product
GMM	Generalised Method of Moments
GVA	Gross Value Added
HK	Helpman-Krugman
IPR	Intellectual Property Right
ISIC	International Standard Industrial Classification
LP	Linear Programming
MNC	Multinational Corporation
ML	Maximum Likelihood
NIC	National Industrial Classification
NMP	National Manufacturing Policy
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
OSME	Output-Oriented Scale-Mix Efficiency
OTE	Overall Technical Inefficiency
R&D	Research and Development

RBI	Reserve Bank of India
REM	Random-Effects Model
RTS	Returns to Scale
SE	Scale Efficiency
SFA	Stochastic Frontier Analysis
SPF	Stochastic Production Frontier
TADF	Technology Acquisition and Development Fund
TE	Technical Efficiency
TFP	Total Factor Productivity
TP	Technological Progress
TRIPS	Trade-Related Aspects of Intellectual Property Rights
UK	United Kingdom
US	United States
VAR	Vector Autoregressive
VRS	Variable Returns to Scale
WIPO	World Intellectual Property Organization
WPI	Wholesale Price Index
WTO	World Trade Organization

Abstract

This thesis analyses the effect of patent reforms on firm-level technical efficiency and productivity growth in selected Indian manufacturing industries. Patent protection is perceived as a mechanism for economic growth. India's compulsion to implement product patents in conjunction with the Trade-Related Aspects of Intellectual Property Rights (TRIPS) agreement remains ambiguous. This thesis brings clarity to this controversy by decomposing productivity growth into technical efficiency change and technological change. Further decomposing technical inefficiency into persistent and transient inefficiency enables investigation of the productivity gain as a result of patent reforms in an intrinsic manner. This study uses firm-level data for 1995 to 2016 from the Prowess database.

Endogenous growth theory predicts that stronger patent rights have positive effects on economic growth through the invention of new products and innovative technologies. Further, the patent institution provides an efficient avenue to expedite knowledge spillover effects, enhance competitiveness and expand trade. This study's empirical analysis is conducted by following the underlying framework of patent protection, such as reward theory and contrary theory (research and development), the market power effect and market expansion effect (trade openness), and technology diffusion. An array of firm-specific variables are also adapted in the analysis, such as private ownership, multinational firms, and local or foreign firms, which are usually considered influential variables for productivity growth.

In examining the specific attributes of the selected manufacturing industries of India and TRIPs, this thesis employs three productivity approaches. The four-component semiparametric smooth-coefficient stochastic frontier production model is used to investigate the effect of patent reform on firm-level productive efficiency. The Färe-Primont productivity index in a panel data framework is subsequently applied to compute productivity growth and its subtler components. Then, the difference-in-difference approach is used to capture pre-TRIPS and post-TRIPS productivity levels. Finally, the panel data estimation framework is used to assess the patent reform's effect on productivity.

The first empirical analysis examines the effects of patent reform on firm-level technical efficiency in four selected Indian manufacturing industries. The findings portray that the smooth coefficients and input elasticities vary across the different industries. The likely cause is the rebound effect, which reflects that the beneficial effects outweigh the behavioural responses of the inputs, such as cost of capital (equipment) or labour (such as training for new technology) at the initial stage. The subsequent analysis delves into the decomposition of productivity growth. The estimation results identify technical change as a major driver of productivity growth over the observed period. The year-on-year trend demonstrates that the pharmaceutical industry achieves continual total factor productivity (TFP) growth, whereas the other three sunrise industries accomplish steady TFP scores. The final empirical analysis is executed to determine the effects of patent reform on productivity growth, and reveals diverse evidence across the four selected industries that patent reform (TRIPS) influences productivity growth.

The empirical results show that the electrical equipment and electronic industries and information technology industries experience persistent technical inefficiencies (PTE). Thus, a combination of long-term efficiency strategies (to scale down PTE) alongside short-term efficiency strategies (to deal with transient inefficiencies) may administer the regulatory progress. In terms of signs and significance, a mixed effect appears for the patent reform variables on the components of TFP across the four sunrise industries. Therefore, by boosting firm-level research and development (R&D) via creating a dynamic and flexible R&D ambience and implementing export-oriented trade policies, Indian manufacturing industries may achieve their potential levels of output. Mixed results are found in terms of firm-specific variables on TFP growth, which validates the need for distinctive strategies and policies for various industries. The pharmaceutical industry should be given priority, as it demonstrates TFP growth and receives benefits from the patent reform during the observed period. However, the electrical equipment and electronics, information technology, and biotechnology industries also require government support to devise suitable strategies in their critical stage of development.

Keywords: patent, productivity, technical efficiency, panel data, semiparametric stochastic frontier model

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Chapter 1: Introduction

1.1 Study Background

Innovation is viewed as critical for the economic growth of a country, and patent systems are engineered to inspire inventions, invigorate innovation and encourage development. As stated by the World Intellectual Property Organization (WIPO) 2004, '[a] patent is an exclusive right granted for an invention, which is a product or a process that provides, in general, a new way of doing something, or offers a new technical solution to a problem'.[1] Customarily, a patent owner acquires the right to conserve their inventions and determine the process of their usage. In exchange, patentees are obliged to publish the patent document, consisting of technical information regarding the invention. Economic growth is often measured through the gross domestic product (GDP), which may be enhanced by two avenues: (i) escalating the number of employed inputs and (ii) intensifying input productivity. The innovation of new products or processes instils productivity.

Expenditures on research and development (R&D) promote economic growth via generating innovative practices. As an emerging economy, India has displayed consistent economic growth, with an average growth rate of 5.5% during the post-liberalisation era, accelerating to 7.1% over the past decade. This robust growth rate makes India unique compared with some of the world's largest emerging economies. The R&D expenditure of India during 2016-17 has demonstrated a steady upwards trend, yet this expenditure encompassed only 0.6 to 0.7% of GDP, which is meagre compared with the 2.8, 2.1, 4.3 and 4.2% of GDP in the United States (US), China, Israel and Korea, respectively (World Bank 2019). The innovation literature advocates patents as a useful measure of innovation (Ahuja and Lampert 2001; Harrigan et al. 2017, 2018; Kaplan and Vakili 2015; Valentinni and Di Guardo 2007, 2012), and India witnessed a 34% upsurge of domestic patent filing during 2018 to 2019, from 22% in 2013 to 2014 (Office of the Controller General of Patents, Design and Trademarks).[2] Major reforms to liberalise India's economy commenced in 1991, with the primary objective of reducing the fiscal deficit through stabilisation and structural adjustment policies (Chandrasekhar and Ghosh 2000).

[1] World Intellectual Property Organization patent definition.
[2] The Office of the Patents, Designs and Trademarks is a subordinate office under the Department of Industrial Policy and Promotion.

The patent regime was envisioned in the fifteenth century as the first mechanism to protect inventions, to foster invention through granting exclusive rights for a stipulated period and providing investors with the opportunity to retrieve costs spent on R&D. Moreover, the patent institution was devised to disperse knowledge and publicise applied and granted patent information. Numerous studies have hypothesised the positive effect of stronger patent rights on economic growth through the invention of new products and innovative technologies (Hudson and Minea 2013; Kanwar and Evenson 2003). In contrast, other studies have demonstrated varied and inconsistent results in this domain, with different results in Organisation for Economic Co-operation and Development (OECD) countries and developing countries, and no correlation between patent rights and economic growth found in emerging economies (Park and Ginarte 1997). One study revealed a positive association between patent rights, GDP per capita and economic growth (Hudson and Minea 2013), while another study found that patents positively influenced labour productivity and R&D expenditure for OECD countries; however, an expanded dataset indicated that patents influenced only R&D expenditure, yet not labour productivity (Park 2003). Further, several researchers found that patents have a positive influence on R&D intensity[3] (Kanwar and Evenson 2003; Kim et al. 2008).

Two theories—reward theory and contract theory—support the prevalent patent system (Denicolò and Franzoni 2003). Reward theory argues that the purpose of the patent system is to trigger invention endeavours through ensuring reward; however, it potentially initiates a monopoly. Conversely, contract theory states that, by publicising information, the patent institution enables the dissemination of innovative knowledge. Hence, a patented firm holds market power as it attains profit from innovative practices, yet social welfare is lost through the creation of a monopoly (Arrow 1962; Nordhaus 1969). The classic approach proclaims that, without a patent mechanism, trade secrecy and complexity would be feasible mechanisms on which innovators could rely (Gabrovski 2017). In this context, no correlation is observed between patent protection and firms' competitiveness, as patenting discourages appropriability. In contrast, firms' competitiveness seems obstructed by patent protection, while patenting enables appropriability. To examine the trade-off between potential monopolistic impediments and incentives towards innovation by the patent system, many researchers have sought to determine the optimal length and scope of patent institutions. Solow's (1957) growth

[3] R&D intensity refers to the ratio of R&D expenditure to GDP.

model examines the accountability of technical progress in economic growth and analyses total factor productivity (TFP) as residual growth. The model explains that growth in factor inputs is incapable of evaluating comprehensive output growth, and thus theorises the residual growth embedded within innovation and technology (Aton 2007). Subsequently, numerous studies have examined the association between economic growth, innovation and patent protection, with the number of patents filed or R&D investment typically employed as proxy variables (Balakrishnan et al. 2000; Das 2004; Goldar and Kumari 2003; Griliches 1980; Kumar 2004; Mansfield 1980; Mitra 1998; Scherer 1982; Shukla 2017).

The effects of patents on international trade can be classified in two ways: market expansion effect[4] and market power effect. First, the market expansion effect states that a firm may increase export volume, as stronger patent protection reduces the abilities of destination firms to imitate the product; hence, the home country may experience greater profitability. Second, the market power effect indicates that a firm's control over its sales in any foreign market will increase with more robust patent protection (Maskus et al. 1995). The countervailing effect between the market expansion effect and market power effect often depends on the intensity of the patent protection regime of the destination economy (Buera and Shin 2017). The scope and span of patents advocate patent protection as a driving force for revenue generation, yet operate in diverse directions and influence the economic behaviour of patent holders in a contrasting manner (Gallini 1992; Gilbert et al. 1990; Klemperer 1990). Denicolò (1996) examined optimal patent breadth and stated that rigorous competition among firms to acquire patent rights for the same or similar technologies is harmful, as it generates social costs, such as duplication of entry cost or inefficient production. In contrast, some empirical studies have found no general market failure for innovations (Moir 2008; Posner 2012), which may be explained by the low cost of the invention or the invention being a first mover in the market, enabling the firm to gain a robust competitive advantage. Thus, there is limited theoretical consensus regarding patent systems, yet their capacity to foster productivity demands empirical evidence.

[4] The strength of protection and trade is positively correlated in the importing country; thus, strengthening IPRs or patent protection may decrease opportunities for duplication and enhance innovative businesses.

Despite numerous attempts to explore the relationship between patent protection and productivity growth, empirical studies have failed to address the theoretical controversy. In this context, four gaps are noteworthy. First, several researchers have customarily employed patent statistics and/or R&D expenditure to evaluate productivity through boosting innovation activities (Griffith et al. 2000). Further, trade was contemplated as one of the conduits for the patent system and productivity growth association (Maskus and Penubarti 1995). Extant studies have examined the effects of patents and trade solely on productivity (Coe and Helpman 1995, Connolly 1997). Likewise, a few studies have investigated the role of patents in productivity growth exclusively through knowledge diffusion (Eaton and Kortum 1999). Hence, the prevailing literature presents a fragmented or partial analysis.

Second, a generous body of literature emphasises parametric or nonparametric frontier models to examine the influence of patent protection on productivity growth. In general, the parametric approach pursues a stochastic frontier production function; in contrast, nonparametric methods employ data envelopment analysis (Charnes et al. 1978). Specification of a function and technological restriction is insignificant for a nonparametric statistical method; however, the idiosyncratic error term is not addressed in this approach. The stochastic frontier model, simultaneously initiated by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977), views the stochastic error term in two components: noise term and inefficiency term. The model incorporates an unknown scalar parameter to capture the time-varying or time-invariant nature of the inefficiency term (Cornwell et al. 1990). In several subsequent empirical studies, the inefficiency term was used as a function of environmental variables (Caudill, Ford and Gropper 1995; Kumbhakar and Sun 2013; Reifschneider and Stevenson 1991; Wang and Schmidt 2002). Although this explanation provides further opportunity to better examine the source of inefficiency, the time-varying component is not estimated as a function of any environmental variables. In reality, inefficiency may comprise persistent and transient over-time components. Knowledge of persistent and transient inefficiency elements and segregation from random error is imperative to evaluate productivity gain, especially from a policy perspective. However, a handful of empirical studies (Heshmati 2018; Kumbhakar, Sun and Tveterås 2018) have deemed persistence and transient inefficiencies as sources of productivity growth.

Third, negative effects may arise from the enforcement of patent systems, especially in developing countries, with no substantial benefits for economic growth. The Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS), which commenced in 1995, was a dramatic shift of paradigm. Prior to the TRIPS agreement, patent rights were usually held by large foreign corporations, who enjoyed a monopoly and prevented developed economies from imitating or adopting patented technologies. TRIPS aimed to integrate domestic patent law and the global patent system; however, in reality, evolves controversies. Many developing countries perceive TRIPS as hazardous and strongly oppose it because of its sluggish and expensive execution. As a member of the World Trade Organization (WTO), India was obliged to implement the TRIPS agreement in 2005, after completion of a transition period of 10 years, in all fields of technology. Previous empirical studies have explored the patent protection and productivity nexus, emphasising either the transition period or the post-TRIPS period. Hence, to investigate the effect of patent protection on productivity growth, a comprehensive comparison of the TRIPS transition period and post-TRIPS period is warranted.

Finally, most prior empirical research analysed productivity growth in light of the patent regime (specifically, the TRIPS agreement) focused on the aggregated manufacturing level, and thus provided only a general picture. Few empirical studies have concentrated on the disaggregated sub-sectoral level, and hence have captured only a limited view. In this context, the subsectors affected by the TRIPS agreement must be studied to attain a complete picture.

This thesis sought to further research in the domain of productivity growth and the patent protection regime in India by bridging the aforementioned gaps. To achieve this objective, three approaches were applied. First, this research undertook a comprehensive analysis by incorporating three avenues of the patent institution—R&D investment, trade and knowledge transfer—to investigate the effect of patent protection on productivity growth, instead of focusing solely on one variable as a proxy. A four-component semiparametric smooth coefficient production frontier model was employed to examine the effect of patent protection on technical efficiency. Second, the Färe-Primont productivity index was used to compute and decompose TFP growth into several measurements, including technical change, scale efficiency change and technical efficiency change. Third, as the key variable, productivity was regressed against the input variables and firm-specific attributes through the static and dynamic econometric models. The differential effect of pre-TRIPS and post-TRIPS on productivity growth was appraised through a difference-in-difference model.

1.2 Research Objectives

The primary objective of this thesis was to determine the contribution of patent protection to productivity growth in the Indian manufacturing industry. The specific objectives were as follows:

1. to investigate the effect of patent protection on firm-level and aggregate-level productive efficiency in the selected Indian manufacturing industry
2. to compute TFP growth and observe its sources in selected four-digit International Standard Industrial Classification (ISIC) manufacturing industries
3. to examine the effect of patent protection on productivity growth and its components in the manufacturing industry at the firm level, and estimate the effect of the TRIPS agreement on productivity growth
4. to recommend relevant policy formulations aligned with patent protection in India.

The neoclassical growth models acknowledge exogenous technological progress as a crucial factor of economic growth while criticising the notion of savings and investment as a determinant of growth.[5] Subsequent literature evaluated the persistency of the growth process while embodying R&D as an endogenous variable in the economic growth model (Lucas 1988; Romer 1990). Economists further extended the endogenous growth doctrine by expressing the perpetual growth process as a function of increasing income (Barro 1991; Grossman and Helpman 1991). Another study examined the R&D investment and income growth nexus, and argued that the intermediate goods generated through innovation are relatively more efficient in final goods production (Aghion and Howitt 1992). Thus, innovations, research productivity and the skilled labour force drive economic growth (Blackburn et al. 2005; Grossman 2007; Khan and Khattak 2007; Lee 2005).

[5] Solow-Swan’s (1956) model demonstrated that exogenous technological progress either by decreasing the capital–output ratio or increasing the efficiency of capital enhances the growth process.

In the post-TRIPS regime, a survey conducted by the Indian Patent Office for 1999 to 2017 indicated that the number of patent applications increased drastically from 4,824 to 45,444. In contrast, the R&D expenditure of India revealed no significant change, comprising 0.639, 0.824 and 0.65% of GDP during 1996, 2005 and 2018, (World Bank 1997, 2006, 2019) respectively. Hence, it is a pertinent question whether TRIPS upholds the economic growth of India. Despite the imperative role of patent protection in Indian manufacturing industries, previous studies have treated the patent institution as synonymous with either R&D investment or technology transfer. Limited attention has been accorded to scale, technical, mix and residual-mix efficiencies as sources of productivity growth.

1.3 Research Methodology

This thesis applied the four-component semiparametric smooth coefficient stochastic frontier production model proposed by Kumbhakar, Sun and Tveterås (2018) which is the extension of their earlier study on the semiparametric smooth coefficient stochastic frontier production model (Sun and Kumbhakar 2013). Further, the Färe-Primont productivity index proposed by O'Donnell (2012); and the difference-in-difference model in panel data framework were applied to accomplish the research objectives in the unbalanced panel data framework. The semiparametric smooth coefficient stochastic production frontier method was employed to estimate the persistent (time-invariant) and transient (time-variant) components of productive inefficiencies. Transient inefficiency was considered a function of the environmental variables. The patent protection variables were used as the environmental variables to estimate the smooth coefficients. Thereon, the marginal effect of the patent variables on these smooth coefficients, output and transient inefficiency, persistent inefficiency, overall technical efficiency, and persistent and transient efficiencies were computed.

The decomposition of TFP growth was performed by introducing the Färe-Primont productivity index developed by O'Donnell (2012) for four selected manufacturing industries that were explicitly influenced by the process patent to product patent shift clause of the TRIPS agreement. This productivity index approach also confirms the multiplicatively complete index[6] measurement, which is essential for an index

[6] The Färe-Primont TFP index was developed by O'Donnell (2012), and is considered 'multiplicatively complete' if aggregator functions, X(.) and Q(.), satisfy all regularity properties of index number theory.

decomposition method. Besides, in contrast to the traditional productivity index approach, the Färe-Primont productivity index can decompose productivity into intrinsic components. Thus, it offered a comprehensive insight into the firm-level productivity growth for the selected sunrise[7] industries.

Finally, the econometric model was performed with the panel data framework constructed with the patented firms of each sub-sector. Both static and dynamic models were executed to enhance the analysis. The primary focus of the study—productivity growth—was regressed against the patent protection variables and firm heterogeneity attributes. The effect of the TRIPS agreement was assessed by the difference-in-difference model.

1.4 Research Significance

This thesis furthers the prevailing literature on patent institutions and productivity spillovers in India with four significant contributions. First, this study is the first attempt to examine productivity spillovers using the four-component semiparametric smooth coefficient stochastic production frontier approaches. Previous studies in this area explored the significance of patent protection on productivity growth usually with either parametric or nonparametric approaches. The parametric approach requires correct specification of the functional form, while the high probability of obtaining high dimension variance of estimates is the weakness of the nonparametric approach. Though the approaches mentioned above have some demerits, the scholars widely used those approaches as they acknowledge the merits of the parametric and non-parametric techniques. The semiparametric regression model overcomes these challenges by using two discrete components, where one part of the predictors captures the predetermined production function, and another part depicts the unknown forms of the production function. This comparatively new approach allows decomposing the productive efficiencies into persistent (time-invariant) and transient (time-variant) components. It further permits the identification of the effect of patent protection (environmental variable) on firms' technical efficiency levels and transient efficiencies. In addition, the four-component semiparametric smooth coefficient stochastic production frontier method segregates the persistent and transient inefficiency elements from random error. Thus,

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[7] A new industry or any of the high-technology industries those growing at a faster pace and that hold promise of future development. (Collins Dictionary).

this study extends previous studies by contemplating the persistent and transient efficiency effects.

Second, this is one of the first studies to employ the Färe-Primont productivity index proposed by O'Donnell (2012) to investigate productivity growth and the effects of patent protection in Indian manufacturing. As per the author's best knowledge, only one other study in the Indian context, conducted by A. Mohammad (2015), has used this productivity index to examine the banking sector. Unlike the conventional index number approach—such as the Divisia index or Malmquist productivity index, which derive three components of productivity growth (technical change, scale efficiency change and technical efficiency change)—under the Färe-Primont productivity index, six major sources of TFP growth can be obtained. Hence, these sophisticated decomposition results offer a more comprehensive analysis.

Third, this thesis used longitudinal panel data from 1995 to 2016, which incorporated the pre-TRIPS (before 2005) and post-TRIPS (2005 onwards) implementation periods. With these data, this analysis could evaluate the effects of patent reforms. Besides the inclusion of the pre-TRIPS and post-TRIPS period, this study could also capture the productivity spillover of India after the enactment of patent reform following TRIPS. Therefore, this study also undertook an extensive comparative analysis. Previous empirical studies explored the patent protection and productivity nexus by either emphasising the aggregated manufacturing level or concentrating on specific industries, such as pharmaceutical and information technology industries. Thus, they provided either a general picture or a partial view. In this context, this study examined four selected sunrise industries and captured industry-specific heterogeneity; consequently, the sphere of this study is broader than that of previous studies.

Finally, this thesis contributes to the literature on patent protection and productivity growth in India by contemplating three channels: innovation, trade and knowledge diffusion. The existing literature has investigated the effect of these variables on productivity growth usually by employing them separately; however, these three channels are inter-linked. Thus, a combination of these three variables provides a more holistic view. This study considered the interaction effect of these three channels on the patent regime on TFP growth, enhancing the analysis beyond previous research and providing valuable assistance to policy development.

1.5 Thesis Structure

This thesis comprises eight chapters. Chapter 1 has provided an introduction to the topic of the thesis, and presented the research problem and study objectives and significance. Chapter 2 reviews the patent policies and designs of patent policies in India over more than two decades, before and after implementing the TRIPS agreement. The chapter summarises different stages of industrial development and the manufacturing sector's policy schemes and challenges, with particular regard to the four selected sunrise industries of India.

Chapter 3 critically examines the extant literature, focusing on productivity spillovers and patent institutions. The critical evaluation of the literature indicates that the effect of patent protection on innovation and growth yields conflicting conclusions, and the empirical evidence remains inconclusive. Regarding theoretical concepts, this study identifies that patent regimes foster technical efficiency and productivity through three channels: innovation, technology spillovers across national borders, and international trade. Further, this chapter discusses international and Indian empirical evidence regarding patent protection and productivity growth.

Chapter 4 discusses an analytical framework to analyse the effect of the patent institution regime on productivity in the selected Indian manufacturing firms. Three methods are described: (i) the four-component semiparametric smooth coefficient model, (ii) the Färe-Primont productivity index and (iii) the difference-in-difference (DiD) econometric model in a panel data framework. The four-component semiparametric smooth coefficient model proposed by Kumbhakar, Sun and Tveterås (2018) is applied to assess the effect of patent protection on technical efficiency. The Färe-Primont productivity index developed by O'Donnell (2012) is used to decompose productivity growth, and the econometric model is employed to estimate the effect of patent protection on productivity growth. In addition, the DiD model is adopted to evaluate the effect of the implementation of the TRIPS agreement holistically and for subsamples of domestic and foreign firms, MNCs, non-MNCs, and privately-owned and non-privately-owned firms.

Three empirical chapters are explored in this thesis. Chapter 5 presents an empirical analysis of the effect of the new patent protection regime on firm-level productivity efficiency. This estimation is performed using the four-component semiparametric smooth coefficient stochastic frontier model on the selected manufacturing industry data for 1995 to 2016. This model decomposes the noise term and inefficiency variable exclusively into persistent inefficiency (time-invariant) and transient inefficiency (time-variant). The transient inefficiency conforms as a function of environmental variables that compute the estimated smooth coefficients (i.e., input elasticities).

In a continuation of Chapter 5, the subsequent Chapter 6 provides an analysis of the decomposition of TFP growth. The Färe-Primont productivity index is adopted to compute and decompose productivity under the assumption that production technology exhibits variable returns to scale (VRS); thus, it indicates that all sectors should experience the same estimated rate of technical change. Four intrinsic sources of productivity growth are examined: technical change, efficiency change, technical efficiency change, and scale-mix efficiency change. This analysis also identifies the industries that accomplished maximum productivity.

The third empirical chapter is Chapter 7, which explains the effects of the patent protection regime on productivity growth. Productivity growth, as the dependent variable, is regressed against the firm characteristics and patent protection variables by employing static and dynamic models. This thesis seeks to obtain broader insights through acknowledging the heterogeneity of the different manufacturing sectors while assessing the influence of the new patent protection regime on productivity. Moreover, the DiD model is used to compare productivity during the pre-TRIPS and post-TRIPS implementation periods.

Finally, Chapter 8 provides the conclusion of the analysis. The key findings and policy implications are presented. In addition, this chapter describes the study limitations and provides recommendations for future research.

Chapter 2: Indian Industrial Growth during Pre-TRIPS and Post-TRIPS Era

2.1 Introduction

The Indian manufacturing sector exhibited a promising growth trend and, as a mainstay of the Indian economy, aspired to emerge as a manufacturing hub. Perceiving the advantages of the organised manufacturing sector, the Government of India has implemented several initiatives to promote the growth of this sector, such as 'Make in India'. The objective of the 'Make in India' campaign, which launched in 2014, was to encourage domestic and multinational manufacturing firms to produce within the Indian territory and eventually establish India as a manufacturing hub. This sector is regarded as an engine of the growth, since the organised and unorganised manufacturing sector collectively employ more than 30 million skilled and semi-skilled workers. Moreover, the Reserve Bank of India (RBI) reported that the contribution of the manufacturing sector to the gross value added (GVA) increased to US$275.20 (INR 18,219) billion from US$245.27 (INR 16,670) billion between 2014 to 2015 and 2015 to 2016 (RBI Bulletin, 2015, 2016, 2017).

The vast domestic market consists of a growing middle class that is estimated to acquire 17% of global consumption by 2030, which indicates robust demand for the manufacturing sector in India. The demographic advantage of an increasing share of the young working populace provides the opportunity for this sector to demonstrate its full potential. India is a resource-rich country with adequate renewable energy resources, and has explicit competitive advantages. Thus, the Indian manufacturing sector has attracted both domestic and foreign investment, with the influx of foreign direct investment (FDI) reaching US$ 72.12 billion in 2020 to 2021 from US$97 million in 1990 to 1991 (RBI 2021).[8] It seems that the manufacturing sector is a key driving force for the economic growth of India through several policy reforms. The general agreement in the modern era is that economic growth is achieved through innovation, and intellectual property rights, especially patents, are an instrument to ensure appreciation of innovation and to expedite

[8] FDI inflow is calculated as net of repatriation/disinvestment.

knowledge-based technology transfer, secures doorway to be marketable and signifies reputation.

Currently, it is almost impossible to consider that owning intellectual property rights was once frowned upon in several countries. Countries that were previously sceptical about intellectual property rights, especially patents, are now defending them. History shows that intellectual property protection has been afflicted by criticism; however, the necessity for intellectual property protection to enable sustainable development has become commonly agreed upon around the globe. Patents are needed to provide the exclusive right to enjoy and exploit innovation and creation, as innovation and creation can be owned as property. A Patent institution is an efficient avenue to boost innovation, expedite technology diffusion, advocate trade and enhance competitiveness. Thus, by granting exclusive property rights, the patent system triggers innovation; however, it can also lead to loss of social welfare through the creation of a monopoly, and may impede attempts to imitate the patented technologies (Boldrin and Levine 2002, Drahos 1995, 1999). Proponents of the patent regime acknowledge the need for industrial progress through technological invention for societal development, and exclusive rights are an efficient stimulus to endorse technological inventions. In the nineteenth century, the anti-patent movement gained some ground; however, this did not persist. The obstacle to universal advocacy of the global intellectual property regime is the defiance to monopoly rights and the cost of receiving the patented technology, especially in developing countries (Moir 2008, Posner 2012). The issue that the patent regime in creating monopoly rights has become controversial.

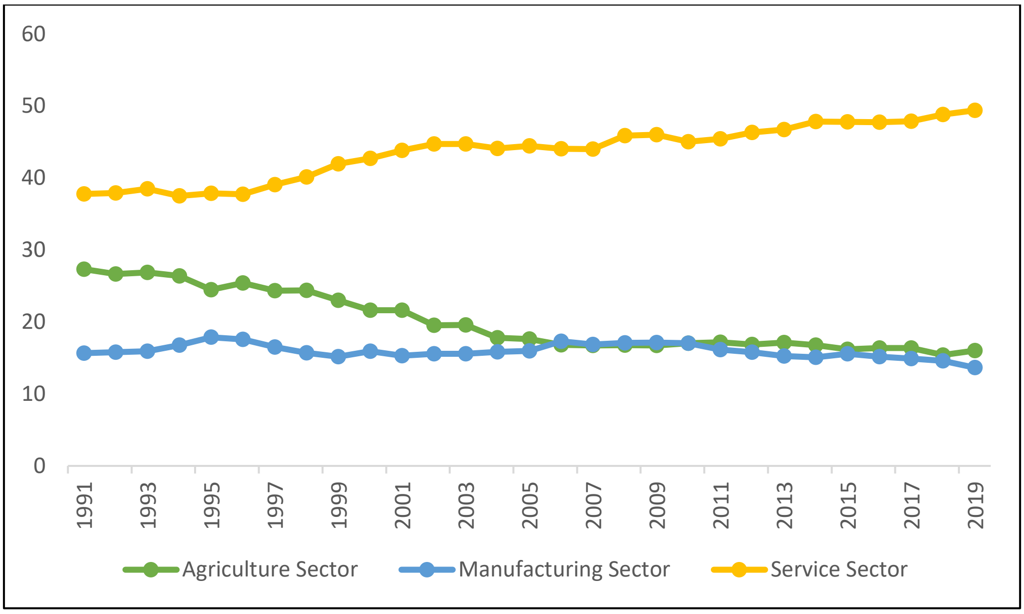
Consequently, the patent system was supported in most countries before the twentieth century. Advocates of intellectual property rights deemed patents a robust mechanism to spur innovation, which brings investments, transfers technical knowhow and spawns economic development, particularly in developing countries. Contrarily, foes of patent protection questioned the affordability aspect of developing countries. Hence, the holistic contributions of the patent system in promoting economic development, especially for developing countries with low adaptability of technology and limited infrastructure, are ambiguous and remain an empirical question (Boldrin and Levine 2002; Drahos 1995, 1999). This chapter evaluates the performance, development and policy formulations of the Indian manufacturing sector in the framework of the patent policy regime implemented in India in compliance with TRIPS.

The remainder of this chapter is organised as follows. Section 2.2 outlines India's structural transformation towards manufacturing from agricultural dominance. Section 2.3 presents the Indian manufacturing sector with Porter's five forces framework (Porter, 2008). Section 2.4 discusses the evolution of the Indian manufacturing sector, while Section 2.5 discusses the performance of this sector in the National Manufacturing Policy. Sections 2.6 and 2.7 describe the pre-TRIPS and post-TRIPS regimes, respectively, including the various patent amendment Acts of India. Section 2.8 identifies the industries that have been affected by the TRIPS agreement and provides a brief overview of those industries, while Section 2.9 discusses the industrial development plan under the 'Make in India' framework. Finally, Section 2.10 concludes the chapter.

2.2 Structural Transformation of Indian Economy

Along the path of economic development, structural transformation is a crucial attribute from the perspective of cause and effect. Structural transformation often occurs because of a shift from relying on agriculture to manufacturing, and dominance of the service sector in economic productivity and employment. The Indian service sector, with the boom in information, communication and technology services, has consistently surpassed the agricultural and manufacturing sector in terms of contributing to economic progress (Figure 2.1),[9] unlike in China. In contrast, the historical evidence demonstrates that, in contemplation of sustainable growth, both developed and developing countries have emphasised the manufacturing sector—probably because manufacturing products are tangible, and the manufacturing sector provides frequent innovations (Mani 2011).

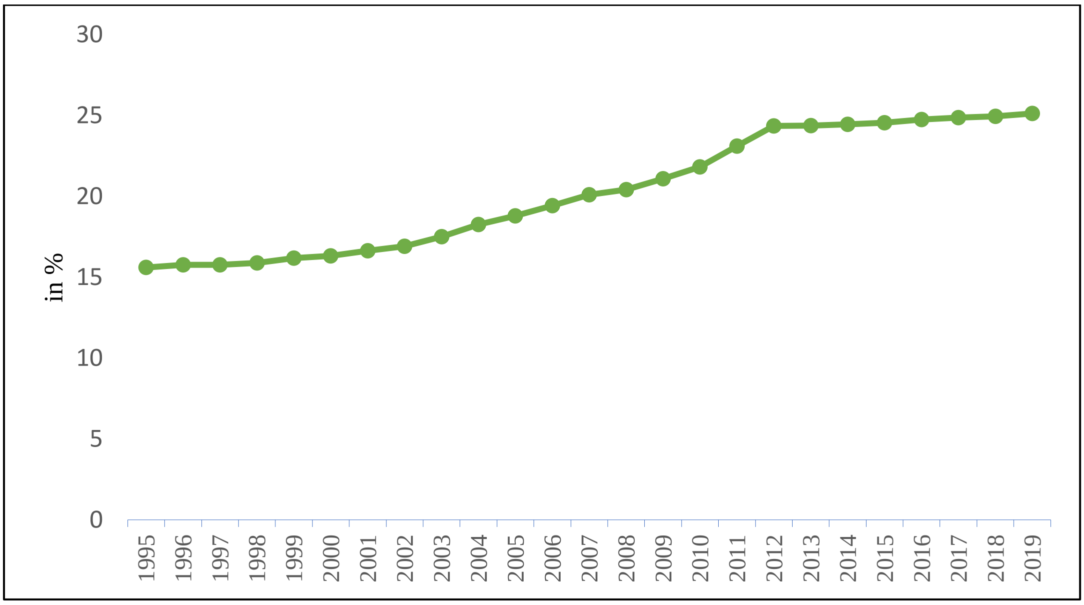
[9] The data from various sources are used in this chapter. The country-level data are mostly available until 2019, whereas the sector-wise, industry-wise or firm-level data available only until 2016.



Sources: Data.gov.in, open govt. data (OGD) platform

Figure 2.1: Manufacturing Value-added (% of GDP) in India's Post-liberalisation Era

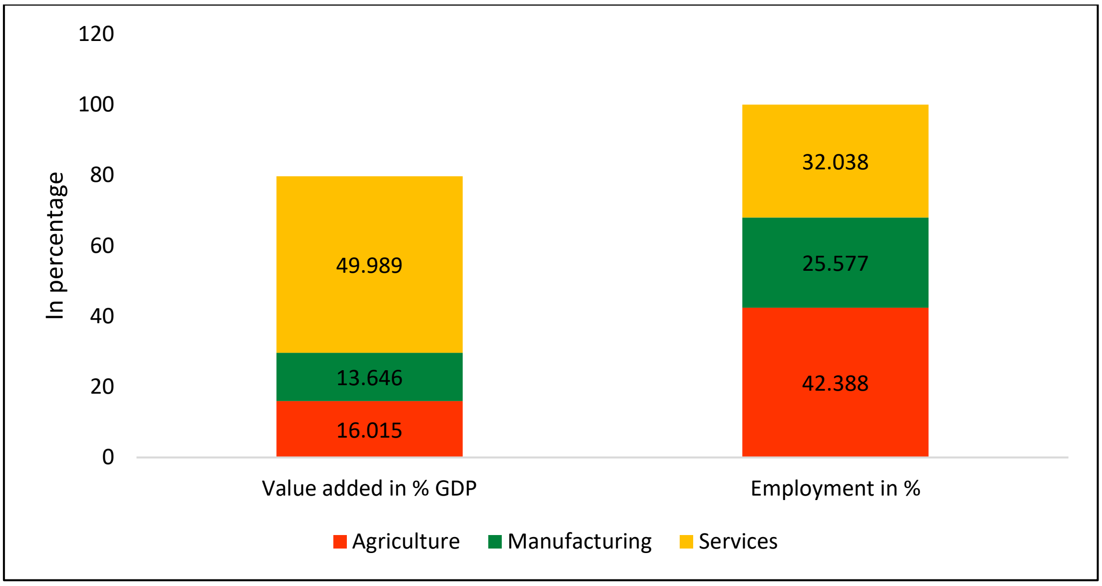
The Indian manufacturing sector is proficient at engrossing excess labour of the agricultural sector. It generates employment for the surging population of India, which is a necessary element for economic prosperity. However, this sector is generating employment only 25% of the total employment until 2019 (Figure 2.2).



Sources: International Labour Organization, ILOSTAT database.

Figure 2.2: Employment of Industry (% to Total Employment)

The share of labour to total employment is another indicator that reflects structural transformation, along with the share of GDP. The contribution of the manufacturing sector to total employment is only 25.577%, stated as a nominal percentage share, in comparison with agriculture, which comprises 42.388% (Figure 2.3)(RBI GDP Data 2019).



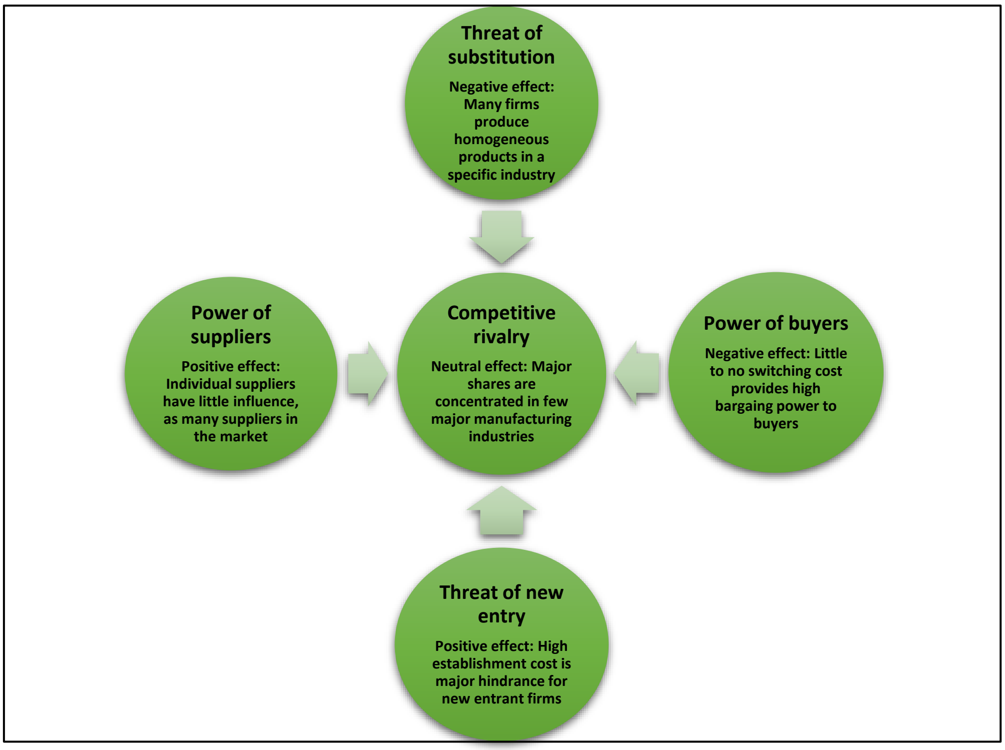
Source: RBI (GDP data); Economic Survey (Workforce data).

Figure 2.3: Labour Distribution and Value-added Percentage of GDP Across Different Industries in 2019 Financial Year

Although neither the value-added in percentage GDP nor percentage share of employment of the Indian manufacturing sector are impressive, they have sufficient potential to instil economic progress.

2.3 Porter’s Five Forces Framework for Indian Manufacturing Sector

Porter’s (1979) five forces analytical framework was employed to examine the competitive forces of an industry that determine profitability. The following figure assessed the Indian manufacturing sector in the context of Porter five forces (Figure 2.4).



Source: www.ibef.org.

Figure 2.4: Porter's Five Forces Analysis Framework

The analysis identified that the suppliers of the Indian manufacturing sector hold limited bargaining power in comparison with buyers. Further, no substantial threat from new entrant firms was detected; however, firms operating under the same industry encounter the threat of substitution. Hence, holistically, this sector demonstrates a neutral effect in competitive rivalry.

2.4 Evolution of Indian Manufacturing Sector

From its independence in 1947, India adopted a closed economy model, encompassed by extensive regulation and constricted government intervention, as did most developing countries. This economic structure exhibited sluggish productivity growth for the following few decades. The Indian manufacturing sector underwent a few stages of growth, beginning with industrialisation in 1950 and the subsequent advent of the 'license raj' during 1965 to 1980. Later, the severe balance of payments crisis in 1991 propelled India to implement comprehensive liberalisation policies (Central Statistics Office, data.gov.in, www.ibef.org, 2020). Consequently, it demonstrated rapid economic growth in the post-trade liberalisation era (Table 2.1).

Table 2.1: Evolution of Indian Manufacturing Sector

Pre-independence period	The dominance of handicraft items in the domestic market and exports prior to the British era. Existing regressive policies led to sluggish growth. Under British colonialism, limited growth occurred since they need to adhered to Britain during the two world wars.
Post-independence period (1948–1991)	The government of India emphasised basic and heavy industries through announcing five-year plans. Adopted extensive industrial policy in 1956. Evolution of 'license raj'[10]system, whereby public enterprises became more inefficient. Paradigm shift to agro-industries.
Post-1991 industrial policy reform	Indian economy embraced open trade policy, with the Indian market opened for global competition. Abolition of the 'license raj' system. Industrial production witnessed volatile growth rates; however, the service sector emerged as a major contributor to growth. The manufacturing sector showed 9.87% growth of GVA at current prices in the period 2012 to 2017.
'Make in India' campaign (2014)	In 2014, the 'Make in India'[11] campaign was launched by the Government of India to encourage FDI. The government of India intended to establish India as a manufacturing hub through sector-specific incentives. Private enterprises acquired 70% of the manufacturing sector.

Source: Central Statistics Office, data.gov.in, www.ibef.org (2020).

2.5 National Manufacturing Policy, 2011

Against a backdrop of low employment and output share, the Government of India introduced the National Manufacturing Policy (NMP) in 2011, with the primary objectives of enhancing the country's employment and share of industrial production in the domestic and global market. Employment generation and growth acceleration are integral to the economic development of any country; thus, the NMP addressed these by elevating the domestic value added. This policy intended to raise the share of manufacturing sectors in India's GDP—which had frozen at 16% since the 1980s—to 25% by 2022 (Government of India, Department of Policy and Promotion 2011). In this context, it is worth mentioning that NMP has introduced after one of the significant

[10] In the late 1950s, Rajaji, the founder of the first market-friendly political party, the Swatantra Party, coined the term 'Quota-Permit-License Raj' to describe the Indian model of socialism.
[11] www.makeinindia.com

structural changes, the Global Financial Crisis (GFC). However, the literature states that few countries like India, China were not experienced any significant negative impact of GFC on their GDP, exports and economic growth (Kelkar and Kalirajan 2021; Kshetri 2011). This policy action had five goals: (i) invigorate foreign investment and technical knowhow, (ii) remodel existing firms' strategy to enhance competitiveness, (iii) relax some regulatory and procedural norms to curtail the compliance burdens of industry, (iv) introduce a counselling system in an attempt to enable continuous holistic improvements and (v) motivate innovation (Mani 2011).

It also envisaged the establishment of national investment and manufacturing zones equipped with high-quality infrastructure. The distinctive feature of the NMP, compared with earlier industrial policies of 1956, 1958 and 1991, is that it recognised the need for specific solutions for different industries. Thus, special attention was devoted to the capital goods industries, such as machine tools, heavy electrical equipment, heavy transport, and earth-moving and mining equipment, as well as strategically significant industries, such as aerospace, shipping, information technology hardware and electronics, telecommunications equipment, defence equipment and solar energy. Special emphasise provide on comparatively advantageous industries of India, such as automobiles, pharmaceuticals and medical equipment. Among several agendas of the NMP, it reinforced innovation to augment firms' productivity, quality standard and efficiency. NMP recommended the establishment of the Technology Acquisition and Development Fund (TADF) to play the role of an autonomous agency for licensing and patent pool (Government of India, Department of Policy and Promotion 2011). Patent holders can sell their intellectual property rights (IPRs) to this fund, and other manufacturers can obtain licences from the TADF, via the payment of royalties, to employ that innovation in their own production process. More than one enterprise is eligible to acquire the right to licence for a typical patent (Government of India, Department of Policy and Promotion 2011).

Thus, rejuvenating the manufacturing sector with priority given to specific subsectors entailed emphasis on innovation. Innovation practices have been measured with patents in numerous studies (Dutta and Weiss 1997; Henderson and Cockurn 1994). The necessary condition for a patent is novelty and originality: 'an invention must be something not already known from prior publication, or not a part of the experience of those skilled in the art' (Walker 1995). Thus, patents can be deemed a useful measure of newly created knowledge and indicator of economic progress.

2.6 Patent Regime of India before TRIPS

From the colonial period, India had adopted the *Patent and Design Act of 1911*, which granted protection for 16 years, from the publication date, for all fields of innovations, with the exemption of atomic energy and associated fields. During the 1960s, a handful of Indian pharmaceutical and chemical firms experienced success while attempting to pursue new technology. Later, a survey revealed that Indian firms solicited patented technologies those mostly granted in developed countries, as the patent owners limited the accessibility of their patented technologies (Desai 1980). In the subsequent period, with the recommendation of the Tek Chand Committee (1948)[12] and Ayyangar Committee (1959),[13] India adopted the *Patent Act of 1970*. This Act defined the word 'invention' and stated the scope of patent protection from domestic and international perspectives. It also specified that, in compliance with community interest for economic, industrial and technological growth, India has acknowledged the individual patent monopoly. Thus, inventions in the areas of agriculture, horticulture, living organisms and atomic energy were not included in the patent protection regime (Mukhopadhyay and Khalkhali 2010). Thus, the process patent was granted to the extent of five to seven years for the invention of chemical and food substances used in the production process in the pharmaceutical, chemical and food industries. The *Patent Act of 1970* stated that the innovations achieved in India on a commercial scale were only eligible to obtain a patent if the intention behind it encouraged domestic inventions. To suspend the dominance of foreign patents, as they portrayed a reluctance to contribute to India's research, economic and industrial development, India refrained from granting patents for the importing patented articles.

2.7 Patent Regime of India after TRIPS

[12] The Government of India constituted a committee under the Chairmanship of Justice (Dr) Bakshi Tek Chand in 1949 to review the patent law of India to ensure the patent system was conducive to the national interest.
[13] In 1957, the Government of India appointed Justice N Rajagopala Ayyangar Committee to revise the patent law and advise the government accordingly. The committee report was submitted in September 1959.

India became a signatory to the TRIPS[14] agreement in 1994 to extend the compatibility of the patent system. However, TRIPS remains contentious from the perspective of developing countries, given its distinctive view towards developed and developing nations. Effective by the early 1990s, with enforcement of the General Agreement on Tariffs and Trade (GATT)[15] framework, the minimum standards for intellectual property protection were endorsed for the conferred members. TRIPS contrived the minimum standards for IPRs, especially patents, based on novelty, innovative process and relevance to industrial practices. These standards came into force on 1 January 1995 with the establishment of the WTO. Under the TRIPS regime, the patent terms were extended to 20 years from 16 years (Article 53(1)). At the initial stage, the emerging economies received a transition period of five years, which was further extended by five more years, to shift the paradigm to product patent from process patent. Therefore, as part of the TRIPS Agreement of the GATT, developing countries in which product patent protection was not recognised prior to TRIPS had to legalise product patents by 2005 (Patent Amendment Act; WIPO 2005).

The *Indian Patent Act, 1970* absolved certain arenas, such as food, medicine or drugs, from product patenting; however, to conform with the TRIPS requirements, the Act was amended in 1999. The amended *Patent Act of 1999* included two new provisions. First, under the 'mailbox rule', the product patent application for pharmaceutical and agro-chemical products could be filed through this channel from 1 January 1995 (Article 70.8). Second, the new Act introduced the system of 'exclusive marketing rights' (EMR), under which the product patent application for pharmaceutical products could be filed; however, the process was withheld until the end of 2004 (Article 70.9). Further, EMR could be acquired for that application, upon meeting the condition that the patent had been granted in some other WTO member country and not been rejected in India; otherwise, it was treated as a non-invention (Patent Amendment Act; WIPO 2005). However, the multifaceted clause of the EMR led to a high patent rejection rate. Most rejections occurred because appropriate tests were conducted before 1st January 1995, while the remainder were refused because of lack of convention status of the country or technical

[14] The TRIPS agreement came into effect on 1 January 1995 and is the most comprehensive multilateral agreement on intellectual property. It is a minimum-standards agreement, which allows members to provide extensive protection of intellectual property.
[15] The GATT is a legal agreement between many countries, with the objective of promoting international trade by reducing or eliminating trade barriers, such as tariffs or quotas.

reasons. With a final amendment to comply with TRIPS, product patents were enforced, yet it was challenged by a huge number of filed pre-grant opposition and subsequently develop the urgency of the abolishment of EMR in 2005.

2.7.1 Patents (Amendment) Act, 2002

India introduced the second phase of amendments through the *Patents Amendment Act, 2002*, which was enforced in the following year. The amended Act demonstrated a couple of distinguishing features. First, to align with the TRIPS provision, the definition of 'invention' was expanded by considering the concept of invention procedures. Second, the amended Act included a system with the deferred examination. Third, the Act abolished the disparity between pharmaceutical and agro-chemical products and other fields by establishing 20-year terms for patents across all arenas. Fourth, the 2002 Act erased the differences between India and other countries by introducing a provision for publication of application 18 months after the date of filing; however, patents on micro-organisms listed in the invention category associated with traditional knowledge were still excluded. Finally, by reinstating Section 39, this amendment ensured that Indian residents should first file in India before applying abroad unless they had received permission to do otherwise.

2.7.2 Patents (Amendment) Act, 2005

To thoroughly align with the provision of TRIPS, India implemented a third amendment to the Patent Act in 2005. Two crucial aspects of this amendment were the removal of the mailbox rule and EMR. Resultantly, the 'product patent regime' commenced in India. The Ayyangar Committee report (1959) stated that 80 to 90% of Indian patents were possessed by foreigners, and more than 90% of inventions were not accomplished in India. This report explained that, in the case of essential industries, such as pharmaceuticals, chemicals and food industries, to gain a monopolistic hegemony, multinational corporations (MNCs) had manoeuvred the existing patent systems. Over the last few decades, medical resources have become more efficient, which is feasible exclusively through research. However, research on new medical techniques and the development of new drugs requires huge financial and time investment, as well as risk. It is challenging, especially for emerging economies, to undertake such investment and risk without exclusive patent rights, as any technological discovery could be imitated, thus reducing its uniqueness. Thus, effective patent protection is indispensable for developing countries, as, under such protection, research and innovation could propel the prevailing technology to enhance efficacy and capability to afford.

2.8 Industries Affected by Paradigm Shift under TRIPS

International IPR structures were remodelled with the TRIPS negotiation of the GATT Uruguay Round[16] for emerging nations, such as India. This led to some vital alterations with the establishment of minimum standards of protection for all spheres of technology in regard to patents. The compulsion to shift the paradigm from process patent to product patent raised concerns for developing economies. Subsequently, another serious concern arose, as the excludability clause for patenting extended to the domain of micro-organisms besides plant varieties. The crucial manufacturing industries that are associated with micro-organisms and this amended patent protection are the pharmaceutical and biotechnology industries. Moreover, Indian patent law incorporated the phrase 'computer per se' and repudiated it from patent protection to align with the TRIPS agreement. In reality, this phrase remained unclear and generated obscurity in India's electrical and electronic industry, as well as the information technology industry.

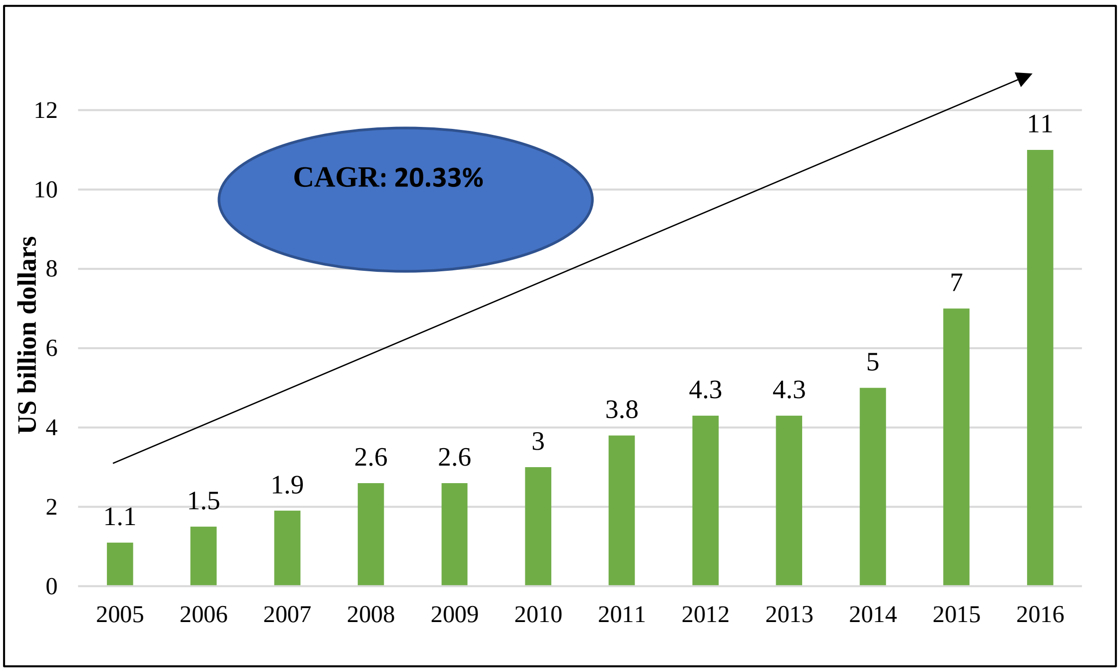
2.8.1 Biotechnology Industry

Biotechnology refers to any procedure or treatment that handles living organisms partially or solely for innovation or modification of existing products, along with the development of specific micro-organisms (Congress of the United States, Office of Technology Assessment 1990). In 1990, Indian pharmaceutical firms paid attention to biotechnology after perceiving the steady commercial success of this industry in the Western world. However, ambiguity in viable returns and involvement of soaring expenses prevented firms from venturing into this new domain. The research and innovations of biotechnology play an influential role in healthcare systems and agricultural and agro-chemical industries, such as the pharmaceutical industry. The possession of IPRs is one of the yardsticks to measure the accomplishment of research and innovation that eventually leads to technological development. However, applicants for US patents had serious concerns due to the inefficacy of the US Patent and Trademark Office to

[16] The Uruguay Round was the eighth round of multilateral trade negotiations conducted within the framework of the GATT, spanning 1986 to 1993 and embracing 123 countries as 'contracting parties'. The WTO was formed during this round of negotiation.

contemplate any invention of the biotechnology domain in a single application (OECD 2004, IBEF 2020).

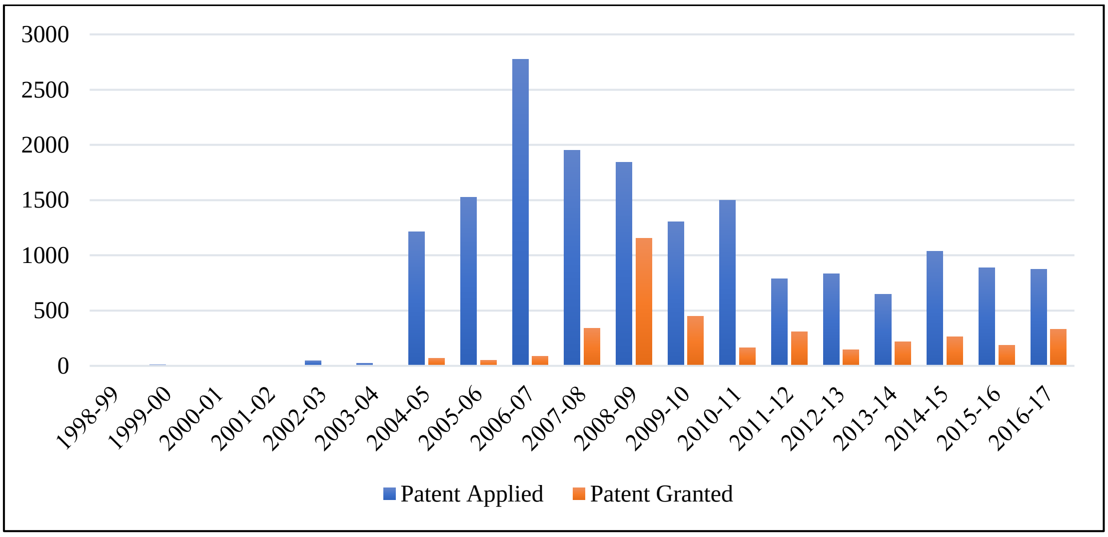
Likewise, India confronted statutory hurdles to patentability in the biotechnology realm. One of the most contentious provisions of the Indian patent law was Section 3(d), owing to the discriminative behaviour in terms of the interpretation of patentability. This section often referred to the improvement of the prevailing stuff with the exemptions of extensive explanation. Thus, it examined the eligibility of patent protection under the condition of 'enhancement of the known efficacy' through a 'new form of a known substance'. The court judgement (2007) highlighted criteria for enhancement of efficacy in the pharmaceutical industry; however, the biotechnology industry has not received this kind of privilege yet. In reality, inconsistency exists between IPRs protection and the provisions for the biotechnology industry. It is imperative to bridge this gap, as the Indian biotechnology industry has enormous potential to progress and enhance the welfare of the country. The Indian biotechnology industry demonstrated the rapid growth of 57.14%, along with a compound annual growth rate of 20.33%, in 2017. The market size of this industry increased from US$1.1 billion to US$11 billion between 2005 and 2016 (Figure 2.5). The Government of India planned to invest US$3.7 billion in the biotechnology industry in the twelfth five-year plan, in contrast to the US$1.1 billion in the eleventh five-year plan (IBEF 2020).



Source: www.ibef.org.

Figure 2.5: Market Size of Biotechnology Industry (in Billion US Dollars)

Despite the ambiguity in terms of the role of the TRIPS agreement for developing communities, it is evident that the patent law provides a great opportunity for investment in the biotechnology industry and to generate vast profits for India. Figure 2.6 depicts the trend of patent applications filed and granted for this industry in the post-TRIPS era. The percentile growth pattern of patent applications filed and granted indicates the steady pursuit of R&D in this industry (Figure 2.7).



Source: Compiled from annual reports of the Office of the Controller General (various years).

Figure 2.6: Number of Patent Applications Filed and Granted for Biotechnology Industry

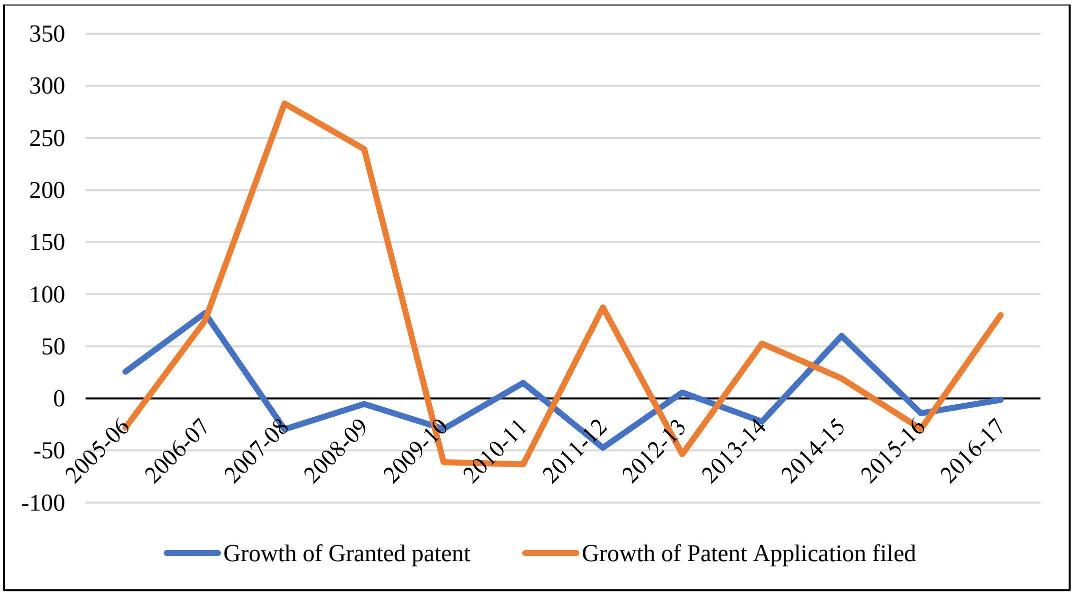


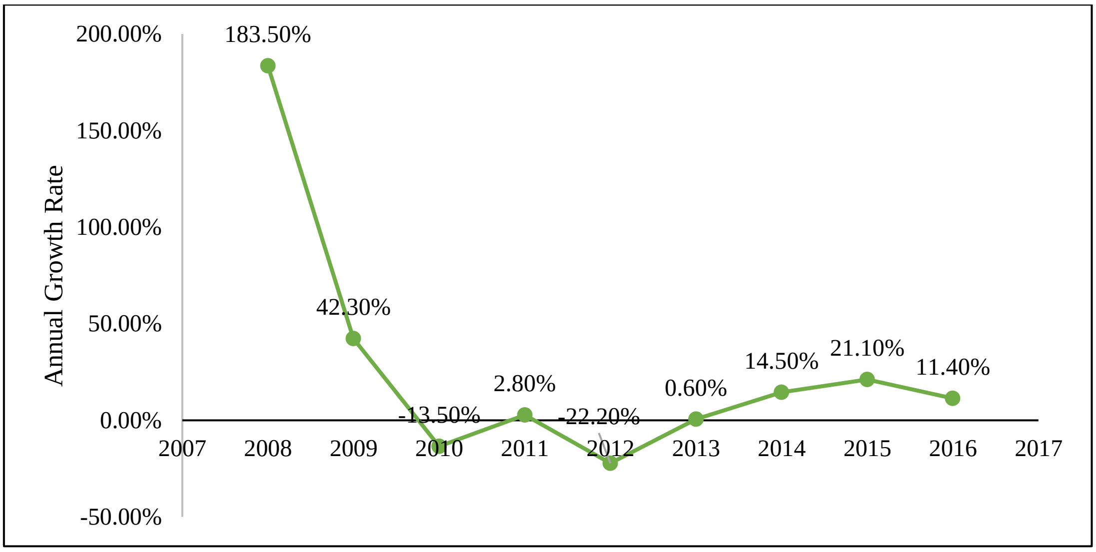
Figure 2.7: Growth in Patent Applications Filed and Granted for Biotechnological Industry

2.8.2 Electrical and Electronics Industry

The enormous growth in the electronics industry is one of the principal causes of the dramatic technological surge around the world. Integrated circuit boards are a vital element of electronics and are likely to be patented in terms of the product or design of the board. As per Section 3 of the *Indian Patent Act*, the design plan of the integrated circuit is not patentable; however, in the case of electronics, productions are based on the initial design plan. Hence, India adopted a flexible patent protection policy for the electronics industry.

The Electrical Machinery Equipment Industry of India provided a way for the Indian economy to achieve high revenue, targeted at US$100 billion. R&D is a powerful tool to accomplish this goal. The industry worked to enhance its efficacy through new inventions that amplified the scope of electrical equipment usage. The global economic crisis of 2008 indicated that innovation is the single avenue for survival and growth in the electrical manufacturing and electronics industry. A rational and synchronised industrial policy is required to sustain this industry and enable firm-level and industry-level productivity. However, some frivolous trade and investment policy formulation impaired and invalidated the strength of local businesses. The Indian electronic industry revealed tremendous import dependence, alongside market failures that evolved from the existing trade and investment liberalisation policy of India. In this context, re-evaluating the nuances of the extant Indian trade and liberalisation policy, including the policies with the perceived objective of advocating global value chains, became imperative. In accordance with the TRIPS agreement, reassessment of the trade and liberalisation policy was crucial, as the electrical equipment industry contributed 2% to the total GDP, with a value of US$40 billion, in 2014 (IBEF 2020).

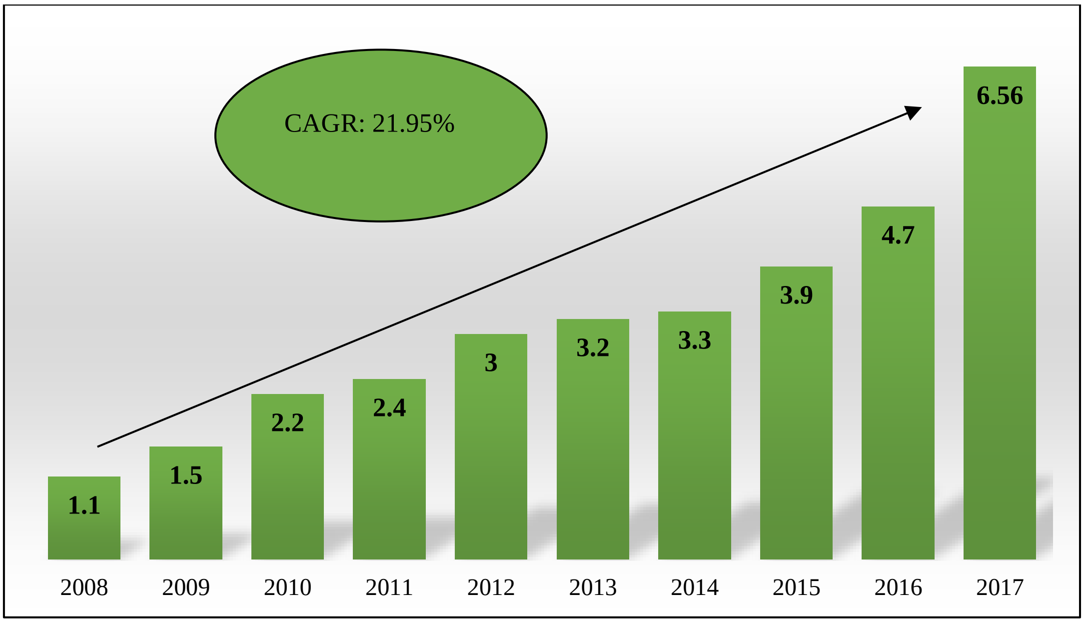
The brief focus of the trade liberalisation policy from its preliminary period enhanced productivity growth in the manufacturing sector, generating higher employment through boosting the productivity of small-scale firms, creating autonomy and reducing monopolisation of economic wealth. Consequently, the primary attention was to entice firms to their process of growth in exports, value-added and TFP. After retaining a consistent growth rate of 6.3% over the past three decades, the Indian economy experienced a sharp decline in GDP of 8.9% in 2011 to 6.7% in 2012, and further to 4.5% in 2013 (World Bank Report, 2014). This deterioration may be a result of the global financial crisis since India has trade and financial relations across the globe. Further, over-reliance in investment on infrastructure and non-infrastructure capital—attributable to easy financing conditions—arose as a corrective measure during post-crisis, disrupting the long-term trend of growth. Many projects that employed huge investment were stalled, as a consequence of this financial instability, it eventually creates a hindrance in output growth. The erroneous policy structure of India may be also partially responsible for this economic downturn (Figure 2.8).



Source: www.ibef.com.

Figure 2.8: Annual Growth Rate of Electrical Machinery and Apparatus Production

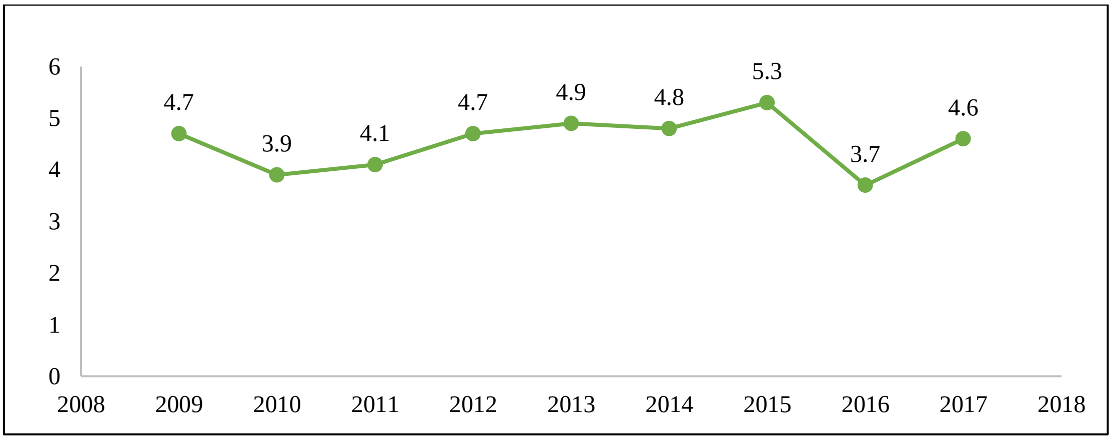
Before NMP came into force, the National Manufacturing Competitiveness Council customarily formulated the manufacturing strategies. With the recommendations of this council, the Ministry of Commerce envisaged accelerating exports. The Indian electrical equipment industry was one of the largest targets for corporates to invest in research and innovations, as cumulative FDI inflows between 2008 and 2017 reached US$6.56billion from US$1.1billion (Figure 2.9) (IBEF 2020).



Source: www.ibef.com.

Figure 2.9: Cumulative FDI Inflows for Electrical Equipment Industry (in Billion US Dollars)

India has travelled a long path in electrical equipment manufacturing and acquired the capability to produce a large variety of electrical items. Regardless of dependence on imported critical inputs, the export growth remained impressive (Figure 2.10).

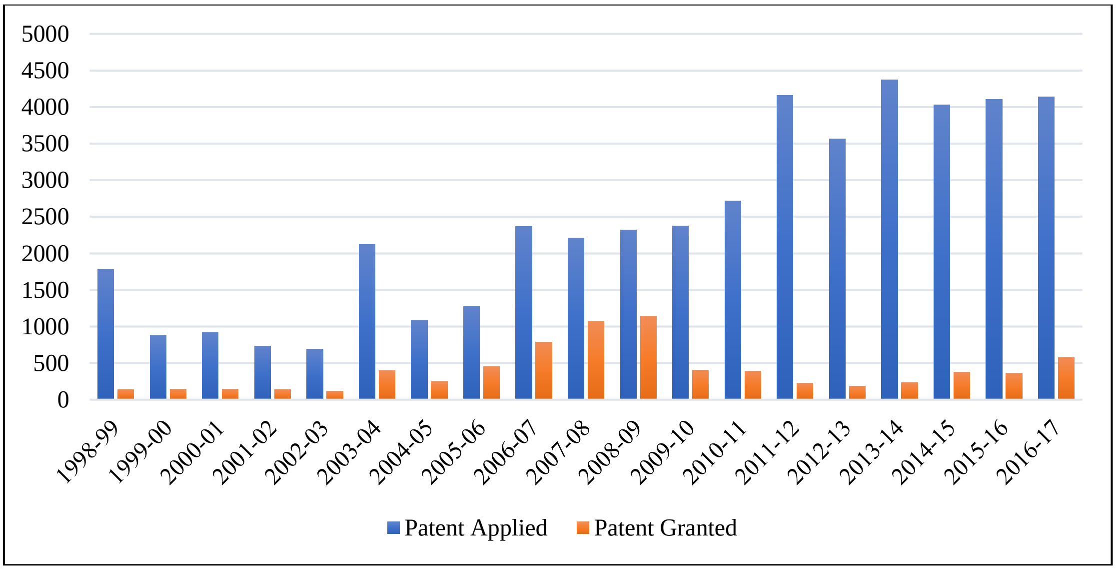


Source: www.ibef.com.

Figure 2.10: Electrical Equipment Industry Exports (in Billion US Dollars)

Despite limited investment and the absence of structured long-term drive in the electrical industry, India's total patent applications filed and granted indicates continuous R&D (Figure 2.11). The data demonstrated an upward trend until 2002 and declined thereafter;

however, the subsequent period of 2005 to 2013 showed a mostly upward pattern with fluctuations, yet 2012 depicted negative growth in patent grants (Figure 2.12).



Source: Compiled from annual reports of the Office of the Controller General (various years).

Figure 2.11: Number of Patents Applied and Granted for Electrical Industry

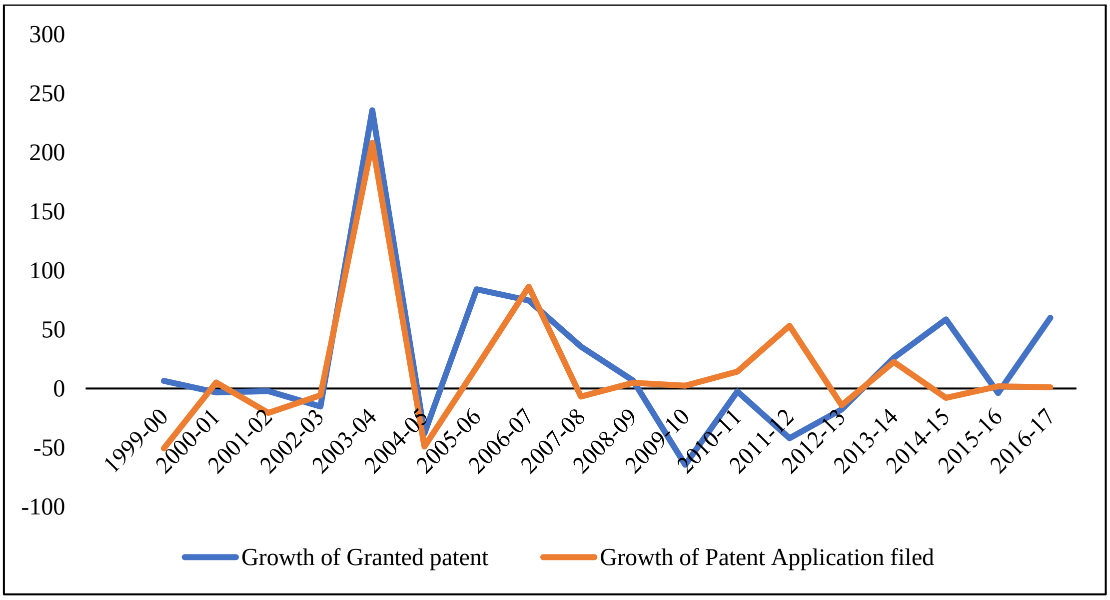


Figure 2.12: Growth of Patent Applications Filed and Granted in Electrical Industry

2.8.3 Information Technology Industry

Information technology (IT) can be delineated as both software and hardware—a powerful tool for handling information through computing and telecommunication technologies. This sector is exciting because of internet growth, the advent of broadband

and the diffusion of e-commerce over the last few decades. The Indian computer policy of 1984 and 1986 emphasised software development in India by using Indian expertise on duty-free sophisticated imported computer. However, the protectionist policy imposed 200% import duties on the essential hardware required to upgrade the IT industry. As a result, foreign companies gained the prospect to expand their business networks in India, and domestic firms encountered higher costs. On the recommendations of the Sondhi Committee report (1978), a handful of domestic IT companies, such as HCL and Wipro, have been established since 1984 (Heeks et al. 1996). Hence, the prevailing economic status of the Indian IT industry strongly urges amendments to the patent protection policy of India.

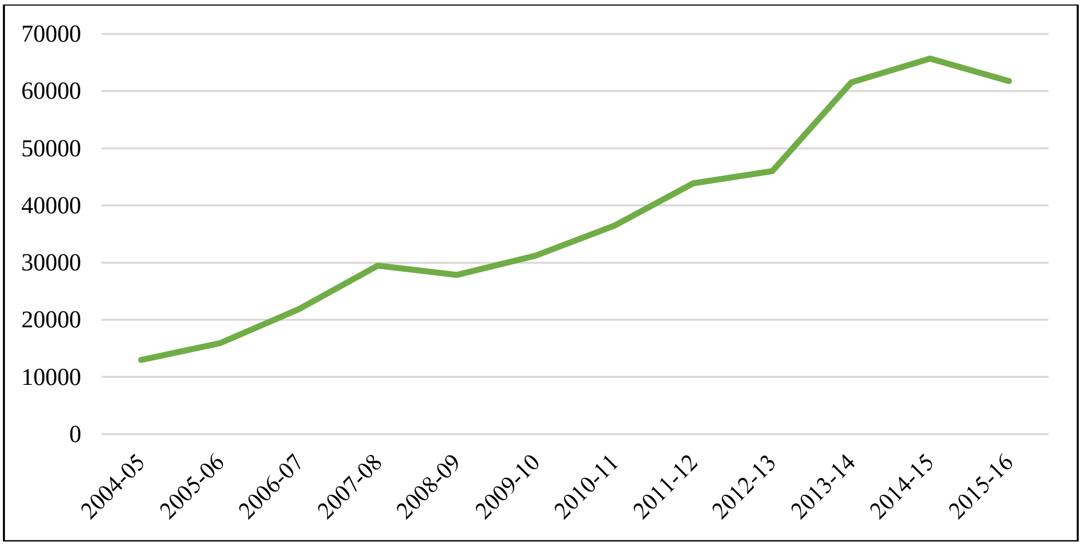
Computer programs were excluded from the patent protection documented in Section 3(K) of the *Patent Act, 1970*. This prohibition generated conflict because of the distinctive attitudes of the patent offices. Some inventions are associated with software that is embedded with hardware, some software and some types of technical applications only had the opportunity to be patentable. The new ordinance of 2004 and Section 3(b) removed the prior exclusion by stating that computer programs with technical application to industry or combined with hardware were eligible under the patent regime. As a consequence, with the new amendment Act of 2005, this exclusion clause was abolished. The evolution of the Indian electronics and semiconductor industry is presented in Table 2.2.

Table 2.2: Evolution of Indian Electronics Industry

1965 to early 1980s Preparatory era	Pursuing a closed market strategy. Production is limited to consumer goods, such as calculators, black and white televisions and transistor radios.
1984 to 1990 Golden era	Speedy and perpetual industrial growth. The arrival of computers and coloured televisions to the market. Establishment of telephone and digital exchanges, generating further opportunities.
1991 to 2005 Liberalisation era	Relaxation of custom tariffs. Obligation to relinquish all tariffs as a signatory of WTO free trade agreement.
Latter half of 2000s Growth era	National Policy on Electronics was endorsed in 2012 and National Electronics Mission was established. The electronics industry received government approval for FDI inflow up to 26%. From 2000 to 2016, cumulative FDI inflows were recorded as US$1,708.99 million. Infused in the sophisticated electronic product market.

Source: Indian Electronic and Semiconductor Association, Corporate Catalyst India; TechSci Research. www.ibef.org.

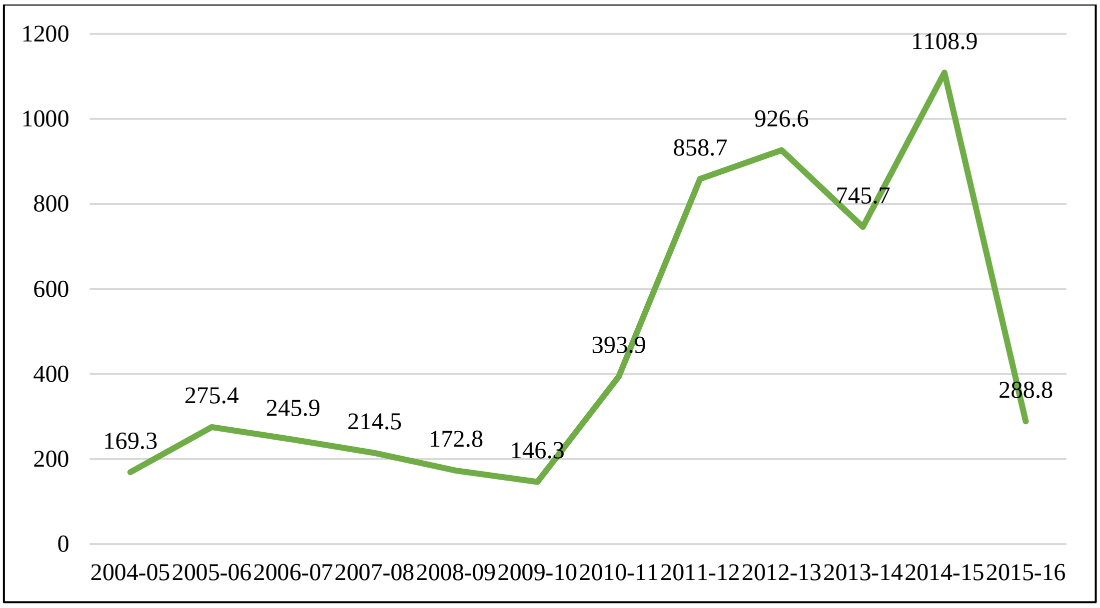
In 2019, the IT industry experienced 6.1% annual growth, worth US$177 billion. The contribution of this industry is noteworthy in terms of GDP, foreign exchange earnings and employment. The share of the IT sector in India's GDP increased from 3.6% to 9.3% between 2005 and 2016. During 2000 to 2016, the Indian computer software and hardware industry held 7% of total FDI equity inflows, equivalent to US$22,832 million. The Union Minister of Information Technology revealed that, as a consequence of the 'Make in India' initiative, this industry was able to attract the highest FDI inflows, of US$18.34 billion, in 2016, compared with US$1.64 billion in 2014. The growth of the Indian IT industry has generated substantial employment, of 0.52 million in 2000 to 2001 to 3.688 million in 2015 to 2016, which in turn boosts the socio-economic level. In the post-TRIPS period, the industrial sales of the Indian IT industry increased from US$12.97 billion to US$61.73 billion (Figure 2.13) (World Bank, 2019).



Source: Prowess Database.

Figure 2.13: IT Industry Sales (in Million US Dollars)

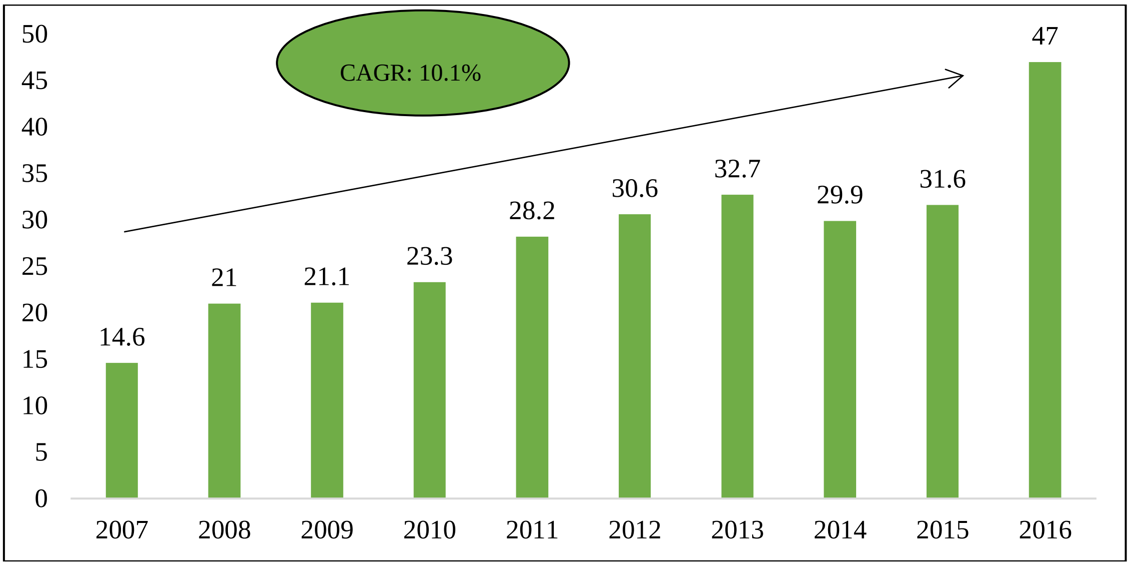
India emerged as a favourable destination for IT industries because of the push effect, such as the enforcement of the government policy to discourage imports, and the pull effect, such as credible domestic demand and government policy to drive exports. The export progress of this industry is captured in Figure 2.14 (World Bank 2019).



Source: Prowess Database.

Figure 2.14: IT Industry Exports of Goods (in Million US Dollars)

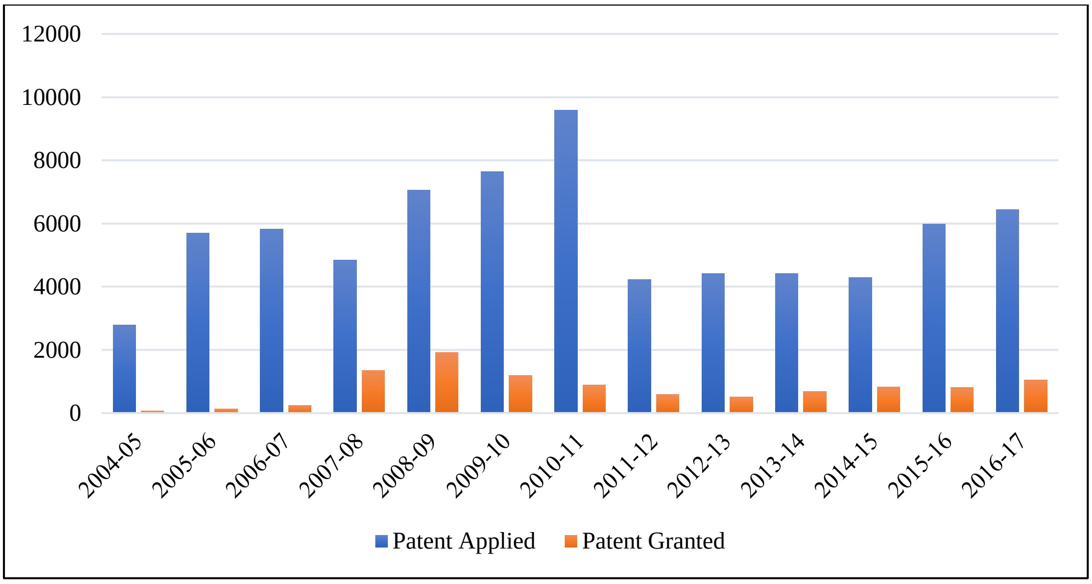
The intensifying demand for sophisticated electronics items has contributed to the output growth and total production of electronic hardware. The value of electronics hardware production reached US$47 billion between the period 2007 to 2016, with a compound annual growth rate (CAGR) of 10.5% (Figure 2.15) (IBEF 2020).



Source: www.ibef.org.

Figure 2.15: Value of Electronic Hardware Production in India (in Billion US Dollars)

Nascent economies have sought to improve innovative proficiencies after realising the significance of innovation. Patent protection is the institutional component used by economies to confirm their competencies. The trends of patent applications filed and granted for the IT industry are described in Figure 2.16, while Figure 2.17 verifies the progress of invention performance of the industry.



Source: Compiled from annual reports of Office of the Controller General (various years).

Figure 2.16: Number of Patents Applied and Granted for IT Industry

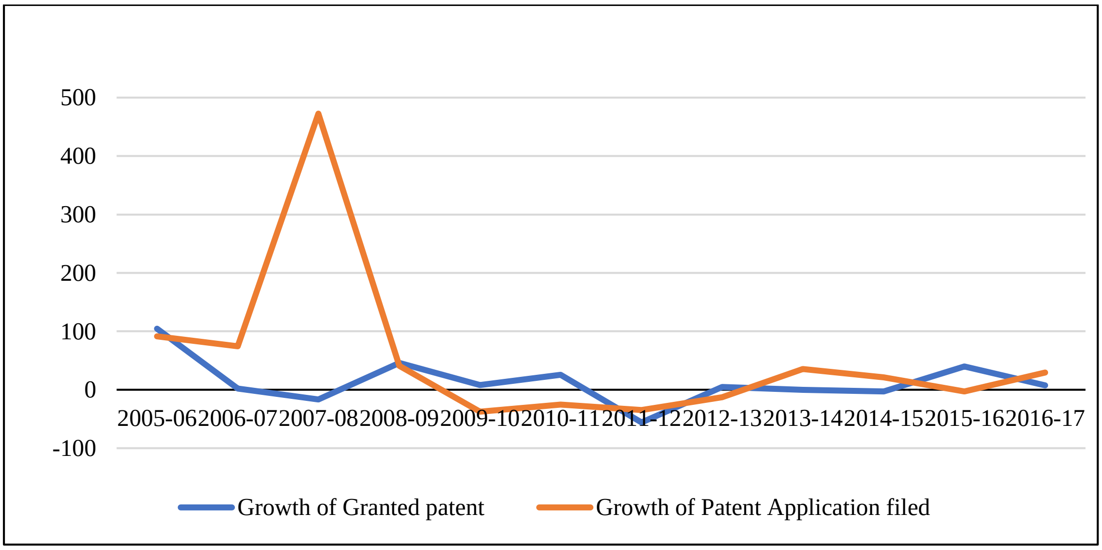


Figure 2.17: Growth of Patent Applications Filed and Granted for IT Industry (in %)

Indian firms, including software and hardware, have limited infrastructure and expenditure on research, and thus have an inadequate contribution to technology development. The R&D practice encountered the major doubt that emerged from the Indian patent system. In compliance with TRIPS, Indian patent law omitted ‘computer program per se’ from patenting; however, this phrase lacked transparency and created confusion. The telecommunications service liberalisation policies support the demand for electronic products; however, these generated more opportunities for foreign firms than domestic firms (Ernst 2014). The inadequacy of a domestic component manufacturing industry, disintegration between design competencies and manufacturing skills, and a decentralised patent system were the principal issues for Indian IT industries. Well-known foreign enterprises showed disinterest in investing in manufacturing inventions in India, perhaps they use the Indian market exclusively for assembling products (Ernst 2014). India achieved specialisation in designing integrated circuits; however, those have mostly devoured in MNC since integration was absent with the domestic electronics manufacturing industry.

2.8.4 Pharmaceutical Industry

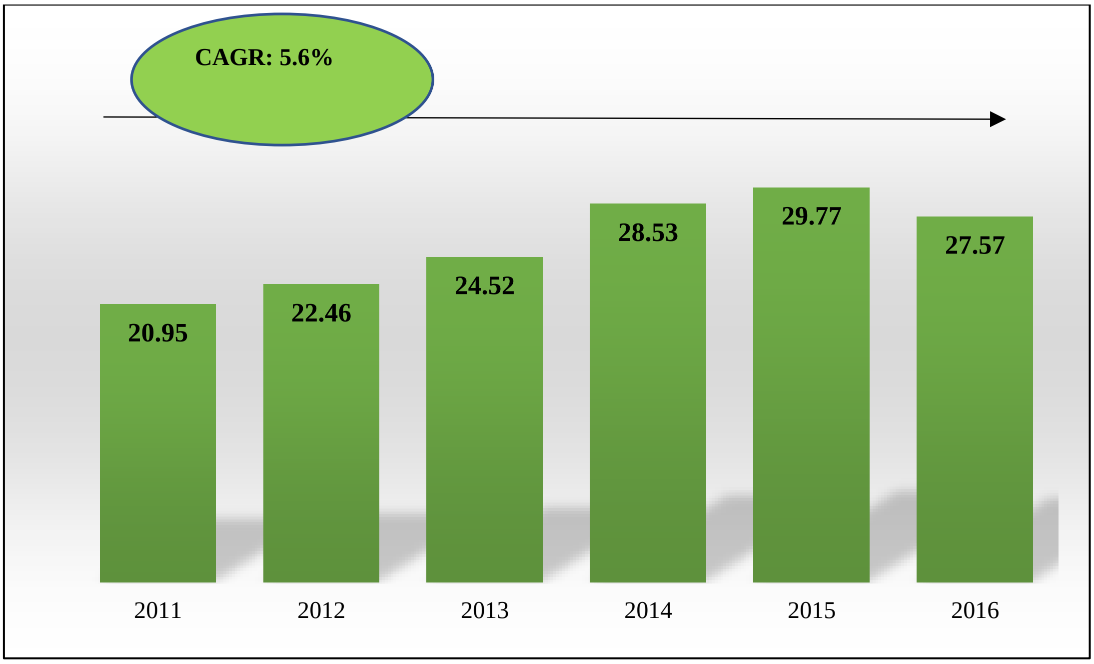
As a consequence of the TRIPS agreement and implementation of the National Drug Policy, the Indian Government sought to support domestic drug manufacturing industries to boost their economic performance. India has been a low-price generic drugs producer in the world market for the last few decades. In 2003, India met only 1% and 10% of global pharmaceutical and generic demand, respectively (Basheer 2005). However, India is currently the largest generic drugs provider in the global market, capturing over 50% of the global demand for vaccines and over 20% of the global generic market (Chakraborty 2020). The evolution of the Indian pharmaceutical industry can be classified into a few phases, as presented in Table 2.3.

Table 2.3: Evolution of Indian Pharmaceutical Industry

Phase I: Pre-1970s Early years	Foreign firms dominated market share. Organised Indian firms were uncommon.
Phase II: 1970–1980 New patent regime	Manoeuvred the dominance of domestic firms. *Indian Patent Act, 1970* introduced. Price of drugs capped.
Phase III: 1980–1990 Development phase	Emphasis on formulation manufacturing and bulk drugs. Creation of infrastructure. Export initiatives implemented.
Phase IV: 1990–2000 Growth phase	TRIPS agreement signed. Domestic market vast expansion and international market growth. Focus on research and invention initiatives. Expedited export of bulk drugs to developing countries.
Phase V: 2000–2010 Innovation-focused phase	Process patent to product patent transitions. Domestic drug manufacturing reinforced. Research orientation. Export focus.
Phase VI: 2010 onwards FDI-focused phase	Pharmaceutical patent filing increased. Medical device firms are allowed to receive 100% of FDI. The number of pharmaceutical manufacturing units increased and reached 10,500. Expenditure on the health sector increased.

Source: www.ibef.org.

India has enormous potential to emerge as a prominent destination for medical tourism. Its significantly lower cost of production (approximately 33% lower than in the US), research capability and competency in manufacturing high-quality medicines demonstrate a favourable environment for the domestic industry. Thus, it is equipped to capture over 10% of global market production. During the financial years 2011 to 2016, this industry experienced an expansion of revenue from US$20.95 billion to US$27.57 billion, representing 5.64% of the CAGR (Figure 2.18) (IBEF 2020).



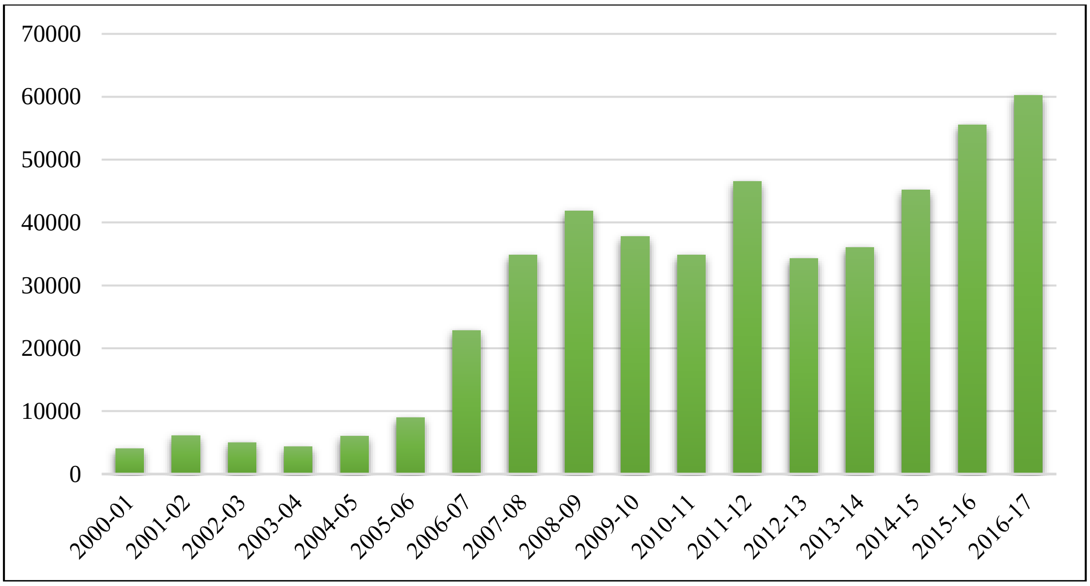
Source: [www.ibef.com.](http://www.ibef.com)

Figure 2.18: Revenue of Indian Pharmaceutical Industry (in Billion US Dollars)

The global export share of India for generic drugs amounts to 20% in terms of volume, worth almost US$11 billion. The export value of the pharmaceutical sector of India increased from US$10.1 billion in 2012 to US$19.1 billion in 2019, with more than $10 billion annually in just drug formulations. In 2020, pharmaceutical exports—including bulk drugs, intermediates, and biological and herbal commodities—were worth US$20.7 billion. India is also proficient in generic medicines, and the overall market revenue share in 2018 was 70% (Statista 2020). The healthcare sector of India was US$140 billion in 2016 and forecast to be US$373 billion in 2022. The contribution of the pharmaceutical sector to GDP was 1.5% directly and 3% indirectly. Hence, the pharmaceutical industry can contribute to the growth of India, as the IT industry did, particularly during the 1990s and 2000s (IBEF 2020).

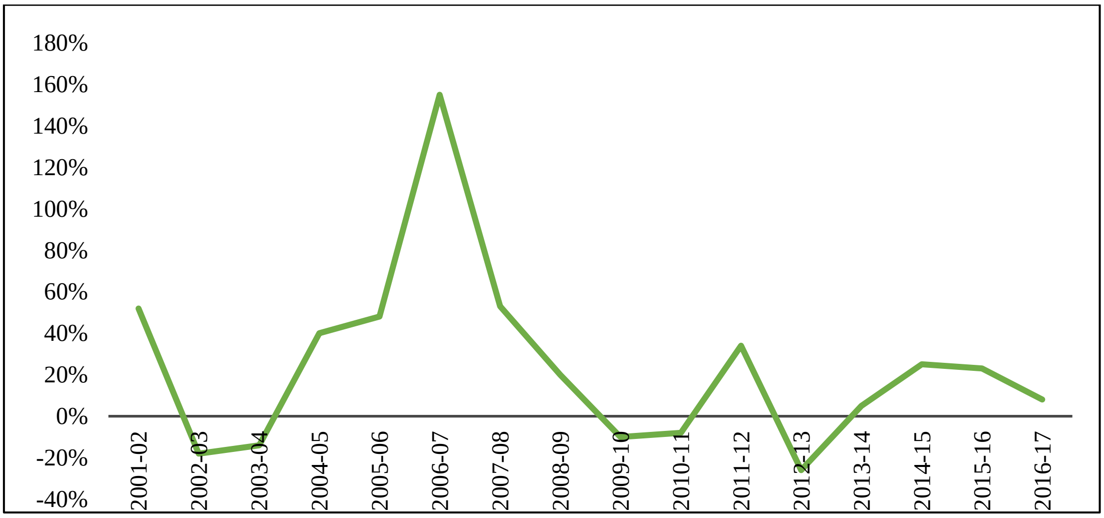
The exports of the pharmaceutical industry increased from US$1 billion to more than US$20 billion between 1996 and 2017, portraying robust performance. India has secured its position in the global market as a supplier of cheap generic drugs. The export market of Indian formulations in the US increased to US$5.2 billion in 2016 from US$0.3 billion in 2005, capturing 39% of the market share. The exports of formulations displayed a sharp increase, but the exports of bulk drugs were sluggish. FDI inflows grew to almost US$15.59 billion during 2000 to 2017 for the Indian pharmaceutical industry (Figure

2.19). The percentage growth of FDI inflows displayed a fluctuating trend and intense growth during 2001 to 2016 (Figure 2.20).



Source: RBI Bulletin (2020).

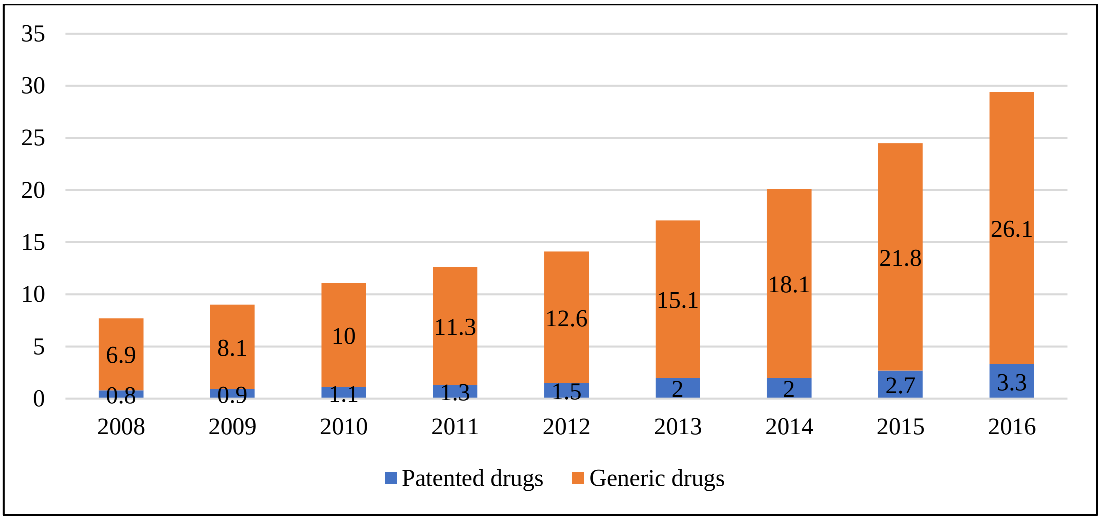
Figure 2.19: Total FDI Inflows to India (Million US Dollars)



Source: World Bank 2019

Figure 2.20: FDI Inflows (in %) to Pharmaceutical Industry

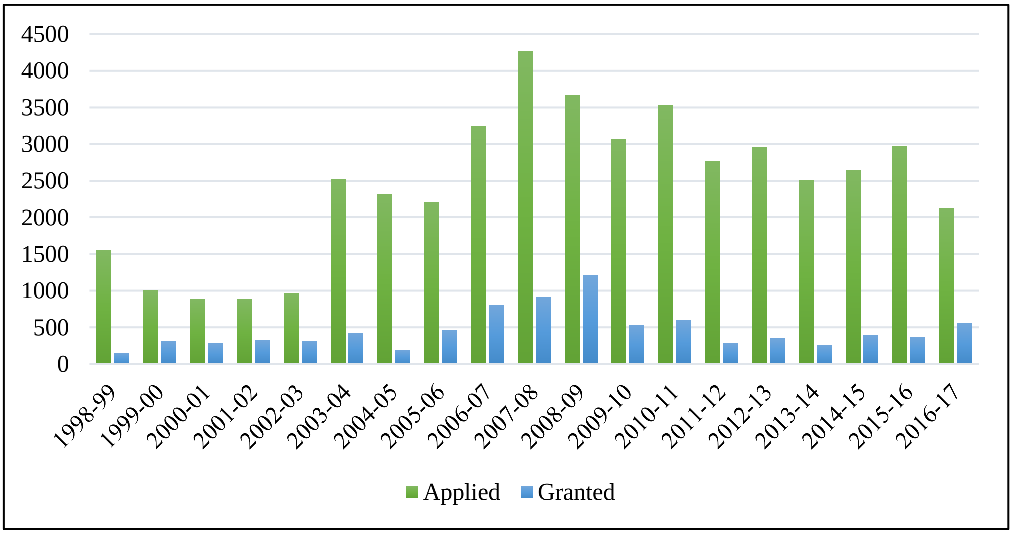
Generic drugs have occupied the largest section of the Indian pharmaceutical industry, with 70% of domestic revenue shares and 20% of global generic drugs exported in terms of volume. Thus, Indian firms received a vast opportunity in the global generic drugs market for their proficiency in this arena. In 2016, the domestic generic drug market expanded to US$26.1 billion from US$6.9 million in 2008 (Figure 2.21).



Source: Business Monitor International, FCCI, Indian Pharma Summit 2014–2015, www.ibef.org.

Figure 2.21: Market Share of Patented and Generic Drugs (% in Billion US Dollars)

The new IPR regime, in accordance with TRIPS, emphasised a few major changes to the Indian patent system. First was the implementation of product patent protection for all disciplines of technology, including pharmaceutical products. Second was the abolition of the discriminatory period of patent protection and the establishment of 20 years of patent protection across every product. Third was the abolition of the distinction between imported and domestic manufactured products. Fourth was the enforcement of the compulsory licensing system. As a result, the number of pharmaceutical industry patent applications filed and granted increased, as displayed in Figure 2.22.



Source: Compiled from annual reports of Office of the Controller General (various years).

Figure 2.22: Number of Patent Applications Filed and Granted to Pharmaceutical Industry

India has an abundant supply of technically skilled workers, which is imperative for comprehensive research and the knowledge-based and technology-driven manufacturing sector. The pharmaceutical industry seemed to be disoriented during the pre-TRIPS era; however, after the TRIPS agreement, Indian researchers, inventors and technical professionals received steady motivation to assimilate the new patent system to upgrade knowledge and work practices. This encouragement also ensured reverse brain drain, as portrayed through the growing trend of patent grants (Figure 2.23) (IBEF 2020).

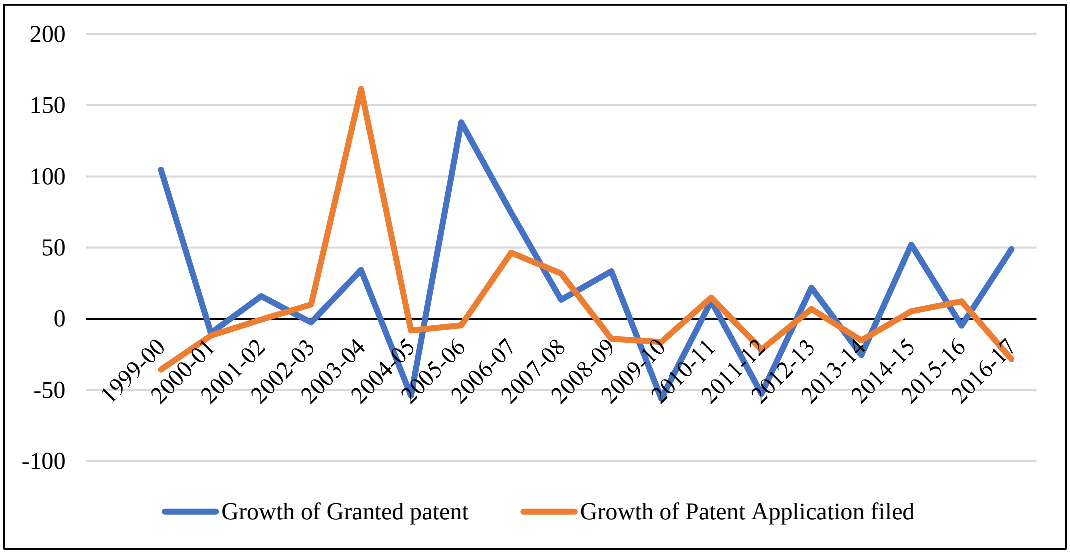


Figure 2.23: Growth of Patent Applications Filed and Granted for Pharmaceutical Industry (in %)

2.9 Manufacturing Sector Development from 'Make in India' Initiative, 2014 to 2025

The 'Make in India' initiative was launched in 2014 with two primary visions: (i) refurbish India into a global design and manufacturing hub and (ii) entrap FDI inflows. It eventually aspired to achieve macroeconomic objectives by enhancing domestic purchasing power and the spillover effect augmenting economic development through stimulating domestic demand, hence benefiting investors. Consequently, it devised the goal of elevating the current contribution of the manufacturing sector up to 25% of the GDP by 2025, instead of the steady 16% of previous years. Several new initiatives were implemented, including stimulating FDI, enforcing IPRs and comprehensive development of the manufacturing sector. With the tagline ‘zero defect, zero effect’, this campaign ensured sustainable development through implementing high-quality manufacturing standards, while reducing environmental and ecological impacts. The following four pillars were the foundation of these initiatives.

(a) New Processes: The Government of India initialised multiple reforms that complied with the ‘Ease of Doing Business’ index parameters developed by the World Bank. These initiatives were adopted to create a conducive business environment. Several restructuring programs were implemented to entice FDI inflows towards the manufacturing sector and exhort business collaboration. For instance, the biotechnology industry has urged the government for a US$5 billion investment to achieve a sizable market size of US$100 billion by 2025.

(b) New Sectors: Twenty-five sectors have been identified to foster the development goals, including the sunrise industries (such as the IT and communication industry and biotechnology industry), the capital goods industry (such as the electrical equipment industry) and other comparatively advantageous industries (such as the pharmaceutical industry). As a result, the government released a maximum cap of FDI in public enterprises, such as the railway and construction sectors, defence and pharmaceutical industries. For example, the electronic hardware manufacturing industry and pharmaceutical industry are permitted to obtain 100% FDI inflows through the automatic route (Das 2017).

(c) New Infrastructure: Infrastructure development and industrial growth are highly correlated; thus, the construction of industrial corridors and technology-equipped smart cities have been included in the policies. The Government of India introduced a swift registration system to boost innovation and research activities, along with reviving the infrastructure for IPR registrations. Accordingly, this initiative endeavoured to incite creativity and innovation, while conforming with effective IPR protection. The vision statement foresees knowledge owned as knowledge transferred, and presumed knowledge as a key indicator of economic growth. Hence, IPRs gratify all stakeholders to motivate invention and creations.

(d) New Mindset: The major drive has taken in terms of shift of paradigm from the regulator to facilitator through behaving as a cohort with the corporates in the economic progress of India.

The ‘start-up India’ initiative introduced in May 2016 within a short span of NMP enforcement embodied features such as the patent examination time reduced to 18 months from seven years, and patent product and trademark reduced to one month from 13 months. The initial success of the ‘Make in India’ initiative was evident, as FDI equity inflows grew about 44%, worth US$56 billion, between the third quarter of 2014 and first quarter of 2016. Despite that the ‘Make in India’ initiative demonstrated that the nation is adopted the alterations those evolved in the course of economic development; yet some drawbacks were quite visible. Natural resources are imperative in the establishment of new manufacturing; thus, there was a fear of depleting the natural resources, representing an eventual threat for humankind. Further, the entry of foreign corporations and MNCs into the Indian manufacturing sector has threatened existing small local entrepreneurs. Moreover, FDI inflows can stagnate as a result of strong competition. However, overall, this campaign rejuvenated the perception of the Indian economy by fostering an optimistic environment.

2.10 Conclusion

This chapter has presented an overview of the evolution of the Indian manufacturing sector, including its structural transformation, performance aligned with various policy prescriptions and formulations, and inevitable transformations in compliance with the TRIPS agreement. It is evident that India has experienced a structural transformation from agricultural dominance to manufacturing; however, the service sector still outperforms the manufacturing sector. In the pre-liberalisation era, the Indian manufacturing sector adopted a closed economy model with a highly protective industrial and foreign trade regime. The liberalisation policy of 1991 pursued openness through abolishing entry barriers and liberalising import restrictions. In accordance with India’s commitment to multilateral trade agreements in the Uruguay Round of WTO, reduction of import duty becomes more crucial. These measures of liberalisation facilitated the growth of India’s export during the 2000s as the export-oriented firms import intermediate inputs at competitive prices. Simultaneously, this accelerated import penetration enhance the efficiency of domestic producers. Hence, investing in research and invention was imperative at this juncture.

The crucial challenge encountered by the Indian manufacturing sector occurred after the TRIPS agreement came into force in 1995. The TRIPS agreement incorporated distinctive views towards developed and developing countries, such as India. The first five years, followed by five more years, were a period of transition for the nascent economies. During the pre-TRIPS period, India followed the *Patent Act of 1970*, which encouraged domestic inventions through the eligibility criterion of production only at a commercial scale. Common practice under the ‘weak IPR’ system of the pre-TRIPS period was ‘technology catching up’ by developing nations; contrastingly, the TRIPS regime travelled in the opposite direction. In adherence to TRIPS agreement clauses, India undertook several policy measures and amendments. The *Patent Amendment Act*, *1999* introduced two systems, ‘mailbox’ and ‘EMR’; however, it was ineffective because of its complex clauses. The second phase of amendments in 2002 incorporated a few provisions and provided a coherent definition of the word ‘invention’. The most significant provision to encourage domestic invention was that domestic inventors needed to file their patent applications in India initially. The final phase of the amendment of the Patent Act in compliance with the TRIPS agreement transpired in 2005. With the abolition of EMR and mailbox, India implemented a ‘product patent’ regime, instead of a ‘process patent’ regime. The presence of the modal verb ‘may’ in the patentability clause of micro-organisms caused serious concern, and the two most vital manufacturing industries associated with micro-organisms—the pharmaceutical and biotechnology industries—were stirred by the TRIPS agreement. Further, in the absence of clarification of another phrase, ‘computer per se’ and excluded from the patent protection generated a struggle for the electrical and electronic industry and IT and communication industry. The patent protection regime is crucial for industrial growth, as patents are deemed a key measure of research and innovation performance. Besides, the regime has had a positive effect on the efficiency and productivity growth of manufacturing firms. In this context, the effect of the patent protection regime in compliance with the TRIPS agreement is yet to be comprehensively explored for the Indian manufacturing industry. The following chapter presents a comprehensive analysis from the perspective of the theoretical notions and their pertinence to the Indian manufacturing sectors.

Chapter 3: Patent Protection, Productive Efficiency and Productivity Growth—A Survey of the Literature

3.1 Introduction

The discussion in Chapter 2 outlined the trends of patent protection regimes in Indian manufacturing. It demonstrated that the patent regimes have shifted the paradigm from process patents to product patents, in compliance with TRIPS. Endogenous growth theory states that innovation leads to higher productivity growth, as technological progress transpires through innovation (Aghion and Howitt 1992; Grossman and Helpman 1994; Lucas 1988; Romer 1986; Stokey 1995). Patent protection is an imperative measure of innovation activities (Christiansen 2008; Patel and Pavitt 1987; Robertson and Patel 2007). Two theories seek to explain the patent institution (Denicolò and Franzoni 2003). Reward theory states that the patent system stimulates firms' invention motivation through ensuring reward. In contrast, contract theory argues that the patent institution propagates innovative knowledge by publicising the information. The patented firm receives a first-mover advantage and yields profits from the innovation practices; however, it causes social welfare loss from transitory monopoly power (Arrow 1962; Nordhaus 1969).

This chapter reviews the existing empirical literature on the effect of patent reform on industrial productivity growth and technical efficiency, and the methods of measuring TFP growth. This review highlights significant issues for empirical analysis of the effect of patent reform on technical efficiency and productivity growth in selected Indian manufacturing industries, provided in Chapters 5, 6 and 7. This chapter proceeds by discussing the theoretical notions of patent protection in Section 3.2, while Section 3.3 discusses various methods of measuring and estimating TFP growth. Section 3.4 reviews the empirical literature related to the effect of patent protection on TFP growth, while Section 3.5 surveys the empirical literature on the effect of patent protection on efficiency growth. Finally, Section 3.6 concludes and relates this chapter to the study's objectives.

3.2 Concept of Patent Protection

Conventional wisdom states that good institutions are an imperative feature of long-run economic performance (e.g., Acemoglu et al. 2001; North 1990). However, the proficiency of patent institutions remains controversial. A patent is a legal right issued by the government to authorise inventors to invent and/or sell their invention for a specific number of years. The historical evidence shows that the debate over patent law was pursued until the Netherlands repealed its patent law in 1869, which was not reinstated until 1912 (Machlup and Penrose 1950).

3.2.1 Patent Puzzle

Patent protection is a case of contradiction. Patent protection motivates innovation activities prior to the invention; however, it later causes a loss of efficiency by virtue of a temporary monopoly. To cope with this trade-off between inherent potential monopolistic drawbacks and incentives towards innovation by the patent system, many researchers have focused on engineering the optimal length and scope of patent institutions. The existing literature has focused on optimal patent design, and has found that the optimal patent life can be either finite (Nordhaus 1969) or infinite (Gilbert and Shapiro 1990; Judd 1985). Contemporary literature argues that the longer the term of patent protection, the larger the associated deadweight loss, even with the existence of a strong incentive to innovate (Nordhaus 1969; Scherer 1972).

The scope and life of patents both arbitrate the terms of the patent and instil the potential revenue generation from patenting an invention. However, these two work in different directions and influence the economic behaviour of the patent holders in a contrasting manner (Gallini 1992; Gilbert et al. 1990; Klemperer 1990). Denicolo` (1996) examined the issue of optimal patent breadth and stated that rigorous competition among firms to acquire patent rights for the same or similar technologies is not socially ideal, as it entails social costs, such as duplication of entry cost or inefficient production. Few distinctive studies only admits the existence of potential dynamic gain in consequence of patent enactment; moreover, Boldrin and Levine (2002) stated that patent institutions' emergence causes dynamic net loss. In contrast, some economists argue that there is no general market failure owing to innovations (Moir 2008; Posner 2012). A possible explanation can be that the low cost of invention evolves economies of scale or just being a first mover in the market, the typical firm gains a robust competitive advantage.

The standard theory of innovation envisages a positive effect of strong patent institutions on innovation; however, in reality, some previous studies found little to almost no increment derived from strengthening the patent system. Dutton's (1984) findings clarified that one group of inventors explicitly earns a profit directly from patents. Another group of 'quasi-professional inventors' only earns a profit by selling or licensing their intellectual properties during the British industrial revolution, contributing greatly to the 'Patent Puzzle'. Khan and Sokoloff (2004) similarly found that the American patent institution required granting significant incentives to 'great inventors' during 1790 to 1930 (identified by 'Dictionary of American Biography'). MacLeod (1988) asserted that a large volume of inventive activities is commenced beyond the territory of a patent institution. In their survey, MacLeod and Nuvolari (2006) raised scepticism regarding whether the evolution of modern patent systems cater to any inventive activities in an economy. Contrarily, a proponent of patent enactment, Shapiro (2007), while criticising the 'Patent Puzzle', claimed that patent systems attempt to evaluate innovation performances for the US economy. Therefore, it is evident that the extant literature evaluating patent systems' contribution to invigorating inventions is largely historical.

In reality, developing countries' economic growth possibly becomes sluggish, instead of being boosted, by the emergence of patent protection, as they confront direct competition from developed countries. Patent enactment may be beneficial for industrialised countries, yet pernicious for developing countries (Deardorff 1992; Helpman 1993). Developing economies can only benefit if strong patent laws promote new technologies that distinctively vary from those invented in developed countries (Diwan and Rodrik 1991). Therefore, empirical results also indicate that the commencement of uniform global patent laws may not generate productive performance and create disparity in innovation between developing and developed countries. Moser (2005) recommended a significant analysis of international patent policies. He claimed that the strong patent laws possibly stimulate the direction of innovative activities in developing countries and initiates crucial changes in the global trend of comparative advantage. Thus, little theoretical consensus exists regarding whether the patent system fosters firm-level productivity, and empirical evidence is required for clarification.

3.2.2 Diverse Channels of Patent Protection

Endogenous growth models present an analytical framework to evaluate the influence of diverse sources of knowledge on TFP growth. The endogenous growth model (Romer 1990) and quality ladder models (Aghion and Howitt 1992; Grossman and Helpman 1991) identify innovation and accumulation of knowledge as major drivers of productivity and economic growth. Eaton and Kortum (1996) examined relative productivity growth by employing the quality ladders model. They identified five determinants that influence the intensity of patenting by source country in destination countries: (i) research effort in the source country, (ii) market size of the destination countries, (iii) ability of the destination countries to protect IPRs, (iv) cost of patenting in the destination countries and (v) compatibility of the inventions in the technical framework of the destination countries. The theoretical doctrine infers that a nation's innovation capability and proficiency in adapting new technology appropriately explains through the relative level of productivity than productivity growth rates. This study quantified a positive nexus between gross inventive output and the magnitude of economic growth. It underpins the competence of a nation to acquire this economic growth relying on human capital stock, bilateral trade relations and accessibility of the innovation resources. In this event, patent via the scope of technology diffusion clarifies as another channel of productivity and growth performance. Besides, impediment of technology diffusion probably leads to variations in productivity growth across nations. Griffith et al. (2000) contributed to the Schumpeterian endogenous growth concepts by exploring the role of R&D on a country's rate of TFP growth through innovation. The cumulative domestic R&D effort was used as a proxy for technological knowledge in the economy that enhances TFP growth (Coe and Helpman 1995). These models further included the international trade of intermediate goods and found that international technology spillovers through imports also influence productivity.

International trade plausibly positively influences productivity, as a wider range of intermediate and capital products are accessible through trade (Rivera-Batiz and Romer 1991). In this context, Maskus and Penubarti (1995) sought to answer a normative question of whether distinctive patent enactments of importing nations stimulate the distribution of international trade across countries, by instituting an empirical version of a static, general equilibrium trade model developed with the Helpman-Krugman (HK) model. This study formulated an econometric model to capture the ambiguity in the direction of international trade upon implementation of stronger patent law, and argued that two reverse effects are accountable: market power effect and market expansion effect. The market power effect implicates that the firms compel to export the patentable products less with the emergence of strong patent law, since, the elasticity demand confronts by the foreign firms reduce. In contrast, the market expansion effect indicates that greater effective market size is generated through the diminishing abilities of local firms to imitate the product. Thus, the strength of the patent regime of a typical country customarily influences the export decisions of foreign countries. Domestic firms face a fundamental trade-off among the market power instigated by local patents and the sales expansion potential under predominant residual market demand governed by local patent law, as well as lower marginal exporting costs. The experimental view finds that bilateral imports are significantly higher in several developing countries than the level estimated for countries with strong patent law, by the HK model. Similarly, Coe and Helpman (1995) stated that the TFP growth of a typical country relies on its own R&D effort and trade. Hence, it is evident that the emergence of the patent system is a distinctive channel of international trade, TFP and growth performance.

Eaton and Kortum (1999) developed a model to demonstrate the linkage between the adaptive capacity of new ideas and the productivity growth of a country. The research effort greatly relies on returns, and patent enactment influences returns. This model relates the value of patent grants to an invention and the cost of acquiring the patent. Therefore, this model establishes the importance of the patent system's role in productivity growth through international technology diffusion. Few more studies also advocated that the accomplishment of R&D on TFP growth is reliant on absorptive capacity or level of technology transfer (Griffith et al. 2003, Madsen, 2010).

3.3 Empirical Studies on Total Factor Productivity

A plethora of studies has sought to evaluate productivity growth in terms of the three conduits of innovation for different economies empirically. Knowledge is generally considered the determinant of TFP growth, while R&D is often synonymous with innovation and comprehension and imitation of others' inventions. The literature suggests that all of these three channels are important in evaluating TFP growth.

3.3.1 Research and Development

A previous study on knowledge creation used US time-series data to estimate the parameters of the knowledge production function (Abdih and Joutz 2005), and found a positive long-run relationship between TFP and patent, which was used as a proxy for knowledge creation. This study is consistent with Romer's (1990) model, identifying the existence of strong intertemporal knowledge spillovers. In contrast, Jones (1995) used US data over the post-war period and found no relation between R&D and TFP growth. Comin (2002) investigated the role of R&D in generating TFP growth with US data. This study revealed no significant evidence for a correlation between R&D and TFP growth, aligning with the study of Jones and Williams (1998). Ulku (2004) asserted that the level of innovation is enhanced through R&D investment only in large OECD countries. Moreover, he argued that innovation generates only a short-term output growth rate. Consequently, this study contradicted the notion that innovation creates perpetual growth by Romer (1990), perhaps consistent with the study of Jones (1995).

Griffith et al. (2000) used industry data of 12 OECD countries during the period 1974 to 1990, and established a positive effect of R&D expenditures on TFP growth. They later extended their model by including human capital and found a positive correlation with TFP growth (Griffith et al. 2004). Kneller and Stevens (2002) studied nine manufacturing industries in 12 OECD countries over 1973 to 1992, and examined the differential effect of human capital and R&D. This study revealed that, although both explanatory variables were statistically significant, only human capital influenced TE across the industries. A subsequent study confirmed this finding (Kneller 2005).

Guellec and van Pottelsberghe de la Potterie (2001) also investigated the long-run relationship between R&D and TFP growth at the aggregate level of the economy for OECD countries between 1980 to 1998. The R&D variable comprised domestic research, public research and business research undertaken by other countries. The study found that domestic research and foreign research created new products and production processes, whereas public research enhanced the scientific knowledge of the country. All three sources generated TFP growth, yet foreign-sourced R&D was the most effective, followed by domestic business research. This study suggested that, to capture the maximum knowledge flows, the correct framework is necessary.

R&D investment is also imperative in the context of new technology. Several empirical studies examined the effect of R&D investment on TFP growth. Lichtenberg and Siegel (1991) used a sample of 2,000 US firms and revealed that R&D investment positively affected TFP growth. Other studies affirmed the positive nexus between TFP growth and R&D investment. By examining large Taiwanese firms for the period 1994 to 2000, Wang and Tsai (2003) also confirmed the previous findings. The findings of Hall and Mairesse (1995), using data of 197 French firms between the period 1980 and 1987, and Dilling-Hansen et al. (1999) on 226 Danish manufacturing firms for 1993 and 1995 are consistent with Lichtenberg and Siegel (1991). Contrastingly, Ahn (2001) argued that, instead of R&D investment, the usage of advanced technology is more influential in generating TFP growth. In a contemporary study, Kinoshita (2001) explored the electrical machinery and electronics (radio and television) industries in Czech manufacturing firms between 1995 and 1998. This study confirmed that R&D is an imperative condition for productivity spillovers. The inconsistent views in the literature require further investigation, especially from a policy viewpoint.

3.3.2 Trade

Another aspect of R&D is the imitation of the new inventions of others. In this context, the literature claims that trade enhances TFP growth. Coe and Helpman (1995) examined 22 OECD countries' data and established a positive correlation between trade and TFP growth. They further extended their study by examining 77 highly industrialised and developing countries and confirmed this finding (Coe et al. 1997). Similar findings arose in the studies of Connolly (1997) and Keller (1998). Mayer (2001) stated that imports, as a component of trade, affect TFP growth through introducing foreign technology into domestic production. Isaksson (2001) examined data on 73 countries between 1960 and 1994 and stated that trade is a significant driver of knowledge, which in turn increases TFP growth. A strong positive and statistically significant direct effect of trade on productivity growth prevails even after controlling for geographical specifications (Rodrik, Subramanian and Trebbi 2002).

Harrison (1996) studied 51 countries between 1960 and 1987 to examine trade openness and TFP growth. This study included human capital and trade openness, and found both of these explanatory variables were statistically significant. Edward (1997) compared the significance of trade openness on TFP among 93 advanced and developing countries through instituting nine distinctive indices—three indices evaluated the role of trade openness, while six estimated the magnitude of distortion owing to trade policies. The empirical findings advocated the robustness of the instrumental variables, such as the openness indicator, estimation technique, time-spa and functional forms, and concluded that trade openness had a positive association with productivity growth. Another study examined technology spillovers in the US and found a positive yet weak relationship between imports and TFP growth (Keller and Yeaple 2003). Another study found that imported equipment generated productivity growth through international R&D spillovers rather than increasing total imports (Xu and Wang 1999). However, a contrasting view found no import-related effects on productivity growth from examining three developing countries (Kraay, Isoalaga and Tybout 2001).

Miller and Upadhyay (2000) studied 83 countries over the period 1960 to 1989 and found that exports were more crucial than imports in determining TFP growth. Cameron, Proudman and Redding (1999) examined data from the United Kingdom (UK) on the industrial productivity level, and found that trade was a means of technology transfer. A mixed view appears when studying the export–TFP nexus. The notion of the learning effect emerges in this context. One viewpoint is that a positive export–productivity linkage indicates learning effects from exporting. Another view highlights the necessity of firms’ productivity to penetrate export markets, which can be accomplished with technical assistance from overseas (Isaksson 2007). The literature does reveal some evidence of learning from exporting, yet it is subjective and appears as reverse causality.

3.3.3 Technology Diffusion

Rodrik et al. (2001) argued that institutions are more important than trade, and the choice of instruments drives results. Several empirical studies (Islam 1981; Kalirajan and Salim 1997) argued that because of the extreme controls of protective regimes during the 1960s to mid-1980s, manufacturing firms struggled with intense unrealised productive capacity. Chen and Dahlman (2004) highlighted the significance of knowledge creation for TFP growth while controlling for some essential elements omitted in previous studies. Domestic innovation consists of the number of patents, utility patents, scientific and technical journal publications, and royalty payments and receipts. The study covered 80 to 90 countries, including developing countries, between 1960 and 2000, and the results showed that the coefficients for patent and journal publication were consistently significant; however, royalties were seldom statistically significant. Technology transfer in a disembodied form includes royalty fees, licence fees and technical knowhow fees, and impedes technology transfer channelled towards domestic firms, negatively affecting TFP growth. Patent enactment provides innovators with a two-dimensional degree of protection. Forward protection evolves through the profit-sharing norms between new and former inventors, endorsed as a compulsory licensing system (Chu 2009; O'Donoghue and Zweimüller 2004). Moreover, backward protection emerges owing to the exclusive rights, restricting competitors from using the publicised information (Klein 2020; Kultti et al. 2007; Kwon 2012). However, each new innovator is required to pay a licence fee to the existing innovator to hold the patent. Thus, the embedded licensing burden decreases R&D incentives and productivity growth.

The empirical literature has often sought to explain knowledge creation, and studies have endeavoured to explain TFP by knowledge. However, knowledge cannot be measured cardinally. Therefore, R&D and patent data are used as a proxy for knowledge creation. In contrast, while analysing TFP by knowledge, R&D and patent data are introduced as the determinants of TFP growth.

3.3.4 Estimation Methods of Total Factor Productivity

Numerous studies have analysed TFP growth and its drivers with various methodologies, and the estimates vary widely based on these methodologies and the chosen time period. Diewert (1981) categorised the TFP growth literature into four sets: parametric estimation, nonparametric estimation/indices, index numbers and linear programming approaches (Heshmati and Rashidghalam 2016). The parametric estimation approach is formulated on the basis of Solow's residual approach. The Cobb-Douglas production and cost functions are primarily estimated under this estimation method. Numerous studies—such as those by Benhabib and Spiegel (1994, 2005), Barro (1991), Kneller and Stevens

(2006), Miller and Upadhyay (2000) and Vandenbussche et al. (2006)—have endeavoured to study the effect of the specific variables for TFP. However, these studies have not sought to explore the main drivers of TFP growth and its components (Heshmati and Rashidghalam 2016).

Nonparametric indices are the second set used to measure TFP growth. This approach computes the distance function with any method, and subsequently estimates the TFP with the Malmquist productivity (MP) index. Studies by Färe et al. (1994), Koop et al. (1999), Maudos et al. (2000) and Henderson and Russell (2001) used nonparametric indices to estimate the TFP and its determinants, technical change and TE. The third set is the index numbers approach that can be used to measure TFP. The chain-type Fisher formula is used to construct the price index and to use these indexes as the values of the deflators (Ahn and Abt 2003). The advantage of the index number approach is that it is consistent with a flexible aggregator function. Finally, Aigner and Chu (1968) introduced nonparametric methods using linear programming with data from Yugoslavia and decomposed TFP growth into technical change and efficiency change.

One of the pioneer studies in the TFP growth literature by Nishimizu and Page (1982) employed the deterministic frontier production function for the decomposition of TFP growth in two components: technical progress and changes in TE. This approach annotates TP as the movement of frontier production over time and all other productivity change as TE changes, yet this theoretical contribution adds a new paradigm for policy formulation. The empirical findings indicated that the Yugoslavian economy which depended on imported technology, portray a dearth of TP at the frontier. Plausibly, this economy is lagged to acquire and adopt new international standard technology. This analysis identified that a reduction in the rate of TP and deterioration in TE enforced a slower process of economic growth in Yugoslavia, while TE change suppressed TP.

Fare et al. (1994), in their pioneer study, found that, as a result of TP, US productivity was marginally higher than the average TFP. This study examined 17 OECD countries' data to estimate productivity growth with a nonparametric programming approach. Conversely, they also found that Japan achieved the highest productivity growth of the entire sample and efficiency change was the major contributor to that. This empirical research compared two different estimation techniques—the index number approach and the GA approach—and identified the relevance of the deviant results. MPI was pertinent, as it was based on distance function and enabled the capture of the movement along the technical frontier. Thus, this approach is compatible with micro-level samples, as it can decompose TFP into catch-up and technical change.

In another study, Tham (1997) found that a reduction in TFP growth primarily depended on increments in capital intensity, while employing the GA approach, which is equivalent to TP in frontier technique. A similar result of a declining trend of TP emerged in the study of Mahadevan (2001, 2002). Further, Mahadevan (2002) assessed TFP growth for Malaysian manufacturing industries for 1981 to 1996 by applying two different approaches—the SFA and DEA—to make a comparison. Successively, the author demonstrated these approaches reflected conflicting views about the growth trend of TFP, yet uniform views about the influence of TE change and TP. These two drivers of TFP growth declined and increased, respectively, in the deceleration of TFP after 1990. Contrastingly, Jajri et al. (2006) focused on a developing country and investigated the growth pattern of TE, technological change and TFP growth in the Malaysian manufacturing sector. They found that TFP growth increased as a result of growth in TE after estimating survey data from 1985 to 2000 with DEA. Further, they found a rising trend for TP. Kim and Han (2001) decomposed TFP growth into a few micro-components—namely, TP, TE change, AE change and scale effects. The study deployed a Korean manufacturing industries dataset with the stochastic production frontier (SPF) approach for the period 1980 to 1994. Empirical evidence portrayed that the primary source of productivity growth is initially TP; however, eventually changes to TE. Both TP and TE affect TFP growth positively. In contrast, AE played an adverse role in explaining productivity growth.

Salim (2003) empirically compared the productivity growth of the Bangladesh food manufacturing sector by examining pre-reform and post-reform firm-level data. This study used the random coefficient frontier production function approach. Unlike the conventional approach, this approach confers input growth as a residual, hence avoiding adjustment problems of quality heterogeneity in inputs. The empirical result indicated that, to a greater extent, input growth is the real driving force for output growth; however, some sectors projected trivial or even negative rates of estimated productivity growth. Thus, the results slightly varied compared with previous studies on developed and developing countries (Corden 1974; Kelly and Williamson 1974; Nishimizu and Page

1982; Smolny 2000; Yuhn and Kwon 2000). This study decomposed TFP and asserted that TP was crucial for productivity growth across all the selected firms, while capital realisation played an insignificant role in accomplishing high and sustainable productivity growth. However, earlier research by Kim and Kwon (1977) stated that stock of factor inputs and magnitudes of realisation of that input stock played an influential role in productivity growth. In a subsequent study, Salim (2008) empirically examined the different variables accounted for by the realisation rates across firms and over time, using the firm-specific productive capacity realisation indices under the stochastic frontier production function framework.

Suyanto et al. (2012) empirically explored the level and growth effects of FDI spillovers on firm-level productivity in Indonesia. The prominent productivity measures, SPF and MPI, were applied to examine the spillover effect on firm-level productivity in two highly disaggregated manufacturing industries (garments and electronics). The study identified a distinct role of industry-specific attributes in achieving FDI spillovers, as firms in the two selected industries reaped contrasting effects. The empirical analysis identified technological change as a prime factor, followed by positive SE; however, TE change had a negligible effect on productivity growth. Moreover, it was evident from the findings that productivity spillover varied with the characteristics of the industry. Fernandes and Paunov (2012) studied the changes in TFP of Chilean manufacturing firms as a consequence of extensive service FDI inflow. The authors examined an unbalanced panel of 4,913 firms of four-digit ISIC industries during 1992 to 2004. The empirical analysis indicated that service FDI not only nurtured innovation activities in the manufacturing sector, but also set forth an ambience for sluggishly growing firms to become the pioneers of the industry. This study formulated unbiased estimates of TFP with OLS and probit estimation, and the associated endogeneity problem was handled through fixed-effects instrumental variable estimation. Three different methodologies by Levinsohn and Petrin (2003), Olly and Pakes (1996) and Ackerberg et al. (2006) were used. This study negated the existing pursuit of the adverse effect of trade openness and FDI inflow on TFP in less advanced firms of emerging economies. The decomposition of TFP growth was not undertaken in this study. Another study by Paz (2014) also used Olly and Pakes (1996) method on the Brazilian industries data during 1989 to 1998 and identified positive and extensive upstream productivity spillovers.

3.3.5 Patent Reform

An extensive body of literature has evaluated economic growth as a consequence of innovations and explored the effect of patent systems on innovation. A critical evaluation of the empirical literature revealed a controversy based on the work of Romer (1990) and Jones (1995). The debate hinges on the magnitude of dependency of the flow of new knowledge on existing knowledge or acquiring the intensity of ‘intertemporal spillover knowledge’. The extant literature views patents as a valuable measure of knowledge and relevant determinant of innovative output (Griliches 1989, 1990; Hausman et al. 1984; Joutz and Gardner 1996; Kortum 1997). Maskus and McDaniel (1999) investigated the effect of patent systems on technical progress, using increments of TFP as a proxy variable, employing Japanese data spanning 1960 to 1993, and identified that both a utility model and patent applications were influential sources of technical change; however, patent applications had a relatively weaker effect. Their study also revealed that the utility model encouraged information diffusion, whereas patent applications stimulated productivity.

In contrast, Chen and Dalman (2004), in their longitudinal study, examined the significance of knowledge creation on TFP for 80 to 90 developed and developing countries. This research computed domestic innovation with the number of patents, utility patents, net royalty earnings and research publications. The authors stated that TFP growth was consistently influenced by patents and research publications, whereas net royalties had an irregular effect. Abdih and Joutz (2005) focused on the cointegration properties among the flow of new patents, patent stock, R&D activities and TFP. They examined a two-stage, long-run cointegration relationship. First, they developed a production function portraying a positive association between knowledge stock proxies by new patents and existing knowledge proxies by existing patent stock, along with the number of activities. Second, patents affected TFP positively, aligning with the study of Romer (1990).

Qian (2007) used a panel of 92 countries for the period 1978 to 2002 of pharmaceutical companies and efficiently adapted generous control covariates that correlated with countries’ implicit potential and patent enforcement. This study employed a nonparametric matching method and effectively controlled the covariates from the control and treated groups through the additive regression equation technique. The empirical research used two procedures to control the covariates. First, it used the Mahalanobis matching method to classify similar categorical countries. Second, it executed pairwise econometric analysis with fixed-effect regression on matched-country pairs controlled methodically for unobserved country characteristics. The author argued that only economically advanced countries could enhance domestic innovative activities under the stronger patent system and eventually enhance productivity growth.

Moser (2005), in his empirical study, recommended that, because enforcement of strong patent laws instils diversification in innovation, countries without patent enactment should emphasise a small set of industries where patents are insignificant. This investigation considered exhibition data for 12 countries in 1851 and 10 countries in 1876. In a similar study, Chen et al. (2008) asserted, while exploring the effect of patent systems on investment rates, that a higher rate of scientific innovations is inspired through enforcement of stronger patent laws in several Western countries. The authors observed two sets of longitudinal statistical data of major inventions from the US and 14 Western European countries. Aside from the US and UK, all other selected countries portrayed robustness in different specifications of cross-country fixed-effects and/or random-effects models, using Poisson regressions and negative binomial regressions.

In a cross-sectional study of 60 International Monetary Fund listed countries, Lerner (2009) found that the significance of patents on TFP was weaker for those countries with stronger patent protection, as it decelerated knowledge diffusion from innovations throughout the economy. Contrarily, a positive association was revealed among the stronger patent via knowledge spillover on TFP (Kim et al. 2014). Therefore, analytical assessment of the literature indicates that the question of whether patents stimulate innovation and growth has yielded conflicting answers, and the empirical evidence remains inconclusive, which aligns with the inferences of several studies (Arora et al. 2008; Hall 2007; Hu et al. 2007). Guellec and Potterie (2001) assessed the long-run association at the aggregate level among R&D and TFP growth in a dataset of 16 OECD countries. The research demonstrated that all three determinants of R&D—domestic, foreign-sourced and public research—had a substantial yet variable effect on TFP growth. Ulku (2004) found no evidence of perpetual growth, which conforms with the work of

Jones (1995), while investigating the effect of innovation, measured in terms of patent applications, on TFP. The study demonstrated that, although R&D investments can enhance innovation in large OECD countries, smaller OECD countries nurture domestic innovation through knowledge spillover.

Arora et al. (2008) developed a model to explore the causal relationship among firms' R&D efforts and patent decisions, as the authors endorsed that both of these elements are governed by numerous factors. This study computed patent premium as a tangible factor of R&D effort, and applied Cobb-Douglas innovation function on cross-sectional survey data for the US manufacturing sector. The model operated in two stages: first, it estimated the increment to the value of an innovation realised by patenting it, and, second, it examined the effect on R&D of altering that premium. The regression outcome revealed that premium varied with industry and firm size, though the notion that patent protection imparts a positive premium was true for only nominal industries. Consequently, the discussion concluded that patent institution fosters R&D growth and eventually promotes variant productivity growth.

Other studies conducted by Kim et al. (2009) and Crosby (2000) concluded that TFP has a positive association with both domestic and foreign patents. However, prior literature also demonstrates a non-uniform nexus between TFP and different categories of patents, such as utility model, design patent and innovative patent, in different time periods, and acknowledges technological innovations and the enactment of stronger patent policy as determining factors (Cubel 2014; Zhao et al. 2011). Cubel et al. (2014), in their empirical study, examined the association among TFP and innovation-related variables, such as domestic stock of knowledge, imports of knowledge and human capital, for the second half of the twentieth century. This study was an extension of Coe and Helpman's (1995) empirical specification with the inclusion of a new variable of human capital, accumulating longitudinal patent data from several European countries (France, Germany, the UK and Spain) and the US, covering 150 years. A perpetual inventory approach was taken to estimate knowledge stock and substantiate heterogeneous linkages between innovation variables and productivity. The regression results established the magnitude of differences in adaptive capacity for technology and the levels of the endowment of such resources explain the differences in TFP dynamics across countries.

The prevalence of substantial disparity between European countries and the US in innovation-related variables was supported by the estimated coefficients.

Crosby (2000) examined two basic issues: the implication of countries' innovation activity to foster economic growth and the divergent effect of foreign and domestic sourced patents in promoting countries' productivity growth. The author considered patent applications instead of granted patents, and argued that patent applications exhibit actual volumes of inventions in a typical year. Through employing a vector autoregressive (VAR) model for the sample period 1901 to 1997 in Australia, the discussion established a positive association with labour productivity, economic growth and innovation activities. Subsequently, this research found that both domestic sourced patents and total innovations were affected as a result of reduced R&D subsidies. This study measured labour productivity in relation to patent stock and R&D stock, and found that patent stock positively influenced labour productivity (Crepons et al. 1998; Crosby 2000). The effect of output elasticity of knowledge on TFP growth was greater when using patent stock as a proxy variable of knowledge, rather than R&D stock, for US manufacturing sectors (Lach 1995). This study pursued the standard model to contextualise the correlation between productivity growth and R&D by positing knowledge as an additional variable while forming the production function at the industry level. Thus, this paper compared the output-based and input-based knowledge (R&D stock) through patent counts by an 'industry of use' indicator and regressed the rate of growth of productivity on the rate of growth of the patent stock. This regression output justified the efficacy of patent stock by demonstrating that the output elasticity of knowledge hovers around 30%, which was three to four times larger than the estimates obtained using the R&D stock.

Kim et al. (2014), in their empirical study on 213 Korean manufacturing firms in the period 1985 to 2007, estimated the influence of knowledge spillovers on knowledge production and productivity growth. This study employed the technology proximity index developed by Jaffe in 1986 and the number of patents as a proxy variable for knowledge. The regression results depicted a few findings (Jaffe, 1986). First, higher-technology groups acquired higher growth rates of patents and patent spillover, as well as TFP growth. Second, firms accomplished more knowledge through the spillover effect, rather than their own stock of knowledge. Third, the spillover effect was more significant in small firms than large firms. This inference may be interpreted as large firms already possessing a pool of knowledge. Fourth, the spillover effect of knowledge was more effective in the long run. Fifth, knowledge spillover stimulated the increment of TFP holistically; however, it was more beneficial for small firms, since small firms are more dependent on the technology invented by large firms. Finally, the empirical evidence indicated enhanced spillover effects after Korean IPRs were strengthened, indicating that knowledge spillover effects on TFP have a positive correlation with strong IPRs.

In a recent study, Lee and Xuan (2019) examined the effect of technology and innovation management on TFP and the economic growth of China. This study applied the unit root test, cointegration test, fully modified least-squares estimation method, canonical cointegrating regression and dynamic least-squares estimation method for the period 1977 to 2016. The authors compared the TFP growth pattern of OECD countries with China and found that technology and innovation positively influenced TFP growth only in the short run. The patent applications revealed a positive correlation with TFP growth in OECD countries, yet were insignificant in the case of China. Table 3.1 below presents the summary of studies related to patent protection, economic growth and productivity growth in India.

Table 3.1: Summary of Selected Empirical Studies on Patent Protection and Productivity Growth

No	Author(s)	Data	Countries	Coverage	Variables	Method/approaches	Finding
1.	Myszczyszyn (2020)	1872–1913	Germany	All industries	TFP growth	Econometric methods, stationary test using Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests, Johansen cointegration test	No clear relationship between IPRs and economic development.
2.	Lee and Xuan (2019)	1977–2016	China	Manufacturing industry	TFP growth	Unit root test, cointegration test, fully modified least-squares estimation method, canonical cointegrating regression and dynamic least-squares estimation method	Technology and innovation positively influence TFP growth, but only in the short run. Patent applications are positively correlated with TFP growth in OECD countries, yet insignificant in China.
3.	Kim and Park (2018)	1975–2014	Middle-income countries	All industries	TFP growth	Production function approach	In analysing the role of factors influencing TFP growth at different income stages, strengthening innovative activities and building innovative capacities are important in overcoming the challenges that middle-income countries face when transitioning to the high-income group.
4.	Acemoglu et al. (2018)	1975–2009	US	All industries	Productivity index	Simulated method of moments	Patenting and R&D improve firm productivity. Reallocation of skilled labour and resources generates broader industrial and economic gains.
5.	Giovanis and Ozdamar (2015)	1976–2009	US	Manufacturing industry	TFP growth	GMM	Patents have positive effects on TFP, during both economic recessions and periods of economic growth. During recessions, the effect of patents

							on TFP is stronger than during growth periods.
6.	Kim et al. (2014)	1985–2007	Korea	Manufacturing industry (213 firms)	TFP growth	Econometric approach	Significant spillover effect on knowledge production and productivity, and small firms acquire larger spillover effect than do large firms.
7.	Cubel (2014)	1950–2000	US and several European countries	All industries	TFP growth	Econometric approach	Imports of knowledge, domestic knowledge stocks, patent stocks and human capital are significant in TFP growth.
8.	Hu and Png (2013)	1981–2000	72 countries	Manufacturing industry	TFP growth	Econometric approach	Effect of stronger effective patent rights on TFP is economically significant. Effect of patent rights on TFP is stronger in developed countries than in developing countries.
9.	Hasan and Tucci (2010)	1980–2003	58 countries	All industries	Economic growth	Econometric approach, OLS method	Panel regression analysis reveals that countries with higher levels of patenting activity have higher growth rates.
10.	Crespi et al. (2008)	1991–2000	UK	Manufacturing industry	TFP growth	Econometric approach	Patents are statistically significant sources of information flows for patenting and eventually TFP growth.
11.	Qian (2007)	1978–2002	92 countries	Pharmaceutical industry	TFP growth, economic growth	Nonparametric matching approach	Economically advanced countries can enhance domestic innovative activities under stronger patent systems and eventually enhance productivity growth.
12.	Abdih and Joutz (2005)	1948–1997	US	All industries	TFP growth	Cointegration techniques	Positive association between patent stock and knowledge diffusion. Patent stocks triggers TFP growth.

13.	Chen and Dahlman (2004)	1960–2000	Developed and developing countries	Manufacturing industry	TFP growth	Knowledge assessment methodology	TFP growth is consistently influenced by patent stocks. Net royalties have an irregular effect on TFP growth.
14.	Crosby (2000)	1901–1997	Australia	Manufacturing industry	Labour productivity	VAR	Increases in patenting activity lead to increases in both labour productivity and economic growth.
15.	Lach (1995)	1958–1983	US	Manufacturing industry	TFP growth	Econometric approach	Effect of knowledge as patent stock to productivity change is three to four times larger than knowledge measured by R&D expenditures.

3.3.6 Indian Studies on Total Factor Productivity

As with the global literature, numerous empirical studies have examined TFP and its determinants at the country level and state level in India. Over the last few decades, the post-reform productivity growth of the Indian manufacturing sector remains controversial. Numerous studies have assessed the productivity performance of the Indian manufacturing sector during the pre-reform and post-reform periods; however, empirical evidence remains inconclusive.

3.3.6.1 Trade Reform

One of the substantial studies in the field of TFP during the post-reform period by Ahluwalia (1991) measured TFP growth by exploiting the pooled cross-section and time-series data captured from the Annual Survey of Industries (ASI) for the Indian manufacturing sector. The estimation used the translog production function for the periods 1964/1965 to 1985/1986, and concluded that TFP increased remarkably by 3.4% per annum, and the economic liberalisation policies of the 1980s significantly contributed to this observed 'turnaround' of productivity growth. Banga et al. (2004) explored whether the productivity and output growth of the Indian manufacturing sector was stimulated because of the operation of services. The multilateral TFP index with and without services was computed through four inputs of the KLEMS model (capital, labour, energy, material and services) involving a sample of 148 three-digit industries. The result attributed services and eventually trade reforms for the drastic increase in output and productivity growth during the post-reform era.

In contrast, based on an analysis of productivity growth for various industry groups during the pre-reform and post-reform period, Srivastava (2000) found mixed results. Most industries experienced a downturn in TFP growth in the 1990s, in comparison with the 1980s, whereas only a handful of industries demonstrated little productivity growth. He identified the robustness of a gestation lag that arose from the surge of investment activities during economic reforms in the 1990s to explain this deceleration in productivity growth. In a similar study, Goldar and Kumari (2003) validated this sluggish productivity growth while comparing TFP growth for Indian manufacturing and major industry groups for the pre-trade and post-trade reform years. They revealed a substantial influence of augmented capacity utilisation on the deterioration of TFP; however, the rate of TFP growth persisted at the same level even after the reform.

The studies by Krishna and Mitra (1998) and Balakrishnan et al. (2000) examined how economic reforms affect industrial productivity. Both studies applied almost the same econometric techniques on the same firm-level sample, yet attained paradoxical outcomes. Krishna and Mitra (1998) found a positive association among economic reforms and industrial productivity by using the production function methods developed by Harrison (1994). This econometric methodology is the extended version of the methodology of Hall (1988) and Domowitz et al. (1988). In contrast, Balakrishnan et al. (2000) used a similar methodology and found a negative or no influence of economic reforms on firm-level productivity growth. They considered 2,300 Indian manufacturing firms who underwent explicit tariff reduction for 1988/1989 to 1997/1998. The authors justified their analysis by hypothesising trade liberalisation as a macroeconomic concept, whereas the notion of productivity growth is built on microeconomic principles. Both studies differentiated the pre-reform and post-reform periods through a reform dummy variable, instead of a coherent trade liberalisation variable, which may have contributed to this difference.

Misra (2006) examined the influence of economic reforms on industrial structure and productivity in India. They argued that economic policies followed under the reform were liable for the dismal performance of the Indian manufacturing sector, based on ASI data for two- and three-digit industries. In line with the previous study, Manjappa et al. (2008) constructed MPI on panel data for the period 1994 to 2004 to estimate TFP growth and its components for 10 selected manufacturing industries. This study categorised its selected industries as labour-intensive (five in each segment) and capital-intensive segments, and found that TFP growth increased moderately in the capital-intensive manufacturing sector, yet productivity regress prevailed in its labour-intensive industries for the survey period. Srivastava (1996) compared firm-level productivity for the pre-reform (1980/1981 to 1984/1985) and post-reform (1985–1986 to 1989–1990) period for 1,941 public limited manufacturing firms in India, employing a GA approach and parametric methodology. The study attributed the growth of the Indian economy to the growth of capital, and found a negligible or even negative effect of productivity growth on overall economic growth in India. Mitra et al. (2014) argued that, despite one of the primary objectives of trade liberalisation being productivity growth in the manufacturing sector, the Indian manufacturing sector experienced a declining trend in productivity growth. The authors stated that, instead of TP, firms' resource optimisation and the aid of infrastructure development probably reinforce productivity growth.

Similar research conducted by Ray (2012) also decomposed TFP into TE change and technological change through MPI for the period 1979/1980 to 2006/2007 for paper industries in India. The author also measured the capacity utilisation adjusted TFP growth by regressing the log-difference of the estimated productivity growth on the log-difference of capacity utilisation rate, and argued that the average annual growth rate reduced while incorporating capital utilisation effects. Thus, this study found an adverse effect of liberalisation on TFP growth, even with technological regress and stagnant TE. In contrast, Pattanayak et al. (2001) argued that opening up the economy for international trade inspired TFP growth, upon examining 70 three-digit organised manufacturing industries during the period 1980/1981 to 1996/1997. This study applied a 'two deflators' GA approach instituted by Harberger (1991, 1998) and found divergent estimates of TFP growth for the study period. Joshi and Singh (2010) employed a nonparametric DEA-based MPI approach for selected garment industries of India and decomposed the TFP into the micro-components of TE change and technological change. Location, scale- size and type of garments were also identified as the determining factors for productivity growth.

Pradhan and Barik (1999) examined the robustness of managerial problems in explaining TFP growth for Indian manufacturing industries. Formulation of the translog cost function enabled the study to be unique to previous literature, as it contemplated simultaneous changes in technical and scale efficiencies. The empirical findings interpreted the interaction effects of the technical and scale efficiencies, as well as trends while analysing TFP growth for the period 1963 to 1993 in the Indian manufacturing sector and eight selected industries. However, the regression output differed when incorporating the unregistered sector in the input – output model, capacity utilisation rate and/or price index, other than wholesale price.

Goldar et al. (2003) measured the consequences of import liberalisation on productivity growth of the manufacturing sector, based on a sample of 70 three-digit organised manufacturing industries during the period 1980/1981 to 1997/1998, using multiple regression analysis. The study recorded that output growth, agricultural growth, real effective exchange rate and non-tariff barriers collectively triggered TFP growth; however, investment rate and effective rate of protection (ERP) affected growth negatively. Further, this research highlighted that, although lowering ERP for industries favourably affected productivity growth, underuse of industrial capacity led to sluggish TFP growth. Contrastingly, Tapalova and Khandelwal (2011) considered 116 industries with 4,100 two-digit manufacturing companies to estimate firm-level productivity growth after trade liberalisation during 1989 to 1996. This study used three variant approaches: (i) formulating Hicks-neutral TFP by taking the differences between actual and predicted output, (ii) measuring the estimated output by Cobb-Douglas production function and (iii) testing the coefficient of that production function through Levinsohn-Petrin method. Input tariff, output tariff and ERP were considered as trade liberalisation variables. Although the reduction in both input and output tariffs led to higher productivity levels, the effect of input tariffs was larger than that of output tariffs across all specifications. Further, the study expressed that TFP increased negligibly with a significant reduction of ERP. Kambhapati (2003) focused on changes in TE in cotton textile industries after implementing economic reform with SFA under a translog production function framework for the period 1986 to 1994. The author identified that manufacturing efficiency was influenced by several determining factors: import intensity, export intensity, age and location of firm, and capital–labour ratio. This research presented another important implication—that the dispersion in efficiency level among the firms reduced significantly in the post-reform phase.

Another earlier study Ramaswamy (1994) applied several approaches—such as the traditional Cobb-Douglas (CD) production function, linear programming (LP), deterministic frontiers and SFA—to calculate the average efficiency in the machine tool, agriculture machinery, plastic product and motor vehicle manufacturing industries in India. The results indicated that the estimated values of average efficiency levels of firms were 0.432 in the machine tools industry when applying the CD production function and LP methods, and 0.349, 0.608 and 0.638 in the agriculture machinery, plastic product and motor vehicle industries, respectively, with the deterministic frontiers approach. The application of SFA demonstrated a marginally higher value of the efficiency estimates for all manufacturing industries. Hence, the study concluded the significance of the choice of estimation technique, as the magnitudes of efficiency variable was not synonymous across the different methodologies for the same period.

A comprehensive survey of the Indian TFP growth literature reveals that a number of studies have examined productivity growth in the context of economic reform, yet the findings provide mixed views regarding the methodologies and industrial attributes. In this context, only a handful of studies have examined the contribution of patent reforms to the productivity growth of India. Diverse empirical analyses demonstrate that, although post-reform estimates of TFP growth do outstrip the pre-reform estimates at the national level in India, segregation of the analysis to the state level is not consistent across the states.

Research by Ray (1997) used DEA-based MPI to estimate the productivity of the manufacturing sector of India at the state level by examining sample data from 1969 to 1984. Through decomposition of TFP into technical change, TE change and SE change, the empirical results depicted that the poor performance of productivity at the state level was primarily caused by technical regress. The subsequent empirical results advocated that persistence of industrial disputes along with the predominance of non-production workers impeded TFP; however, a higher capital–output ratio accompanied by greater urbanisation would probably stimulate productivity growth.

Trivedi (2004) studied the influence of inter-state differences on productivity growth, especially employment and output trend, for the organised manufacturing sectors, covering 10 major states of India for the periods 1980/1981 to 2000/2001. The regression results indicated that both TFP growth and economic growth were influenced by inter-state differences, which was empirically supported by the fact that the Bihar and West Bengal states were diverging away from the average productivity level. Another empirical study by Kumar (2004) adopted nonparametric LP methods to estimate TFP growth in the manufacturing sector, capturing sample data of 15 major states between almost the same periods—1982/1983 to 2000/2001. The empirical results indicated the prevalence of regional differences; however, the extent of variations declined in the post-reform era, and supported the convergence in TFP growth among the Indian states.

Mitra (1999) assessed the time-varying TE and TFP growth for 17 two-digit industries by applying Cornwell et al.'s (1990) techniques. Unlike standard methodologies, this technique is not based on the assumptions of perfect competition and CRS. Several states generally constituted with an organised industrial sector experienced positive TFP growth during 1976/1977 and 1992/1993, from a phase of ‘no growth’, ‘sluggish growth’ or ‘negative growth’; however, at the aggregate level until 1976/1977 and 1984/1985, they barely achieved any TFP growth. The author stated that the acquisition of technological capabilities and infrastructural development was attributable to such variances. Deb and Ray (2014) also compared the TFP growth of Indian manufacturing firms during the pre-reform and post-reform period using input–output data from the ASI for a longitudinal sample of 1970/1971 to 2007/2008. This study computed a biennial Malmquist index of TFP, applying the DEA technique for different states. The finding showed TFP growth during the post-reform period in most states of India. At the country level, the TFP growth rate in manufacturing was higher during the post-reform period. In addition, this study recognised TP as the main driver of TFP growth.

Hitherto, numerous studies have measured the productivity performance of Indian industry both at aggregate and disaggregate level (Ahulwalia 1991; Goldar 1986; Manjappa and Majesha 2008; Misra 2006; Unel 2003), while few studies have analysed the inter-state variations with respect to productivity performance (Veeramani and Goldar 2005; Kumar 2004; Ray 1997, 2002; Trivedi 2004). Largely, the analyses at the aggregate or firm-level were anchored in a GA framework. Nevertheless, the review of the literature also indicates a paucity of studies exploring different dimensions of TFP and its components and allied issues at the regional and disaggregate levels.

3.3.6.2 Research and Development and Patents

Critical evaluation of the literature reveals only a handful of studies exploring the linkage between stronger patent laws as a conduit of R&D and productivity or economic growth, especially for developing countries. Moreover, the empirical evidence is ambiguous when investigating the influence of R&D on firms’ productivity in developing countries, such as India, with relatively low investment in technology and low adaptability. Contemporary research focused on developing countries, manifest that the process of knowledge-generating triggers productivity growth is quite perplexing. No strong association has been found between the effects of R&D investment and firms’ productivity performance (Basant et al. 1996; Raut 1995; Sharma 2011). Contrastingly, R&D intensity, measured as the ratio of in-house R&D expenditure to total sales, positively affects firms' productivity performance (Mitra et al. 2014). In an extensive study, Raut (1995) estimated the magnitude of productivity growth influenced by several factors—in-house R&D capital, industry-wide external capital, physical capital and labour hours—using selected private manufacturing firms in India. This research used panel data covering the period 1976 to 1986 to estimate an extended CD production function. This study empirically demonstrated a heterogeneous trend, although the majority of firms benefitted significantly from aggregate industry-level spillover R&D capital.

Basant et al. (1996) estimated the effect of productivity as a consequence of a firm's own R&D expenditure, technology purchase expenditure, and foreign and domestic R&D spillovers, using panel data for Indian manufacturing firms for 1974/1975 to 1981/1982 and R&D statistics from nine developed countries. A diverse view obtains from the discussion regarding technology purchases and firm's own R&D. The estimates of private returns on technology purchases were relatively higher and statically significant in comparison with private returns on firms' own R&D expenditures. Through implementing an extended CD approach, this study established the existence of both international and domestic spillover effects in the Indian manufacturing sector. In this context, another paper examined the association between R&D activities and firms' performance, emphasising the Indian pharmaceutical industry, by examining data of the post-reform period (1994 to 2006). This empirical analysis was based on a two-stage model: first, it compared the relative productivity trend of R&D in respect of non-R&D and successively designs two conventional notions like GA approach and production function. The empirical results indicated that R&D firms had leverage over non-R&D firms. Consequently, the GA model indicated that R&D intensity instilled productivity growth and local firms functional in the industry were less susceptible to R&D intensity. This study found fluctuating output elasticity through the production function approach (Sharma 2011). It was evident that, although India predominantly entrusts technology transfer, instead of domestic R&D, in-house R&D is crucial to attaining technology frontiers and sustainable productivity growth (Mitra et al. 2014).

In this context, a few comprehensive empirical studies have explored the effect of technology transfer through licensing across Indian manufacturing firms, and found no correlation among them (Basant et al. 1996; Branstetter et al. 2006). Conversely, another study examined the intensity of technology transfer as a proxy variable, defined as the ratio of expenditure on royalties for technology to total sales, and reflected a positive effect of technology transfer on industry productivity and efficiency (Mitra et al. 2014). Hasan (2002) studied Indian manufacturing firms for 1976 to 1977 and 1986 to 1987, examining the various embodied and disembodied technology inputs to productivity growth, considering Indian chemical industries. This study found a positive effect of imported new capital goods on productivity. However, the positive effect of investment in disembodied capital on productivity has been found only for foreign origin, while domestic R&D is consistently statistically insignificant. Pannu, Kumar and Farooquie (2010) examined the effect of R&D and innovation on relative efficiency, productivity change and firm performance during 1998 to 2007, using the DEA approach, and found a positive correlation between innovation and patents on productivity. Saranga and Banker (2010) examined a dataset for the period 1994 to 2003 and analysed productivity change and relevant drivers, employing the DEA approach. They found that only a few firms with higher technical and R&D capabilities experienced technical and productivity gains.

By applying SPF to various Indian manufacturing sectors, Kathuria (2000) examined the long-held belief that domestic firms obtain negative spillovers in the existence of foreign firms, yet receive positive spillovers from international technical capital stock. The study classified panel sample sectors into R&D active and non-active subgroups, and found not only knowledge spillovers from foreign firms, but also generous investment in firms' own R&D activities, supported efficiency and potential gain. This study presented an important assertion—that foreign firms do not automatically generate productivity spillovers, and this greatly relies on the adaptive capacity of domestic firms. Another study by Leachman et al. (2005) examined R&D intensity measured by the ratio of expenditure on R&D and sales, as one of the explanatory variables to estimate the level of efficiency for manufacturing industries. This investigation employed a two-stage model on a sample of eight large automobile manufacturing firms, and the results indicated that a strong R&D commitment and capability are essential to reduce time of production and eventually enhance TE.

Empirical studies have analysed the effect of the patent protection regime on the productivity growth of the Indian manufacturing sector by focusing on the pharmaceutical industry. The SFA approach was employed by some studies to estimate the productivity growth of the Indian pharmaceutical sector. Neogi et al. (2012) examined the significant role of the firm's size in productivity growth and found increased TFP growth from the process patent regime. Another study applied the SFA method to establish the relationship between R&D, technology transfer and productivity in pharmaceutical industries during 1994 to 2010 (Sharma 2016). The literature revealed that some studies used the econometric approach to estimate the productivity growth of the Indian pharmaceutical sector. Chakraborty and Ghose (2017) applied time-series econometric analysis to estimate the output growth and related endogenous structural breaks of the Indian pharmaceutical industry. Other research employed the nonparametric DEA approach to analyse TFP growth. Mazumdar and Rajeev (2009) found higher technological innovation and efficiency for vertically integrated firms using the DEA approach with firm-level data of the Indian pharmaceutical industry.

A relatively new study contradicted these findings while examining the productivity growth of the Indian pharmaceutical industry under the new product patent enactment (Pal et al. 2018). This study applied the biennial Malmquist index under a DEA approach for the period 2000 to 2013, and revealed that vertically integrated firms exhibited diminishing productivity growth. Another recent study also employed the Malmquist index in the DEA approach to data on the Indian pharmaceutical industry during the period 2000 to 2015 (Mahajan 2020). This research found a stable or negligible regression in TFP growth in the product patent regime. TE change was accountable for this marginal regression in TFP; however, the increment in technological change stabilised the TFP growth. The extant literature has endeavoured to estimate productivity growth in the context of the product patent regime, mostly emphasising the pharmaceutical industry. Further, a few studies have estimated the effect of R&D intensity on TE using stochastic frontier production function during the patent reform period (Chaudhuri and Das 2006).

This comprehensive review of the literature signifies a dearth of studies on TFP growth, especially after the implementation of the new patent regime complying with the TRIPS agreement. Most studies analysed TFP growth in the context of trade reform. While some studies endeavoured to estimate the effect of the patent regime on TFP growth, they used data from prior to the implementation of the product patent clause. However, studying the effect of the new patent regime on the productivity growth of the Indian manufacturing sector is crucial, as India is obliged to shift the paradigm to product patent from process patent. The new clause of the TRIPS agreement affects the pharmaceutical, biotechnology, electric and electronics, and IT and communication industries. However, extensive studies have focused on the pharmaceutical industries only. Moreover, these studies used different methodologies, with inherent advantages and disadvantages. Thus, by using contemporaneous data, using the pertinent and advanced methodology and analysing all affected industries, this thesis will provide a holistic view to enrich the existing growth literature. Table 3.2 summarises few empirical studies on productivity growth in India.

Table 3.2: Summary of Selected Empirical Studies on Patent and TFP Growth in India

No.	Authors	Period of data	Coverage	Method/approach	Key finding
1.	Dhanora et al. (2021)	2000–2013	Pharmaceutical industry	Levinsohn and Petrin (2003)	Both product and process patent have positive impact on firms' productivity. MNEs are more benefited by innovation activities under new patent regime.
2.	Mishra et al. (2021)	2013–2014	Different sectors of Indian economy (firm-level)	Crépon-Douget, Mairesse (CDM) model	The productivity of firms is not substantially affected by either product or process innovation outputs.
3.	Mahajan (2020)	2000–2015	Pharmaceutical industry	Ray and Desli's (1997) Malmquist productivity index	Negligible effect of product patent regime on productivity. Marginal regression in TFP owing to TE change; however, there is progress in technological change. The coefficient of R&D intensity is negative and insignificant.
4.	Pal et al. (2018)	2000–2013	Pharmaceutical industry	DEA using biennial Malmquist index	An increase in overall TFP growth of the Indian Pharmaceutical Industry after the TRIPS agreement is evident. Efficiency change dominates over technical change.
5.	Kale and Rath (2018)	1980–2014	Indian economy (country level)	ARDL model	Innovation activities, such as patent counts, have positively affected TFP growth. Trade openness indicates a negative relationship with TFP growth.
6.	Das (2017)	2004–2015	IT industry	DEA using Malmquist productivity index	Progress in TFP, yet TE declines. R&D expenditure has positive influence on innovation and TFP growth. Royalty expenditure has a positive effect on TE.
7.	Chakraborty and Ghose (2017)	1983–2008	Pharmaceutical industry (state-wise)	Modern time-series technique of Sen (2003)	Output growth rates vary across the states. Large firms and trade variables enhance the growth of output.
8.	Sharma (2016)	1994–2010	Pharmaceutical industry	GA and production function	GA analysis suggests R&D intensity has negligible effect on firms' TFP growth. Technological spillover is the imperative source of retrieving technology and enhancing productivity.
9.	Mitra (2014)	1994–2008	Manufacturing industries (selected)	System GMM, panel cointegration and fully modified OLS	The effect of the core infrastructure is strong on TFP and TE; however, the effect of Information and Communication Technology appears slightly smaller.

10.	Neogi et al. (2012)	2000–2005	Pharmaceutical industry	SFA in panel data	TFP growth and TE increase with fluctuation. The positive association between firm size and TE and TFP growth.
11.	Pannu, Kumar and Farooquie (2010)	1998–2007	Pharmaceutical industry	DEA and Malmquist productivity index	The positive effect of innovation and patents on productivity.
12.	Saranga and Banker (2010)	1994–2003	Pharmaceutical industry	DEA	Higher technical and R&D capabilities and wider new product portfolios of MNCs contribute to positive technical and productivity changes.

3.4 Empirical Studies on Patent Activity

In studying productivity growth, the literature rarely focuses specifically on patents, yet views patents as a measure of innovation. However, some scholars claim that patents are not an ideal measure of innovation, as patent applications target to isolate the patents from existing knowledge, instead of prospective knowledge dissemination (Leydesdorff, Rotolo and de Nooy 2013). In contrast, potential profits entice venture capitalists and risk capital investors to invest in patenting activities (Santos and Qin 2019). In this context, Mumtaz and Smith (2017) employed the GARCH-BEKK multivariate autoregressive model to evaluate the effect of patent activities on TFP growth in Pakistan. They found that innovations delineated in file patents generated perpetual TFP growth with a simultaneous increase in domestic skilled labour. Acemoglu et al. (2018) examined firm-level US data during the period 1987 to 1997 and established a general equilibrium model. Patent filing and R&D intensity were identified as reliable determinants of productivity spillover. Moreover, this study stated the crucial role of industrial policies in reallocating resources to the best R&D active firms, rather than the incumbent, to accomplish higher TFP growth.

Using the GMM on US data for 1976 to 2009, Giovanis and Ozdamar (2015) found a positive effect of patents on TFP during periods of economic recessions and economic growth. Interestingly, the effect was stronger during recessions, and substantially low during growth periods. The findings of this study were consistent with the study of Maskus and McDaniel (1999), which examined the Japanese patenting system that assisted firms suffering economic difficulties in the post-war period to catch up through permitting them to file for multiple patents. Another study in this arena stated that incentives are not the same for firms in the US patent system, as market competition leads to higher incentives for firms (Correa and Ornaghi 2014). The authors found an association between patents and productivity growth, while contemplating patents as a measure of innovation. Christian (2008) examined the effect of R&D investment and patents on labour productivity for manufacturing industries in OECD countries, and found that both explanatory variables positively affected productivity. Employing the system GMM model, Romero and Britto (2015) revealed a similar result. In pioneering research on patent literature, patents were extensively recognised as a measure of innovation.

Robertson and Patel (2007) stated that, although the benefits of receiving patents is unclear for firms but patents demonstrate firms' competence for improvement.

As discussed in Section 3.2, the productivity growth from patent protection should be delineated extensively, since it evolves not only from new technology also from new knowledge. The comprehensive knowledge comprises new technology, perceptive managerial skills, insight of scale of production, and perception of input–output allocation that can generate TP and enhance TE, SE and mixed efficiency. A detailed discussion of the semiparametric stochastic frontier and decomposition analysis is provided in the following chapters.

3.5 Conclusion

This chapter has reviewed the theoretical and empirical literature on stimulating productivity growth via patent protection. The theoretical literature has highlighted three channels of patents that trigger productivity growth and examined numerous models to evaluate the mechanism of these effects. Interestingly, the empirical literature has demonstrated mixed evidence. Some studies endorse the evidence of positive productivity spillovers, while other studies have found no or even negative productivity growth. The mixed evidence evolves from variations in methodology, time periods, technical factors, model specifications and economic environments. Further, the absence of critical channels, especially regarding the variables of construction, may account for the inconclusive literature.

Scholars have employed numerous approaches in this field. Most empirical studies contribute to the controversy of Romer (1991) i.e., the endogenous growth theory and the study of Jones (1995). Some studies have examined international trade (Maskus et al. 1995) and technology diffusion (Eaton and Kortum 1999) as the crucial channel of patents while evaluating productivity growth. Moreover, substantial TFP growth literature has studied the effect of patent protection for developed or advanced industrialised countries. It is assumed that considerable patent activities are accomplished in developed or OECD countries. Various indicators have been used as proxies for variables. Research focusing on analysing economic growth has used output growth or labour productivity as a proxy for productivity growth. TFP growth can only be computed with data for capital stock available throughout the survey period. Some studies have examined patent protection and productivity growth using general proxy variables, such as R&D expenditure, R&D investment, R&D intensity and patent stock, to describe the environmental variable of R&D. In addition, the environmental variable of trade has been proxied as import cost, export earning, import and export intensity, or trade openness. Finally, use licences, royalties and technical know-how fees have been commonly envisaged as proxy variables for technology diffusion or technology transfer.

The empirical evidence uses different methodologies to compute TFP growth, such as the parametric estimation approach, nonparametric indices approach, index number approach and nonparametric approach with LP. Broadly, the econometric model is employed to analyse the effect of patent protection on productivity growth. The semiparametric approach is a relatively new econometric approach that accommodates the attributes of both parametric and nonparametric approaches. While decomposing TFP growth, empirical research uses different productivity indexes—primarily either the DEA or SFA framework. This thesis ascribes to the endogenous growth theory and envisages innovation (R&D and patent stock), trade and technology diffusion as conduits of the patent institution. Extensive international literature has explored the effect of patent protection regimes in different manufacturing industries; however, most studies focused on only the pharmaceutical sector. Recent research by Mahajan (2020) evaluated the TFP in the product patent regime by using only R&D expenses as the explanatory variable, and computed the Malmquist productivity index.

This comprehensive review of the literature signifies a dearth of studies on TFP growth in India, especially after the implementation of the new patent regime complying with the TRIPS agreement. In this context, this study analysed the relationship between patent protection and TFP growth using the pertinent and advanced methodology and contemporaneous data. The study was performed on selected manufacturing industries. The four-component smooth coefficient stochastic frontier production model proposed by Kumbhakar, Sun and Tveterås (2018) was applied to evaluate the effect of patent protection on TE. Further, the Färe-Primont productivity index proposed by O'Donnell (2012) was adopted to compute and decompose TFP growth. The following chapter presents the analytical framework for the core empirical analysis in Chapters 5, 6 and 7.

Chapter 4: Analytical Framework

4.1 Introduction

The primary objective of this thesis was to investigate the effects of patent protection on firm-level productive efficiency and productivity growth, along with decomposition of TFP growth, and identification of the different determinants of TFP growth from the perspective of India's new patent protection regime. These objectives could be achieved by employing the relevant methodology; hence, this chapter delineates the analytical frameworks used in this thesis.

Prior research has explored the significance of patent protection on productivity growth usually with either parametric or nonparametric approaches. Parametric methods are pertinent when the functional form of the relationship between the predictors and response variable is correctly denoted. While parametric models are relatively easy to estimate and interpret, incorrect specification of the functional form leads to larger bias (Fan and Yao 2003). Contrarily, prior information of the functional form or the assumption of linearity is not an absolute requirement for the nonparametric model. Hence, this approach provides more opportunities to examine data in a more flexible manner. The limitation of the nonparametric approach is the rapidly rising high dimensions variance of the estimates, which is a curse of dimensionality. A semiparametric approach addresses the drawbacks of both parametric and nonparametric models. Semiparametric regression models comprise two distinct components. One part of the predictors captures the predetermined production function, and another part captures the unknown forms of the production function. The semiparametric model is an amalgamation of the parametric and nonparametric models.

To estimate the effect of different policy procedures—such as trade liberalisation (Amiti and Konings 2007; De Loecker 2007; Pavcnik 2002), antidumping protection (Konings 2008) and the magnitude of foreign ownership (Smarzynska Javorcik 2004)—TFP measurement has often been applied. The conventional method of TFP estimation is ordinary least squares (OLS); however, this may generate problems of simultaneity and endogeneity. Numerous studies have proposed various parametric and nonparametric estimators to overcome simultaneity and endogeneity problems; however, these were not accounted for, especially in the case of the production function. To address these limitations, Olley and Pakes (1996) and Levinsohn and Petrin (2003) introduced a semiparametric estimator. Later, several extensions, such as that by De Loecker (2007), were established. A further concern is that, while estimating productivity growth, the previous literature mostly employed a balanced panel; however, this may cause selection bias. Moreover, the productivity of a firm to a certain extent depends on the product decision of the firm (Bernard, Redding and Schott 2005).

The estimation procedures of productivity growth and decomposition of TFP and TE may use either aggregate industry-level or firm-level data. The methodological development that evolved from the literature (Ackerberg et al. 2007), with compliance to availability of firm-level data (Bartelsman and Doms 2000), permits computing TFP at the micro-level. Given that the nature of the R&D and innovation aligned with patent protection is a micro-behaviour, employing firm-level data provides an intrinsic analysis. This thesis is one of the first to employ the four-component semiparametric SPF model developed by Kumbhakar, Sun and Tveterås (2018) to explore the relationships among patent protection and TFP growth, involving an unbalanced panel data framework. This most recent methodology envisages technology parameters as an unknown smooth function of environmental variables, and the random error term comprises four components, rather than the two conventional components. Thus, this approach enables empirical studies to display an elaborate view.

This chapter explains the analytical tools used to evaluate the significance of patent protection for productivity growth, and is organised into eight sections. Following this introduction section, Section 4.2 discusses the concept of efficiency. Section 4.3 demonstrates the SFA for estimating TE for static and dynamic panel data models, while Section 4.4 discusses the four-component semiparametric smooth coefficient model for estimating the effect of patent protection variables on firm-level productive efficiency. Section 4.5 explains the decomposition of TFP growth, while Section 4.6 describes the estimation procedures for computing the effect of the patent protection variables on firm-level productivity growth. Further, Section 4.7 describes the decomposition of TFP growth with the Färe-Primont productivity index, and Section 4.8 concludes.

4.2 Technical Efficiency

Economic efficiency is accomplished when the maximum feasible output is derived through the available resources. This contentment owing to the consumption of goods and services; thus, economic efficiency implies the utmost level of production (Färe and Lovell 1978). TE is imperative for economic efficiency. Battese and Coelli (1992) demonstrated the significance of frontier production functions in estimating firm-level technical efficiencies. This literature commenced with the pioneering work of Farrell (1957), which identified that firms operating below the production frontier are considered inefficient. The ratio of estimated minimum inputs of production to actual inputs of production for a specified output is measured as inefficiency. Economists have applied several approaches to constitute the true production function. The classic approach is the OLS approach with two-sided error (Christensen, Jorgenson and Lau 1973; Diewert and Wales 1988). The estimator obtained through the OLS approach depicts a firm's average production function, yet does not ensure that a firm operates above the frontier observed best practice. Hence, the modified OLS method (Afriat 1972) and corrected OLS method (Greene 2005; Richmond 1974) based on regression techniques emerged. Modified OLS techniques essentially compute an expected value for the inefficiency distribution and consequently lift the production function. Corrected OLS methods enfold the data through adjusting the intercepts. The SFA approach was almost simultaneously proposed by Aigner, Lovell and Schmidt (1977) and Meeusen and van den Broeck (1977). This technique relies on maximum likelihood estimates modifies the economic theory in precision. The contemporary approach of DEA developed by Charnes et al. (1978) and Färe et al. (1985) measures TE based on the Linear Programming model.

Numerous scholars have argued for the redeeming features of the DEA and SFA methods. Akin to the basic nonparametric statistical method, specification of a function and technological restriction are not prerequisites for the DEA approach. However, it overlooks the significance of the exogenous variables and has challenges in performing hypothetical tests (Featherstone and Moss 1994). By comparing DEA and SFA techniques, it was found that DEA is more accurate, yet regression-type models are more stable with estimations (Thanassoulis 1993). Among the parametric statistical methods, SFA first secludes the inefficiency term from the error term (Aigner et al. 1977; Meeusen and van den Broeck 1977). The maximum likelihood (ML) methods estimate the inefficiency error term under the SFA approach, and demand a strict assumption of non-correlation among the input variable (x_i) and the inefficiency term (u_i), as well as a distributional assumption for the two error components, v_i and u_i. Aigner et al. (1977) proposed normal and half-normal distributions for v_i and u_i, respectively, while Meeusen and van den Broeck (1977) purported normal and exponential distribution, respectively. Extensive literature has been found in the SFA model those delve with cross-sectional and panel data. Both primal and dual approaches have been used to compute production, input or output distance functions (Coelli and Perelman 1999).

4.3 Stochastic Production Frontier

The SFA literature permits the removal of the strong distributional assumptions for TE under panel data structure though these assumptions are imperative for cross-sectional studies. Schmidt and Sickles (1984) argued in favour of panel data models, as they provide more definite estimates of TE. Lee (2006) justified that the panel data framework provides an alternative for the distributional assumption of TE, as it uses the repeated observations over time for the same firms.

Panel data versions of the Aigner et al. (1977) model can be written in the general form

$$y_{it} = \exp(x_{it}\beta + v_{it} - u_{it}) \tag{4.1}$$

where y_{it} denotes the production at the t-th observation (t=1,2,…, T) for the i-th firm (i=1,2,…,N); x_{it} is a *(1xk)* vectors of values of inputs of production and other explanatory variables associated with the i-th firm at the t-th observations; β is a $(kx1)$vector of unknown slope parameters to be estimated; v_{it} is statistical noise or random error, assumed to be $iid\ N(0, \sigma_v^2)$ and independently distributed of the TIE term. u_{it} is a non-negative random variable, termed as technical inefficiency (TIE) of production.

The assumption of independent distribution for the random error v_{it} and TIE term u_{it} may be conducive while estimating the unknown parameter but fail to examine the changes in TEs and the latent production technology for it. Thus, it is necessary to categorise the SF model into either time-variant or time-invariant groups.

The elementary restriction can be appointed on the inefficiency effects is,

$$u_{it} = u_i \qquad\qquad i = 1,2, \dots, I; t = 1,2, \dots, T$$

If u_i is assumed to be fixed-parameter, hence fixed-effect model can be estimated in a standard regression framework incorporating dummy variables. Otherwise, u_i can be treated as a random variable and this random effect model can be measured either through the least-square method or the Maximum Likelihood (ML) method. The ML approach gains more repute as it accommodates stronger distributional assumptions on u_i .

Extension of the cross-sectional model to a panel data structure under ML estimation applying SFA initiated by Pitt and Lee (1981). Subsequently, Schmidt and Sickles (1984) emphasise on fixed effect and random effect panel data model on SFA. Later, Kumbhakar (1987) and Battese and Coelli (1988) generalises the distribution that concern TE while reinforcing the model of Pitt and Lee (1981). In this regard, Pitt and Lee (1981) assumed a half-normal distribution whereas Battese and Coelli (1988) considered the more general truncated normal distribution: $u_i \sim iidN^+(\mu, \sigma_u^2)$.

Therefore, the linear version of the time-invariant model can be written as,

$$y_{it} = \alpha_0 + x_{it}\beta + v_{it} - u_i = \alpha_i + x_{it}\beta + v_{it} \tag{4.2}$$

Or

$$y_{it} = \alpha_i + [x_{1t} \;\; x_{2t} \ldots x_{kt}] \begin{bmatrix} \beta_1 \\ \beta_2 \\ \beta_3 \\ \vdots \\ \beta_k \end{bmatrix} + \; v_{it}$$

where y_{it} denotes the production at the t-th observation (t=1,2,…, T) for the i-th firm (i=1,2,…,N); x_{it} is a *(1xk)* vectors of values of inputs of production and other explanatory variables associated with the i-th firm at the t-th observations; β is a $(kx1)$vector of unknown slope parameters to be estimated; v_{it} is statistical noise or random error, $\alpha_i = \alpha_0 - u_i$ is the time-invariant intercept for firm i for all time t.

In contrastingly, implementation of the time-variant model is justifiable as the firm learns from its previous experiences during the production process and the existing efficient firms would continue with the same level of efficiency (Coelli et al. 2005). Two models in a row developed by Kumbhakar (1990) and Battese and Coelli (1993) relax the assumptions of time-invariant TE component under the ML technique framework.

The linear version of the general time-variant SFA model can be written as,

$$y_{it} = \alpha_{0t} + x_{it}\beta + v_{it} - u_{it} = \alpha_{it} + x_{it}\beta + v_{it} \tag{4.3}$$

where α_{0t} , is the common intercept for all firms in time t, $\alpha_{it} = \alpha_{0t} - u_{it}$ is the time-variant intercept for firm i (i=1,2,…,N) for all time t (t=1,2,…, T).

It is almost impossible to compute (NxT) estimates of the intercepts and the unknown parameter β with the panel structure of (NxT). Hence, various scholars attempt to tackle this issue through formulating the basic forms of TE in different way.

The general time-variant TE can be specified as $u_{it} = f(t).u_i$; where, $f(.)$ is a function that determines how TIE varies over time.

Kumbhakar (1990), devises TE as a parametric function of time,

$$f(t) = [1 + \exp(\theta t + \delta t^2)]^{-1} \tag{4.4}$$

Thus, $u_{it} = [1 + \exp(\theta t + \delta t^2)]^{-1}.u_i$

where, θ and δ are two additional unknown parameters to be estimated using ML technique. The function expressed in equation (4.6) lies between zero and one, also can be monotonically non-increasing, non-decreasing, concave or convex depending on the signs and magnitudes of θ and δ (Coelli *et al*., 2005).

Battese & Coelli (1992) provide an SFA model with an alternate function of time-varying TE, under the ML method that can be written as,

$$f(t) = \exp[\eta(t - T)] \tag{4.5}$$

Hence, $u_{it} = \exp[\eta(t - T)]\,.\,u_i$; (4.6)

where, the unknown parameter η to be estimated.

Battese and Coelli (1992) model interpreted time-variant TE as a function of time differential and involves only one unknown parameter. Therefore, this function is definitely less flexible and positive in nature. It holds the properties, $f(T) = 1$ and convex for all values of η. Though whether it is monotonically non-increasing or non-decreasing depends on the sign of η.

Kumbhakar (1990) and Battese and Coelli (1992), both the models assumes that the TE term u_i follows a truncated normal distribution: $u_i \sim iidN^+(\mu, \sigma_u^2)$. The hypotheses about individual coefficients can be tested through a z test or an LR test (Coelli et al. (2005)). The variance of parameters in the likelihood functions are expressed as $\sigma_s^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \frac{\sigma_u^2}{\sigma_s^2} = \frac{\sigma_u^2}{\sigma_v^2+\sigma_u^2}$, where γ denotes the variance of technical inefficiency effects that is bounded between zero and one, while σ_s^2 denotes the variance of stochastic production function (Battese and Coelli (1992)). The drawback of this model mainly confines the assumption of a monotonous production frontier that could be crucial in the case of large time dimensional panel data structure. However, the capability to perform even if the panel data structure is unbalanced, evidently indicating the competency of this model.

Subsequently, Cuesta (2000) and Orea (2002) disentangle the assumption of monotonic pattern in TE over time of Battese and Coelli's (1992) model. Cuesta (2000) specifies a time-varying TE as,

$$u_{it} = \exp[-\eta_i(t - T)] . u_i \tag{4.7}$$

The parameters to be estimated increases largely from one to the number of cross-sections *(i=1,2, …, N)* as this model use η_i instead of η. This substitution demonstrating the typical temporal pattern of TE owning by each individual firm. Hence, the model involves a specific disadvantage in the case of large cross-sectional observation.

Alternatively, Orea (2002) exhorts a time-varying TE that can be depicted as,

$$u_{it} = \exp[-\eta_1 (t - T) - \eta_2 (t - T)^2] . u_i \tag{4.8}$$

Orea (2002), employs two unknown parameters namely, η_1 and η_2 instead of one η in order to disentangle the monotonous temporal distribution of TE across the firms. In order to comprehend the determinants of inefficiency, some subsequent studies examine the inefficiency term as a function of some environmental variables (e.g., Reifschneider and Stevenson (1991), Caudill, Ford and Gropper (1995), Battesse & Coelli (1995), Wang and Schmidt (2002), Kumbhakar and Sun (2013), among others).

Thus, the general form of the SFA model of panel data now transformed as,

$$y_{it} = \alpha_{0t} + x_{it}\beta + v_{it} - u_{it} \text{ and} \tag{4.9}$$

$$u_{it} = z_{it}\delta + w_{it} \tag{4.10}$$

Where, z_{it} is $(1xm)$ vector of explanatory variables affecting TE of production of firms over time and δ is a $mx1$ vector of unknown parameters of TE function and w_{it} is a random variable.

In another way,

$$u_{it} = [z_{it}\ z_{2it} \ldots z_{mit}]\begin{bmatrix}\delta_1 \\ \delta_2 \\ \vdots \\ \delta_m\end{bmatrix} + w_{it}$$

The literature reveals that initial studies applied a two-stage approach to incorporate exogenous variables into productivity performance (Kalirajan 1981; Pitt and Lee 1981). In the first stage, SPF was measured as depicted in the equation for y_{it} and estimated the TE index for each individual firm successively. In the second stage, the estimated TE index was regressed against a set of exogenous variables, as expressed in equation u_{it}, using the standard OLS method. Numerous empirical studies employed this two-stage approach, although it has at least two demerits. First, bias estimates of production frontier can be obtained, as TE may correlate with the production inputs. Second, the assumptions of one-sided TE may lead to inaccuracy problems. Wang and Schmidt (2002) concluded that these two shortfalls can be critical in the Monte-Carlo simulation method. As a consequence, successive researchers recommended a one-stage approach, where TE is defined as a function of a set of firm-specific exogenous variables, like the two-stage model (Battese and Coelli 1995; Heshmati and Kumbhakar 1994; Huang and Liu 1994; Kumbhakar et al. 1991; Reifschneider and Stevenson 1991). The one-stage method uses the ML technique to estimate both parameters of production frontier and efficiency effect concurrently, with a distributional framework for the random errors, v_{it} and u_{it}. The present research sought to adopt the one-step SF model developed by Battese and Coelli (1995), as it is consistent with the panel data structure and possessed excellence in accommodating variable inefficiency with z_{it}.

The inefficiency effects in the frontier model have distributions that vary with z_i, so they are no longer identically distributed. The likelihood function is a generalisation of the likelihood function for the conventional model, as are measures of firm-specific and industry efficiency. The model was generalised to the panel data case by Battese and Coelli (1993, 1995).

Following Battese & Coelli (1995), the stochastic frontier production function for panel data version can be written as,

$y_{it} = \exp(x_{it}\beta + v_{it} - u_{it})$ or

$$y_{it} = f(x_{it};\beta).\exp\,(v_{it} - u_{it}) \tag{4.11}$$

$$u_{it} = z_{it}\delta + w_{it} \tag{4.12}$$

where y_{it} denotes the production at the t-th observation (t=1, 2, …, T) for the i-th firm (i=1,2, …, N)

x_{it} is a *(1xk)* vectors of values of inputs of production and other explanatory variables associated with the i-th firm at the t-th observations; β is a $(kx1)$vector of unknown slope parameters to be estimated; v_{it} is statistical noise or random error, assumed to be $iid\ N(0,\sigma_v^2)$ and independently distributed of the TE term u_{it}.

Thus, $v_{it}{\sim}iid\ N(0,\sigma_v^2)$

And $E(v_{it}u_{it}) = 0$

u_{it} is a non-negative random variable, termed as technical inefficiency (TIE) of production, assumed to be independently distributed in a way that truncated at $(-z_{it}\delta)$ with the normal distribution with mean $z_{it}\delta$ and variance σ_u^2

$u_{it}\ \sim N^+(z_{it}\delta,\sigma_u^2\ )$

and $E(x_{it}u_{it}) = 0$

z_{it} is $(1xm)$ vector of explanatory variables affecting TIE of production of firms over time and δ is a $mx1$ vector of unknown parameters of TIE function to be estimated the random variable, w_{it}, is defined by the truncation of the normal distribution with mean 0 and variance σ^2 in a way that the point of truncation (-$z_{it}\delta$) i.e w_{it} ≥ -$z_{it}\delta$.

$w_{it}{\sim}N^+(0,\sigma_u^2)$, subject to the point of truncation is (-$z_{it}\delta$)

The assumption regarding the random variable w_{it} could be negative if $z_{it}\delta > 0$ that is $w_{it} \geq$ -$z_{it}\delta$ is consistent with u_{it} being non-negative truncation of the $N(z_{it}\delta, \sigma_u^2)$ distribution as depicted in equation $u_{it} \sim N^+(z_{it}\delta, \sigma_u^2$ (Battese & Coelli (1995)).

Following the one-stage properties, this model estimates the parameters of SF production function β and inefficiency effect δ by applying the ML method. Battese & Coelli (1995) replaces the variance of error components σ_v^2 and σ_u^2 with $\sigma_s^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \frac{\sigma_u^2}{\sigma_v^2+\sigma_u^2}$ and obtain the estimated parameters namely, $\hat{\beta}, \hat{\delta}, \widehat{\sigma_s^2}, \hat{\gamma}$ from the partial derivation of the log-likelihood function.

4.4 Four-component Semiparametric Stochastic Production Frontier Model

Empirical studies further extended this parametric model by incorporating the determinants of inefficiency term directly into the production frontier (Li et al. 2002; Sun and Kumbhakar 2013). Qi Li et al. (2013) suggested a useful yet flexible model—the semiparametric smooth coefficient model—to analyse a general regression relationship with varying coefficients. Both parametric and semiparametric models acknowledge the significance environmental factors. Sun and Kumbhakar (2013) also advocated a semiparametric smooth coefficient SPF model, where inputs are assumed to be exogenous, and the technology parameters of a production function are unknown smooth functions of the environmental variables. A prevalent semiparametric specification is a partial linear model (Robinson 1988; Stock 1987), which can be written as:

$$y_i = \alpha(z_i) + x_i'\beta_0 + \epsilon_i \ , \tag{4.13}$$

where $x_i'\beta_0$ is the parametric component and $\alpha(z_i)$ is the nonparametric part of the model (the functional form of $\alpha(.)$ is not specified). Qi Li et al. (2002) envisaged a special case of a semiparametric smooth coefficient model nested in a partially linear model. The model is considered as:

$$y_i = \alpha(z_i) + x_i'\beta(z_i) + \epsilon_i$$

where $\beta(z_i)$ is a vector of unspecified smooth functions of z_i. This special feature enables the capture of firm heterogeneity characteristics, and hence is more flexible than its parametric counterpart. The subsequent literature endeavoured to estimate technical inefficiency through the relation of production function and environmental variables. Zhang et al. (2012) computed the intercept and slope coefficients as the smooth function of environmental variables that devise the technology flexible and in turn cause non-neutral movement of the production function.

Contrarily, Bhaumik, Kumbhakar and Sun (2014) established a model in which only the intercept was a function of the environmental variables and shifted the frontier neutrally. Sun, Kumbhakar and Tveterås (2015) decomposed inefficiency into the firm- and time-specific components and productivity change into inefficiency change, technical change and scale change. Following Cornwell, Schmidt and Sickles's (1990) method the suggested semiparametric stochastic cost frontier model enables to estimate the inefficiency and then decompose it. However, the environmental variables are not the determinants of time-varying inefficiency or transient inefficiency. The study further separated the firm effects from both persistent and transient inefficiency, and concluded that, even though firm effects and persistent inefficiency do not affect productivity directly, omission of these effects may demonstrate biased outcomes.

Recently, Kumbhakar, Sun and Tveterås (2018) further extended their research by proposing a semiparametric smooth coefficient SPF model with some precise assumptions: (i) a meticulous production function framework where inputs are endogenous and (ii) technology parameters that are unknown smooth functions of the environmental variables. This study provides a deeper insight by decomposing the error term into four components. The literature has traditionally split the error term into two major elements—noise variable and inefficiency. Kumbhakar, Sun and Tveterås (2018) decomposed the noise variable further into one time-variant and one time-invariant term, and the inefficiency term constituents of persistent inefficiency (time-invariant) and transient inefficiency (time-variant). The transient inefficiency has been adapted as a function of environmental variables, which enables researchers to compute the estimated smooth coefficients (i.e., input elasticities); marginal effects of the environmental variable on these smooth coefficients; output; transient inefficiency; and persistent, transient and overall TE scores. The current study adopted this methodology, as it provided the opportunity to analyse the error term into further micro-components to compare with prior research, and permitted estimation of the marginal effects of the environmental variable on the smooth coefficients.[17]

4.4.1 The Model

A semiparametric smooth coefficient SPF panel data model written as,

$$y_{it} = \beta_0(z_{it}) + x_{it}'\beta(z_{it}) + \varepsilon_{it}, \tag{4.14}$$

where y is output in log, x are k possibly endogenous inputs in logs, z are environmental variables or exogenous factors and the error term is considered as,

$$\varepsilon_{it} = b_i + v_{it} - (\eta_i + u_{it}), \tag{4.15}$$

where b_i stands for the mean-zero random firm effects, v_{it} represents the mean-zero noise term, $\eta_i \geq 0$ and $u_{it} \geq 0$ are the persistent inefficiency and the transient inefficiency respectively. The specific assumptions are taken as follows,

η_i is mean-independent from the environmental variable z_{it}, thus, mathematically, $E(\eta_i|z_{it}) = E(\eta_i) = \alpha_1$

u_{it} is dependent on the environmental variables z_{it} and can be expressed as $E(u_{it}|z_{it}) = \alpha_2(z_{it})$. If $E(b_i|z_{it}) = 0$ and $E(v_{it}|z_{it}) = 0$, then, distinctly,

$$E(\varepsilon_{it}|z_{it}) = -E(\eta_i|z_{it}) - E(u_{it}|z_{it}) = -\alpha_1 - \alpha_2(z_{it}) \neq 0$$

The non-zero conditional mean problem can be rectified by considering, $E(\cdot\,|z_{it})$ on both sides of (4.14), and the following,

$$E(y_{it}|z_{it}) = \beta_0(z_{it}) + E(x_{it}|z_{it})'\beta(z_{it}) + E(\varepsilon_{it}|z_{it}), \tag{4.16}$$

Subtracting equation (4.16) from equation (4.14) and obtain,

$y_{it} - E(y_{it}|z_{it}) = x_{it}'\beta(z_{it}) - E(x_{it}|z_{it})'\beta(z_{it}) + \varepsilon_{it} - E(\varepsilon_{it}|z_{it})$, that can be expressed as,

[17] One of the examiners highlighted that there might be a lagged correlation between ‘transient and persistent inefficiencies with the longitudinal (1995-2016) data, so this comment is acknowledged and considered in future work.

$$\tilde{y}_{it} = \tilde{x}'_{it}\beta(z_{it}) + \tilde{\varepsilon}_{it} \tag{4.17}$$

where, $\tilde{y}_{it} = y_{it} - E(y_{it}|z_{it})$; $\tilde{x}'_{it}\beta(z_{it}) = x'_{it}\beta(z_{it}) - E(x_{it}|z_{it})'\beta(z_{it})$ and

$\tilde{\varepsilon}_{it} = \varepsilon_{it} - E(\varepsilon_{it}|z_{it})$, Thus,

$$\tilde{\varepsilon}_{it} = \varepsilon_{it} - \{-E(\eta_i|z_{it}) - E(u_{it}|z_{it})\}$$

$$\tilde{\varepsilon}_{it} = \varepsilon_{it} + E(\eta_i|z_{it}) + E(u_{it}|z_{it}) \tag{4.18}$$

$$\tilde{\varepsilon}_{it} = \varepsilon_{it} + \alpha_1 + \alpha_2(z_{it})$$

It is quite likely as Robinson's (1988) transformation. Mathematically, $E(\tilde{\varepsilon}_{it}|z_{it})$ = 0. Then, the Nadaraya-Watson kernel estimator (Nadaraya 1965, Watson 1964) has been applied to estimate $E(y_{it}|z_{it})$ and $E(x_{it}|z_{it})$. Thereon, equation (4.17) can be estimated with the Cai and Li's (2008) smooth coefficient estimation method presuming $E(\tilde{\varepsilon}_{it}|z_{it}) = 0$ but $E(\tilde{\varepsilon}_{it}|\tilde{x}_{it}) = E(\tilde{\varepsilon}_{it}|x_{it}) \neq 0$. This assumption allows equation (4.17) to contain endogenous regressors. The model employed instrumental variables w_{it}, following Cai and Li (2008) estimation method in a manner, where $E(\tilde{\varepsilon}_{it}|W_{it}) = 0$ and

Hence $E(\tilde{\varepsilon}_{it}|W_{it}, z_{it}) = 0$ (4.19)

The conditional moment restriction can be procured by multiplying $Q(W_{it}|z_{it})$,

$$E[Q(W_{it}|z_{it})(\tilde{\varepsilon}_{it}|W_{it}, z_{it})] = 0. \tag{4.20}$$

In order to estimate the smooth coefficients along with marginal effects of z on these coefficients, a local-linear approximation of (4.17) is:

$$y_{it} = \tilde{X}'_{it}\alpha(z) + \tilde{\varepsilon}_{it} \tag{4.21}$$

where,

$$\tilde{X}'_{it} = \begin{pmatrix} \tilde{x}_{it} \\ \tilde{x}_{it} \otimes (z_{it} - z) \end{pmatrix}$$

z_{it} are the training data and z are the evaluation data. This model applies the training data as evaluation data.

$$\alpha(z) = \begin{pmatrix} \beta(z) \\ \nabla\beta(z) \end{pmatrix}$$

where, $\nabla\beta(z) = [\partial\beta_1(\cdot)/\partial z', \cdots, \partial\beta_k(\cdot)/\partial z']'$. The locally weighted sample counterpart of (4.20) based on (4.21) is

$$\sum_i \sum_t Q\,(W_{it}, z_{it}\,)[y_{it} - \tilde{X}_{it}'\alpha(z)]K_h(z_{it} - z) = 0 \tag{4.22}$$

here, $K_h(\cdot)$ is considered as a product kernel function, and h is a bandwidth vector for z.

The smooth coefficients and their gradient estimates can be deduced by multiplying equation (4.22) through $S(z)' = \sum_i \sum_t \tilde{X}_{it}'\,Q(W_{it}, z_{it})'K_h(z_{it} - z)$ as,

$$\hat{\alpha}(z) = [S(z)'S(z)]^{-1}S(z)'T(z) \tag{4.23}$$

here, $S(z) = \sum_i \sum_t Q(W_{it}\,, z_{it})\tilde{X}_{it}'K_h(z_{it} - z)$ and

$$T(z) = \sum_i \sum_t Q(W_{it}\,, z_{it})y_{it}K_h(z_{it} - z)$$

$Q(W_{it}, z_{it}) = \begin{pmatrix} W_{it} \\ W_{it} \otimes (z_{it} - z)/h \end{pmatrix}$ (Cai and Li, 2008)

and h is conscripted through the least square cross validation (LSCV) method.

$$\hat{h} = arg\,\min_h \sum_i \sum_t [y_{it} - \tilde{x}_{it}'\hat{\beta}(z_{it})_{-it}] \tag{4.24}$$

in which $\tilde{x}_{it}'\hat{\beta}(z_{it})_{-it}$ is the leave-one-out estimator of the conditional mean.

Usually, the probable snags that accompanied by a random choice of bandwidth, however this method can desist it (Li and Racine, 2007).

Since then, the slope smooth coefficients in equation (4.17), $\beta(z_{it}\,)$ are estimated, we can then re-write equation (4.14) as,

$$y_{it} - x_{it}'\beta(z_{it}\,) = \beta_0(z_{it}) + \varepsilon_{it},$$

$$R_{it} = \beta_0(z_{it}) + \varepsilon_{it},$$

$$R_{it} = \beta_0(z_{it}) + \tilde{\varepsilon}_{it} - \alpha_1 - \alpha_2(z_{it}),$$

$$R_{it} = \{\beta_0(z_{it}) - \alpha_1 - \alpha_2(z_{it})\} + \tilde{\varepsilon}_{it}$$

$$R_{it} = \beta_0^*(z_{it}) + \tilde{\varepsilon}_{it} \tag{4.25}$$

Now, $\tilde{\varepsilon}_{it}$ can be decomposed into a time-invariant and time-varying component.

Recalling equation (4.18),

$\tilde{\varepsilon}_{it} = \varepsilon_{it} + \alpha_1 + \alpha_2(z_{it})$, Substituting the value of ε_{it} from equation (4.15), $\tilde{\varepsilon}_{it} = b_i + v_{it} - (\eta_i + u_{it}) + \alpha_1 + \alpha_2(z_{it})$

$\tilde{\varepsilon}_{it} = \{b_i - \eta_i + \alpha_1\} + \{v_{it} - u_{it} + \alpha_2(z_{it})\}$

$$\tilde{\varepsilon}_{it} = \chi_{0i} + \chi_{it} \tag{4.26}$$

Thereon, the model replaces the $\tilde{\varepsilon}_{it}$ in (4.26) with the residuals estimated from (4.25), and then estimate (4.25) as either a fixed effects or random effects model without any regressors and obtain the $\hat{\chi}_{0i}$ and $\hat{\chi}_{it}$.

Consequently, the persistent and transient inefficiencies can be estimated and the persistent technical estimates (PTE) is expressed as,

$$\chi_{0i} = b_i - \eta_i + \alpha_1 \tag{4.27}$$

Presuming $b_i \backsim iidN(0, \sigma_b^2)$, $\eta_i \sim iidN^+(0, \sigma_\eta^2)$ and b_i and η_i are independent of each other, the model , χ_{0i} replaces by $\hat{\chi}_{0i}$. The above expression transpires the proposed model as a typical stochastic frontier model with one intercept. The eminent estimation techniques developed by Jondrow, Lovell, Materov and Schmidt's (1982) and Battese and Coelli's (1988) can be employed to estimate the PTE. A standard statistical package is useful for this estimation.

Simultaneously, the transient inefficiency is articulated as,

$$\chi_{it} = v_{it} - u_{it} + \alpha_2(z_{it}) \tag{4.28}$$

In practice, $\hat{\chi}_{it}$ substitutes χ_{it} with the assumption of

$v_{it} \sim iidN(0, \sigma_v^2)$,

$u_{it} \sim iidN^+(0, \sigma_u^2(z_{it}))$,

$\alpha_2(z_{it}) = E(u_{it}|z_{it}) = \sqrt{2/\pi}\,\sigma_u = \sqrt{2/\pi}\exp\,(c_1 + \gamma' z_{it})$, and v_{it} and u_{it} are independent of each other. This model is also basically a stochastic frontier model though with non-linear characteristics. All the parameters cited in equation (4.28) can be computed with the ML function. The log likelihood functions can be expressed as,

$$lnL = Constant - \frac{1}{2}\sum_i \sum_t \ln\left[\sigma_u^2\left(z_{it}\right) + \sigma_v^2\right] + \sum_i \sum_t ln\phi\left(-\frac{e_{it}\lambda_{it}}{\sigma_{it}}\right) - \frac{1}{2}\sum_i \sum_t \frac{e_{it}^2}{\sigma_{it}^2} \quad (4.29)$$

where, $\sigma_u^2(z_{it}) = \exp\left[2(c_1 + \gamma' z_{it})\right],\ e_{it} = \chi_{it} - \sqrt{2/\pi}\,\sigma_u(z_{it}) = v_{it} - u_{it}$,

$\sigma_{it}^2 = \sigma_v^2 + \sigma_u^2(z_{it}) = \sigma_v^2 + \exp\left[2(c_1 + \gamma' z_{it})\right]$

and $\lambda_{it} = \sigma_u(z_{it}) / \sigma_v = \exp\left(c_1 + \gamma' z_{it}\right)/\sigma_v$.

Forthwith, the transient inefficiency scores can be estimated with the aid of Jondrow et al.’s (1982) and Battese and Coelli’s (1988) estimators. Moreover, marginal effects of z_{it} on the inefficiency can be computed through Kumbhakar and Sun’s procedures. Finally, the overall technical inefficiency (OTE) scores are computed by multiplying the PTE and TTE, thus mathematically, OTE = PTE·TTE. The mathematical derivation is presented in Appendix 4.

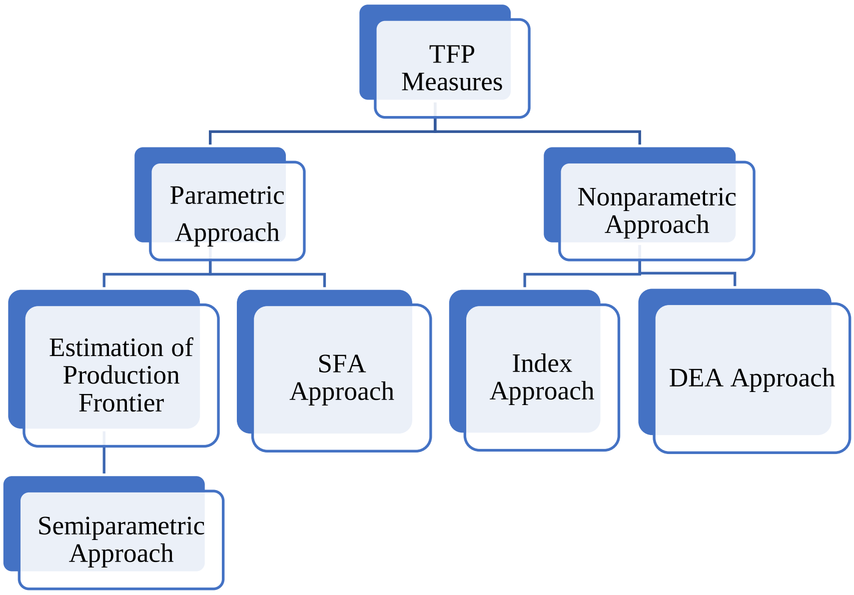
4.5 Decomposition of Total Factor Productivity Growth

An estimate of the association between the factors of production—especially exhausted capital and labour hours—and outputs is defined as productivity. Mathematically, it is measured as the output divided by input. Productivity can be classified into labour productivity and TFP. Labour productivity is regarded as the total output divided by units of labour, while TFP can be defined as the part of output growth that cannot be explained by input growth (Comin 2008). TFP has been viewed as a determinant of economic growth generation since the seminal work of Solow (1957). TFP is often referred to as the Solow residual. Over long periods, economic growth manifests only partially through the growth of inputs to production, such as labour hours or the amount of exhausted capital. Traditionally, TFP growth is denoted as the residual part ascribed to conjoint production factors. TFP has become the choice measure of productivity. Endogenous growth models (Romer 1990) aim to interpret the Solow residual, as observed growth cannot be explained through capital accumulation. In the endogenous growth models, the law of diminishing returns on capital can be offsets through R&D, learning by doing, and public goods etc. The role of institutions is regarded as an imperative element of TFP (Acemoglu and Robinson 2012; North 1989). TFP captures the effects of changes in technology, institutions and other productivity shocks, yet offers little insights, as it is endogenous to the technology. The sustainable growth and structural change of an economy are often measured by TFP growth.

Initially, researchers documented TFP growth as identical to TP. Later, empirical studies demonstrated that TP and capacity realisation are the two principal components. Innovation and new technology diffusion are captured as TP, while capacity realisation denotes the proficiency and aspiration of firms or decision-making units (DMUs) to produce the maximum possible output with the available production technology and inputs (Salim 1999). The capacity realisation is imperative, especially in developing nations with inadequate resources, which have a very high opportunity cost of not realising full production capacity. Hence, policies should be prescribed in such a manner that the country can accomplish the maximum productive capacity, and eventually obtain a level of output that is almost to a country's full potential. Further, it is difficult to reconcile TFP with various models of factor augmenting technological change. It is worthwhile investigating the determinants of TFP growth, as TFP offers an opportunity for welfare maximisation within society. Hence, the policy requires to formulate accordingly to strengthen the performance of TFP. Consequently, technical change, AE and SE are identified as the three primary sources of productivity growth. AE is defined as the proficiency of DMUs to produce at the optimal level with accessible resources and technology (Farell 1957). Economists such as Färe, Grosskopf, Norris and Zhang (1994) and Coelli et al. (2005) have demonstrated an explicit relationship among the productivity analysis and efficiency measurements.

4.5.1 Approaches of Total Factor Productivity Estimation

The literature has proposed three primary approaches for TFP estimation: the index number approach, production function approach and cost function approach (Bauer 1990; Cowing and Stevenson 1981; Denny et al. 1981). The widely used conventional method of estimation is the index number approach. The cost function approach requires cost information; thus, the production function approach is more adaptable than the cost function (Li and Liu 2011). The frontier and non-frontier approaches are the two major approaches of TFP measurement. The non-frontier approaches comprise parametric and nonparametric methods. The parametric methods are categorised as programming and econometric approaches, while nonparametric methods comprise the GA and indexing method. TFP growth is the difference between aggregate output and aggregate input growth. With the existence of economies of scale, TFP can be decomposed into the scale of operations and TP, which reflects a shift in the production function, technical inefficiency and idiosyncratic error. Figure 4.1 depicts the various approaches used in empirical studies to measure TFP growth.



Source: Adapted from Sulimierska's (2014) working paper, compiled based on Beveren (2007); Coelli et al. (2005); Eberhardt and Helmers (2010); Abramovitz (1990); and Daraio and Simar (2008).

Figure 4.1: Measures of TFP Growth

4.5.1.1 Parametric Approaches

In general, the SFA approach and estimation of production frontiers are the two approaches applied to compute the production function under the parametric approach (Abramovitz 1990; Coelli et al. 2005; Eberhart and Helmers 2010; Daraio and Simar 2008). The parametric approach requires the specification of the functional form of the production function. Thus, the necessary condition for expressing a production function, with respect to inputs as the explanatory variable and specifying an algebraic functional form. A production function can be described as $Y_t = f(x_{1t}, x_{2t}, \cdots, x_{nt})$, where *Y* is the output, *x* is the input, *t* is the time period, *I*=1, …, *n*, and *n* is the number of inputs—namely, capital (*K*), labour (*L*), energy (*E*), material inputs (*M*) and so forth. The literature has revealed several mathematical forms of the production function, such as linear, CD, normalised quadratic, constant elasticity of substitution, translog and generalised Leontief (Coelli et al. 2005). In the applied economic literature, the frequently used functional form is a parametric linear model or linear CD function (Abramovitz 1990; Beveran 2007; Danka-Borsiak, 2011; Dowrick, Duc-Tho and Nguyen 1989; Eberhardt and Helmers 2010; Felipe 1997; Gasiorek, Augier and Varela 2005; Smarzynska 2002). The linear CD function can be expressed as $lnY_t = \beta_0 + \sum_{i=1}^{n} \beta_i \, lnx_i$, where β_i is the parameter measuring the elasticities and β_0 is the Hicksian-neutral efficiency. The required condition for estimation of the parametric model is the specification of a finite number of parameters, β. Coelli et al. (2005) enumerated the importance of industry-specific knowledge of technological developments and the transmission bias problem. This problem emerges because omission of the input variables that are not independent affects productivity measures and causes biased and inconsistent coefficient estimates, $\hat{\beta}_i$.

4.5.1.1.1 Stochastic Frontier Approach

The alternative method of economic modelling is denoted as SFA, and was simultaneously introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977). The CD model under the SFA approach can be written as $lnY_j = \beta_0 + \sum_{i=1}^{n} \beta_i \, lnx_i - u_j$, where x_i is the input vector and u_j is the non-negative random variable associated with technical inefficiency. A negative sign of this random variable indicates a downward shift that refers to a firm's inability to attain the optimal output with the available resources, hence moved the production function down. After inclusion of the idiosyncratic error in the SFA model, the transformed equation appears as $lnY_j = \beta_0 + \sum_{i=1}^{n} \beta_i \, lnx_{ij} - u_j + \gamma_j$, where γ_j is the idiosyncratic error. A two-stage approach has been employed, where the inefficiency effects are assumed to be identically distributed while estimating the stochastic frontier production function and predicting the technical inefficiency. The second stage required to designate a regression model for the prior estimated technical inefficiency effects (Kalirajan 1981; Pitt and Lee 1981); however, this negates the assumption of the first stage. Later, the model involved cross-sectional data, introduced by Kumbhakar, Ghosh and McGuckin (1991); Reifschneider and Stevenson (1991); and Huang and Liu (1994), in which the parameters of the stochastic frontier and inefficiency effects could be computed simultaneously, with suitable distributional assumptions. The inclusion of a time component in the SFA model and employed panel data frame has been further provided with the opportunity to estimate time-variant TE (Battese and Coelli 1995).

4.5.1.2 Nonparametric Approaches

The DEA and index numbers approaches are the most popular nonparametric approaches for measuring productivity.

4.5.1.2.1 Data Envelope Analysis Approaches: Linear Programming Procedure

The DEA approach was proposed by Charnes, Cooper and Rhodes (1978). Unlike the SFA approach, the assumption of a specific production function is not a requirement in this approach; hence, it provides more flexibility. The DEA method accommodates an input or output orientation, a constant or variable return scale, price information, AE and the effect of non-discretionary variables. This approach initially identified the decision-making unit (DMU) that obtained the optimal efficiency and thereafter compare the other DMUs with the efficient firm. The one method to solve an LP computation with the additional convexity constraint might not be able to explain the real economic situation, especially for the manufacturing sector (Coelli et al. 2005).

4.5.1.2.2 Indexing Approach

Usually, a TFP index is explained as the ratio between an index of output growth and an index of input growth. Alternatively, the TFP index is a weighted average of changes in output quantities relative to a weighted average of changes in input quantities. Indexing procedures produce results that are easily reproducible. Moreover, the indexing technique is transparent, which ensures data consistency (Lawrence, Diewert and Fallon 2009). This approach focuses on the decomposition of the TFP index and the measurement of changes in TFP. There are several advantages of applying TFP indexes—it is simple, robust and suitable even for a small number of observations. The literature has portrayed several TFP index methods, such as the Divisia index, Törnqvist index, Hicks-Moorsteen index, Malmquist TFP index and Färe-Primont productivity index.

Divisia Index

The Divisia index was formulated by François Divisia (1926) as a theoretical construct with respect to continuous time-series data on prices and quantities of goods exchanged.

It can be expressed with a set of prices $[P_1(t), \dots, P_N(t)]$ and commodities $[Q_1(t), \dots, Q_N(t)]$. Total expenditure is given by:

$$Y(t) = P_1(t)Q_1(t) + \cdots + P_N(t)Q_N(t)$$

Total differentiation of the above equation is expressed as:

$$\frac{\dot{Y}(t)}{Y(t)} = \sum_{i=1}^{N} \frac{P_i(t)Q_i(t)}{Y(t)} \frac{\dot{P}_i(t)}{P_i(t)} + \sum_{i=1}^{N} \frac{P_i(t)Q_i(t)}{Y(t)} \frac{\dot{Q}_i(t)}{Q_i(t)}$$

The first and second summation terms of the right-hand side are the Divisia index of price and quantity, respectively. The Divisia price and quantity indexes are weighted averages of the growth rates of the individual $P_i(t)$ and $Q_i(t)$. The weights in either case are the relative value shares to the total value for each component. If the form of the potential economic relationship among the variables being indexed is known a priori and theoretically related, the value of the index number can be estimated directly from the functional relationship.

Hicks-Moorsteen Index

The well-known Hicks-Moorsteen index is proposed for use as the TFP index (Bjurek 1996), and this index is further illustrated numerically to analyse the TFP (Grifell-Tatjé and Lovell 1999). The Hicks-Moorsteen index mathematically can be written as:

$$TFP = \frac{Growth\ in\ output}{Growth\ in\ input} = \frac{output\ quantity\ index}{input\ quantity\ index}$$

Specifically, it is the ratio between output and input growth rates. Hence, following the Hicks-Moorsteen index, the TFP index can be expressed as $TFP_{jt} = \frac{Y_{jt}}{K_{jt}^{\beta_k} L_{jt}^{\beta_l}}$, where K_j and L_j are the capital and labour of the j^{th} firm, respectively; the time period is denoted as t; and β_k and β_l are the capital cost-share and labour cost share, respectively.

Malmquist Index

The Malmquist index for TFP estimation was developed by Caves, Christensen and Diewert (1982) through estimating a distance function. The distance function accommodates a multi-input and multi-output production technology without any specific behavioural assumption. Basically, with the given technology, the output-oriented and input-oriented Malmquist TFP indexes are formulated to estimate the radial distance of the observed output and input vectors in two different periods (Coelli et al. 2005). The output-oriented Malmquist index TFP estimation for *s* period technology and *t* period technology, respectively, can be expressed mathematically as: $m_0^s(y_s, y_t, x_s, x_t) = \frac{d_0^s(y_t, x_t)}{d_0^s(y_s, x_s)}$ and $m_0^t(y_s, y_t, x_s, x_t) = \frac{d_0^t(y_t, x_t)}{d_0^t(y_s, x_s)}$. Thus, the Malmquist TFP index is demonstrated as the geometric mean of these two plausible multi-factor productivity indexes:

$$m_0(y_s, y_t, x_s, x_t) = [m_0^s(y_s, y_t, x_s, x_t)\ x\ m_0^t(y_s, y_t, x_s, x_t)]^{0.5} = \left[\frac{d_0^t(y_t, x_t)}{d_0^t(y_s, x_s)}\ x\ \frac{d_0^t(y_t, x_t)}{d_0^t(y_s, x_s)}\right]^{0.5}$$

Decomposition of the TFP index into TP and TE change can be captured. The term $\frac{d_0^t(y_t, x_t)}{d_0^s(y_s, x_s)}$ is denoted as efficiency change and the second term $\left[\frac{d_0^s(y_t, x_t)}{d_0^t(y_t, x_t)}\ x\ \frac{d_0^s(y_s, x_s)}{d_0^t(y_s, x_s)}\right]^{0.5}$ explains the technical change. With the existence of the CRS and inverse homotheticity, the Malmquist and Hicks-Moorsteen productivity indexes are alike, yet not identical (Färe, Grosskopf and Margaritis 2008). Further, when the technology follows CRS, the output-oriented and input-oriented Malmquist indexes coincide.

Törnqvist Index

The Theil-Törnqvist index number is a discrete approximation of the Divisia index. It is consistent in aggregation and exemplary for a linear homogeneous trans-logarithmic production function. Numerous literature has advocated the theoretical concept of the Törnqvist index for productivity measurement (Antle and Capalbo 1988; Christensen 1975; Coelli et al. 2005; Diewert 1978, 1980). The output-oriented and input-oriented Törnqvist index can, respectively, be expressed as:

$$ln\left(\frac{Y_t}{Y_{t-1}}\right) = \frac{1}{2}\sum_j \left(R_{j,t} + R_{j,t-1}\right) ln\left(\frac{Y_{j,t}}{Y_{j,t-1}}\right)$$

and:

$$ln\left(\frac{X_t}{X_{t-1}}\right) = \frac{1}{2}\sum_i \left(S_{i,t} + S_{i,t-1}\right) ln\left(\frac{X_{i,t}}{X_{i,t-1}}\right)$$

Hence, the TFP index can be computed as the difference between the output-oriented and input-oriented Törnqvist index:

$$ln\left(\frac{TFP_t}{TFP_{t-1}}\right) = ln\left(\frac{Y_t}{Y_{t-1}}\right) - \; ln\left(\frac{X_t}{X_{t-1}}\right)$$

where output *j* in *t* period and input *i* in *t* period are denoted by $Y_{j,t}$ and $X_{i,t}$ respectively; $R_{j,t}$ is the share of output in the total revenue; and $S_{i,t}$ is the share of input in the total cost.

It is not absolutely necessary to postulate the production function in the index number method, though this approach is essentially an extension of the GA approach. The index number method appears as an eyeball and explains the differences between feasibility and infeasibility while estimating TFP in aggregation. Various index number methods were proposed broadly under two major approaches—namely, the economic and axiomatic approaches (Diewert 1987; Diewert and Lawrence 1999). One of the popular indexes is the Törnqvist index in the econometric approach comprehensively used to compute the TFP. This index considers two major assumptions: (i) the assumptions of the translog production function and (ii) producers are assumed to be either revenue maximisers or cost minimisers (Diewert and Lawrence 1999). In contrast, the features of the different index numbers used to analyse first and then TFP has been computed through applying the most appropriate index number formulation. The Malmquist index used in DEA compares ratios of outputs with inputs (TFP) across units and presumes all DMUs have identical production functions (Fare et al. 1994; Fare, Grosskopf and Margaritis 1996).

4.5.1.3 Production Function Approach: Four Views of Total Factor Productivity

Assuming that aggregate technology can be represented by the following two-input, one-output production function:

$$y_t = \; f\left(x_{K,t}, x_{L,t}, t\right)$$

With the assumption of the linearly homogeneous, increasing production function that is concave with respect to the two input quantities. Moreover, it is assumed that firms' objective is to optimise and that factors are mobile between firms; thus, the usual first-order conditions hold:

$$\frac{\partial f(\cdot)}{\partial x_{K,t}} = \frac{w_{K,t}}{p_t} \qquad \frac{\partial f(\cdot)}{\partial x_{L,t}} = \frac{w_{L,t}}{p_t}$$

Differentiation with respect to time further yields $\frac{\partial f(\cdot)}{\partial t} = \mu_t y_t$, where μ_t is the instantaneous rate of technological change. Applying Euler's theorem to the usual first-order conditions obtains:

$$p_t y_t = w_{K,t} x_{K,t} + w_{L,t} x_{L,t}$$

Following Diewert and Morrison (1986), the TFP index can be written as:

$$T_{t,t-1} = \sqrt{\frac{f(x_{t-1},t)\, f(x_t,t)}{f(x_{t-1},t-1)\, f(x_t, t-1)}}$$

This TFP index indicates the geometric mean of the two corresponding indices, which gives the index a Fisher form; however, to make this index operational, a specific functional form for the production function is required. With the translog production function:

$$lny_t = \alpha_0 + \beta_K lnx_{K,t} + (1-\beta_K) lnx_{L,t} + \frac{1}{2}\emptyset_{KK}\left(lnx_{K,t} - lnx_{L,t}\right)^2 + \beta_t t + \emptyset_{KT}\left(lnx_{K,t} - lnx_{L,t}\right)t + \frac{1}{2}\emptyset_{TT} t^2$$

The translog production function is also flexible with respect to time, as well as the quantities of inputs. Consequently, the inverse demand function can be derived as the form of share through logarithmic differentiation:

$$s_{K,t} = \frac{\partial lnf(\cdot)}{\partial lnx_{L,t}} = \beta_K + \emptyset_{KK}\left(lnx_{K,t} - lnx_{L,t}\right) + \emptyset_{KT} t$$

$$s_{L,t} = \frac{\partial lnf(\cdot)}{\partial lnx_{L,t}} = (1-\beta_K) - \emptyset_{KK}\left(lnx_{K,t} - lnx_{L,t}\right) - \emptyset_{KT} t$$

Now, differentiating with respect to time yields the instantaneous rate of technological change:

$$\frac{\partial lnf(\cdot)}{\partial t} = \mu_t = \beta_T + \emptyset_{KT}\left(lnx_{K,t} - lnx_{L,t}\right) + \emptyset_{TT} t$$

Introducing the translog production function into the Diewert and Morrison index and establish the TFP as:

$$lnT_{t,t-1} = \beta_T + \frac{1}{2}\emptyset_{KT}\left(lnx_{K,t} - lnx_{L,t}\right) + \frac{1}{2}\emptyset_{KT}\left(lnx_{K,t-1} - lnx_{L,t-1}\right) + \frac{1}{2}\emptyset_{TT}(2t-1),$$

TFP can be interpreted as the change in output with the over-time input quantities remaining unchanged. The second interpretation of TFP can be explained as the average of the instantaneous rates of technological change of times $t-1$ and t. Mathematically, it can be written as:

$$lnT_{t,t-1} = \frac{1}{2}(\mu_t + \mu_{t-1})$$

The logarithm of $T_{t,t-1}$ is equal to the average of the instantaneous rates of technological change of time $t-1$ and time t. TFP can be documented as the average rate of technological change between two consecutive periods, times $t-1$ and t. Assuming that $\bar{\mu}_{t,t-1}$ is the average rate of technological change between times t and $t-1$. Following Diewert's (1976) lemma, $\bar{\mu}_{t,t-1} = \frac{\mu_t+\mu_{t-1}}{2}$ and hence $\ln T_{t,t-1} = \bar{\mu}_{t,t-1}$.

TFP can also be construed as the output growth that cannot be explained by input growth. Mathematically:

$$lnY_{t,t-1} = lnY_t - lnY_{t-1} = \beta_K\left(lnx_{K,t} - lnx_{K,t-1}\right) + (1-\beta_K)\left(lnx_{L,t} - lnx_{L,t-1}\right) + \frac{1}{2}\emptyset_{KK}\,[\![\left[\left(lnx_{K,t} - lnx_{L,t}\right)\right]\!]^2 - \left(lnx_{K,t-1} - lnx_{L,t-1}\right)^2\right] + \emptyset_{KT}\left[\left(lnx_{K,t} - lnx_{L,t}\right)t - \left(lnx_{K,t-1} - lnx_{L,t-1}\right)(t-1)\right] + \beta_T + \frac{1}{2}\emptyset_{TT}(2t-1)$$

$$= \beta_K\left(lnx_{K,t} - lnx_{K,t-1}\right) + (1-\beta_K)\left(lnx_{L,t} - lnx_{L,t-1}\right) + \frac{1}{2}\emptyset_{KK}\,[\![\left[\left(lnx_{K,t} - lnx_{L,t}\right)\right]\!]^2 - \left(lnx_{K,t-1} - lnx_{L,t-1}\right)^2\right] + \frac{1}{2}\emptyset_{KT}\left[\left(lnx_{K,t} - lnx_{L,t}\right) - \left(lnx_{K,t-1} - lnx_{L,t-1}\right)\right](2t-1) + \beta_T + \frac{1}{2}\emptyset_{TT}(2t-1)$$

$$= [\beta_K + \frac{1}{2}\emptyset_{KK}\left[\left(lnx_{K,t} - lnx_{K,t-1}\right) + \frac{1}{2}\emptyset_{KT}(2t-1)\right]\left(lnx_{K,t} - lnx_{K,t-1}\right) + \left[(1-\beta_K) - \frac{1}{2}\emptyset_{KK}\left(lnx_{L,t} + lnx_{L,t-1}\right) - \frac{1}{2}\emptyset_{KT}\,(2t-1)\right]\left(lnx_{L,t} - lnx_{L,t-1}\right) + \beta_T + \frac{1}{2}\emptyset_{KT}\left(lnx_{K,t} - lnx_{L,t}\right) + \frac{1}{2}\emptyset_{KT}\left(lnx_{K,t-1} - lnx_{L,t-1}\right) + \frac{1}{2}\emptyset_{TT}(2t-1)$$

Again:

$$\ln X_{t,t-1} = \left[\beta_K + \frac{1}{2}\ \emptyset_{KK}\left(lnx_{K,t} - lnx_{K,t-1}\right) + \frac{1}{2}\emptyset_{KT}\ (2t-1)\right]\left(lnx_{K,t} - lnx_{K,t-1}\right) + \left[(1-\beta_K) - \frac{1}{2}\emptyset_{KK}\left(lnx_{L,t} + lnx_{L,t-1}\right) - \frac{1}{2}\emptyset_{KT}\ (2t-1)\right]\ \left(lnx_{L,t} - lnx_{L,t-1}\right)$$

Computing:

$$\ln Y_{t,t-1} - \ln X_{t,t-1} = \beta_T + \frac{1}{2}\emptyset_{KT}\left(lnx_{K,t} - lnx_{L,t}\right) + \frac{1}{2}\emptyset_{KT}\left(lnx_{K,t-1} - lnx_{L,t-1}\right) + \frac{1}{2}\emptyset_{TT}(2t-1) = \ln T_{t,t-1}$$

This is same as the translog production function. This extensive discussion of the various TFP measures has revealed the merits and demerits of individual estimation procedures. The following Table 4.1 demonstrates the strengths and weaknesses of the aforesaid measures.

Table 4.1: Weaknesses and Strengths of Different TFP Measures

Parameter	Semiparametric	Parametric		Nonparametric	
		Estimation of production frontier	SFA approach	Index number theory	DEA approach
Specification of function form	Required	Required	Required	Required	Not required
Outliers	Not as sensitive	Not as sensitive	Not as sensitive	Sensitive	Inaccurate efficiency assessment
Sample size	A moderate sample size is required	A moderate sample size is required	A large sample size is required	Small sample size sufficient	Small sample size sufficient
Prevalence of high collinearity among inputs	Possible misleading interpretations	Possible misleading interpretations	Possible misleading interpretations	Not evident	Better discrimination
Noise/measurement errors	Not evident	Less sensitive	Strong distributional assumptions required	Sensitive	Highly sensitive
Statistical test	Easy to perform	Easy to perform	Easy to perform	Not possible	Complex

Source: Adapted from Sulimierska's (2014) working paper, compiled based on Coelli et al. (2005) and Kathuria, Raj and Sen (2011).

4.6 Estimation of Total Factor Productivity Growth with Index

This thesis analysed the effect of patent protection reform on productivity growth by employing a two-stage procedure. In the first stage, TFP growth was measured by applying a TFP measurement method developed by O'Donnell (2011). In the second step, the patent reform variables were regressed against the obtained TFP growth from the first stage. Several factors argue in favour of using this index. The Färe-Primont productivity index is conceived as a 'multiplicatively complete' productivity index (O'Donnell 2011), as it can be used to compute pertinent multilateral (many firms) and multi-temporal (many periods) comparisons. The advantage of the Färe-Primont productivity index permits computing the TFP index and its decomposition without data on price. Another advantage is that any restrictive assumptions associated with the structure of technology, competition in input and output markets, or firms' optimising behaviour are required while computing this index. This thesis advances the existing literature, as it measures productivity growth by employing a relatively new approach. As per the author's best knowledge, this is the first application of the Färe-Primont productivity index in the productivity and patent literature in India. This approach is one of the most suitable approaches for the thesis, as price data on inputs and outputs were not available in the dataset used in this study. This study adopted the nonparametric technique of DEA to estimate the Färe-Primont productivity index. The rationale behind this is that the DEA does not require any explicit assumptions regarding the error term and there are no statistical issues associated with estimating multiple-output and multiple-input technologies. Besides, the available computer package (DPIN 3.0) helps estimate this productivity growth with the Färe-Primont productivity index approach.

This section is organised as follows. The following subsection provides a brief discussion of O'Donnell's (2012) approach to the definition and decomposition of TFP. This is followed by the decomposition of efficiency in the second subsection. The third subsection presents the decomposition of technical change. The final subsection discusses the use of panel data analysis to test the effect of patent reform on productivity growth.

4.6.1 O'Donnell's Approach on Total Factor Productivity Definition and Decomposition of Total Factor Productivity

The aggregate quantity framework proposed by O'Donnell (2012) is adopted in this chapter to analyse the decomposition of productivity change. This section illustrates the aforesaid framework concisely.

Let $y_{it} \equiv y_{1it}, \dots y_{kit}$ and $x_{it} \equiv x_{1it}, \dots, x_{kit}$ denote the vectors of output and input quantities for firm i at time t, respectively. The TFP of a firm defines as the ratio between the aggregate output and aggregate input in the aggregate quantity framework following O'Donnell (2012a) and expressed as,

$$TFP_{it} = \frac{y_{it}}{x_{it}} \tag{4.30}$$

where TFP_{it} implies TFP of firm i in period t, $Y_{it} = Y(y_{it})$ and $X_{it} = X(x_{it})$ are aggregate output index and aggregate input index, respectively. $Y(\cdot)$ and $X(\cdot)$ are non-negative, non-decreasing and linearly, homogenous aggregator functions.

The overall productive efficiency of a firm is measured as the ratio of observed TFP to the maximum possible TFP given the available technology. Thus, mathematically can be written as,

$$TFPE_{it} = \frac{TFP_{it}}{TFP_t^*} = \frac{Y_{it}/X_{it}}{Y_t^*/X_t^*} \leq 1 \tag{4.31}$$

where, $TFPE_{it}$ is the TFP efficiency of firm i in period t. TFP_{it} is the TFP of firm i in period t, TFP_t^* is the maximum possible TFP with the given technology. Y_t^* and X_t^* indicate the aggregate output and aggregate input vector at the TFP-maximising point.

Several intricate measures of output-oriented efficiency are procured by following O'Donnell (2012),

Output-oriented TE, $OTE_{it} = \frac{Y_{it}/X_{it}}{\bar{Y}_{it}/X_{it}} = \frac{Y_{it}}{\bar{Y}_{it}} \leq 1$ (4.32)

Output-oriented SE, $OSE_{it} = \frac{\bar{Y}_{it}/X_{it}}{\tilde{Y}_{it}/\tilde{X}_{it}} \leq 1$ (4.33)

Output-oriented mix efficiency, $OME_{it} = \frac{\bar{Y}_{it}/X_{it}}{\hat{Y}_{it}/X_{it}} = \frac{\bar{Y}_{it}}{\hat{Y}_{it}} \leq 1$ (4.34)

Residual output-oriented SE, $ROSE_{it} = \frac{\hat{Y}_{it}/X_{it}}{TFP_t^*} \leq 1$ (4.35)

Residual mix efficiency, $RME_{it} = \frac{\tilde{Y}_{it}/\tilde{X}_{it}}{TFP_t^*} \leq 1$ (4.36)

where, $\bar{Y}_{it}$ is the maximum aggregate output that is technically viable to produce a scalar multiple of y_{it} by using the input x_{it}. $\hat{Y}_{it}$ is the maximum achievable aggregate output by using the input x_{it} to produce any output vector. $\tilde{Y}_{it}$ and $\tilde{X}_{it}$ represent the aggregate output and input quantities procured at the point at which TFP is maximised subject to the constraint that the output and input vectors are scalar multiples of y_{it} and x_{it} respectively. Y_{it}^* and X_{it}^* denote the aggregate output and input quantities obtained at the point of maximum productivity.

The equation (4.32) is depicted the overall TE (OTE), ascribed to Farrell (1957). This dissertation is contemplated the SE (OSE) represented in equation (4.33), following the traditional definition of Balk (2001). O'Donnell (2008) defined the other several finer measures. The output-oriented scale-mix efficiency is proposed by O'Donnell, 2010b as one of the pertinent efficiency measures and mathematically expressed as,

$$OSME_{it} = OSE_{it} \times RME_{it} = OME_{it} \times ROSE_{it} \quad (4.37)$$

Thus, output-oriented scale-mix efficiency is devised as the product of SE and residual mix efficiency or as the devised as product of output-oriented mix efficiency and residual output-oriented SE.

4.6.2 Decomposition of Total Factor Productivity Growth

The TFP of firm i in period t compares with the TFP of firm h in period s under the aggregate quantity framework of O'Donnell (2012), is captured in the productivity index define as,

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \frac{Y_{it}/X_{it}}{Y_{hs}/X_{hs}} = \frac{Y_{hs,it}}{X_{hs,it}} \quad (4.38)$$

where $Y_{hs,it} \equiv \frac{Y_{it}}{Y_{hs}}$ is an output quantity index or a measure of output growth and $X_{hs,it} \equiv \frac{X_{it}}{X_{hs}}$ is an input quantity index or a measure of input growth. Index numbers that can be written as a measure of relative productivity as represented in equation (6.9) are known as multiplicatively complete (O'Donnell 2012). The adoption of different functional forms for the aggregator functions Y(.) and X(.) provide different multiplicatively complete indexes. Usually, any multiplicatively complete TFP index as described in equation (6.9) can be decomposed into several distinctive measures of technical change and efficiency change (O'Donnell, 2012b). In a straight-forward manner equation (6.2) can be expressed as,

$TFP_{it} = TFP_t^* \times TFPE_{it}$, for the firm i (where, i= 1, …, N, t=1, …, T).

Thus, the relative TFP index of firm *i* in period *t* and firm *h* in period *s* is,

$$TFP_{hs,it} = \frac{TFP_t^*}{TFP_s^*} \times \frac{TFPE_{it}}{TFPE_{hs}} \tag{4.39}$$

The first component of the righthand side compares the maximum feasible TFP in period *t* with the maximum feasible TFP in period *s* and indicates as a measure of TP or broadly technical change. Besides, the second component of the righthand side indicates the comparison between the measures of the efficiency change of firm *i* in period *t* and firm *h* in period *s*. Further, the efficiency change component can be decomposed into few inherent components such as various measures of technical, scale-mix efficiency change.

Following O'Donnell (2012a), the TFP decompositions are expressed as,

$$TFP_{it} = TFP_t^* \times (OTE_{it} \times OME_{it} \times ROSE_{it})$$

$$= TFP_t^* \times (OTE_{it} \times OSE_{it} \times RME_{it}) \tag{4.40}$$

Thus, a similar decomposition carries for firm *h* in period *s*. The relative TFP index that compares TFP of firm *i* in period *t* with the TFP of firm *h* in period *s* can be decomposed meticulously as,

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}} \times \frac{OME_{it}}{OME_{hs}} \times \frac{ROSE_{it}}{ROSE_{hs}}\right) \tag{4.41}$$

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}} \times \frac{OSE_{it}}{OSE_{hs}} \times \frac{RME_{it}}{RME_{hs}}\right) \tag{4.42}$$

Based on Equations (4.31), (4.37), (4.41) and (4.42), the similar decomposition of TFP change in Equation (4.39) can be expressed in the following way,

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}}\right)\left(\frac{OSME_{it}}{OSME_{hs}}\right) \tag{4.43}$$

The output-oriented scale-mix efficiency (OSME) captures the increment of TFP owing to the movements from the technically efficient point to the feasible maximum productivity point.

This chapter relies on the way of decompositions as described in Equation (4.39) and (4.43). The Equation (4.43) construes the TFP change into three innate components, firstly, a technical change that measures movements in the production frontier, secondly, a TE change component that measures movements towards or away from the frontier and lastly, a scale-mix efficiency change component that measures movements around the frontier surface to capture the economies of scale and scope (O'Donnell, 2011, 2012). The OSME captures the increment of TFP owing to the movements from the technically efficient point to the feasible maximum productivity point.

This chapter relies on the way of decompositions as described in Equation (4.39) and (4.43). Equation (4.43) construes the TFP change into three innate components, firstly, a technical change that measures movements in the production frontier; secondly, a TE change component that measures movements towards or away from the frontier and lastly, a scale-mix efficiency change component that measures movements around the frontier surface to capture the economies of scale and scope (O'Donnell, 2011, 2012).

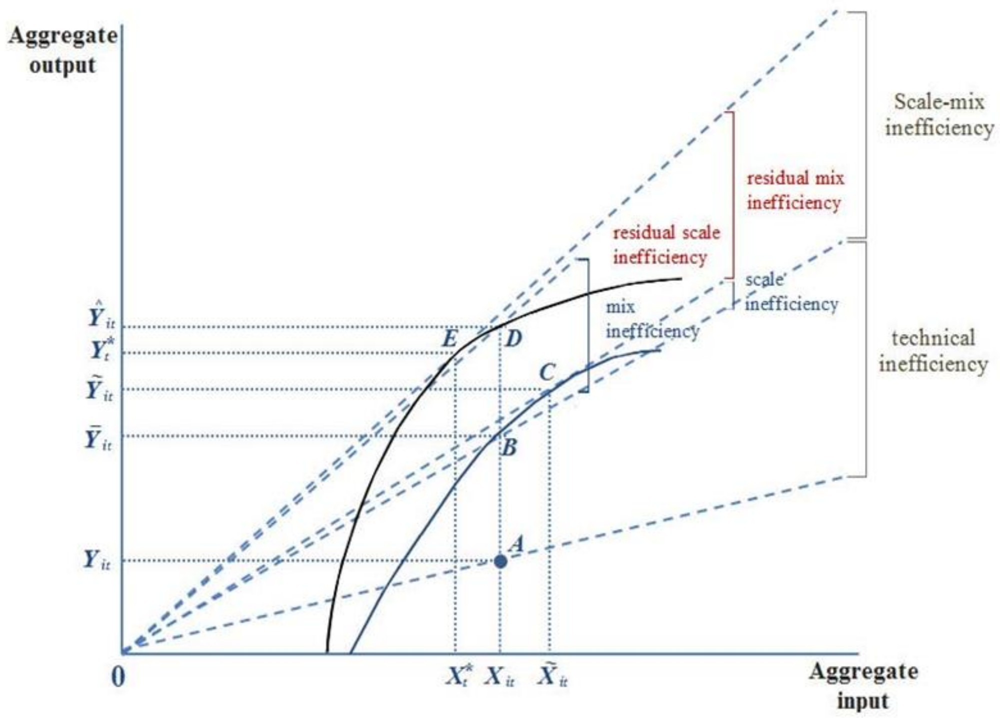


Figure 4.2: Output-oriented Components of TFP Change

4.6.3 Estimation Procedures for Färe-Primont Total Factor Productivity Index Using Data Envelopment Analysis

The index number can estimate the change in a variable or collection of variables over time or dimensions. The DPIN 3.0 computer program developed by O'Donnell (2008) is made this estimation and decomposition of the Färe-Primont productivity index simple and easy. This computer program applies the aggregate-quantity framework for the computation and decomposition of productivity index numbers.

A two-step procedure is used for the estimation and decomposition of productivity. The DEA linear program (LP) is used as the first step to estimate the production technology and levels of productivity and efficiency. The DPIN 3.0 computer program decomposes the productivity, and efficiency changes into intrinsic components are pure technical change, TE change, SE change, and mix efficiency change as the second step. Besides, the DPIN program permits computing the drivers of productivity change despite the prices unavailable and/or the specific degree of competition of the industry. This dissertation uses the DPIN 3.0 computer program to compute the production frontier and decompose the productivity growth.

The first step is to estimate a functional representation of technology, while computing the Färe-Primont TFP index. The primary assumption of DEA is the local linearity of the frontier. O'Donnell (2011) is used the term 'locally linear' is refer to that if firm i in period t is technically efficient, precisely, on the frontier, subsequently, in the neighbourhood that means locally of the point (y_{it}, x_{it}) the frontier takes the form $y_{it}'\alpha = \gamma + x_{it}'\beta$ in linear form. Thus, in a linear structure for firm *i* in period *t*, the (local) output distance function production frontier can be demonstrated as,

$$D_0(x_{it}, y_{it}, t) = (y_{it}'\,\alpha)/(\gamma + x_{it}'\beta) \tag{4.44}$$

where α and β denotes non-negative unknown parameters. Besides, γ denotes the assumptions about returns to scale. More precisely, the technology exhibits local CRS is embedded with the imposition of a restriction of $\gamma = 0$, local non-increasing returns to scale (NIRS) can be exhibited as $\gamma \geq 0$. In a similar way, the local increasing returns to scale (IRS) can be addressed as $\gamma > 0$ and), $\gamma < 0$ to address local decreasing returns to scale (DRS).

The output-oriented DEA problem selects the values of the unknown parameters in equation 4.44, to minimise $OTE_{it}^{-1} = D_0(x_{it}, y_{it}, t)^{-1}$. Therefore, the resultant DEA LP for the Färe-Primont index is (O'Donnell 2011) is expressed as,

$$D_0(x_{it}, y_{it}, t)^{-1} = OTE_{it}^{-1} =$$

$$\min_{\alpha,\gamma,\beta}\{\gamma + x_{it}'\beta : \gamma\iota + X'\beta \geq Y'\alpha;\ y_{it}'\,\alpha = 1; \alpha \geq 0, \beta \geq 0\} \tag{4.45}$$

where Y is a $J\ x\ M_t$ matrix of observed outputs, X is $a\ K\ x\ M_t$ matrix of observed inputs, and ι is an $M_t x$ 1 unit vector, M_t and denotes the number of observations used to estimate the frontier in period *t*. The DPIN 3.0 program uses LP Equation 4.45 to compute the output-oriented productivity index and various measures of output-oriented efficiency change.

The aggregated outputs and inputs of Färe-Primont index are estimated as (O'Donnell 2011),

$$Y_{it} = (y_{it}'\alpha_0)/(\gamma_0 + x_0'\beta_0) \tag{4.46}$$

$$X_{it} = (x_{it}'\eta_0)/(y_1'\phi_0 - \delta_0) \tag{4.47}$$

where estimates of $\alpha_0, \beta_0, \gamma_0, \eta_0$ and δ_0 solve the equations (4.46) and (4.47) and use to estimate the representative frontier. The DPIN 3.0 uses sample mean vectors as representative output and input vectors in LP Equation 4.45. The representative technology in this LP is the technology obtained under the assumption and allows the technology to exhibit VRS.

The second step after estimating the production frontier is to decompose productivity and diverse efficiency changes. The DPIN program 3.0 computes the pure technical change, TE change, SE change, and mix efficiency change by solving the LPs for all of these efficiency components. The residual efficiency, namely, residual SE, residual mix efficiency and scale mix efficiency and productivity measures are also measured by following the DPIN program 3.0 as explained by O'Donnell (2011 , 2012).

4.7 Testing Effect of Patent Reform on Total Factor Productivity Growth

4.7.1 Panel Data Model

The subsequent section, after computing the TFP growth and its drivers using the Färe-Primont index, endeavours to test empirically the hypothesis of the impact of patent protection reform on TFP growth. Patent reform variables are regressed against each component of TFP growth separately using a panel data regression. empirically. The panel data regression model can be written as,

$$\Delta TFP_{jit} = \beta_0 + \beta_1 PAT_{jit} + \varepsilon_{ijt} \tag{4.48}$$

where TFP_{jit} denotes the productivity growth for firm i , j TRIPs periods, at time t. The Färe-Primont productivity index is employed to compute the productivity growth scores. PAT_{jit} denotes the patent variable that comprises the number of patents, R&D intensity, technology transfer and trade-openness variables.

Three econometric panel data models are as follows, common effect (or pooled), fixed-effect (or Least Squares Dummy Variable, LSDV), and random-effect (or Generalised Least Squares, GLS) models used in this dissertation. The Hausman test, and Lagrange Multiplier test is performed to determine the appropriate model. Further, the 'Arellano' method is used to treat the model and establish the corrected version of the selected model.

4.7.2 Impact of TRIPS Agreement on Total Factor Productivity Growth

To assess the differential effect of the implementation of the TRIPS agreement, 2005 on firm-level productivity, this dissertation employs a DiD model. The dummy variable is incorporated for TRIPS. The basic assumption of this model, $E(Y_{1jit} - Y_{0jit}\,\big|_{i,t})$ is a constant, denoted β, where

$$Y_{jit} = \gamma_i + \lambda_t + \beta D_{it} + \varepsilon_{jit} \tag{4.49}$$

This study uses the Regression Difference in Difference methodology to estimate the differential impact of the implementation of TRIPS agreement on the productivity growth as well as the interaction effect of the related firm-specific characteristics and the TRIPS agreement. The transformed Regression DiD model can be exhibit as,

$$Y_{jit} = \alpha + \gamma post\_TRIPS_j + \lambda d_t + \beta(post\_TRIPS_j * d_t) + \varepsilon_{jit} \tag{4.50}$$

The R interface provides a conducive way to coherently estimate the regression formulation of the DiD model and standard error for this thesis.

4.8 Conclusion

This chapter has discussed the empirical approaches employed in this thesis to investigate the effects of patent protection on firm-level productive efficiency and productivity growth. The study objectives were achieved by employing a few approaches. Generally, statistical modelling is based on the relationship between the explained variable, explanatory variables and distribution of random error. Subject to the availability of information, regression models can be classified into parametric, nonparametric and semiparametric regression models. Initially, this thesis applied the semiparametric smooth-coefficient SPF model proposed by Sun and Kumbhakar (2013) and later extended by Kumbhakar, Sun and Tveterås (2018) to evaluate the effect of patent protection on firm-level efficiency. This model presumes a precise production function framework, where inputs are endorsed to be endogenous along with the technology parameters, which are undefined smooth functions of the environmental variables. The conventional literature generally decomposes the idiosyncratic error into statistical noise term and inefficiency term; however, the aforementioned methodology decomposes the statistical noise term and inefficiency term into further micro-components. Thus, this thesis could decompose the noise variable into one time-variant and one time-invariant terms. Moreover, the four-component semiparametric smooth-coefficient model enables decomposition of the inefficiency term into a further two elements—persistent inefficiency (time-invariant) and transient inefficiency (time-variant). Transient inefficiency has been adapted as a function of environmental variables (number of patents, R&D intensity, trade openness and technology transfer variables) that provide the opportunity to compute the estimated smooth coefficients (i.e., input elasticities). In addition, this study computed the marginal effects of the environmental variables on these smooth coefficients, output and transient inefficiency, along with the persistent, transient and overall TE scores.

Next, the Färe-Primont TFP index proposed by O'Donnell (2012) was applied for the decomposition of productivity growth. The literature has proposed several approaches for that, including parametric and nonparametric approaches. The primary interest in a parametric model is to estimate the vector of parameters under a finite-dimensional plane. Contrastingly, the primary interest in a nonparametric model is to estimate the infinite-dimensional vector of parameters, where the set of parameters is the subset of the infinite-dimensional vector. This method decomposes productivity growth into four intrinsic components—technological change, TE change, SE change and mix efficiency change—and thus provides a more holistic analysis while identifying the drivers of TFP changes. In the second step, the patent reform variables are regressed against TFP growth and each component of efficiency to estimate the effect of patent protection on TFP growth using a panel data regression.

Subsequently, the panel data estimation framework was applied in this thesis to examine the effect of implementing the TRIPS agreement on productivity growth. An econometric estimation using either static or dynamic model panel data was employed to address the efficacy of patent reforms on productivity growth. The DiD model was applied to analyse the differential effect of the TRIPS agreement.

The following Chapters 5, 6 and 7 present the reports and estimation results for the empirical application. Chapter 5 evaluates the effect of patent protection on TE of the selected Indian manufacturing industries. Chapter 6 presents the decomposition analysis of TFP growth. Chapter 7 provides the second-stage analysis of the effect of patent reform on the various components of TFP change and the differential effect of the patent reforms.

Chapter 5: Effects of Patent Protection on Firm-level Technical Efficiency

5.1 Introduction

Economic efficiency is accomplished when the maximum feasible output is derived through available resources. The technical efficiency of production is basically reflecting the magnitude in which the actual output of a firm verge upon the maximum output. Thus, economic efficiency entails the utmost level of production (Färe and Lovell 1978). TE is imperative for economic efficiency. Battese and Coelli (1992) demonstrated the significance of frontier production functions in estimating firm-level technical efficiencies. The endogenous growth theory advocates R&D as a key element of enhancing productivity growth, and patents are a universal measure of R&D. Over the last few decades, TFP growth has been acknowledged as a popular measure of productivity growth. Theoretically, patents grant exclusive property rights. The patent system can generate innovation; however, it can also reduce social welfare through the creation of a monopoly, and may inhibit imitation of the patented technologies. Thus, the contributions of the patent system in fostering economic development are ambiguous and demand empirical evidence.

Numerous researchers have investigated patent institutions' optimal length and scope to balance the trade-off between inherent potential deadweight loss and incentives towards innovation by the patent system. One school of thought argues that rigorous competition among firms to acquire patent rights for the same or similar technologies or products is not socially ideal, as it entails social costs, such as duplication of entry costs. Another school of thought claims the non-existence of general market failure for innovations, with a possible explanation being that, as a first mover in the market, a typical firm gains a robust competitive advantage. Further, coupled with uncertainty regarding theoretical concepts, the patent–productivity growth nexus is inconsistent even from the empirical perspective. The contrasting results in previous studies may have arisen from the usage of different methodologies and differences in the effects of patent reform across industries, as explained in Chapter 3. It is interesting to explore the holistic contributions of patent protection in promoting TE and TFP growth, especially for developing countries with low adaptability of technology.

This study substantially contributes to the literature because patent protection may enhance TE and productivity in several developing countries, including India. Earlier studies analysing productivity growth and innovation stated that firm-level analysis imparts a more precise vision, compared with aggregate analysis. It is likely that the attributes of each firm differ across countries and within industries, so they may innovate in a diversified manner, and macro-analyses ignore the heterogeneity in typical firms. In contrast, micro-level analysis enables the research to frame the channels in which the effect of specific firm's knowledge assets on their productivity could be incorporated. Based on previous assertions, two methods were developed in the previous chapter to examine the effects of patent reform on firm-level TE and productivity.

A four-component semiparametric smooth coefficient SPF model proposed by Kumbhakar, Sun and Tveterås (2018) is employed in this chapter to estimate the effects of patent reform on TE in four selected industries—the biotechnology, electrical and electronics, IT and communication, and pharmaceutical industries—as described in Chapter 4. This model is an extension of the semiparametric smooth-coefficient SPF model developed by Sun and Kumbhakar (2013). Section 5.2 explains the empirical model and estimation method, while Section 5.3 exhibits the applied data sources used and construction of the dataset, followed by the definition and measurement of variables in Section 5.4. Section 5.5 presents the results and interpretations, while the concluding Section 5.6 draws inferences.

5.2 Empirical Model and Estimation Method

Recently, Kumbhakar, Sun and Tveterås (2018) proposed a semiparametric smooth-coefficient SPF model with some precise assumptions: (i) a meticulous production function framework where inputs are endogenous and (ii) technology parameters that are unknown smooth functions of the environmental variables. This study provided deeper insight while decomposing the error term into four components. The literature traditionally splits the error term into two major elements: noise variable and inefficiency. Kumbhakar, Sun and Tveterås (2018) decomposed the noise variable further into one time-variant and one time-invariant term, and the inefficiency term comprised persistent inefficiency (time-invariant) and transient inefficiency (time-variant). Transient inefficiency has been considered as a function of environmental variables, which enables researchers to compute the estimated smooth coefficients (i.e., input elasticities); marginal effects of the environmental variable on these smooth coefficients; output; transient inefficiency; and persistent, transient and overall TE scores. The current study adopted this methodology, as it provided the opportunity to analyse the error term in more micro-components, compared with prior research, and permitted estimation of the marginal effects of the environmental variable on the smooth coefficients.

A semiparametric smooth coefficient SPF panel data model written as,

$$y_{it} = \beta_0(z_{it}) + x'_{it}\beta(z_{it}) + \varepsilon_{it}, \tag{5.1}$$

where y is output in log, x are k possibly endogenous inputs in logs, z are environmental variables or exogenous factors and the error term is considered as,

$$\varepsilon_{it} = b_i + v_{it} - (\eta_i + u_{it}), \tag{5.2}$$

where b_i stands for the mean-zero random firm effects, v_{it} represents the mean-zero noise term, $\eta_i \geq 0$ and $u_{it} \geq 0$ are the persistent inefficiency and the transient inefficiency respectively. The specific assumptions are taken as follows,

η_i is mean-independent from the environmental variable z_{it}, thus, mathematically, $E(\eta_i|z_{it}) = E(\eta_i) = \alpha_1$

u_{it} is dependent on the environmental variables z_{it} and can be expressed as $E(u_{it}|z_{it}) = \alpha_2(z_{it})$. If $E(b_i|z_{it}) = 0$ and $E(v_{it}|z_{it}) = 0$, then, distinctly,

$$E(\varepsilon_{it}|z_{it}) = -E(\eta_i|z_{it}) - E(u_{it}|z_{it}) = -\alpha_1 - \alpha_2(z_{it}) \neq 0$$

The non-zero conditional mean problem can be rectified by considering, $E(\cdot\,|z_{it})$ on both sides of (5.1), and the following,

$$E(y_{it}|z_{it}) = \beta_0(z_{it}) + E(x_{it}|z_{it})'\beta(z_{it}) + E(\varepsilon_{it}|z_{it}), \tag{5.3}$$

Subtracting equation (5.3) from equation (5.1) and obtain,

$y_{it} - E(y_{it}|z_{it}) = x'_{it}\beta(z_{it}) - E(x_{it}|z_{it})'\beta(z_{it}) + \varepsilon_{it} - E(\varepsilon_{it}|z_{it})$, that can be expressed as,

$$\tilde{y}_{it} = \tilde{x}'_{it}\beta(z_{it}) + \tilde{\varepsilon}_{it} \tag{5.4}$$

where, $\tilde{y}_{it} = y_{it} - E(y_{it}|z_{it})$; $\tilde{x}'_{it}\beta(z_{it}) = x'_{it}\beta(z_{it}) - E(x_{it}|z_{it})'\beta(z_{it})$ and

$\tilde{\varepsilon}_{it} = \varepsilon_{it} - E(\varepsilon_{it}|z_{it})$

$\tilde{\varepsilon}_{it} = \varepsilon_{it} - \{-E(\eta_i|z_{it}) - E(u_{it}|z_{it})\}$

$$\tilde{\varepsilon}_{it} = \varepsilon_{it} + E(\eta_i|z_{it}) + E(u_{it}|z_{it}) \qquad (5.5)$$

$\tilde{\varepsilon}_{it} = \varepsilon_{it} + \alpha_1 + \alpha_2(z_{it})$

It is quite likely as Robinson's (1988) transformation. Mathematically, $E(\tilde{\varepsilon}_{it}|z_{it})$ = 0. Then, the Nadaraya-Watson kernel estimator (Nadaraya 1965, Watson 1964) has been applied to estimate $E(y_{it}|z_{it})$ and $E(x_{it}|z_{it})$. Thereon, equation (5.4) can be estimated with the Cai and Li's (2008) smooth coefficient estimation method presuming $E(\tilde{\varepsilon}_{it}|z_{it}) = 0$ but $E(\tilde{\varepsilon}_{it}|\tilde{x}_{it}) = E(\tilde{\varepsilon}_{it}|x_{it}) \neq 0$. This assumption allows equation (5.4) to contain endogenous regressors. The model employed instrumental variables w_{it}, following Cai and Li (2008) estimation method in a manner, where

$$E(\tilde{\varepsilon}_{it}|W_{it}) = 0 \text{ and hence } E(\tilde{\varepsilon}_{it}|W_{it}, z_{it}) = 0 \qquad (5.6)$$

The conditional moment restriction can be procured by multiplying $Q(W_{it}|z_{it})$,

$$E[Q(W_{it}|z_{it})(\tilde{\varepsilon}_{it}|W_{it}, z_{it})] = 0 \qquad (5.7)$$

In order to estimate the smooth coefficients along with marginal effects of z on these coefficients, a local-linear approximation of (5.4) is:

$$y_{it} = \tilde{X}'_{it}\alpha(z) + \tilde{\varepsilon}_{it} \qquad (5.8)$$

where,

$$\tilde{X}'_{it} = \begin{pmatrix} \tilde{x}_{it} \\ \tilde{x}_{it} \otimes (z_{it} - z) \end{pmatrix}$$

z_{it} are the training data and z are the evaluation data. This model applies the training data as evaluation data.

$$\alpha(z) = \begin{pmatrix} \beta(z) \\ \nabla\beta(z) \end{pmatrix}$$

where, $\nabla\beta(z) = [\partial\beta_1(\cdot)/\partial z', \cdots, \partial\beta_k(\cdot)/\partial z']'$.The locally weighted sample counterpart of (5.7) based on (5.8) is

$$\sum_i \sum_t Q\,(W_{it}, z_{it})[y_{it} - \tilde{X}_{it}'\alpha(z)]K_h(z_{it} - z) = 0 \qquad (5.9)$$

here, $K_h(\cdot)$ is considered as a product kernel function, and h is a bandwidth vector for z.

The smooth coefficients and their gradient estimates can be deduced by multiplying equation (5.9) through $S(z)' = \sum_i \sum_t \tilde{X}_{it}'\, Q(W_{it}, z_{it})' K_h(z_{it} - z)$ as,

$$\hat{\alpha}(z) = [S(z)'S(z)]^{-1}S(z)'T(z) \qquad (5.10)$$

here, $S(z) = \sum_i \sum_t Q(W_{it}, z_{it})\tilde{X}_{it}' K_h(z_{it} - z)$

and $T(z) = \sum_i \sum_t Q(W_{it}, z_{it}) y_{it} K_h(z_{it} - z)$

$Q(W_{it}, z_{it}) = \begin{pmatrix} W_{it} \\ W_{it} \otimes (z_{it} - z)/h \end{pmatrix}$ (Cai and Li, 2008)

and h is conscripted through the least square cross validation (LSCV) method.

$$\hat{h} = arg \min_h \sum_i \sum_t [y_{it} - \tilde{x}_{it}'\hat{\beta}(z_{it})_{-it}] \qquad (5.11)$$

in which $\tilde{x}_{it}'\hat{\beta}(z_{it})_{-it}$ is the leave-one-out estimator of the conditional mean.

Usually, the probable snags that accompanied with a random choice of bandwidth, however, this method can desist it (Li and Racine, 2007). Since then the slope smooth coefficients in equation (5.4), $\beta(z_{it})$ are estimated, we can then re-write equation (5.1) as,

$$y_{it} - x_{it}'\beta(z_{it}) = \beta_0(z_{it}) + \varepsilon_{it},$$

$$R_{it} = \beta_0(z_{it}) + \varepsilon_{it},$$

$$R_{it} = \beta_0(z_{it}) + \tilde{\varepsilon}_{it} - \alpha_1 - \alpha_2(z_{it}),$$

$$R_{it} = \{\beta_0(z_{it}) - \alpha_1 - \alpha_2(z_{it})\} + \tilde{\varepsilon}_{it}$$

$$R_{it} = \beta_0^*(z_{it}) + \tilde{\varepsilon}_{it} \qquad (5.12)$$

Now, $\tilde{\varepsilon}_{it}$ can be decomposed into a time-invariant and time-varying component.

Recalling equation (5.5),

$\tilde{\varepsilon}_{it} = \varepsilon_{it} + \alpha_1 + \alpha_2(z_{it}),$

Substituting the value of ε_{it} from equation (5.2),

$\tilde{\varepsilon}_{it} = b_i + v_{it} - (\eta_i + u_{it}) + \alpha_1 + \alpha_2(z_{it})$

$\tilde{\varepsilon}_{it} = \{b_i - \eta_i + \alpha_1\} + \{v_{it} - u_{it} + \alpha_2(z_{it})\}$

$$\tilde{\varepsilon}_{it} = \chi_{0i} + \chi_{it} \tag{5.13}$$

Thereon, the model replaces the $\tilde{\varepsilon}_{it}$ in (5.13) with the residuals estimated from (5.12), and then estimate (5.13) as either a fixed effects or random effects model without any regressors and obtain the $\hat{\chi}_{0i}$ and $\hat{\chi}_{it}$.

Consequently, the persistent and transient inefficiencies can be estimated and the persistent technical estimates (PTE) is expressed as,

$$\chi_{0i} = b_i - \eta_i + \alpha_1 \tag{5.14}$$

Presuming $b_i \backsim iidN(0, \sigma_b^2)$, $\eta_i \sim iidN^+(0, \sigma_\eta^2)$ and b_i and η_i are independent of each other, the model , χ_{0i} replaces by $\hat{\chi}_{0i}$. The above expression transpires the proposed model as a typical stochastic frontier model with one intercept. The eminent estimation techniques developed by Jondrow, Lovell, Materov and Schmidt's (1982) and Battese and Coelli's (1988) can be employed to estimate the PTE. A standard statistical package is useful for this estimation.

Simultaneously, the transient inefficiency is articulated as,

$$\chi_{it} = v_{it} - u_{it} + \alpha_2(z_{it}) \tag{5.15}$$

In practice, $\hat{\chi}_{it}$ substitutes χ_{it} with the assumption of

$v_{it} \sim iidN(0, \sigma_v^2),$

$u_{it} \sim iidN^+(0, \sigma_u^2(z_{it})),$

$\alpha_2(z_{it}) = E(u_{it}|z_{it}) = \sqrt{\frac{2}{\pi}}\,\sigma_u = \sqrt{\frac{2}{\pi}}\exp(c_1 + \gamma' z_{it})$

and v_{it} and u_{it} are independent of each other. This model is also basically a stochastic frontier model though with non-linear characteristics. All the parameters cited in equation (5.15) can be computed with the ML function. The log-likelihood functions can be expressed as,

$$lnL = Constant - \frac{1}{2}\sum_i \sum_t \ln\left[\sigma_u^2 (z_{it}) + \sigma_v^2\right] + \sum_i \sum_t ln\phi\left(-\frac{e_{it}\lambda_{it}}{\sigma_{it}}\right) - \frac{1}{2}\sum_i \sum_t \frac{e_{it}^2}{\sigma_{it}^2} \quad (5.16)$$

where, $\sigma_u^2(z_{it}) = \exp\left[2(c_1 + \gamma' z_{it})\right]$, $e_{it} = \chi_{it} - \sqrt{2/\pi}\,\sigma_u(z_{it}) = v_{it} - u_{it}$,

$\sigma_{it}^2 = \sigma_v^2 + \sigma_u^2(z_{it}) = \sigma_v^2 + \exp\left[2(c_1 + \gamma' z_{it})\right]$

and $\lambda_{it} = \sigma_u(z_{it}) / \sigma_v = \exp(c_1 + \gamma' z_{it})/\sigma_v$.

Forthwith, the transient inefficiency scores can be estimated with the aid of Jondrow et al.'s (1982) and Battese and Coelli's (1988) estimators. Moreover, marginal effects of z_{it} on the inefficiency can be computed through Kumbhakar and Sun's procedures. Finally, the OTE scores are computed by multiplying the PTE and TTE, thus mathematically, OTE = PTE·TTE. The entire methodology can be computed using the default options of the *npreg* function of the *np* package developed by Hayfield and Racine 2008) in the R interface.

5.3 Data Sources and Construction of Dataset

5.3.1 Description of Data Sources

This study used data provided by a comprehensive database, Prowess, generated and maintained by a private Indian organisation, the Centre for Monitoring Indian Economy (CMIE). This database provides data from the annual financial statements of listed and unlisted enterprises and participant companies of the Indian Stock Exchange. The database is commonly used in empirical studies at the firm level (Chadha 2009; Edwards and Sundaram 2017; Malik 2015). The database covers a wide continuum of companies, with 60 to 70% of the economic activities related to the organised industrial sector. Approximately 80% of manufacturing output emanates from the organised sector. These firms are registered under Sections 2m (i) and 2m (ii) of the *Indian Factories Act*.[18] The

[18] Section 2(m) of *The Factories Act, 1948* where the (m) 'factory' means any premises including the precincts thereof—m(i) whereon ten or more workers and m(ii) whereon twenty or more workers are

data were collected from the years 1995/1996 to 2015/2016. The first step was to adjust the firm-level data based on their codes. The Prowess database provides firms' code or reference code—namely, the National Industrial Classification (NIC) code—in their annual industrial survey. These NIC codes mostly align with the ISIC code. Based on the NIC code, the firm-level data from 1995 to 2016 were synchronised to obtain the panel dataset.

The use of panel data enabled the incorporation of a greater number of observations, and offered deep insight into the trend of distribution of TE among the firms over time. Given that India becomes a signatory of the TRIPS agreement in 1994, the years 1995 to 1996 were taken as the threshold. Further, the year 2005 was conscripted as the reference point, as India amended its patent policy in 2005 in compliance with the TRIPS agreement. The usage of panel data in a dynamic model supported robust outcomes, as it incorporated more observations and permitted this study to examine the pattern of distribution of TE among firms.

The firm-level patent data were extracted from a database published by the Indian Patent Office, Government of India. Further, the unbalanced panel for each industry were arranged based on code (such as A61K for the pharmaceutical industry) and the field of inventions provided in the database published by the Indian Patent Office. This procedure avoided the reoccurrence of the same firm in different industries.

5.3.2 Limitations of Data and Procedure for Constructing Consistent Panel Set

The Prowess database is commonly used in empirical studies at the firm level (Chadha 2009; Edwards and Sundaram 2017; Malik 2015). The data are primarily drawn from information in firms' annual reports. The Prowess database covers firms from 22 NIC two-digit industries. However, this database has certain limitations that require adjustments to obtain a consistent dataset. In this study, a consistent panel dataset was constructed by following several steps of adjustment, as follows.

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working or were working on any day of the preceding twelve months, and in any part of which a manufacturing process is being carried on with the aid of power, or is ordinarily so carried on.

Step 1: Abating white noise

To abate white noise, this study followed two steps: (i) drop firms with zero or missing output values from the sample set and (ii) consider firms that acquired at least one patent during this timeframe.

Step 2: Handling missing input values

Although the Prowess database is a comprehensive database, values of some variables for some periods were unavailable. These missing values were estimated by using a multiple imputation methodology in the R platform.

Step 3: Dealing with the unavailable input variable

Labour is an imperative input for any production practice. However, in the case of many firms, the Prowess database provides the number of employees as zero, despite positive sales and capital. This inconsistency rendered the data inappropriate for the purpose of this study. Thus, this study identified a proxy variable in the absence of data on the number of employees. The labour data were computed by dividing the cost of labour by the industrial wage rate, assuming industry-wise wages are equal.

5.3.3 Sample Industries for Empirical Analysis

By the early 1990s, with the enforcement of the GATT framework, a minimum standard for intellectual property protection was endorsed for the conferred members. As part of the TRIPS Agreement of the GATT, developing countries where product patent protection was not recognised prior to TRIPS had to legalise product patents by 2005 (*Patent Amendment Act*; WIPO 2005). Accordingly, India amended its patent policy in 2005. This study chose four industries that were directly affected by this paradigm shift of the TRIPS agreement. The statistical evidence ensured that these industries were sunrise industries in India in the current period, as explained in Chapter 2.

5.3.3.1 Biotechnology Industry

The unbalanced panel of 3696 observations on 168 firms has constructed from biotechnology firms. Manufacture of 'Ayurvedic' or 'Unani' pharmaceutical preparation, Manufacture of other pharmaceutical and botanical products, amino acid liquids, homeopathic medicaments, bio-tech based drugs etc. are contemplated as the subsectors with the 21001, 21003, 21004 and 21009 NIC codes.

5.3.3.2 Electrical and Electronics Industry

The unbalanced panel of 2530 observations on 115 firms have been constructed from the electrical & electronics industry. This unbalanced panel comprises of the subsectors namely Manufacture of electric power distribution transformers etc., Manufacture of electric motors etc., Manufacture of electricity distribution and control apparatus & switchgears etc., Manufacture of electric accumulator including parts thereof (separators, containers, covers) etc., Manufacture of other electronic and electric wires and cables (insulated wire and cable made of steel, copper, aluminium), Manufacture of other electrical equipment and Electrical machinery other than electronics with 27102, 27103, 27104, 27202, 27900 and 28199 five digits NIC codes respectively.

5.3.3.3 Information Technology and Communication Industry

The unbalanced panel of 1870 observations on 85 firms has constructed from IT and Communication related firms with six subsectors namely manufacturer of microprocessors, manufacturer of the circuit board and loading of components, manufacturer of all computers (all categories), communication equipment (such as bridges, routers and gateways), other communication equipment and Industrial process control equipment with 26107, 26104, 26201, 26303, 26309 and 26512, five digits NIC codes respectively.

5.3.3.4 Pharmaceutical Industry

The unbalanced panel of 3278 observations on 149 firms has constructed from four subsectors namely manufacturer of basic pharmaceuticals including vaccines, manufacture of medicinal substances used in the manufacture of pharmaceuticals, antibiotics, endocrine products, basic vitamins, opium derivatives, sulpha drugs, serums and plasmas, salicylic acid, its salts and esters, glycosides and vegetable alkaloids, chemically pure sugar etc., manufacturer of drug formulations, manufacturer of IV fluids etc. and empty capsules with 21001, 21002, 21003, and 21009 five digits (NIC) codes.

The number of firms was finalised from the above dataset upon acquiring at least one patent during the time span of 1995 to 2016.

5.4 Definition and Measurement of Variables

The definition of variables is an essential element of empirical studies. Using the definition of data provided by the Prowess database and previous literature, this study defined variables for the empirical model in Equations (5.1) and (5.2). The variables were divided into two sets—a semiparametric smooth coefficient SPF and the environmental variables formulated in Equation (5.1). This semiparametric smooth coefficient SPF model had four specific attributes:

1. The inputs could be endogenous in a production function framework.
2. The technology parameters were unknown smooth functions of the environmental (that is, patent) variables.
3. The error term had four components—two noise components and two inefficiency components. The noise component consisted of the time-invariant and time-varying elements. The inefficiency components consisted of persistent and transient inefficiencies.
4. Transient inefficiency could be a function of the patent variables.

5.4.1 Output and Input Variables in Semiparametric Smooth Coefficient Stochastic Production Frontier

This study considered output the dependent variable and capital, labour, material and energy the independent variables of the SPF. The following subsection provides detail of the variables used in the production frontier equation.

5.4.1.1 Output

Output was denoted Y and measured the gross sales of goods in the current year and inventories. Hence, it needed to deflate at a constant price. This study used the Wholesale Price Index (WPI) for the two-digit (NIC) code level to deflate at a constant price of 2011/2012. The Government of India decided to change base years for the WPI for 2011/2012 from 2004/2005 (Government of India, Ministry of Commerce & Industry

2017)[19]; therefore, the year 2011/2012 was selected as the base year. The WPI data were collected from the database provided by the Department of Policy and Promotion.

5.4.1.2 Capital

The capital was denoted K and measured the gross fixed assets of the firm at a constant price. This study adopted the perpetual inventory adjustment method, computed as $K_t = (1-d)K_{t-1} + I_t$, where K_t is the capital stock, I_t is the deflated gross investment and d is the depreciation rate. Aligned with prior empirical studies (Ghosh 2009; Mitra et al. 2014), the rate of depreciation was 7%.

5.4.1.3 Labour

As explained earlier, the Prowess database provides the number of employees' data as zero, despite positive sales and capital. This inconsistency made the data inappropriate for the purpose of this study. Thus, this study identified a proxy variable in the absence of data on the number of employees. The labour data were computed by dividing the cost of labour by the industrial wage rate. The cost of labour includes salaries and wages, bonuses and ex-gratia payments, contributions to provident funds, gratuities and superannuation, staff welfare and staff training.

5.4.1.4 Material

Material was denoted by M and represented the raw materials used for the production process, including domestic and imported material. The material variable consisted of raw materials, packaging expenses and purchase of finished goods, advertising expenses, marketing expenses, and distribution expenses.

5.4.1.5 Energy

The energy was denoted by E and comprised the energy used during the production process from different sources, such as power, water and fuel expenses. These three sources of energy were measured in monetary values. This study used the WPI of fuel and power at the 2011/2012 constant price provided by the Department of Promotion of Industry and Internal Trade, Government of India, to deflate the monetary values of

[19] As part of an exercise to capture structural changes in the economy and improve the quality, scope and representation of indices, the All-India WPI revised the base year from 2004/2005 to 2011/2012.

electricity inputs. The Prowess database presents annual data in monetary value in ‘000 per million. All input and output variables, except the time component, were considered as their logarithmic value.

5.4.2 Patent Protection Variables (Environmental Variables)

Historically, patent regimes foster TE through a few channels. The enforcement of patents stimulates innovation in the source country. This effect of a patent regime on international trade can be classified in two channels: market expansion effect and market power effect. First, the market expansion effect reflects that firms may increase exports, as stronger patent protection reduces the abilities of local firms to imitate products; hence, the home country may experience greater profitability. In contrast, the market power effect indicates that a firm has the option to increase/decrease its sales in a foreign market in response to stronger patent protection due to enhanced market power (Maskus et al. 1995). Another school of thought argues that patent systems encourage innovation-oriented countries to develop new technologies, which are eventually adopted by follower countries. This is conducive for both the leader and follower countries in accomplishing continuous TE. An international patent is acknowledged as another channel for technology diffusion (Eaton et al. 1996). Foreign patenting is a channel of technology spillovers across national borders, via a technology catch-up process. Technology dispersed in intangible form is accounted as spillover effects of technology dissemination. International patents are accepted as a robust source of TE through the channel of knowledge spillover effect beyond the national territory. Hence, in this study, the technical inefficiency effect was a function of a set of patent reform variables—the number of patents, R&D intensity, trade openness and technology transfer.

5.4.2.1 Number of Patents

Firm-level patent data were collected from the database provided by the Indian Patent Office, Government of India, for 1995 to 2016. This study specifically considers the field of inventions stated in the database and the code (such as A61K for the pharmaceutical industry and B60L for the electrical industry).This procedure prevented the reoccurrence of the same firm in different industries. It was hypothesised that the number of patents has a positive/negative effect on firms’ technical efficiency/inefficiency, and a greater number of patents indicates more involvement in innovation.

5.4.2.2 Research and Development Intensity

The R&D intensity variable was computed as the ratio between R&D expenditures and total expenditures. R&D expenditures and total expenditures data were available from the Prowess database. R&D expenditures and total expenditures are both provided in monetary value; therefore, it was necessary to deflate the values into real values or constant price. The 2011/2012 WPI constant prices were used to deflate R&D expenditures and total expenditures before computing the ratio.

5.4.2.3 Trade Openness

The trade openness variable was computed as the ratio between export expenditures and total trade expenditures. The Prowess database provided data for both the export expenditures and trade expenditures in '000 million Indian Rupees. Thus, this ratio was estimated after deflating the export expenditures and total trade expenditures by the WPI 2011/2012 constant prices.

5.4.2.4 Technology Transfer

The technology transfer variable comprised royalty, technical know-how fees and licence fees. This variable was also deflated at the WPI 2011/2012 constant prices. Like the other patent variables, the technology transfer variable was hypothesised to have a negative effect on firms' technical inefficiency.

Table 5.1 presents a summary of the expected signs between the output and input variables of the production frontier and between technical inefficiency and the independent variables discussed above. The descriptive statistics for the variables of production frontier and inefficiency function are given in Appendix 5.1.

Table 5.1: Expected Signs of Parameter Estimates of SPF

Variables		Expected sign	
Semiparametric smooth coefficient SPF			
Dependent variable (ln Y)			
K(ln)		+	
L(ln)		+	
M(ln)		+	
E(ln)		+	
Inefficiency and error term	**Expected sign**	**Efficiency**	**Expected sign**
Dependent variable (u)			
PAT (z1)	-	PAT (z1)	+
RNDI (z2)	-	RNDI (z2)	+
TO (z3)	-	TO (z3)	+
TT (z4)	-	TT (z4)	+

5.5 Results and Interpretation

5.5.1 Empirical Model

Given the semiparametric SPF model where the technology parameters are unknown smooth functions of environmental variables, and inputs are allowed to be endogenous, the empirical model is as follows,

$$\log Y_{it} = \beta_0(z_{it}) + \beta_1(z_{it})\log(K_{it}) + \beta_2(z_{it})\log(L_{it}) + \beta_3(z_{it})\log(M_{it}) + \beta_4(z_{it})\log(E_{it}) + \beta_5(z_{it})\mathrm{t} + \varepsilon_{it} \quad (5.17)$$

The summary statistics of the key variables used in the empirical analysis for the four industries, pharmaceutical, electrical & electronic, IT & communication and biotechnology industries are demonstrated in Appendix 5.1.

5.5.2 Results for Four Selected Industries

5.5.2.1 Summary Statistics of Regression Coefficients and Returns to Scale

The following Tables 5.2a, 5.2b, 5.2c and 5.2d present the mean and quartile values (Q1-Q3) of the estimated smooth coefficients and returns to scale (RTS) for the selected four industries.

Table 5.2a: Summary Statistics of Regression Coefficients and RTS of Biotechnology Industries

	$\beta_1(\cdot)$ log(*capital*)	$\beta_2(\cdot)$ log(*labour*)	$\beta_3(\cdot)$ log(*material*)	$\beta_4(\cdot)$ log(*energy*)	$\beta_5(\cdot)$ time	RTS
Mean	0.284 (0.014)	0.217 (0.017)	0.400 (0.086)	0.092 (0.020)	0.013 (0.005)	0.992 (0.043)
Q1	0.103 (0.001)	0.029 (0.000)	0.296 (0.002)	0.046 (0.002)	0.023 (0.000)	0.836 (0.076)
Q2	0.206 (0.003)	0.114 (0.004)	0.587 (0.008)	0.159 (0.004)	0.006 (0.000)	1.057 (0.005)
Q3	0.291 (0.016)	0.230 (0.019)	0.705 (0.016)	0.261 (0.010)	0.003 (0.006)	1.173 (0.035)

Table 5.2b: Summary Statistics of Regression Coefficients and RTS of Electrical and Electronics Industries

	$\beta_1(\cdot)$ log(*capital*)	$\beta_2(\cdot)$ log(*labour*)	$\beta_3(\cdot)$ log(*material*)	$\beta_4(\cdot)$ log(*energy*)	$\beta_5(\cdot)$ time	RTS
Mean	0.081 (0.014)	-0.098 (0.005)	0.693 (0.014)	0.144 (0.012)	0.013 (0.004)	0.917 (0.018)
Q1	-0.011 (0.000)	-0.134 (0.000)	0.291 (0.008)	0.008 (0.009)	0.010 (0.002)	0.639 (0.049)
Q2	0.061 (0.004)	0.015 (0.004)	0.727 (0.011)	0.080 (0.004)	0.000 (0.000)	1.011 (0.006)
Q3	0.266 (0.012)	0.131 (0.007)	0.957 (0.021)	0.228 (0.021)	0.020 (0.005)	1.146 (0.029)

Table 5.2c: Summary Statistics of the Regression Coefficients and RTS of IT and Communication Industries

	$\beta_1(\cdot)$ log(*capital*)	$\beta_2(\cdot)$ log(*labour*)	$\beta_3(\cdot)$ log(*material*)	$\beta_4(\cdot)$ log(*energy*)	$\beta_5(\cdot)$ time	RTS
Mean	-1.149 (0.020)	0.194 (0.021)	0.521 (0.020)	0.295 (0.015)	-0.076 (0.008)	1.010 (0.032)
Q1	0.020 (0.002)	-0.081 (0.000)	0.162 (0.010)	0.142 (0.002)	-0.013 (0.014)	0.324 (0.008)
Q2	0.147 (0.006)	0.062 (0.004)	0.304 (0.006)	0.239 (0.005)	-0.002 (0.008)	0.844 (0.003)
Q3	0.473 (0.912)	0.233 (0.573)	0.480 (0.717)	0.409 (0.698)	0.061 (0.093)	1.096 (0.020)

Table 5.2d: Summary Statistics of Regression Coefficients and RTS of Pharmaceutical Industries

	$\beta_1(\cdot)$ log(*capital*)	$\beta_2(\cdot)$ log(*labour*)	$\beta_3(\cdot)$ log(*material*)	$\beta_4(\cdot)$ log(*energy*)	$\beta_5(\cdot)$ time	RTS
Mean	0.001 (0.007)	0.234 (0.006)	0.702 (0.003)	0.076 (0.005)	0.000 (0.000)	1.013 (0.003)
Q1	0.007 (0.000)	0.149 (0.001)	0.679 (0.009)	0.046 (0.003)	0.016 (0.000)	1.009 (0.005)
Q2	0.014 (0.006)	0.209 (0.002)	0.751 (0.002)	0.059 (0.000)	0.010 (0.000)	1.040 (0.000)
Q3	0.354 (0.012)	0.233 (0.010)	0.785 (0.002)	0.084 (0.000)	0.004 (0.009)	1.070 (0.002)

Author's calculation using R and the standard errors are in the parentheses (Table 5.2a, 5.2b, 5.2c and 5.2d).

Tables 5.2a, 5.2b, 5.2c and 5.2d present the mean and quartile values (Q1 to Q3) of the estimated smooth coefficients and RTS of the biotechnology electrical and electronics, IT and communication, and pharmaceutical industries, respectively. The mean capital elasticity ($\beta_1(\cdot)$) was 0.001343 for the pharmaceutical industry. This means that, on average, with a 1% increase in capital, ceteris paribus, the output of the pharmaceutical industry increased by about 0.001343%. The marginal increase of capital intensity probably reflects a lofty fixed cost and variable cost, as firms must pay interest for their financing institutions in the pharmaceutical industry. The IT and communication industry demonstrated an even higher decline in output with a 1% increase in capital. The possible rationale behind this is that firms' huge, short-run capital investment is not aligned with the elongated production process. In contrast, the biotechnology and electrical and electronics industries revealed, on average, 0.08053% and 0.2835% increments in output against a 1% increase of capital, respectively.

Likewise, the mean labour elasticity of the pharmaceutical industry was 0.2339, revealed as ($\beta_2(\cdot)$), which implies a 1% increase in labour increases output by 0.2339%. The mean labour intensity for the biotechnological and IT and communication industries was 0.21670 and 0.19432, respectively. However, the electrical and electronics industry depicted a negative labour input elasticity. Possibly, the requirement of more specialised labourers in different departments may elevate the cost of labour and affect the production level adversely. The mean material elasticity of the pharmaceutical industry was denoted by ($\beta_3(\cdot)$) and captured the value as 0.7017, indicating a 1% increase in material consumption, leading to a 0.7017% increase in output. All four industries portrayed positive mean material elasticity, indicating that, with a 1% increase of material cost, the output increased on average. Similarly, in the biotechnology industry, the mean energy elasticity ($\beta_4(\cdot)$) was 0.09230, indicating a 1% increase in energy consumption, increasing output by 0.0923%, ceteris paribus. As expected, the mean energy elasticity had positive values for the pharmaceutical, electronics and electrical, and IT and communication industries. Under the ceteris paribus clause, the component $\beta_5(\cdot)$ denoted technical change, where, on average, output increased each year. The technical change in the biotechnology industry was 0.012962 and output increased over a year by 1.296%. The technical change in biotechnology and electrical and electronic industries depicted 0.0012962 and 0.013405, respectively and both the values are statistically significant. However, the value indicates no technical change appeared in pharmaceutical industry. In contrast, the IT and communication industries showed negative values of technical change. The likely cause was the rebound effect, reflecting a reduction in expected gains from new technologies that increase resource use efficiency attributable to behavioural responses. Generally, the beneficial effects of new technology outweigh these behavioural responses at the initial stage (Alcott 2005).

The sixth column of Tables 5.2a, 5.2b, 5.2c and 5.2d depicts the RTS. This RTS is estimated as the summation of all input elasticities. Mathematically, $\mathrm{RTS} = \sum_j \partial lny/\partial lnx_j$. Given that the negative input elasticities were not statistically meaningful, they were dropped while calculating the RTS. The value of the RTS was 1.0126 and 0.9922 in the pharmaceutical and biotechnology industries, respectively, which was not statistically different from 1 at the 5% level of significance. Likewise, the mean RTS value of the IT and communication industry was 1.00962 (at the 5% level), which was also not significantly different from unity. Though the rebound effect of capital exists in the IT and communication industry, yet it is not strong enough to outweigh the positive impact of the other inputs. Contrarily, the electrical and electronic industry had an RTS value of 0.917461. Possibly, the rebound effect of the labour input substantially offset the positive part of the other inputs in the case of the electrical and electronic industry. Lack of improved market-relevant skills to adopt the new technology and the benefit from the R&D expenditure may have a stronger negative impact.

The least-squares cross-validated bandwidth estimates for the environmental variables—the number of patents, R&D intensity, trade openness and technical transfer—separately were 6.0567, 0.0143, 0.0235 and 3.476, those are much less than twice the standard deviation of the respected variables, 19.49025, 0.346795, 14.56309 and 0.540315 in the pharmaceutical industry. Consequently, the least-squares cross-validated bandwidth estimates for the environmental variables jointly also justified the rule of thumb that the coefficients were nonlinear functions of the environmental variables. The other industries also ratified the same nonlinearity notion. It was intriguing to examine the marginal effect of individual environmental variables on each smooth coefficient in this context.

5.5.2.2 Marginal Effects of Environmental Variables

The following Tables 5.3a, 5.3b, 5.3c and 5.3d report the marginal effects of the environmental variables, namely, number of patents (z1), research and development intensity (z2), trade openness (z3) and technology transfer (z4) on each smooth coefficient in all the selected industries.

Table 5.3a: Marginal Effects of z_1, z_2, z_3, z_4 on Each Smooth Coefficient (Biotechnology Industry)

	$d\ \beta_1(\cdot)\ /\ dz_1$	$d\ \beta_1(\cdot)\ /\ dz_2$	$d\ \beta_1(\cdot)\ /\ dz_3$	$d\ \beta_1(\cdot)\ /\ dz_4$
Mean	0.062 (0.004)	2.086 (0.007)	-0.700 (0.183)	2.020 (0.120)
Q1	0.020 (0.002)	-2.926 (0.006)	-0.077 (0.129)	0.900 (0.165)
Q2	0.031 (0.014)	3.088 (0.001)	-0.061 (0.064)	1.729 (0.015)
Q3	0.055 (0.008)	5.684 (0.007)	0.016 (0.295)	1.949 (0.146)

	$d\ \beta_2(\cdot)\ /\ dz_1$	$d\ \beta_2(\cdot)\ /\ dz_2$	$d\ \beta_2(\cdot)\ /\ dz_3$	$d\ \beta_2(\cdot)\ /\ dz_4$
Mean	-0.029 (0.005)	1.125 (0.005)	-1.677 (0.254)	-0.163 (0.131)
Q1	-0.006 (0.129)	-0.896 (0.010)	-0.712 (0.369)	-0.994 (0.208)
Q2	0.020 (0.017)	2.100 (0.001)	-0.009 (0.211)	-0.136 (0.005)
Q3	0.040 (0.106)	3.831 (0.001)	0.383 (0.349)	0.031 (0.134)

	$d\ \beta_3(\cdot)\ /\ dz_1$	$d\ \beta_3(\cdot)\ /\ dz_2$	$d\ \beta_3(\cdot)\ /\ dz_3$	$d\ \beta_3(\cdot)\ /\ dz_4$
Mean	-0.008 (0.102)	1.508 (0.003)	0.421 (0.360)	-2.743 (0.123)
Q1	-0.065 (0.176)	-5.793 (0.005)	-0.318 (0.467)	-8.658 (0.161)
Q2	-0.009 (0.017)	4.442 (0.001)	-0.292 (0.004)	-0.977 (0.113)
Q3	0.033 (0.193)	9.762 (0.004)	0.031 (0.547)	-0.342 (0.186)

	$d\ \beta_4(\cdot)\ /\ dz_1$	$d\ \beta_4(\cdot)\ /\ dz_2$	$d\ \beta_4(\cdot)\ /\ dz_3$	$d\ \beta_4(\cdot)\ /\ dz_4$

Mean	0.050 (0.074)	-1.209 (0.003)	1.069 (0.284)	-0.260 (0.094)
Q1	-0.014 (0.004)	-4.491 (0.004)	-0.113 (0.197)	-0.592 (0.006)
Q2	0.040 (0.001)	-2.963 (0.056)	-0.046 (0.002)	1.081 (0.019)
Q3	0.093 (0.003)	-1.509 (0.004)	0.127 (0.349)	1.485 (0.182)

	$d\,\beta_5(\cdot)\,/\,dz_1$	$d\,\beta_5(\cdot)\,/\,dz_2$	$d\,\beta_5(\cdot)\,/\,dz_3$	$d\,\beta_5(\cdot)\,/\,dz_4$
Mean	0.012 (0.317)	1.141 (0.000)	0.008 (0.074)	-0.060 (0.021)
Q1	-0.007 (0.444)	-0.190 (0.000)	-0.128 (0.057)	-0.177 (0.036)
Q2	0.003 (0.000)	-0.087 (0.020)	-0.020 (0.001)	-0.134 (0.003)
Q3	0.008 (0.027)	1.982 (0.001)	0.000 (0.114)	0.170 (0.021)

Table 5.3b: Marginal Effects of z_1, z_2, z_3, z_4 on Each Smooth Coefficient (Electrical and Electronics Industry)

	$d\,\beta_1(\cdot)\,/\,dz_1$	$d\,\beta_1(\cdot)\,/\,dz_2$	$d\,\beta_1(\cdot)\,/\,dz_3$	$d\,\beta_1(\cdot)\,/\,dz_4$
Mean	-0.085 (0.024)	15.569 (0.998)	0.021 (0.006)	-82.780 (0.583)
Q1	-0.025 (0.046)	-12.464 (0.606)	-0.062 (0.002)	-1.727 (0.170)
Q2	0.026 (0.001)	0.000 (0.224)	-0.000 (0.001)	0.000 (0.038)
Q3	0.093 (0.003)	7.832 (0.414)	0.024 (0.011)	1.730 (0.125)

	$d\,\beta_2(\cdot)\,/\,dz_1$	$d\,\beta_2(\cdot)\,/\,dz_2$	$d\,\beta_2(\cdot)\,/\,dz_3$	$d\,\beta_2(\cdot)\,/\,dz_4$
Mean	-0.054 (0.016)	-20.214 (0.969)	-1.865 (0.796)	90.669(0.154)
Q1	-0.239 (0.004)	-24.326 (0.939)	-0.011 (0.005)	-0.825 (0.095)
Q2	-0.043 (0.003)	-4.506 (0.312)	0.003 (0.000)	0.000 (0.031)
Q3	0.001 (0.031)	3.984 (0.500)	0.0318 (0.042)	2.032 (0.252)

	$d\,\beta_3(\cdot)\,/\,dz_1$	$d\,\beta_3(\cdot)\,/\,dz_2$	$d\,\beta_3(\cdot)\,/\,dz_3$	$d\,\beta_3(\cdot)\,/\,dz_4$
Mean	0.003 (0.008)	10.392 (0.996)	0.560 (0.516)	-91.893 (0.809)
Q1	-0.127 (0.008)	-10.165 (0.778)	-0.057 (0.161)	-3.724 (0.233)
Q2	0.000 (0.002)	7.236 (0.001)	0.000 (0.005)	0.000 (0.023)
Q3	0.038 (0.011)	29.853 (0.566)	0.059 (0.132)	1.667 (0.291)

	$d\,\beta_4(\cdot)\,/\,dz_1$	$d\,\beta_4(\cdot)\,/\,dz_2$	$d\,\beta_4(\cdot)\,/\,dz_3$	$d\,\beta_4(\cdot)\,/\,dz_4$
Mean	0.113 (0.027)	1.938 (0.907)	-0.167 (0.036)	55.391 (0.495)
Q1	-0.042 (0.017)	-15.732 (0.523)	-0.058 (0.072)	-0.984 (0.102)
Q2	0.027(0.000)	-1.728 (0.135)	-0.011 (0.000)	0.550 (0.019)
Q3	0.046 (0.046)	3.509 (0.622)	0.007 (0.046)	12.025 (0.456)

	$d\,\beta_5(\cdot)\,/\,dz_1$	$d\,\beta_5(\cdot)\,/\,dz_2$	$d\,\beta_5(\cdot)\,/\,dz_3$	$d\,\beta_5(\cdot)\,/\,dz_4$
Mean	-0.014 (0.002)	1.631 (0.146)	-0.026 (0.009)	-12.484 (0.314)
Q1	-0.018 (0.004)	-0.923 (0.010)	-0.003 (0.017)	-0.130 (0.627)
Q2	0.000 (0.000)	-0.006 (0.022)	-0.000 (0.000)	0.092 (0.011)
Q3	0.013 (0.001)	1.118 (0.227)	0.002 (0.003)	0.853 (0.030)

Table 5.3c: Marginal Effects of z_1, z_2, z_3, z_4 on Each Smooth Coefficient (IT and Communication Industry)

	$d\,\beta_1(\cdot)\,/\,dz_1$	$d\,\beta_1(\cdot)\,/\,dz_2$	$d\,\beta_1(\cdot)\,/\,dz_3$	$d\,\beta_1(\cdot)\,/\,dz_4$
Mean	-0.016 (0.004)	14.010 (0.545)	5.898 (0.019)	-0.090 (0.391)
Q1	-0.086 (0.005)	1.470 (0.777)	0.000 (0.034)	-0.051 (0.499)
Q2	-0.007 (0.003)	14.280 (0.295)	3.090 (0.081)	-0.028 (0.001)
Q3	0.117 (0.004)	23.960 (0.681)	6.168 (0.015)	0.017 (0.390)

	$d\,\beta_2(\cdot)\,/\,dz_1$	$d\,\beta_2(\cdot)\,/\,dz_2$	$d\,\beta_2(\cdot)\,/\,dz_3$	$d\,\beta_2(\cdot)\,/\,dz_4$
Mean	-0.018 (0.018)	18.150 (0.722)	0.648 (0.025)	-0.163 (0.131)
Q1	-0.044 (0.035)	-25.590 (0.458)	-4.027 (0.047)	-0.011 (0.240)
Q2	0.006 (0.000)	-8.870 (0.337)	-0.069 (0.116)	-0.009 (0.000)
Q3	0.076 (0.006)	-0.120 (0.774)	4.853 (0.009)	0.007 (0.289)

	$d\,\beta_3(\cdot)\,/\,dz_1$	$d\,\beta_3(\cdot)\,/\,dz_2$	$d\,\beta_3(\cdot)\,/\,dz_3$	$d\,\beta_3(\cdot)\,/\,dz_4$
Mean	0.016 (0.004)	11.938 (0.396)	-0.558 (0.018)	0.015 (0.504)
Q1	-0.072 (0.003)	-6.227 (0.257)	-4.516 (0.037)	-0.011 (0.349)
Q2	0.027 (0.002)	-4.480 (0.082)	-0.986 (0.073)	0.018 (0.000)
Q3	0.085 (0.005)	0.000 (0.591)	1.045 (0.001)	0.026 (0.568)

	$d\,\beta_4(\cdot)\,/\,dz_1$	$d\,\beta_4(\cdot)\,/\,dz_2$	$d\,\beta_4(\cdot)\,/\,dz_3$	$d\,\beta_4(\cdot)\,/\,dz_4$
Mean	-0.006 (0.004)	-18.042 (0.832)	-2.567 (0.031)	-0.001 (0.620)
Q1	-0.112 (0.003)	-0.424 (0.954)	-2.084 (0.014)	-0.053 (0.406)
Q2	-0.057 (0.003)	6.028 (0.208)	0.251 (0.043)	-0.002 (0.001)
Q3	0.087 (0.003)	15.416 (0.595)	1.186 (0.023)	0.012 (0.756)

	$d\,\beta_5(\cdot)\,/\,dz_1$	$d\,\beta_5(\cdot)\,/\,dz_2$	$d\,\beta_5(\cdot)\,/\,dz_3$	$d\,\beta_5(\cdot)\,/\,dz_4$
Mean	0.020 (0.002)	-1.779 (0.454)	-0.287 (0.004)	-0.003 (0.070)
Q1	-0.005 (0.002)	-1.663 (0.898)	-0.944 (0.009)	-0.005 (0.059)
Q2	0.016 (0.001)	0.758 (0.053)	0.130 (0.034)	-0.003 (0.000)
Q3	0.053 (0.002)	2.406 (0.064)	1.618 (0.000)	-0.001 (0.111)

Table 5.3d: Marginal Effects of z_1, z_2, z_3, z_4 on Each Smooth Coefficient (Pharmaceutical Industry)

	$d\,\beta_1(\cdot)\,/\,dz_1$	$d\,\beta_1(\cdot)\,/\,dz_2$	$d\,\beta_1(\cdot)\,/\,dz_3$	$d\,\beta_1(\cdot)\,/\,dz_4$
Mean	-0.008 (0.001)	0.013 (0.038)	0.137 (0.000)	0.021 (0.035)
Q1	0.006 (0.001)	-0.045 (0.001)	0.009 (0.000)	0.006 (0.047)
Q2	0.001 (0.000)	-0.019 (0.003)	0.207 (0.005)	0.006 (0.001)
Q3	0.001 (0.001)	0.089 (0.074)	0.214 (0.000)	0.042 (0.051)

	$d\,\beta_2(\cdot)\,/\,dz_1$	$d\,\beta_2(\cdot)\,/\,dz_2$	$d\,\beta_2(\cdot)\,/\,dz_3$	$d\,\beta_2(\cdot)\,/\,dz_4$
Mean	0.051 (0.001)	1.697(0.013)	-0.166 (0.003)	0.067 (0.001)
Q1	0.021 (0.045)	1.670 (0.006)	-0.252 (0.000)	0.024 (0.222)
Q2	0.068 (0.001)	1.751 (0.001)	-0.248 (0.003)	0.091 (0.001)
Q3	0.068 (0.000)	1.776 (0.006)	-0.009 (0.004)	0.092 (0.001)

	$d\,\beta_3(\cdot)\,/\,dz_1$	$d\,\beta_3(\cdot)\,/\,dz_2$	$d\,\beta_3(\cdot)\,/\,dz_3$	$d\,\beta_3(\cdot)\,/\,dz_4$
Mean	-0.046 (0.002)	-1.668 (0.032)	0.219 (0.000)	-0.089 (0.013)
Q1	-0.063 (0.001)	-1.869 (0.045)	0.024 (0.000)	-0.159 (0.015)
Q2	-0.062 (0.001)	-1.818 (0.048)	0.319 (0.005)	-0.156 (0.003)
Q3	-0.017 (0.003)	-1.807 (0.037)	0.331 (0.000)	0.043 (0.021)

	$d\,\beta_4(\cdot)\,/\,dz_1$	$d\,\beta_4(\cdot)\,/\,dz_2$	$d\,\beta_4(\cdot)\,/\,dz_3$	$d\,\beta_4(\cdot)\,/\,dz_4$
Mean	0.011 (0.001)	-0.536 (0.033)	1.069 (0.284)	-0.260 (0.094)
Q1	-0.014 (0.004)	-1.314 (0.047)	-0.095 (0.000)	-0.029 (0.060)
Q2	0.010 (0.000)	0.573 (0.025)	-0.088 (0.001)	-0.028 (0.001)
Q3	0.010 (0.001)	0.624 (0.043)	-0.014 (0.000)	0.076 (0.042)

	$d\,\beta_5(\cdot)\,/\,dz_1$	$d\,\beta_5(\cdot)\,/\,dz_2$	$d\,\beta_5(\cdot)\,/\,dz_3$	$d\,\beta_5(\cdot)\,/\,dz_4$
Mean	0.003 (0.000)	0.057 (0.007)	-0.014 (0.000)	-0.027 (0.010)
Q1	0.002 (0.000)	0.217 (0.003)	-0.020 (0.000)	-0.037 (0.019)
Q2	0.003 (0.000)	-0.214 (0.003)	-0.018 (0.000)	-0.037 (0.001)
Q3	0.004 (0.000)	0.442 (0.012)	-0.005 (0.000)	-0.037 (0.000)

Author's calculation using R and the standard errors are in the parentheses (Table 5.3a, 5.3b, 5.3c and 5.3d).

Given that the smooth coefficients are nonlinear functions of environmental variables, the marginal effects of environmental variables on input productivity and efficiency provide deep insight. These estimates of the marginal effects of the environmental variables—the number of patents, R&D intensity, trade openness and technology transfer—on input productivity and efficiency are captured in Tables 5.3a, 5.3b, 5.3c and 5.3d. These estimates are from the biotechnology, electrical and electronics, IT and communication, and pharmaceutical industries, respectively. The tables show that, on average, an increase in the environmental variables had a mixed effect on the smooth coefficients. Predominantly, all environmental variables, except the trade openness variable, reduced the productivity of material inputs for the pharmaceutical industry. The import dependence for raw materials can be the plausible reason for this. However, on average, an increase in environmental variables, except for number of patents, caused capital to be mostly more productive. Similarly, the input variable labour was more productive with an average increment of the environmental variables, apart from the trade openness variables. However, the number of patents and trade openness influenced the energy input variable to become more productive. These higher productivities could be the result of a learning effect. The learning effect of environmental variables, such as R&D intensity, trade openness and technology transfers, could offset the depreciation effect on capital inputs in the pharmaceutical industry. Tables 5.3a, 5.3b, 5.3c and 5.3d indicate that the increase of the number of patents on average led capital input to be less productive for the pharmaceutical, electrical and electronics, and IT and communication industries; however, the biotechnology industry revealed otherwise. A probable explanation for this finding is that the biotechnology industry is an emerging industry in India. The labour input was less productive with an additional number of patents for all three industries, apart from the pharmaceutical industry. This could be because labourers are required to adapt and adjust to new patented research strategies. The IT and communication industry only showed that energy input was less productive with an increase in a number of patents.

Further, the increment of the next environmental variable of R&D intensity made capital input more productive for all four industries. Likewise, in general, on average, labour inputs were more productive, except for the electrical and electronics industry. The average depreciation rates of knowledge are affected with the alteration of the R&D activity composition, sporadically (Parham 2006). The electrical and electronics, IT and communication, and biotechnology industries demonstrated more productive material inputs with additional R&D intensity variable. In contrast, energy inputs reduced productivity on average, which could be a result of the depreciation effect in the pharmaceutical, IT and communication, and biotechnology industries.

On average, an increase in technology transfer variable led material input to be less productive in the biotechnology, electrical and electronics, and pharmaceutical industries. However, it is only statistically significant for the pharmaceutical industry. Likewise, technology transfer variable led labour input also less productive, though pharmaceutical industry demonstrates statistically significant. The slower adaptability of new technology may be a reason for the sluggish productivity of material input for the pharmaceutical industry. In contrast, the biotechnology industry exhibited a contrasting trend for the productivity of energy and capital inputs but not statistically significant. Finally, the effect of the increase of the environmental variable of trade openness demonstrated diverse trends for different industries. An increase in the trade openness variable generated more significantly productive capital inputs, yet less productive energy input for the electrical and electronic industry. The shift of paradigm from process patent to product patent, would thus have increased the average rates of depreciation in material, energy and knowledge. However, the electrical and electronic industries revealed the exact opposite picture, except for material inputs. Hence, it is evident that the marginal effect of the environmental variables on the inputs had a distinctive trend.

The estimates of technical progress captured in the last panes of the Tables 5.3a, 5.3b, 5.3c and 5.3d show that, on average, technical progress fell with increased technology transfer for all four industries though statistically significant for only biotechnology and pharmaceutical industries. Similarly, the increment of trade openness caused a decline in the technical progress of each industry, except the biotechnology industry. In contrast, on average, the magnitude of technical progress increased as the number of patents increased, apart from in the electrical and electronic industry and no impact on biotechnology industry. Moreover, increased R&D intensity led to increased technical progress, except in the electrical and electronic industry and IT and communication industry. The fall in the magnitude of technical progress since trade openness and technology transfers increased may have occurred because, as a developing country, India must bear colossal licensing fees and technology transfer costs.

5.5.2.3 Marginal Effects of Patent Variables on Transient Inefficiency

Table 5.4a: Marginal Effects of z_1, z_2, z_3, z_4 on Transient Inefficiency (u) of Biotechnology Industry

	du / dz_1	du / dz_2	du / dz_3	du / dz_4
Mean	-0.014 (0.000)	-5.436 (0.191)	0.085 (0.003)	-0.210 (0.007)
Q1	-0.023 (0.001)	-9.092 (0.275)	0.000 (0.000)	-0.350 (0.011)
Q2	-0.006 (0.000)	-2.255 (0.117)	0.035 (0.003)	-0.087 (0.005)
Q3	0.000 (0.000)	0.000 (0.014)	0.142 (0.004)	0.000 (0.001)

Table 5.4b: Marginal Effects of z_1, z_2, z_3, z_4 on Transient Inefficiency (u) Electrical and Electronic Industry

	du / dz_1	du / dz_2	du / dz_3	du / dz_4
Mean	0.617 (0.011)	-5.828 (0.102)	0.101 (0.002)	0.059 (0.001)
Q1	0.364 (0.004)	-6.766 (0.001)	0.060 (0.028)	0.035 (0.000)
Q2	0.576 (0.004)	-5.438 (0.053)	0.095 (0.001)	0.055 (0.001)
Q3	0.717(0.012)	-3.431(0.048)	0.118 (0.002)	0.068 (0.001)

Table 5.4c: Marginal Effects of z_1, z_2, z_3, z_4 on Transient Inefficiency (u) of IT and Communication Industry

	du / dz_1	du / dz_2	du / dz_3	du / dz_4
Mean	-0.033(0.013)	4.388(0.147)	-11.229 (0.002)	0.933(0.001)
Q1	-0.051(0.006)	0.000 (0.027)	-17.233(0.001)	0.000 (0.001)
Q2	-0.025 (0.001)	3.263(0.088)	-8.349(0.001)	0.694 (0.027)
Q3	0.000 (0.020)	6.734 (0.198)	0.000 (0.003)	1.432 (0.002)

Table 5.4d: Marginal Effects of z_1, z_2, z_3, z_4 on Transient Inefficiency (u) of Pharmaceutical Industry

	du / dz_1	du / dz_2	du / dz_3	du / dz_4
Mean	0.014 (0.013)	0.271 (0.313)	-0.138(0.159)	-0.103 (0.119)
Q1	0.000 (0.005)	0.000 (0.093)	-0.190 (0.001)	-0.141 (0.120)
Q2	0.013 (0.014)	0.251 (0.276)	-0.128(0.097)	-0.095 (0.072)
Q3	0.019 (0.016)	0.372 (0.316)	0.000(0.151)	0.000 (0.035)

Author's calculation using R and the standard errors are in the parentheses.(Table 5.4a, 5.4b, 5.4c and 5.4d).

The mean marginal effect of the number of patents and R&D intensity on transient inefficiency was 0.01372 and 0.2711, respectively, implying that, under the ceteris paribus clause, transient inefficiency would account for 1.37% and 2.71% of output loss with an increased number of patents and R&D intensity, respectively, for the pharmaceutical industry. However, relatively higher accountability of transient inefficiency of 10.13% and 5.87% was demonstrated in the electrical and electronic industry if the trade openness and technology transfer costs increased on average. A similar picture prevailed in the IT and communication and biotechnology industries. Hence, it is evident that, in general, with a marginal increase of technology transfer costs and trade openness, output loss was higher than the number of patents variable because of transient inefficiency. Figures 5.1a, 5.1b, 5.1c and 5.1d present histograms of the marginal effects of the individual environmental variables on transient inefficiency for the biotechnology, electrical and electronics, IT and communication, and pharmaceutical industries.

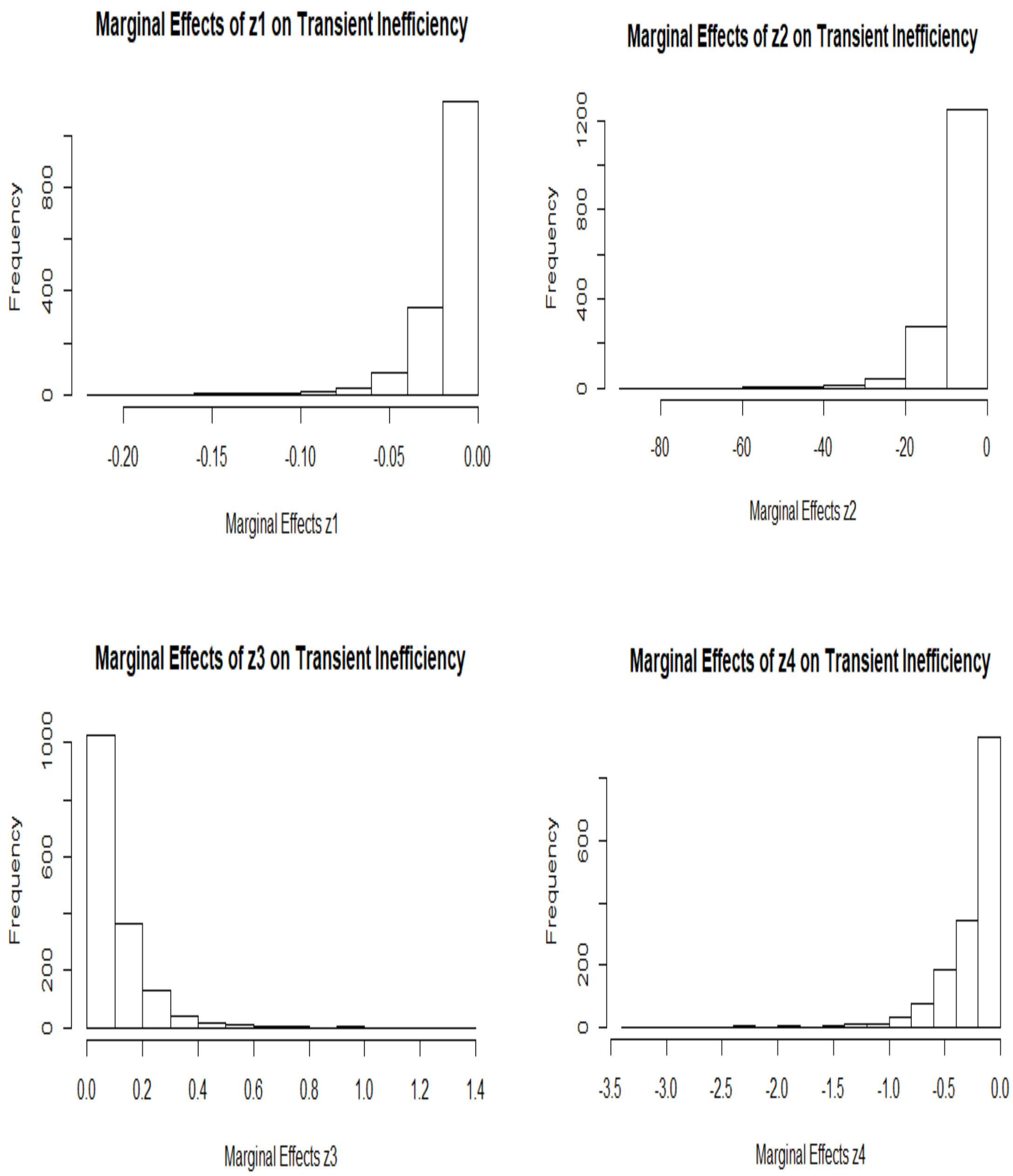


Figure 5.1a: Marginal Effects of Number of Patents (z1), RNDI (z2), Trade Openness (z3) and Technology Transfer (z4) on Transient Inefficiency in Biotechnology Industry

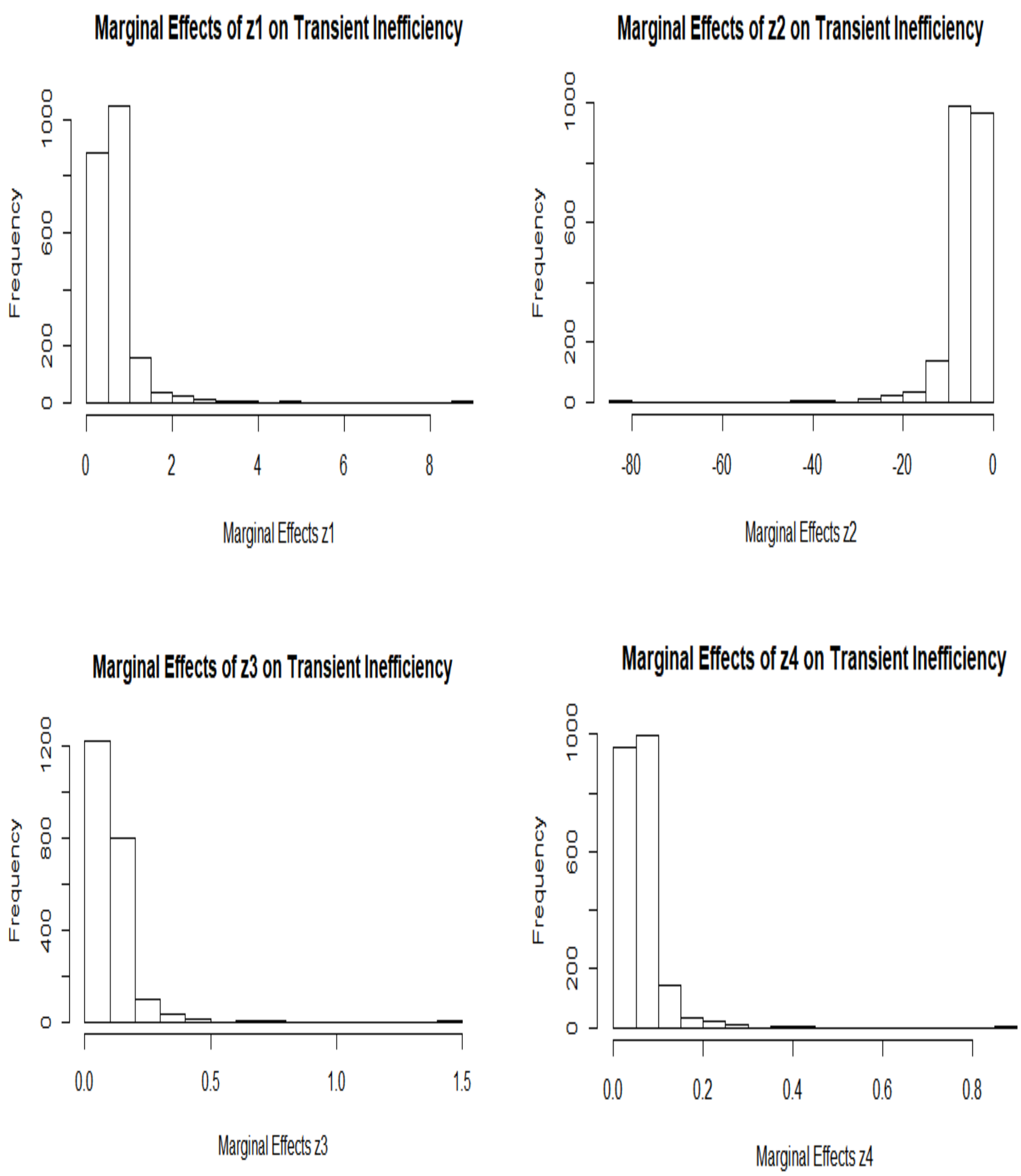


Figure 5.1b: Marginal Effects of Number of Patents (z1), RNDI (z2), Trade Openness (z3) and Technology Transfer (z4) on Transient Inefficiency in Electrical and Electronics Industry

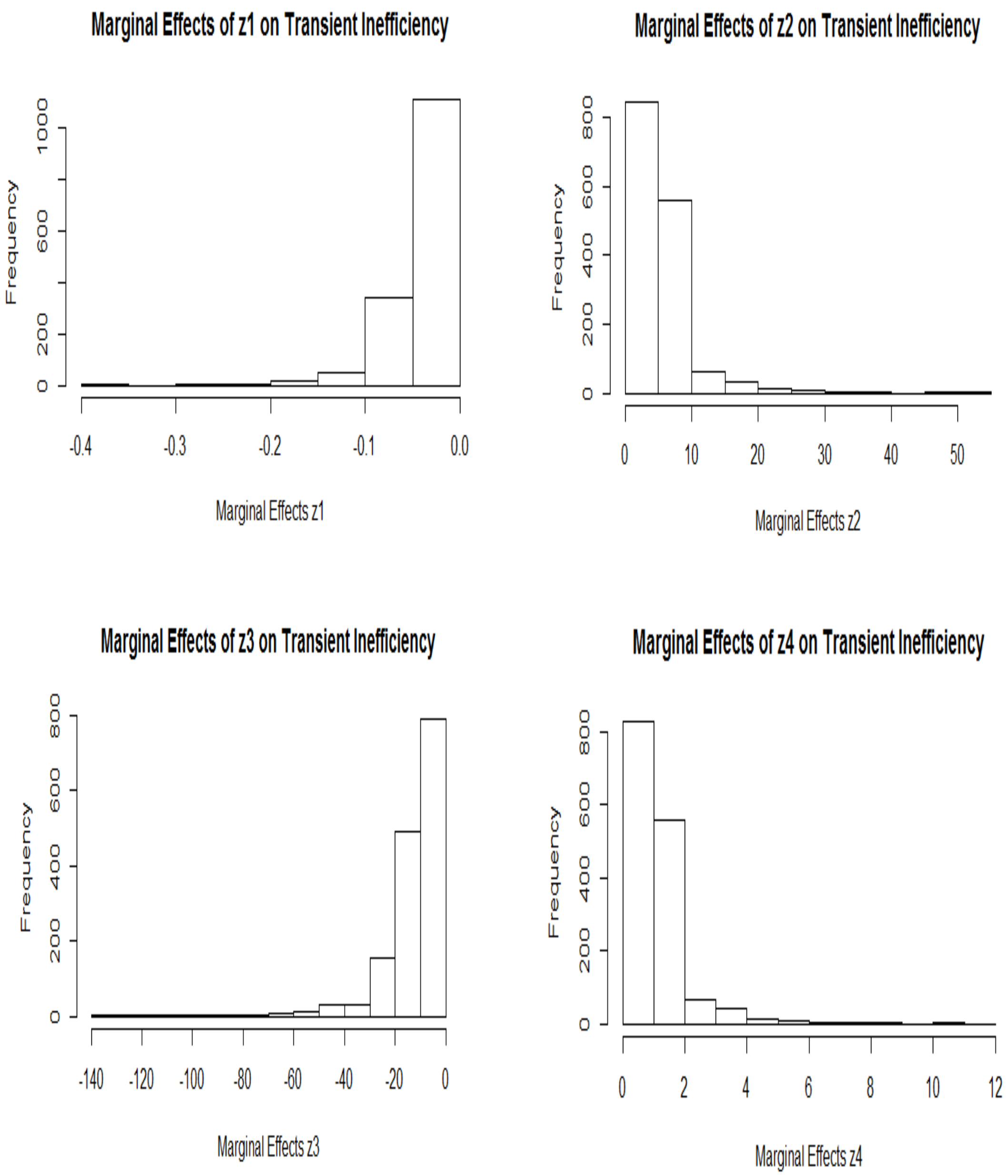


Figure 5.1c: Marginal Effects of Number of Patents (z1), RNDI (z2), Trade Openness (z3) and Technology Transfer (z4) on Transient Inefficiency in IT and Communication Industry

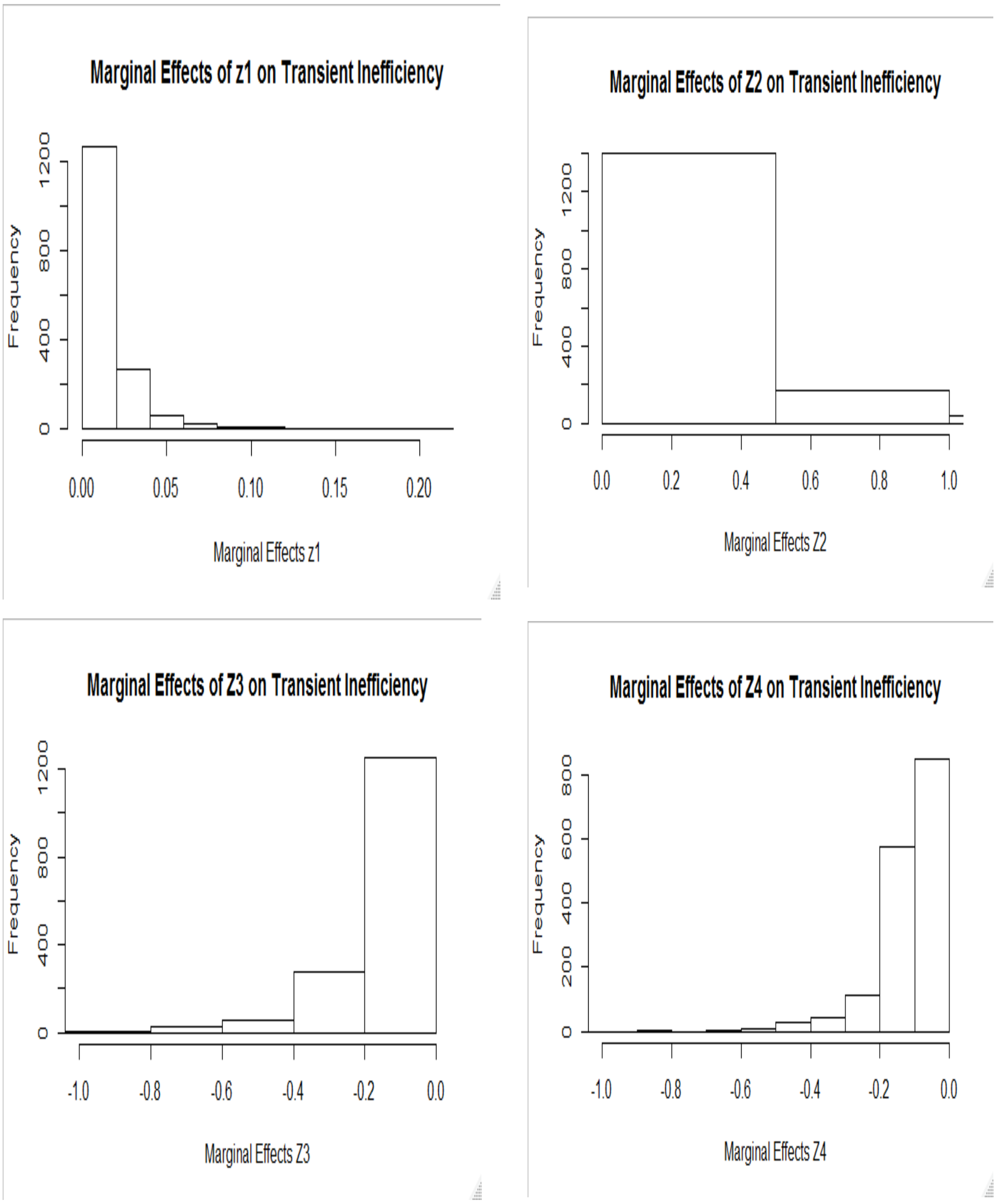


Figure 5.1d: Marginal Effects of Number of Patents (z1), RNDI (z2), Trade Openness (z3) and Technology Transfer (z4) on Transient Inefficiency in Pharmaceutical Industry

5.5.2.4 Comparative Effects of Patent Variables on Log Output

Table 5.5: Comparative Effects of Environmental Variables on Log Output

	Biotechnology	Electrical and electronics	IT and communication	Pharmaceutical
Mean	1.844 (0.049)	3.213 (0.280)	1.285 (0.046)	0.920 (0.042)
Q1	-0.817 (0.036)	-2.256 (0.418)	-3.684 (0.048)	-0.040 (0.040)
Q2	0.848 (0.042)	1.183 (0.044)	1.547 (0.006)	0.481 (0.010)
Q3	5.829 (0.025)	6.590 (0.037)	3.168 (0.048)	1.098 (0.047)

Author's calculation using R and the standard errors are in the parentheses. All the values are rounded-off to 3 decimal points.

Table 5.5 depicts the overall mean marginal effect of the environmental variables on the log output of all four industries. These estimates are 0.92013, 3.2130, 1.2845 and 1.8440 for the pharmaceutical, electrical and electronics, IT and communication, and biotechnology industries, respectively, and all are statistically significant at the 5% level, apart from the electrical and electronic industry. Hence, in general, the output gained of the individual firms from the learning effect of the input variables offsets the output loss of fewer firms due to the depreciation effect of the input variables in the case of biotechnology, IT and communication and pharmaceutical industries.

5.5.2.5 Persistent Technical Efficiency, Transient Technical Efficiency and Overall Technical Efficiency Scores for Selected Industries

Table 5.6a: Persistent TE, Transient TE and Overall TE Scores (Biotech Industry)

Biotech industry	PTE	TTE	OTE
Mean	0.632 (0.003)	0.685 (0.009)	0.432 (0.006)
Q_1	0.622 (0.004)	0.397 (0.008)	0.232 (0.005)
Q_2	0.634 (0.000)	0.848 (0.008)	0.537 (0.005)
Q_3	0.650 (0.003)	1.000 (0.001)	0.634 (0.001)

Table 5.6b: Persistent TE, Transient TE and Overall TE Scores (Electrical and Electronics Industry)

Electrical and electronics industry	PTE	TTE	OTE
Mean	0.171 (0.003)	0.100 (0.003)	0.015 (0.000)
Q_1	0.092 (0.001)	0.010 (0.000)	0.001 (0.000)
Q_2	0.133 (0.002)	0.078 (0.001)	0.009 (0.000)
Q_3	0.241 (0.003)	0.129 (0.004)	0.018 (0.001)

Table 5.6c: Persistent TE, Transient TE and Overall TE Scores (IT and Communication Industry)

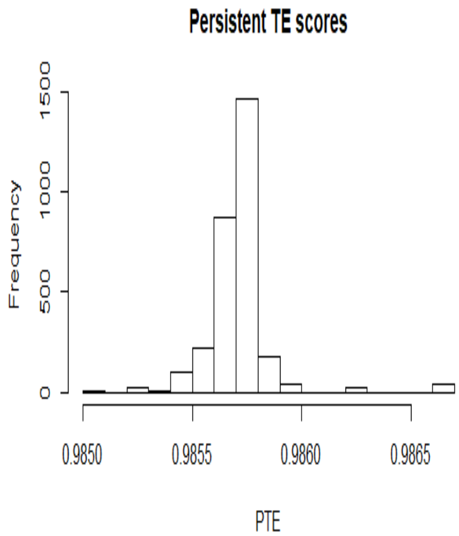
IT and communication industry	PTE	TTE	OTE
Mean	0.232 (0.004)	0.499 (0.011)	0.107 (0.003)
Q_1	0.142 (0.002)	0.094 (0.003)	0.022 (0.001)
Q_2	0.204 (0.002)	0.240 (0.003)	0.054 (0.000)
Q_3	0.309 (0.005)	1.000 (0.009)	0.190 (0.003)

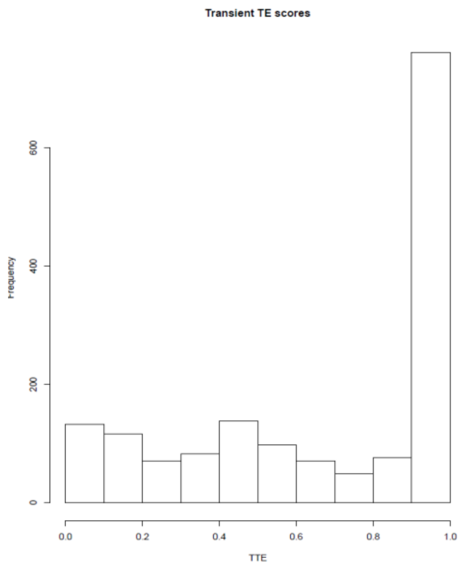
Table 5.6d: Persistent TE, Transient TE, and Overall TE Scores (Pharmaceutical Industry)

Pharmaceutical industry	PTE	TTE	OTE
Mean	0.785 (0.002)	0.880 (0.003)	0.694 (0.004)
Q_1	0.738 (0.003)	0.850 (0.004)	0.632 (0.004)
Q_2	0.805 (0.001)	0.887 (0.002)	0.708 (0.002)
Q_3	0.855 (0.001)	1.000 (0.002)	0.784 (0.002)

Author's calculation using R and the standard errors are in the parentheses (Table 5.6a, 5.6b, 5.6c and 5.6d).

Tables 5.6a, 5.6b, 5.6c and 5.6d demonstrate the mean and quartile values (Q1 to Q3) of the estimated persistent TE, transient TE and overall TE scores of the biotechnology, electrical and electronics, IT and communication, and pharmaceutical industries, respectively. The average PTE score of the pharmaceutical industry was 0.785 with 0.002 standard deviation that is statistically significant at a 5% level. This indicates that a substantial number of firms in the sample of the pharmaceutical industry did not experience persistent inefficiency. The biotechnology industry revealed a mean PTE score of 0.63221 with a 0.003 standard deviation, indicating a similar picture to the pharmaceutical industry, with only 7.967378% of the sample firms acquiring 50% or less persistent TE scores. In contrast, 96.7% and 92.27% of firms in the sample set in the electrical and electronics and IT and communication industries, respectively, experienced persistent technical inefficiency. The mean PTE scores were 0.17085 and 0.232070, respectively, for those two industries. Figures 5.2a, 5.2b, 5.2c and 5.2d present histograms of the PTE, TTE and OTE scores of the biotechnology, electrical and electronics, IT and communication, and pharmaceutical industries, respectively. The rationale behind the high persistent technical inefficiency scores of the electrical and electronics and IT and communication industries may be that India has not concentrated on exporting such products even though these have very low non-tariff-barriers.(Kelker and Kalirajan 2021; Pohit and Basu 2012). Moreover, increasing reliance on other countries for integral parts, to some extent, hindered the catch-up process and establishment of backward linkages in the electrical and electronics and IT and communication industries (Saripalle 2015).





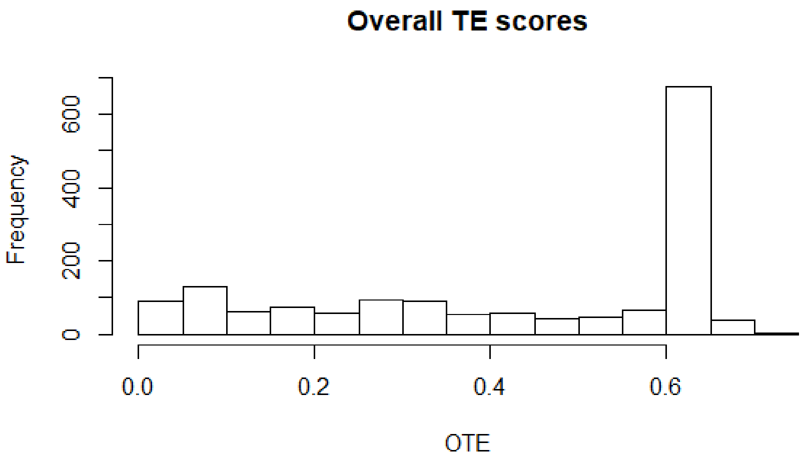


Figure 5.2a: Histograms of Estimated TE Scores (Biotechnology Industry)

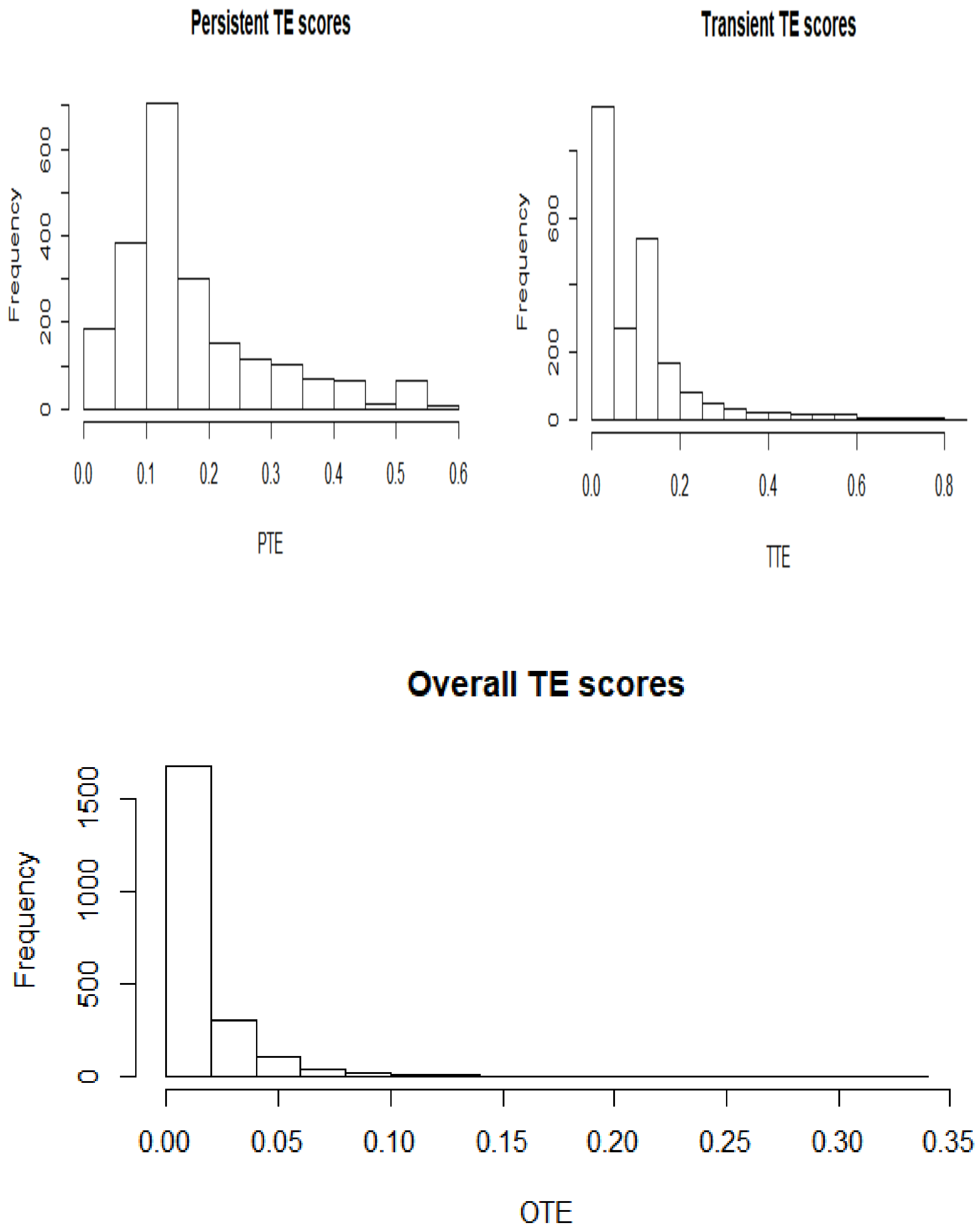


Figure 5.2b: Histograms of Estimated TE Scores (Electrical and Electronics Industry)

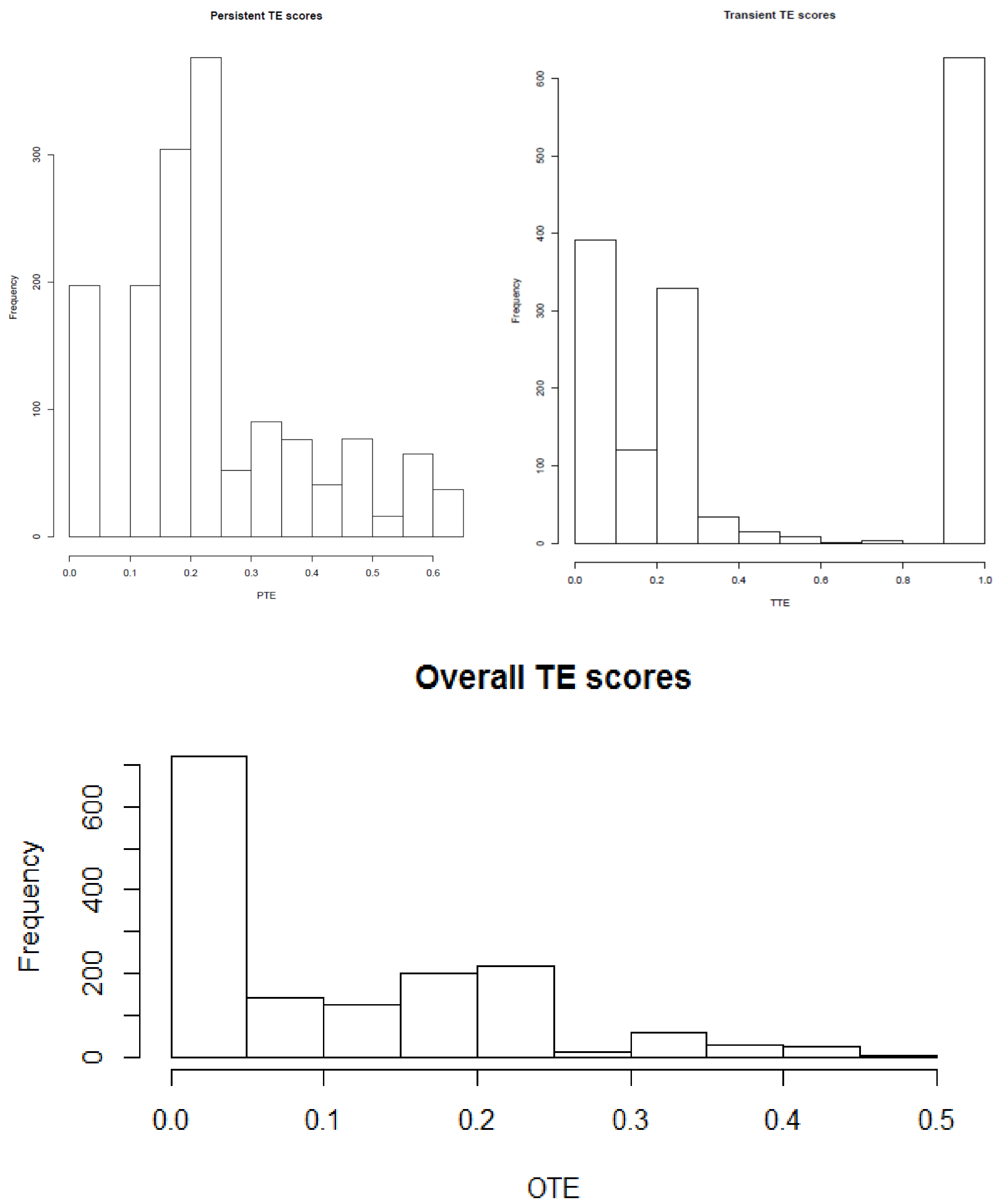


Figure 5.2c: Histograms of Estimated TE Scores (IT and Communication Industry)

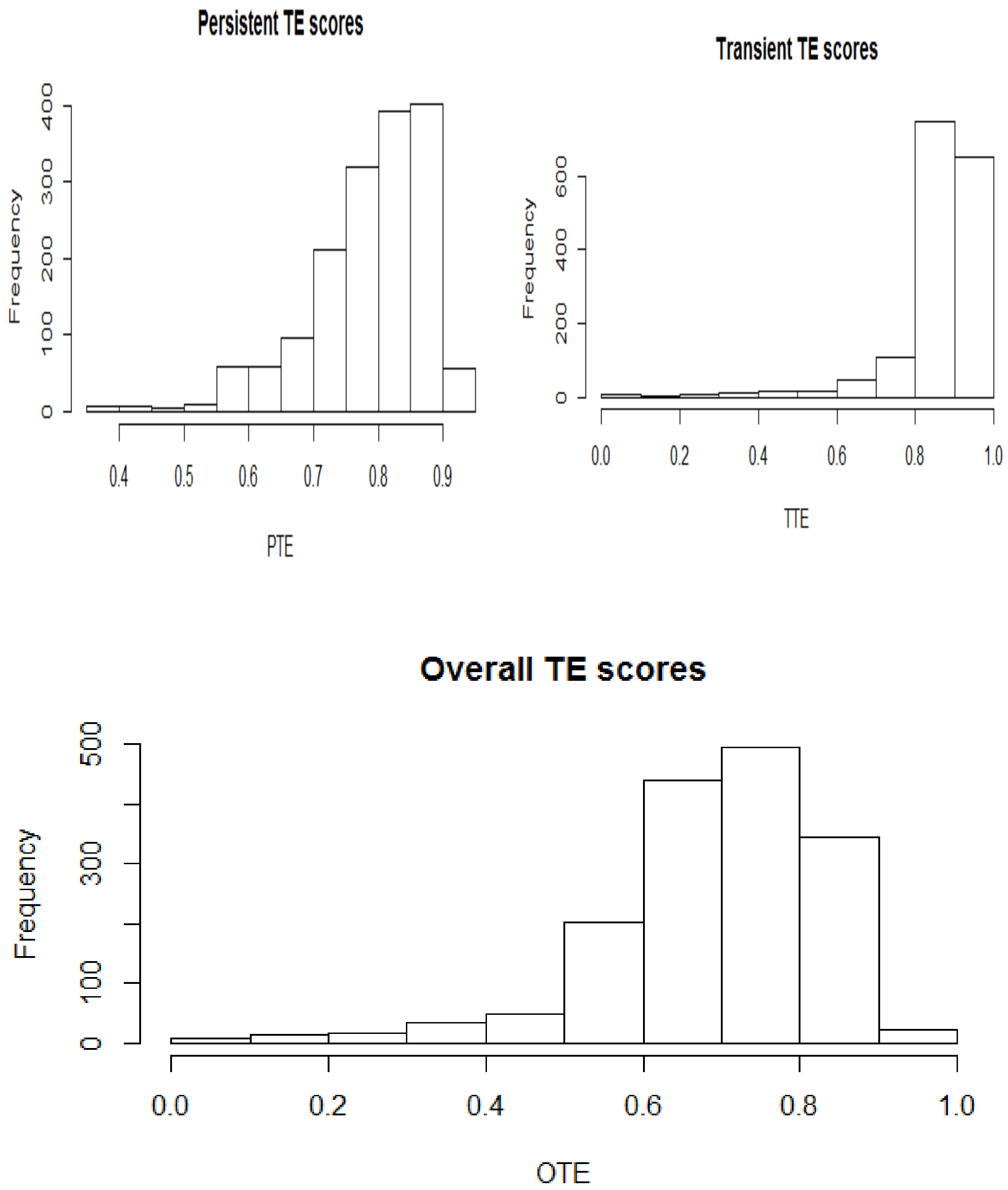


Figure 5.2d: Histograms of Estimated TE Scores (Pharmaceutical Industry)

5.6 Conclusion

This chapter has presented a detailed analytical framework examining the effect of patent reforms on firm-level TE. The intrinsic effect of the patent protection variable on TE was determined by the SFA. A semiparametric smooth-coefficient SPF model was employed, where the inputs were acknowledged to be endogenous in a production function framework, and the technology parameters were unknown smooth functions of the environmental variables. Moreover, the error component was split into four elements: one time-variant and one time-invariant noise term, and two inefficiency term constituents of persistent inefficiency (time-invariant) and transient inefficiency (time-variant). Further, the time-variant transient inefficiency is considered also as a function of the environmental variables.

The estimation results of the smooth coefficients and input elasticities varied among the different industries. In general, India's manufacturing industries—the electrical and electronics and biotechnology industries—indicated technical progress, represented by a positive coefficient for time (*T*); however, the IT and communication industry experienced adverse technical progress. On the other hand, the pharmaceutical industry has no statistically significant values, thus implicating practically no technical change. The output percentage escalated with the percentage growth of input variables (capital, labour, material and energy) in the biotechnology and pharmaceutical industries during the period 1995 to 2016. Contrastingly, the labour input elasticity in the electrical and electronics and capital input elasticity for the IT and communication industry showed a negative value. A likely cause of this result is the rebound effect, reflecting that the beneficial effects of new technology through the cost of capital (such as equipment) or labour (such as training) outweigh behavioural responses at the initial stage. The overall RTS scores aligned with the expectation.

The smooth coefficients were a nonlinear function of the environmental variables; hence, the marginal effects of individual environmental variables provided deeper insight. On average, an increase in the environmental variables had a mixed effect on the smooth coefficients. However, overall, trade openness and technology transfers adversely influenced the magnitude of technical progress. A plausible explanation for this is that, as a developing country, India must bear colossal licensing fees and technology transfer costs. Moreover, in general, the estimates indicated that, with a marginal increase of technology transfer costs and trade openness, output loss was higher than the number of patents variable because of transient inefficiency. The estimates of the overall mean marginal effect of the environmental variables on the log output of all four industries were positive. The output gained of individual firms from their learning effect of the input variables is more than the output loss of individual firms due to the depreciation effect of the input variables. Thus, output gained to offset the output loss and ultimately portrayed the output gain in the industry. Finally, the estimated PTE, TTE and OTE scores indicated that a significant percentage of firms in the IT and communication and electrical and electronics industries experienced persistent technical inefficiencies. Thus, the estimation results signify that the Indian government should emphasise creating a dynamic R&D ambience, especially while formulating national industrial policy. Firms can achieve more patents to eventually enhance their output at the micro-level and industry output at the macro-level. Moreover, policy prescription should focus on the two-way technology transfer process between India and across the globe. The new government resolutions should be trade policy revision. Precisely the export-oriented trade policies with special focus on the merchandise that has low non -tariff barriers plausibly enhance India's export. Furthermore, export efficiency can improve through effective institutional, practical and infrastructural reforms.

Chapter 6: Decomposition of Total Factor Productivity Growth

6.1 Introduction

The previous chapter discussed the significance of patent protection for firm-level TE. The notion of TE plays a pivotal role in estimating firms' economic efficiency. TE can be conceptualised as a firm's proficiency either to produce the maximum feasible output from available inputs and technology or to produce a specified level of output from the minimum amount of inputs for a given technology. Hence, TE conceivably portrays feasible movement towards the production frontier without exploiting any additional inputs (Coelli et al. 2005; Färe, Grosskorf and Lovell 1985, 1984). This thesis applied the four-component semiparametric smooth coefficient SPF model (Kumbhakar, Sun and Tveterås 2018) and decomposed the efficiency term into transient efficiency and persistent efficiency. Productivity change is a critical perspective in terms of structural change and competitiveness. TFP growth encompasses efficiency change as one principal component, technical change and AE (Salim 1999). The decomposition of TFP change can be explained as the sources of productivity change. Hence, it is imperative to identify whether productivity change is owing to a shift in the frontier (explicitly technical change) or a change in the firm's practices (specifically, efficiency change).

This chapter concentrates on the decomposition of TFP growth in selected Indian manufacturing industries for the period 1995 to 2016 as a continuation of Chapter 5. The referred time span is critical for India's economic history, as India signed the GATT in 1994 and was obligated to enforce TRIPS in all fields of technology from January 1995. However, a transition period of 10 years from 1995 to 2005 was granted to shift the paradigm to product patents from process patents, considering the developing status of the country (WTO, 1994). Thus, the decomposition of TFP enabled this study to identify the major driver of the productivity growth of Indian manufacturing industries to assist in formulating effectual policies accordingly.

This thesis employed the prominent Färe-Primont productivity index (developed by O'Donnell 2010, 2012). The rationale behind applying the Färe-Primont index to estimate TFP growth derived from the holistic nature of this index, since it can capture the overall change in productivity and decompose it into various intricate measures of efficiency change. O'Donnell (2011) also provided evidence in favour of the Färe-Primont index over other indexes, such as the Hicks-Moorstern index, in estimating productivity changes and its components.

This chapter comprises seven sections. Section 6.2 provides a brief discussion of the measurement of TFP growth and its decomposition. The following Section 6.3 analyses measures of productivity and efficiency. Section 6.4 explains the decomposition of productivity, while Section 6.5 describes the data used for estimation. Section 6.6 presents the results and analysis of TFP change and its decomposition. Finally, Section 6.7 concludes the chapter.

6.2 Measurement of Total Factor Productivity and Decomposition

The TFP growth literature has demonstrated numerous ways to estimate TFP growth, and its decomposition was discussed in Chapter 4. The frontier and non-frontier approaches are the two primary approaches of TFP measurement, and, among these, the non-frontier approaches comprise parametric and nonparametric methods. In contrast, the parametric estimation of production/cost/distance functions is classified into two approaches: programming and econometric approaches. Likewise, the GA and indexing methods are the two approaches of the nonparametric method. The primary interest in a parametric model is to estimate the vector of parameters under a finite-dimensional plane. Contrastingly, the primary interest in a nonparametric model is to estimate the infinite-dimensional vector of parameters. The set of parameters is the subset of the infinite-dimensional vector (Salim 1999).

An essential requirement of the parametric approach is to enumerate the production function with respect to inputs as the explanatory variable and an algebraic function form. At first, a flexible, functional form—commonly the CD or translog production function—must conscript the algebraic formulae of the technical change, and a scale change component can be derived from that production function in the parametric procedure. Finally, the estimated parameter scores and data were used to compute technical change and a scale change component (Kumbhakar and Sun 2012). The empirical literature has widely applied the SFA estimation procedure as a parametric method to measure TFP growth. Unlike the DEA approach, this procedure grants to seclude the inefficiency component from the random error that includes other statistical noise sources, such as measurement errors and omitted exogenous variables. In contrast, any misspecification of the required explicit parametric functional form and an explicit distributional assumption for the inefficiency terms may provide the bias outcomes. The endogeneity problem associated with SFAs has received considerable attention, as it generates inconsistent parameter estimates. Two factors have been identified those causing this issue: (i) the existence of a correlation between the inefficiency term and two-sided error term and (ii) the existence of a correlation between the two-sided error term and the determinants of the frontier.

Both the parametric and nonparametric approaches have distinctive drawbacks. The DEA method (Charnes et al. 1978)[20] is the most eminent nonparametric approach, and possesses a few strengths. First, it has no presumption of explicit parametric functional forms for the production frontiers that indicates the assumption for the specific shape of the frontier is absolutely trivial in the nonparametric approach. Second, it has no restrictions for the application of distributional assumptions on the disturbance term. Third, it is possible to refrain from the subjective interpretation of multiple outputs and inputs, as this approach adapts these multiple outputs and inputs concurrently. Fourth, a mathematical program is required to solve to determine the optimal input–output weights in the DEA procedure. However, the drawbacks of the DEA procedure are as follows: (i) all the deviation from the frontier is captured as inefficiency; (ii) the procedure is sensitive to outliers in the data, as DEA is deterministic; and (iii) using a small sample size to compute the TE generates upwards bias estimates (O’Donnell 2011). The semiparametric approach is a synthesis of the parametric and nonparametric approaches, addressing the limitations of both. Thus, the predictors consist of a predetermined production function portion and an unknown form of the production function (O’Donnell 2011a, 2012).

The productivity growth literature often employs the indexing approach—such as Fisher (1922), Divisia index (1925), Törnqvist index (1936), Malmquist index (1953), Hicks-Moorsteen index (1996) and the lately developed Färe and Primont productivity index (O’Donnell 2012)—as the estimates are replicable, transparent and consistent with the available data (Lawrence, Diewert and Fallon 2009). Moreover, the indexing approach is

[20] DEA is a nonparametric method used to measure productive efficiency empirically for DMUs to estimate production frontiers.

robust and suitable for a small sample size. The Färe-Primont productivity index was used in this thesis to compute the TFP and the decomposition. Several justifications exist in favour of using this index. First, it is convenient, as it can be calculated directly from the available data, and no a priori strong assumptions pertaining to the production technology or nature of technical change are required to compute the index. Second, the econometric techniques are more reliable when price data are unavailable. The Färe-Primont productivity index permits computing the TFP index and its decomposition without data on price. Besides, no restrictive assumptions related to the random error term are required while computing the Färe-Primont productivity index (Khan, Salim and Bloch 2015). Third, the Färe-Primont productivity index is a 'multiplicatively complete' productivity index (O'Donnell 2011), as it can be used to compute pertinent multilateral (many firms) and multi-temporal (many periods) comparisons. It meets all the required axioms of productivity index measurement, including transitivity (Khan, Salim and Bloch 2015). Fourth, the optimising behaviour of firms or degree of competition in the product market is not a required assumption while estimating TFP using the Färe-Primont index. Fifth, the Färe-Primont productivity index is a widely applied nonparametric model and can interpret TFP growth and decompose it in a flexible manner, precisely, in even more intrinsic components. Sixth, no prior empirical TFP growth literature on India has applied this index in the TRIPS context yet; hence, using this index will advance the existing literature. Finally, using a computer software package—namely, DPIN 3.0, which was developed by O'Donnell (2011)—can decompose TFP growth in a convenient manner.

6.3 Measures of Total Factor Productivity Growth Formulation and Efficiency

This study measured productivity change using the TFP index. This index was used because it contemplates the potential input substitution between labour and capital, unlike partial productivity measures, such as labour productivity (Brynjolfsson and Hitt 2003). The TFP literature presented two initial approaches for TFP estimation: (i) computing an average production function and measuring the TFP using the estimated Solow residual and (ii) SPF. Although the time variable is accounted for in these two approaches, both remain controversial in terms of policy enforcement. Omitting variables in the first step is the major drawback of the two-step approach, as it produces bias coefficients in the second step (Wang and Schimidt 2002). Thus, the estimates of the determinants of TFP become inefficient as a result of this ambiguity in the two-step approach (Newey and McFadden 1994). Direct inclusion of TFP in a regression model, expressed as time trend and residual variables, along with value-added dependent variables, was used in attempt to resolve this ambiguity (Harris and Trainor 2005). However, this approach was also contentious. Thus, the index number approach was the third approach developed to estimate TFP. The Färe-Primont index employed in this thesis satisfies all economically meaningful axioms and transitivity tests of index number theory. This section has already discussed this framework in brief.

6.3.1 Different Measures of Productivity and Efficiency

The aggregate quantity framework proposed by O'Donnell (2012) was adopted in this chapter to analyse the decomposition of productivity change. This section briefly illustrates this framework.

Let $y_{it} \equiv y_{1it}, \ldots y_{kit}$ and $x_{it} \equiv x_{1it}, \ldots, x_{kit}$ denote the vectors of output and input quantities for firm i at time t, respectively. The TFP of a firm defines as the ratio between the aggregate output and aggregate input in the aggregate quantity framework following O'Donnell (2012a) and expressed as,

$$TFP_{it} = \frac{y_{it}}{x_{it}} \tag{6.1}$$

where TFP_{it} implies TFP of firm i in period t, $Y_{it} = Y(y_{it})$ and $X_{it} = X(x_{it})$ are aggregate output index and aggregate input index, respectively. $Y(\cdot)$ and $X(\cdot)$ are non-negative, non-decreasing and linearly homogenous aggregator functions.

The overall productive efficiency of a firm is measured as the ratio of observed TFP to the maximum possible TFP given the available technology. Thus, mathematically can be written as,

$$TFPE_{it} = \frac{TFP_{it}}{TFP_t^*} = \frac{Y_{it}/X_{it}}{Y_t^*/X_t^*} \leq 1 \tag{6.2}$$

where, $TFPE_{it}$ is the TFP efficiency of firm i in period t. TFP_{it} is the TFP of firm i in period t, TFP_t^* is the maximum possible TFP with the given technology. Y_t^* and X_t^* indicate the aggregate output and aggregate input vector at the TFP-maximising point.

Several intricate measures of output-oriented efficiency are procured by following O'Donnell (2012),

Output-oriented TE, $OTE_{it} = \frac{Y_{it}/X_{it}}{\bar{Y}_{it}/X_{it}} = \frac{Y_{it}}{\bar{Y}_{it}} \leq 1$ (6.3)

Output-oriented SE, $OSE_{it} = \frac{\bar{Y}_{it}/X_{it}}{\tilde{Y}_{it}/\tilde{X}_{it}} \leq 1$ (6.4)

Output-oriented mix efficiency, $OME_{it} = \frac{\bar{Y}_{it}/X_{it}}{\hat{Y}_{it}/X_{it}} = \frac{\bar{Y}_{it}}{\hat{Y}_{it}} \leq 1$ (6.5)

Residual output-oriented SE, $ROSE_{it} = \frac{\hat{Y}_{it}/X_{it}}{TFP_t^*} \leq 1$ (6.6)

Residual mix efficiency, $RME_{it} = \frac{\tilde{Y}_{it}/\tilde{X}_{it}}{TFP_t^*} \leq 1$ (6.7)

where, $\bar{Y}_{it}$ is the maximum aggregate output that is technically viable to produce a scalar multiple of y_{it} by using the input x_{it} . $\hat{Y}_{it}$ is the maximum achievable aggregate output by using the input x_{it} to produce any output vector. $\tilde{Y}_{it}$ and $\tilde{X}_{it}$ represent the aggregate output and input quantities procured at the point at which TFP is maximised subject to the constraint that the output and input vectors are scalar multiples of y_{it} and x_{it} respectively. Y_{it}^* and X_{it}^* denote the aggregate output and input quantities obtained at the point of maximum productivity.

The equation (6.3) is depicted the overall TE (OTE), ascribed to Farrell (1957). This dissertation is contemplated the SE (OSE) represented in equation (6.4), following the traditional definition of Balk (2001). O'Donnell (2008) defined the other several finer measures. The OSME is proposed by O'Donnell, 2010b as one of the pertinent efficiency measures and mathematically expressed as,

$OSME_{it} = OSE_{it} \times RME_{it} = OME_{it} \times ROSE_{it}$ (6.8)

Thus, OSME is devised as the product of SE and residual mix efficiency or as devised as the product of output-oriented mix efficiency and residual output-oriented SE.

6.4 Decomposition of Total Factor Productivity Growth

The TFP of firm i in period t compares with the TFP of firm h in period s under the aggregate quantity framework of O'Donnell (2012), is captured in the productivity index define as,

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \frac{Y_{it}/X_{it}}{Y_{hs}/X_{hs}} = \frac{Y_{hs,it}}{X_{hs,it}} \tag{6.9}$$

where $Y_{hs,it} \equiv \frac{Y_{it}}{Y_{hs}}$ is an output quantity index or a measure of output growth and $X_{hs,it} \equiv \frac{X_{it}}{X_{hs}}$ is an input quantity index or a measure of input growth. Index numbers that can be written as a measure of relative productivity as represented in equation (6.9) are known as multiplicatively complete (O'Donnell 2012). The adoption of different functional forms for the aggregator functions Y(.) and X(.) provide different multiplicatively complete indexes. Usually, any multiplicatively complete TFP index as described in equation (6.9) can be decomposed into several distinctive measures of technical change and efficiency change (O'Donnell, 2012b). In a straight-forward manner equation (6.2) can be expressed as,

$TFP_{it} = TFP_t^* \times TFPE_{it}$, for the firm i (where, i= 1, …, N, t=1, …, T).

Thus, the relative TFP index of firm *i* in period *t* and firm *h* in period *s* is,

$$TFP_{hs,it} = \frac{TFP_t^*}{TFP_s^*} \times \frac{TFPE_{it}}{TFPE_{hs}} \tag{6.10}$$

The first component of the righthand side compares the maximum feasible TFP in period *t* with the maximum feasible TFP in period *s* and indicates as a measure of TP or broadly technical change. Besides, the second component of the right hand side indicates the comparison between the measures of the efficiency change of firm *i* in period *t* and firm *h* in period *s*. Further, the efficiency change component can be decomposed into few inherent components such as various measures of technical, scale-mix efficiency change.

Following O'Donnell (2012a), the TFP decompositions are expressed as,

$$TFP_{it} = TFP_t^* \times (OTE_{it} \times OME_{it} \times ROSE_{it})$$

$$= TFP_t^* \times (OTE_{it} \times OSE_{it} \times RME_{it}) \tag{6.11}$$

Thus, a similar decomposition carries for firm *h* in period *s*. The relative TFP index that compares TFP of firm *i* in period *t* with the TFP of firm *h* in period *s* can be decomposed meticulously as,

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}} \times \frac{OME_{it}}{OME_{hs}} \times \frac{ROSE_{it}}{ROSE_{hs}}\right) \tag{6.12}$$

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}} \times \frac{OSE_{it}}{OSE_{hs}} \times \frac{RME_{it}}{RME_{hs}}\right) \tag{6.13}$$

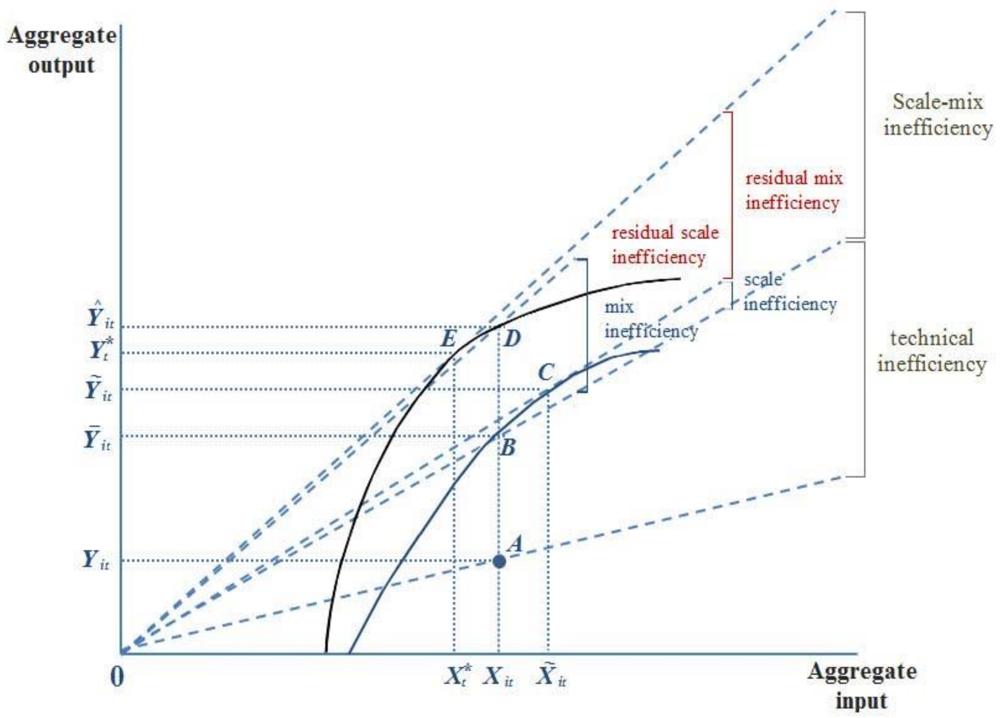
Based on Equations (6.2), (6.8), (6.12) and (6.13), the similar decomposition of TFP change in Equation (6.10) can be expressed in the following way,

$$TFP_{hs,it} = \frac{TFP_{it}}{TFP_{hs}} = \left(\frac{TFP_t^*}{TFP_s^*}\right)\left(\frac{OTE_{it}}{OTE_{hs}}\right)\left(\frac{OSME_{it}}{OSME_{hs}}\right) \tag{6.14}$$

The OSME captures the increment of TFP owing to the movements from the technically efficient point to the feasible maximum productivity point.

This chapter relies on the way of decompositions as described in Equation (6.10) and (6.14). The Equation (6.14) construes the TFP change into three innate components, firstly, a technical change that measures movements in the production frontier, secondly, a TE change component that measures movements towards or away from the frontier and lastly, a scale-mix efficiency change component that measures movements around the frontier surface to capture the economies of scale and scope (O'Donnell, 2011b, 2012). The OSME captures the increment of TFP owing to the movements from the technically efficient point to the feasible maximum productivity point.

This chapter relies on the way of decompositions as described in Equation (6.10) and (6.14). Equation (6.14) construes the TFP change into three innate components, firstly, a technical change that measures movements in the production frontier; secondly, a TE change component that measures movements towards or away from the frontier and lastly, a scale-mix efficiency change component that measures movements around the frontier surface to capture the economies of scale and scope (O'Donnell, 2011b, 2012).



Output-Oriented Measures of Efficiency for a Multiple-Input Multiple-Output Firm

Figure 6.1: Output-oriented Components of TFP Change

Proceeding with O'Donnell (2011b, 2012) this study employs the nonnegative, non-decreasing and linearly homogenous Färe-Primont aggregator function as represented below, to solve the productivity index of equation (6.10).

$$Y(y) = D_0(x_0, y, t_0) \tag{6.15}$$

$$X(x) = D_0(x, y_0, t_0) \tag{6.16}$$

where x and y are vectors of input and output quantities and $D_0(\cdot)$ and $D_1(\cdot)$ are the Shephard output and input distance functions, respectively. These, Shephard output and input distance functions portray the available production technology in period t. Hence, the Färe-Primont productivity index is depicted by (O'Donnell 2012) as,

$$TFP_{hs,it} = \frac{D_0(x_0, y_{it}, t_0)}{D_0(x_0, y_{hs}, t_0)} \frac{D_1(x_{hs}, y_0, t_0)}{D_1(x_{it}, y_0, t_0)} \tag{6.17}$$

compares the measures of TFP of firm i in period t with the measures of TFP of firm h in period s.

6.5 Data

6.5.1 Data Sources

The computation and decomposition of the Färe-Primont TFP indexes are performed in this study using the data provided by one of the comprehensive databases; namely, PROWESS is generated and maintained by a private organisation of India, the CMIE. The data from the annual financial statement of listed and unlisted enterprises and participant companies of the Indian Stock Exchange are available in this database. As mentioned in Chapter 2, the sunrise industries of India's manufacturing sectors emphatically affected with the enforcement of the TRIPs agreement in India has cogitated in this thesis. Thus, the data for the biotechnology, electrical and electronics IT and communication and pharmaceutical industries are collected from the year 1995-1996 to 2015-2016.

6.5.2 Variables

The output variable (Y) measures the output of industry (Y), and input variables are capital (K), labour (L), raw materials (M) and energy (E). The definitions and measurement details are demonstrated in Chapter 5. The computer software DPIN 3.0 uses the LP technique to decompose productivity into various efficiency changes.

6.6 Findings and Analysis

This section reports the findings in detail and analyses the TFP growth doctrine and its components in the context of the Indian manufacturing sector. As explained in Sections 6.3 and 6.4, the aforementioned decomposition method was executed using the DPIN 3.0 program developed by O'Donnell (2011). The DPIN 3.0 uses DEA LP to estimate production technology, productivity scores and efficiency. The estimation comprises the technical, scale and mix efficiency scores, as presented in Equations (6.3), (6.4), (6.5) and (6.6).

The default DEA LP used in DPIN 3.0 does not entail any random error terms. It requires no assumption regarding the distribution of parameters; hence, this approach is nonparametric. Specifically, the assumption of a locally linear frontier strengthens the DEA approach (O'Donnell 2011). The Färe-Primont indexes computed in this thesis assume that production technology demonstrates VRS. The production possibilities set are also stated in both types of technological change—technical progress and technical regress.

6.6.1 Total Factor Productivity Change and Efficiency Change, 1995 to 2016

The microeconomic theory states that technical change estimates should display a non-negative value in usual circumstances, portraying technical progress. This indicates that a particular level of output should not require a higher level of inputs over time. Technical progress or regress is generally estimated as the effect of time on the total output. Similarly, input coefficients should be non-negative values.

To provide an in-depth analysis, this section examines four major industries. These are not affected by the 'process patents regime' until 1995 and during the transition period of the TRIPS agreement until 2005. Prior to discussing the TFP change and its components, this thesis illustrates the findings in terms of industry levels for the specified period of 1995 to 2016.

The following Table 6.1 reports the Färe-Primont estimates for the technical change and various efficiency change components of TFP change over the period of 1995 to 2016. The results presented in Table 6.1 presume the production technology that followed VRS. Thus, it estimates efficiencies and productivity scores under the assumption that no proportional change in the outputs or inputs appears because of an increase or decrease in input or outputs, respectively (Cooper, Seiford and Zhu 2011). Therefore, the DEA program reasonably contemplates increasing, constant and decreasing RTS. The transitive attribute of this index portrays that all the estimates presented in this table are significantly comparable in performance, either spatial or intertemporal.

Table 6.1: TFP Change, Technical Change and Efficiency Change, 1995–2016 (Comparative Scenario)

	TFP			TFP*			TFPE			OTE			OSME		
Industry	1995	2016	ΔTFP	1995	2016	ΔTFP*	1995	2016	ΔTFPE	1995	2016	ΔOTE	1995	2016	ΔOSME
Biotechnology	0.513	0.492	0.959	0.783	0.798	1.019	0.655	0.617	0.941	0.799	0.933	1.167	0.822	0.661	0.804
Electrical and electronics	0.659	0.658	0.999	0.793	0.866	1.092	0.831	0.760	0.915	0.902	0.922	1.022	0.922	0.825	0.895
IT and communication	0.723	0.720	0.997	0.844	0.959	1.136	0.856	0.751	0.877	0.928	0.906	0.977	0.923	0.832	0.901
Pharmaceutical	0.377	0.359	0.952	0.705	0.502	0.711	0.535	0.716	1.338	0.614	0.932	1.519	0.887	0.768	0.866

Author's calculation using DPIN 3.0.
All the values are rounded off to 3 decimal points.

The first column of Table 6.1 exhibits the estimates of TFP. It infers that the IT and communication industry is the most productive, and the pharmaceutical industry is the least productive industry among these four selected industries in 1995 and 2016 . The productivity differs between the two industries is 91.5% (ΔTFP = 0.722/0.377= 1.915) and 100.63% (ΔTFP =0.7203 /0.359) in 1995 and 2016 respectively. Thus, the IT and communication industry are 91.5% more productive than the pharmaceutical industry in 1995 and 100.63% more productive in 2016.

The second column of Table 6.1 describes that over the period the IT and communication industry on an average procures ΔTFP* = 1.0059, which equates to an average rate of technical progress of $\Delta lnTFP^{*} = \frac{ln(1.0059)}{2016-1995}$ = 0.000278 or 0.028% per annum. On the other hand, the pharmaceutical industry, on average, procures ΔTFP* = 0.9849, thus implies that technical regress by 1.51311%.

The third column demonstrates the TFPE (OTE x OSME) estimates of the four industries and reveals that the overall efficiency has progressed over the period only in the pharmaceutical industry.

The overall efficiency estimates (ΔTFPE = ΔOTE x ΔOSME) are entirely owing to the scale-mix efficiency (OSME = OME x ROSE = OSE x RME) component. As the results show that instead of the IT and communication industry, the other three industries are highly technically efficient (OTE) throughout the sample period.

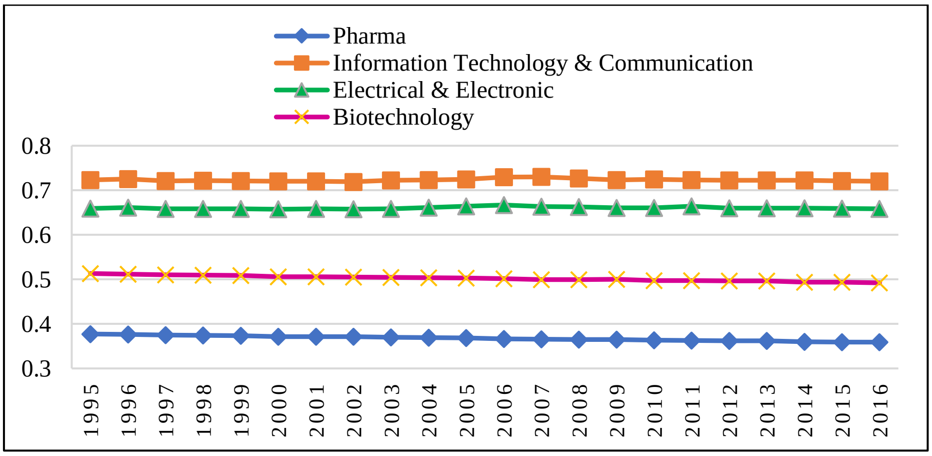


Figure 6.2: Levels of Productivity by Industry, 1995–2016

Figure 6.2 shows that the productivity levels of all the selected four industries that have precisely been affected by the enforcement of the TRIPs agreement are comparatively stable. The IT and communication industry render a higher level of productivity.

Several plausible explanations support these industries having the highest TFP. India's position on the global economy is owing to the significant contribution of the IT and communication industry. India is a convenient venue for global IT industries, and the Government of India has adopted crucial steps to propel the growth of this industry. Push effects, such as discouraging imports, and pull effects, such as boosting domestic demand and drive for the exports, are considered critical measures (Dijck et al. 1987).

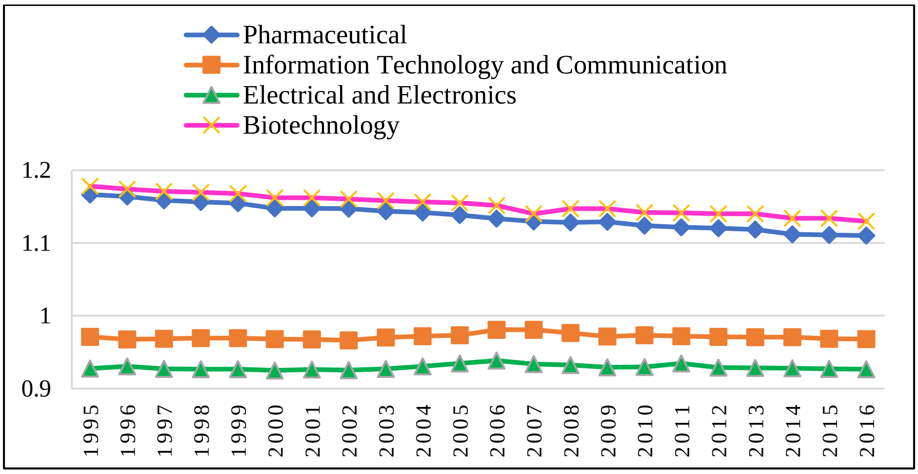


Figure 6.3: Productivity Growth by Industry, 1995–2016

Figure 6.3 demonstrates the productivity growth of the various industries and portrays a minor decline in the biotechnology and pharmaceutical industry. However, the annual productivity growth is higher for the overall period for the biotechnology and pharmaceutical industries. This study found higher productivity in the biotechnology industry than in the pharmaceutical industry. This aligns with the observation of Keller (2001) and Miller (2002) that biotechnological methods are an evidence-based approach; thus, the invention and modification of drugs lead to better productivity. In reality, the Indian pharmaceutical industry captured more than 50% of global demand for a variety of vaccines, 40% of US demand for generic drugs and 25% of UK demand for medicine during 2019 (IBEF 2020).[21] Along with the US's prime market, Indian drugs are exported to more than 200 countries across the globe (IBEF, 2020). The intensive innovation and

[21] Indian Brand Equity Foundation Reports (2020).

robust growth are expected to be a mainstay of the economic attributes of these industries, establishing them as ‘sunrise industries’.

6.6.2 Total Factor Productivity Change, Technical Change and Efficiency Change by Industry

This section discusses TFP change, technical change and efficiency change by industry to shed light on the analysis. The biotechnology and pharmaceutical industries experienced a relatively decreasing trend in TFP changes commencing from 1995 with the enforcement of the GATT framework until 2016, even after 10 years of mandatory legalisation of product patents in 2005. The minimum standards for intellectual property protection were endorsed for conferred members, such as India, through the TRIPS regime.

6.6.2.1 Biotechnology Industry

The Department of Biotechnology was instituted in 1986 to establish a conduit for technology transfer between research institutes and private firms, and eventually generate an enhanced biotechnology environment (Fan and Watanabe 2008; Li et al. 2007). In 1990, Indian pharmaceutical firms became more attentive to the biotechnology arena after noting the steady commercial success of this industry in the Western world. However, ambiguity in viable returns and soaring expenses restricted firms from entering this new domain. Indian biotechnology firms saw improved innovation capability through constructing parallel manufacturing units (Fan and Watanabe 2008). The following Table 6.2 (and Appendix) 6.1 reports the Färe-Primont estimates of annual TFP, technical change and efficiency components of TFP over the period 1995 to 2016 for the biotechnology industry.

Table 6.2: Annual TFP, Technical and Efficiency Estimates, 1995–2016

Period	TFP	TFP*	TFPE	OTE	OSME
1995	0.513	0.783	0.655	0.799	0.822
1996	0.512	0.785	0.652	0.808	0.810
1997	0.510	0.784	0.650	0.817	0.799
1998	0.509	0.784	0.650	0.827	0.789
1999	0.509	0.784	0.649	0.832	0.782
2000	0.506	0.784	0.646	0.839	0.772
2001	0.506	0.785	0.652	0.808	0.810
2002	0.505	0.782	0.646	0.859	0.754
2003	0.505	0.783	0.644	0.875	0.739
2004	0.504	0.783	0.643	0.884	0.729
2005	0.503	0.780	0.645	0.900	0.718
2006	0.502	0.781	0.642	0.907	0.710
2007	0.500	0.783	0.638	0.905	0.706
2008	0.500	0.784	0.638	0.910	0.702
2009	0.500	0.777	0.643	0.915	0.704
2010	0.497	0.776	0.641	0.910	0.706
2011	0.497	0.790	0.630	0.912	0.692
2012	0.497	0.780	0.637	0.910	0.702
2013	0.497	0.784	0.634	0.912	0.696
2014	0.494	0.830	0.595	0.919	0.648
2015	0.494	0.883	0.559	0.929	0.602
2016	0.492	0.798	0.617	0.933	0.661

Author's calculation using DPIN 3.0.

Table 6.2 reveals that productivity estimates declined nominal over the entire sample period. The two major determinants required to compute TFP estimates—best-practice estimates and overall efficiency (TFPE) estimates—fluctuated. The estimates of the two intrinsic components, output-oriented TE and output-oriented scale mixed efficiency, usually drive the TFPE. The TFPE was stable throughout the period except for the last four years of the sample period. The research and innovations of biotechnology have played an influential role in healthcare systems and the agricultural and agro-chemical industries during the last few years. Besides, possession of patents is a yardstick to measure the accomplishment of innovation that eventually leads to technical development. However, India has many challenges associated with research, technology transfer and technology absorption, including statutory hurdles to patentability in the biotechnology realm (IBEF, 2020).

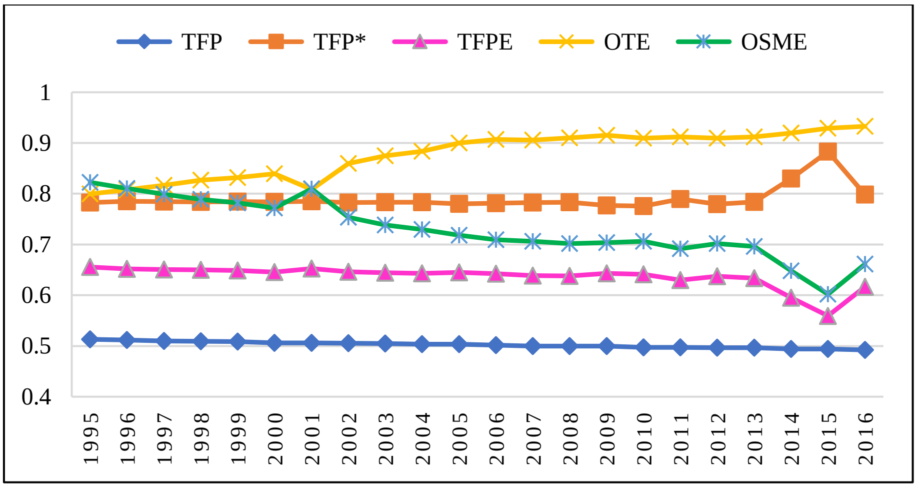


Figure 6.4: Levels of Productivity and Efficiency in Biotechnology Industry, 1995–2016

Figure 6.4 shows the Färe-Primont estimates of levels of TFP for the biotechnology industry. The figure presents the steady movement of TFP, with a marginal decrease towards the end of the selected period. Interestingly, technical progress and overall TE present a mirror image of each other. Besides, the two constituents of TE—output-oriented TE and OSME—moved in the opposite direction until 2013. Thus, the respective effects nullified each other. However, during 2013 to 2016, OSME influenced overall TE. The objective of this thesis was to evaluate productivity growth for the various industries affected by the provisions of the TRIPS agreement. Hence, the following Table 6.3 describes the estimates of TFP growth and its components.

Table 6.3: Annual TFP Change, Technical Change and Efficiency Change, 1995–2016

Period	TFP change dTFP	Technical change dTech	Efficiency change dTFPE	TE change dOTE	Scale-mix efficiency change dOSME
1995	1.178	1.000	1.178	1.354	0.873
1996	1.174	1.003	1.171	1.367	0.860
1997	1.171	1.002	1.169	1.383	0.848
1998	1.170	1.001	1.168	1.401	0.837
1999	1.168	1.002	1.166	1.409	0.830
2000	1.162	1.001	1.161	1.421	0.819
2001	1.162	1.000	1.162	1.440	0.809
2002	1.160	0.999	1.161	1.455	0.800
2003	1.158	1.001	1.158	1.481	0.784
2004	1.157	1.001	1.156	1.497	0.774
2005	1.155	0.997	1.159	1.524	0.762
2006	1.152	0.998	1.154	1.536	0.753
2007	1.140	1.02	1.120	1.551	0.724
2008	1.147	1.001	1.146	1.542	0.745
2009	1.147	0.993	1.156	1.55	0.747
2010	1.142	0.991	1.152	1.541	0.750
2011	1.142	1.009	1.132	1.545	0.734
2012	1.140	0.996	1.145	1.541	0.745
2013	1.140	1.001	1.139	1.545	0.739
2014	1.134	1.094	1.038	1.565	0.663
2015	1.134	1.128	1.005	1.574	0.639

2016	1.130	1.020	1.108	1.580	0.702
1995–2005	0.981	0.997	0.984	1.126	0.873
2006–2016	0.981	1.022	0.960	1.029	0.932
1995–2016	0.972	1.019	0.954	1.097	0.867

Author’s calculation using DPIN 3.0.

The biotechnology industry experienced a marginal decline in TFP change during 1995 to 2016. In 2016, TFP exhibited a 12.993% improvement; however, the maximum change of 16.224% occurred in 1995. TFP change is a reflection of the combined effect of technical progress (by 1.95%) and overall efficiency change (by 10.837%). Similarly, efficiency change became almost the major (16.208%) contributor to productivity growth. Figure 6.5 depicts the trend of productivity growth and its components for the period 1995 to 2016.

The lower panel of Table 6.1 demonstrates another important feature—during 1995 to 2005, TFP decreased by 1.929%, and both technical change and overall efficiency change affected this jointly, as both also declined by 0.34% and 1.592%, respectively. However, in the period 2006 to 2016, TFP declined by 1.898% as a combined effect of technical change by 2.1748% and overall efficiency change by -3.979%. Thus, it is evident that the effect of efficiency change outweighed the effect of technical progress. Further, the diminution of scale-mix efficiency by 6.831% was the primary driver of the inverse inclination of TFP growth.

The aforesaid periods were crucial for the Indian manufacturing sector, as India was obliged to enforce a new patent policy under the TRIPS agreement in 1995. A transition period of 10 years during 1995 to 2005 was granted to shift the paradigm to product patent from process patent, considering the developing status of the country. The biotechnology industry experienced a more negligible decrease in productivity growth during the post-TRIPS regime. The OSME was the prime driver; thus, the productive performance of firms was on average associated with the combined effect of the economies of scale and scope.

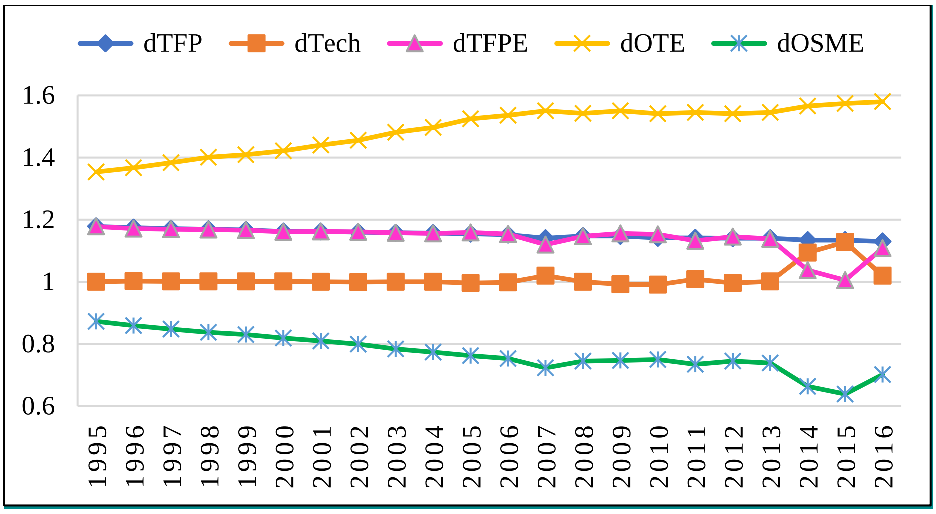


Figure 6.5: TFP Growth and its Components (%) in Biotechnology Industry, 1995 to 2016

Figure 6.5 shows the pattern of TFP change and its components from 1995 to 2016. Technical change (*dTech*) displayed an overall monotonous trend, except for a significant increment in 2014 and 2015. During these periods, technological change was the major contributor, and it is noteworthy that efficiency change moved in the opposite direction. This implies that the individual effect of technical change and efficiency change offset each other while determining TFP growth. The rationale behind this could be that the movement of the production frontier appears in pursuit of technical progress, generating a rift between the technology used and best-practice technology.

This study examined both technical progress and technical regress. Technical change is observed as the movement alongside production possibilities as a result of changes in external factors, such as new policy implementation (O'Donnell 2010). In practice, during 2010, the formulation of a few new policies—such as stem cell research guidelines, pharma policy, seed policy, the Special Economic Zone Act and foreign trade policy—provided a significant boost to strengthen the innovation effect and technical progress in the subsequent period.

6.6.2.2 Electrical and Electronics Industry

The enormous growth of the electronics industry was one of the principal causes of the dramatic technological surge around the world. Integrated circuit boards are a vital element of electronics and are likely to be patented in terms of the product or the design of the board. In the *Indian Patent Act*, under Section 3, the design plan of an integrated circuit is not patentable; however, the elementary production of the electronic industry is based on the initial design plan. Moreover, the phrase ‘computer per se’ was included in Indian patent law and rejected it from patent protection to comply with the TRIPS agreement. This phrase generated confusion and inarticulacy in the Indian electrical and electronics industry, as well as the IT industry. The following Table 6.4 (and Appendix 6.2) reports the Färe-Primont estimates of annual TFP, technical change and efficiency components of TFP over the period 1995 to 2016 for the electrical and electronic industry.

Table 6.4: Annual TFP, Technical and Efficiency Estimates, 1995–2016

Year	TFP	TFP*	TFPE	OTE	OSME
1995	0.659	0.793	0.831	0.902	0.922
1996	0.661	0.787	0.840	0.914	0.919
1997	0.659	0.781	0.844	0.914	0.924
1998	0.659	0.773	0.852	0.918	0.928
1999	0.658	0.787	0.836	0.921	0.908
2000	0.657	0.777	0.846	0.925	0.914
2001	0.658	0.773	0.851	0.929	0.916
2002	0.657	0.812	0.809	0.919	0.881
2003	0.659	0.801	0.822	0.908	0.906
2004	0.661	0.815	0.812	0.897	0.905
2005	0.664	0.815	0.815	0.893	0.912
2006	0.667	0.865	0.771	0.872	0.885
2007	0.664	0.819	0.811	0.943	0.860
2008	0.663	0.825	0.803	0.942	0.853
2009	0.661	0.830	0.796	0.940	0.847
2010	0.661	0.838	0.789	0.950	0.831
2011	0.664	0.850	0.781	0.918	0.853
2012	0.660	0.847	0.780	0.942	0.828
2013	0.660	0.851	0.775	0.938	0.828
2014	0.659	0.858	0.769	0.932	0.825
2015	0.659	0.861	0.765	0.920	0.833
2016	0.658	0.866	0.760	0.922	0.825

Author's calculation using DPIN 3.0.

Table 6.4 reveals that, on average, the estimate of TFP was 0.6604 during 1995 to 2016. The best-practice TFP estimates and overall efficiency estimates were, on average, 0.8193 and 0.8071, respectively. The Färe-Primont index enables computing of the output-oriented TE and OSME change. The average estimates of output-oriented TE and OSME change were 0.920857 and 0.877455, respectively.

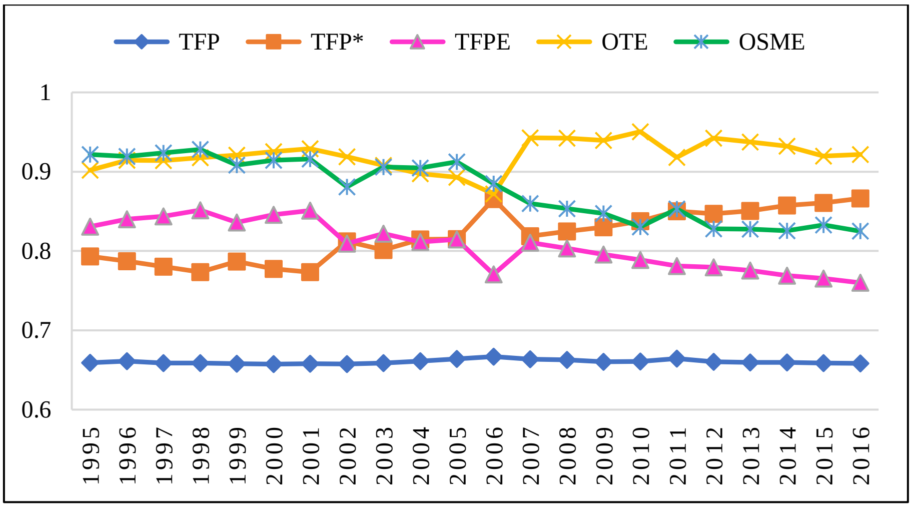


Figure 6.6: Levels of Productivity and Efficiency in Electrical and Electronics Industry 1995–2016

Figure 6.6 presents the Färe-Primont movement of the estimates of TFP and its constituents for the electrical and electronics industry of India. The figure depicts an average annual TFP estimate of 0.66036, with a nominal increase after 2005, implying that the post-TRIPS period had relatively higher TFP scores. It is evident that the higher annual TFP estimates owing to technical progress. The result is consistent with the findings of the prior study by Kalirajan and Bhide (2005). To analyse the productivity growth of the Indian electrical and electronic industry, the following Table 6.5 reports the decomposition of TFP growth for the time span of 1995 to 2016.

Table 6.5: Annual TFP Change, Technical Change and Efficiency Change, 1995–2016

Period	dTFP	dTech	dTFPE	dOTE	dOSME
1995	0.927	1.000	0.927	0.902	1.028
1996	0.931	0.992	0.938	0.914	1.026
1997	0.927	0.984	0.942	0.914	1.031
1998	0.927	0.975	0.950	0.918	1.036
1999	0.927	0.992	0.934	0.922	1.014
2000	0.925	0.980	0.944	0.925	1.020
2001	0.926	0.975	0.950	0.929	1.023
2002	0.925	1.024	0.903	0.919	0.983
2003	0.927	1.011	0.917	0.908	1.011
2004	0.930	1.027	0.906	0.897	1.010
2005	0.934	1.028	0.909	0.893	1.018
2006	0.939	1.091	0.860	0.872	0.987
2007	0.934	1.032	0.905	0.943	0.960
2008	0.933	1.040	0.897	0.942	0.953
2009	0.930	1.047	0.888	0.940	0.946
2010	0.930	1.056	0.881	0.950	0.927
2011	0.935	1.072	0.872	0.918	0.952
2012	0.929	1.068	0.870	0.942	0.924
2013	0.928	1.073	0.865	0.938	0.924
2014	0.928	1.081	0.858	0.932	0.921
2015	0.927	1.085	0.854	0.920	0.930
2016	0.926	1.092	0.848	0.922	0.921
1995–2005	1.008	1.028	0.981	0.990	0.990

2006–2016	0.987	1.001	0.986	1.057	0.932
1995–2016	0.999	1.092	0.915	1.022	0.895

Author’s calculation using DPIN 3.0.

In general, the electrical and electronics industry displayed a marginal decline in TFP change during 1995 to 2016. The highest improvement in TFP transpired in 2006, and the lowest level of TFP improvement occurred in 2000. The period between 2000 and 2006 experienced around 1.4506% (ΔTFP* = 0.9385/0.9251 = 1.4506%) productivity growth. This TFP change was predominantly a reflection of the combined effect of technical progress by 11.3458% and -8.89% of overall efficiency change or catching-up effect. Figure 6.7 shows the trend of productivity growth and its component for the period 1995 to 2016.

The lower panel of Table 6.5 demonstrates an important feature—during the pre-TRIPS period, TFP increased by 0.7585%, and the innovation effect or technical progress by 2.76%. However, the overall efficiency change declined by 1.9492%. In contrast, in the post-TRIPS period TFP declined by 1.2804% as a combined effect of technical change by 0.09% and overall efficiency change by -1.36909%. The estimated results indicate that, although the innovation effect was stronger during the pre-TRIPS period, the post-TRIPS period catching-up effect became more intense. Noticeably, in both periods, OSME influenced the overall TE (TFPE = OTE × OSME = -1.36909 = -5.72% × -6.756% and -1.9492 = -0.9788% × -1.01765).

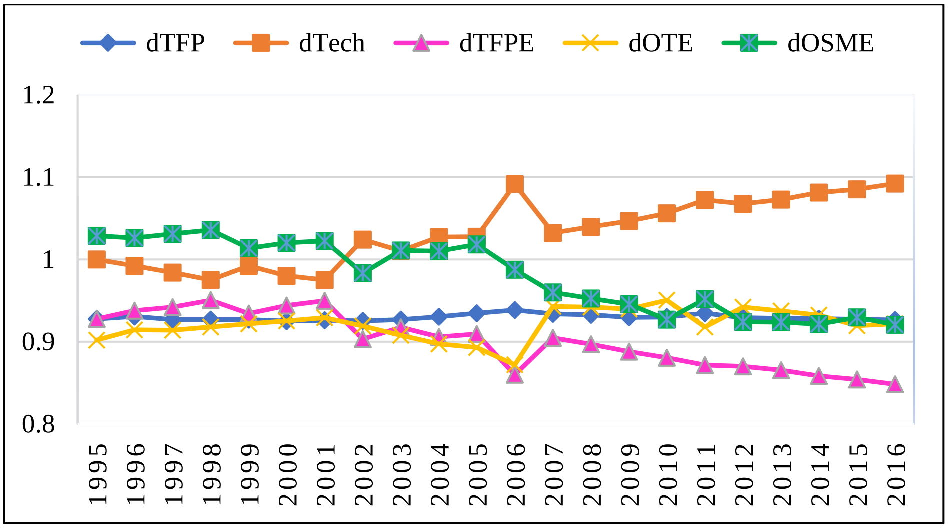


Figure 6.7: TFP Growth and its Components (%) in Electrical and Electronic Industry, 1995 to 2016

Figure 6.7 reveals that the movement of changes in overall efficiency and technical progress occurred in the opposite direction, perhaps portraying each other’s mirror image. This industry also indicated that technical change was the major driver of TFP growth.

This critical finding conforms with a prior study (Majumdar 2010) that decomposed TFP growth into technical progress and TE change by using the methodology established by Kalirajan et al. (1996). A further 6.1898% ($dTech_{2006}$ – $dTech_{2005}$) of technical progress occurred in 2006, and a credible reason for this may be the amendment of the Indian patent law in 2002, as the scope of 'invention' was redefined in this amendment. The new ordinance endorsed in 2004 and Section 3(b) authenticated the prior exclusion by stating that computer programs with technical application to industry or combined with hardware were eligible under the patent regime. As a consequence of this conflict, ultimately, with the new amendment Act of 2005, the exclusion clause was abolished. Contrastingly, the entire sample period shows regressive TE change driven by regressive OSME. A plausible justification of this is that the predominance of the pool of small firms unable to cater advantage of SE.

6.6.2.3 Information Technology and Communication Industry

This thesis broadly identified seven product categories in the Indian IT hardware and communication market: consumer electronics, controls, instrumentation and industrial electronics, electronic data processing (IT hardware), communication and broadcast equipment, strategic electronics and electronic components. Considering all these categories, this research found steady growth in this industry. However, this result differs from the previous study using the translog production function model, where TFP growth experienced a steady decline, with some revival during post-2001 to 2002 (Majumdar 2010). The following Table 6.6 and Appendix 6.3 present the Färe-Primont estimates of annual TFP, technical change and efficiency components of TFP over the period 1995 to 2016 for the IT and communication industry.

Table 6.6: Annual TFP, Technical and Efficiency Estimates, 1995–2016

Year	TFP	TFP*	TFPE	OTE	OSME
1995	0.723	0.840	0.856	0.928	0.923
1996	0.725	0.835	0.869	0.935	0.930
1997	0.721	0.828	0.871	0.937	0.929
1998	0.721	0.820	0.879	0.945	0.931
1999	0.721	0.808	0.893	0.948	0.942
2000	0.720	0.809	0.891	0.952	0.936
2001	0.720	0.810	0.889	0.954	0.932
2002	0.719	0.818	0.879	0.958	0.918
2003	0.722	0.816	0.885	0.957	0.925
2004	0.723	0.822	0.880	0.958	0.919
2005	0.724	0.833	0.869	0.955	0.911
2006	0.730	0.846	0.863	0.940	0.919
2007	0.730	0.855	0.854	0.950	0.900
2008	0.727	0.865	0.840	0.949	0.887
2009	0.723	0.873	0.829	0.941	0.882
2010	0.724	0.885	0.818	0.936	0.875
2011	0.723	0.895	0.808	0.932	0.869
2012	0.723	0.904	0.799	0.928	0.862
2013	0.722	0.913	0.791	0.921	0.860
2014	0.722	0.924	0.782	0.922	0.851
2015	0.721	0.942	0.765	0.914	0.840
2016	0.720	0.959	0.751	0.906	0.832

Author’s calculation using DPIN 3.0.

The above Table 6.6 provides that, on average, the estimate of TFP is 0.72305 highest among the selected four industries during the period of 1995-2016. The best practice TFP estimates, and overall efficiency estimates are on average depict as 0.85936 and 0.84363, respectively. The Färe-Primont index decomposes the overall efficiency into the output-oriented TE and OSME change. The average estimates of output-oriented TE and OSME changes are 0.93938 and 0.898725, respectively.

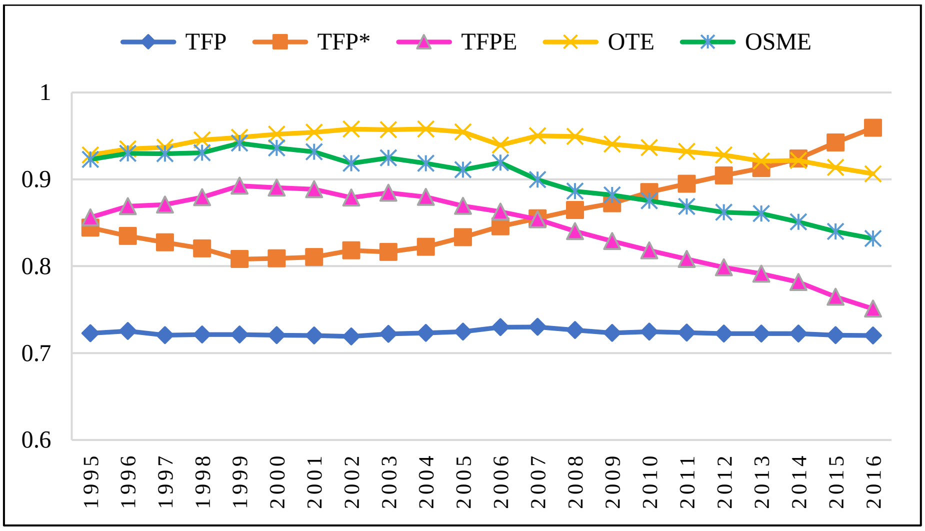


Figure 6.8: Levels of Productivity and Efficiency in IT and Communication Industry, 1995–2016

Figure 6.8 presents the Färe-Primont movement of the estimates of TFP and its constituents for the IT and communication industry of India. The figure depicts an almost steady average annual TFP estimate of around 0.72305, with marginal fluctuations. Like the electrical and electronic industry, this industry also experienced higher annual TFP estimates owing to the technical progress throughout the sample period. The results differ from a previous study (Majumdar 2010) that identified efficiency estimates as predominant during 1995 to 2001. To analyse the productivity growth of the Indian IT and communication industry more intrinsically, the following Table 6.7 presents the decomposition of TFP growth for the period 1995 to 2016.

Table 6.7: Annual TFP Change, Technical Change and Efficiency Change, 1995–2016

Period	dTFP	dTech	dTFPE	dOTE	dOSME
1995	0.971	1.000	0.971	0.928	1.047
1996	0.968	0.989	0.979	0.942	1.039
1997	0.968	0.980	0.988	0.937	1.055
1998	0.969	0.972	0.998	0.945	1.056
1999	0.969	0.957	1.013	0.948	1.068
2000	0.968	0.958	1.010	0.952	1.062
2001	0.968	0.960	1.008	0.954	1.057
2002	0.966	0.969	0.997	0.958	1.042
2003	0.970	0.967	1.004	0.957	1.049
2004	0.972	0.974	0.998	0.958	1.042
2005	0.974	0.987	0.986	0.955	1.034
2006	0.981	1.002	0.979	0.940	1.043
2007	0.981	1.013	0.969	0.950	1.021
2008	0.977	1.024	0.954	0.950	1.005
2009	0.972	1.033	0.940	0.940	1.001
2010	0.974	1.049	0.928	0.936	0.993
2011	0.972	1.060	0.917	0.932	0.986
2012	0.971	1.071	0.906	0.928	0.978
2013	0.971	1.081	0.898	0.921	0.976
2014	0.971	1.094	0.887	0.922	0.965
2015	0.968	1.116	0.868	0.914	0.953
2016	0.968	1.136	0.852	0.906	0.944
1995–2005	1.002	0.987	1.015	1.029	0.987

2006–2016	0.987	1.134	0.870	0.965	0.905
1995–2016	0.997	1.136	0.877	0.977	0.901

Author’s calculation using DPIN 3.0.

Like the electrical and electronics industry, the IT and communication industry demonstrated a marginal decline of 0.341 in TFP change from 1995 to 2016. The highest TFP growth appeared in 2007, while the lowest level of TFP growth was in 2002. Around the period 2002 to 2007, this industry experienced 1.51% (ΔTFP* = 0.98098/0.9664 = 1.0151) productivity growth. This TFP change was predominantly a reflection of the combined effect of TP by 4.499% and -2.8687% of overall efficiency change or catching-up effect. A new era began in 2005 for the computer hardware industry, as a zero-duty regime was implemented in 2005, after India signed the 'Agreement of IT' under the WTO (Department of Electronics and Information Technology 2004). Figure 6.9 shows the trend of productivity growth and its component for the period 1995 to 2016.

Significantly, during the pre-TRIPS period, TFP increased by only 0.2243%; however, technical progress and TE changed by -1.29% and 1.5341%, respectively, as displayed in the lower panel of Table 6.5. However, the improvement of overall efficiency change was 2.8595%, and OSME was -1.264%. In comparison, in the post-TRIPS period, TFP declined by 1.308% as a combined effect of technical change by 13.383% and overall efficiency change by -12.96%. Distinctly, in the pre-TRIPS period, change in OTE (2.8595%) was more influential than OSME (by -1.2645) in determining the efficiency change (dTFPE = dOTE × dOSME=1.0153 = 1.0286 × 0.9874). Contrarily, OTE and OSME followed the same direction, with change in OSME (by -9.5080%) exercising a stronger effect than a change in OTE (by -3.5183%) on change in TFPE (TFPE = OTE × OSME = 0.8704 = 0.9648 × 0.9013) during the post-TRIPS period.

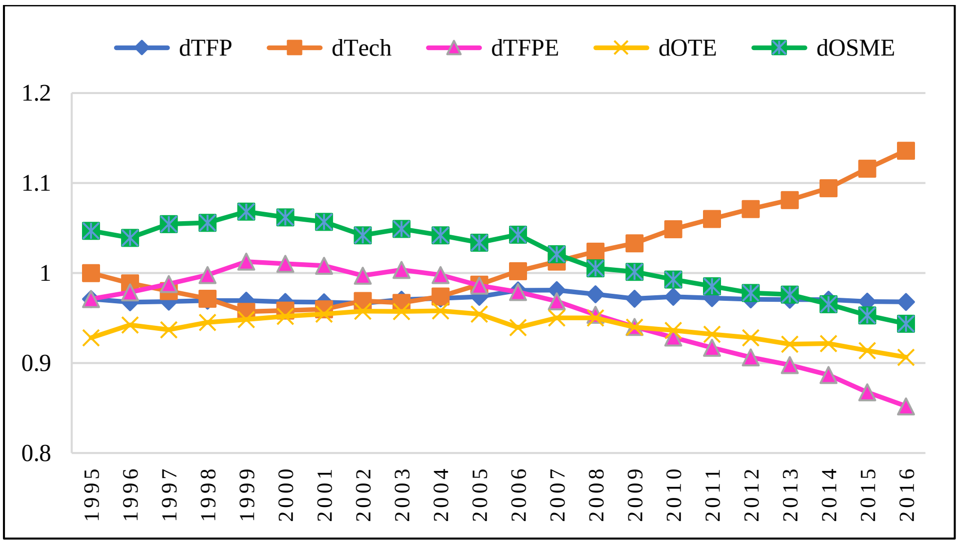


Figure 6.9: TFP Growth and its Components (%) in IT and Communication Industry, 1995 to 2016

Figure 6.9 demonstrates that, unlike in the biotechnology industry, the technical progress component seemed the primary driver of TFP growth in the IT and communication industry. In contrast, efficiency change demonstrated a decline during the post-TRIPS period, as shown in Figure 6.9. This result differs from a previous study using the translog production function model and revealing that overall efficiency change led to TFP growth during post-1995 to 2001. Technical progress is defined as the movement on the production possibility set, usually a result of innovation. A plausible rationale for this reverse movement of technological change and efficiency change is the rebound effect, which implies that a firm’s efficiency level deteriorates initially with the inception of new technology (Khazzoom 1980; Brookes 1990; Sauder 1992). The Government of India is endeavouring to create an investor-friendly platform for foreign investors. The trade liberalisation policy of 1991 and subsequent policies, such as relaxation of custom duties or allowance of FDI, generate innovation opportunities. However, the production unit firms may not promptly acquire the expertise to embrace the new technology (Huggett and Ospina 2001). Thus, the technical progress portrayed during the sample period was perhaps incapable of catering for sufficient productivity growth.

6.6.2.4 Pharmaceutical Industry

In compliance with the TRIPS agreement and after enforcement of the National Drug Policy, the Indian government sought to strengthen domestic drug manufacturing industries to encourage economic performance. Over the last few decades, India has become positioned as a low-price generic drugs producer in the world market. In 2003, India met only 1% and 10% of global pharmaceutical and global generic demand, respectively (Basheer 2005). In comparison, currently, India captures over 50% of the global demand for various vaccines and over 20% of the global generic market. Thus, India appears to be the largest generic drug provider in the global market (Goldar 2017).

Table 6.8: Annual TFP, Technical and Efficiency Estimates, 1995–2016

Year	TFP	TFP*	TFPE	OTE	OSME
1995	0.377	0.705	0.535	0.614	0.887
1996	0.376	0.687	0.548	0.627	0.888
1997	0.375	0.669	0.560	0.637	0.893
1998	0.374	0.651	0.575	0.653	0.893
1999	0.373	0.633	0.590	0.665	0.899
2000	0.371	0.615	0.603	0.677	0.903
2001	0.371	0.597	0.621	0.692	0.906
2002	0.371	0.580	0.640	0.708	0.911
2003	0.370	0.562	0.658	0.741	0.896
2004	0.369	0.545	0.678	0.761	0.898
2005	0.368	0.527	0.699	0.779	0.903
2006	0.367	0.510	0.719	0.799	0.906
2007	0.365	0.492	0.742	0.809	0.921
2008	0.365	0.476	0.767	0.827	0.930
2009	0.365	0.466	0.784	0.853	0.922
2010	0.364	0.473	0.769	0.874	0.882
2011	0.363	0.467	0.777	0.898	0.867
2012	0.362	0.470	0.771	0.873	0.885
2013	0.362	0.491	0.737	0.920	0.802
2014	0.360	0.486	0.740	0.921	0.805
2015	0.359	0.494	0.728	0.931	0.782
2016	0.359	0.502	0.716	0.932	0.768

Author's calculation using DPIN 3.0.

Table 6.8 and Appendix 6.4 report that during the time period of 1995-2016, on average, the estimate of TFP in the pharmaceutical Industry is 0.367609, which is the lowest among the selected four industries. The best practice TFP estimates, and overall efficiency estimates are on an average report as 0.549845 and 0.679874, respectively. The two constituents of the overall efficiency commonly obtained from the Färe-Primont index are namely the output-oriented TE and OSME change. The average estimates of output-oriented TE and OSME changes are 0.781423 and 0.879407, respectively. Thus, it can be argued that, in general, the large firms capture the market shares of the pharmaceutical Industry and inheriting the benefits of the economies of scale.

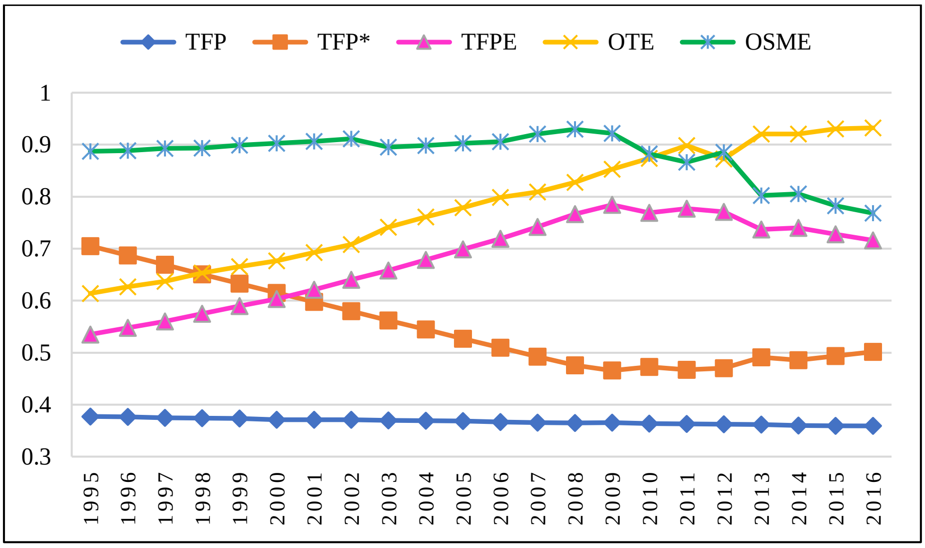


Figure 6.10: Levels of Productivity and Efficiency in Pharmaceutical Industry, 1995–2016

Figure 6.10 shows the Färe-Primont estimates of levels of TFP for the pharmaceutical Industry. The figure presents a monotonous flow of TFP, with gradual marginal decline. The annual estimates of best practice TFP and overall TE move in the opposite direction yet optimistic over the entire period. Besides, the two constituents of TE, namely output-oriented TE, and OSME appears also in a reverse direction until 2013. However, during the period 2013-2016, OSME influences the overall TE. Contemplating the objective of this thesis to evaluate the productivity growth for the various industries in the context of the TRIPS agreement, the following Table 6.9 explains the estimates of TFP growth and its components.

Table 6.9: Annual TFP Change, Technical Change and Efficiency Change, 1995–2016

Period	dTFP	dTech	dTFPE	dOTE	dOSME
1995	1.167	1.000	1.167	1.122	1.059
1996	1.164	0.974	1.195	1.145	1.060
1997	1.159	0.949	1.222	1.164	1.065
1998	1.157	0.923	1.253	1.193	1.066
1999	1.155	0.898	1.286	1.215	1.073
2000	1.148	0.872	1.316	1.236	1.077
2001	1.148	0.847	1.355	1.265	1.082
2002	1.147	0.822	1.395	1.293	1.087
2003	1.144	0.797	1.435	1.354	1.069
2004	1.142	0.772	1.478	1.390	1.072
2005	1.139	0.748	1.523	1.423	1.078
2006	1.133	0.723	1.568	1.459	1.081
2007	1.130	0.698	1.618	1.478	1.099
2008	1.128	0.675	1.672	1.511	1.109
2009	1.129	0.660	1.710	1.558	1.100
2010	1.124	0.670	1.677	1.596	1.053
2011	1.122	0.662	1.694	1.641	1.034
2012	1.120	0.667	1.680	1.594	1.057
2013	1.119	0.697	1.606	1.681	0.957
2014	1.112	0.689	1.614	1.682	0.961
2015	1.111	0.700	1.587	1.700	0.934
2016	1.110	0.711	1.561	1.703	0.917
1995–2005	0.952	0.748	1.306	1.269	1.018

2006–2016	0.979	0.984	0.995	1.167	0.848
1995–2016	0.952	0.711	1.338	1.519	0.866

Author’s calculation using DPIN 3.0.

The above Table 6.9 reveals that the TFP change (*dTFP*) between the sample periods of 1995 and 2016 was 16.667% and 11.0215%, respectively, indicating a gradual 4.840% decline of TFP growth in the Indian pharmaceutical industry. The argument favouring the TRIPS agreement is that it would inspire the developing country's generic drug manufacturing firms for innovation (Kyle and McGahan, 2012). However, both the pre-TRIPS and post-TRIPS periods experienced technical regress. In contrast, the overall efficiency change showed a gradual increase from 16.6682% in 1995 to 70.9725% in 2009, and then fluctuating movement. Therefore, it is evident that the catching-up effect was dominant in the pre-TRIPS period and the beginning of the post-TRIPS period, compared with the innovation effect. In the subsequent period, the intensity of both effects weakened. A plausible reason for this is that, during the post-TRIPS period, Indian firms were restricted to manufacturing newly patented generic drugs unless they obtained patents or licences (Mahajan 2020). In this context, MNCs have the opportunity to capture more market share of generic drugs.

In this context, it is noteworthy to mention another salient attribute—that regressive growth of overall efficiency (by 6.9238%) after 2009 was mostly driven by the regressive growth of OSME (by 12.9007%). Probably, the embargo on the production of generic drugs diffused the economic scale advantages of the large Indian ownership firms. Besides, MNCs were enticed to capture the entire market, instead of only the patented generic drug market. Figure 6.11 shows the trend of the productivity growth and its component for the period 1995 to 2016.

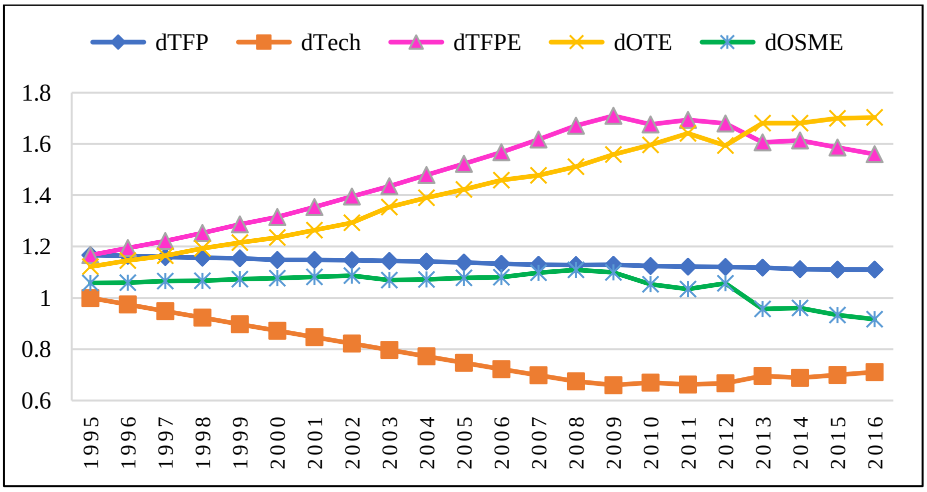
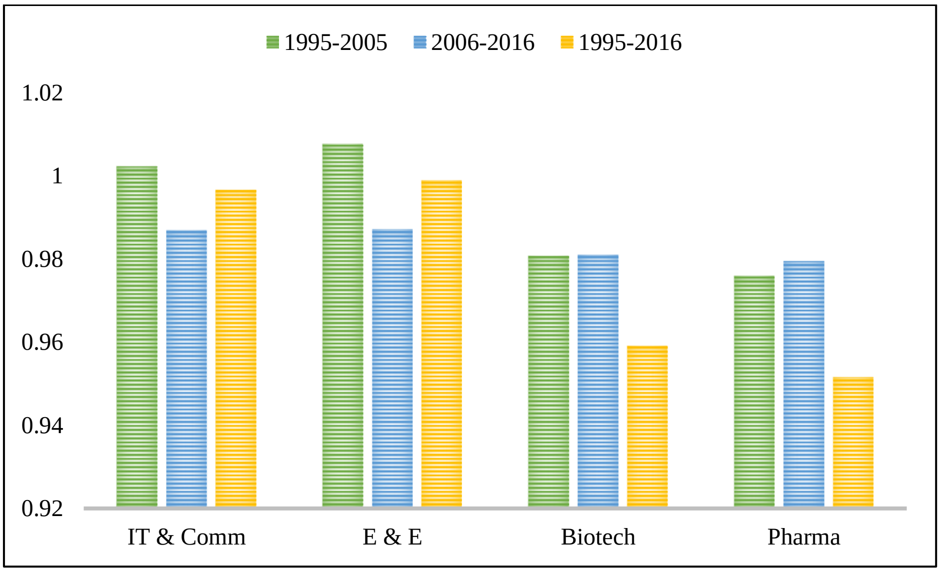


Figure 6.11: TFP Growth and its Components (%) in Pharmaceutical Industry, 1995 to 2016

In general, the decomposition of TFP growth into technical progress/regress and TE progress/regress effectively segregated the adoption of new technology by best-practice firms and the improved TE for catching-up firms owing to the diffusion of that new advanced technology. Figure 6.11 portrays the TE increment and technical regress movement until 2009. The OTE and OSME moved in the same direction, following a similar pattern; however, after 2009, they moved in the opposite direction. It is conceivable that the allowance of receiving more FDI and enhanced expenditure on the health sector under the new policy regime drove the innovation effect and eventually generated a marginal increase in the technical change component (Aldieri and Vinci 2018).

This study found that the product patent protection regime had a trivial effect on generating productivity growth. This result is consistent with a previous study using Ray and Desli's Malmquist productivity index for the period 2000 to 2015 (Mahajan 2020). However, the result differs in the context of the dominance of the major components of TFP growth. Further, though there is the coexistence of large firms along with small firms in India; however, viewing the downward trend of OSME, India may ascribe that the firms are incapable of procuring the benefits of the economies of scale. Holistically, the simultaneous existence of high efficiency changes and technical regress throughout the sample period possibly indicates deficiencies in acquiring productivity growth.



Note: Biotech = biotechnology industry, E & E = electrical and electronics industry, IT & Comm = IT and communication industry, Pharma = pharmaceutical industry.

Figure 6.12: Changes in Productivity Growth Trends in Various Industries

Figure 6.12 presents a comprehensive view of TFP growth during pre-TRIPS and post-TRIPS regimes for the selected industries. This analysis has indicated some valuable observations for these industries during the sample period. Deceleration of the average productivity growth was evident in all four selected industries. The first insight is that, in the pre-TRIPS period, the long-term productivity growth was significantly higher in the electrical and electronics industry (0.7585%), followed by the IT and communication industry (0.2243%). In contrast, the long-term productivity growth was substantially lower in the biotechnology (1.92927%) and pharmaceutical (2.40279%) industries in the pre-TRIPS period. Second, all four industries experienced regressive long-run productivity growth during the post-TRIPS period. Those industries can be ranked as the electrical and electronics (by -1.28048%), IT and communication (by -1.30765%), biotechnology (by -1.89752%) and pharmaceutical (by -2.05323%) industries, based on productivity growth. Third, the productivity growth marginally reduced for both the electrical and electronics industry (0.10491%) and the information and technology industry (0.34132%) over the entire sample period (1995 to 2016). In contrast, productivity growth substantially dropped for the other two industries—biotechnology (4.08793%) and pharmaceutical (4.83992%) industries—throughout the entire sample period. The distinctive attributes of the different industries imply that firm-level individual characteristics play a crucial role in productivity growth.

6.6.3 Robustness

To evaluate whether the patent policy reforms implemented by the Government of India to comply with the TRIPS agreement had different effects on specific manufacturing industries , this thesis used the mean TFP scores and its components to compare the pre-TRIPS and post-TRIPS period. An inferential statistical test, namely, the t-test is used to verify the significance of the implementation of the TRIPS agreement. Thus, the hypothesis tested is defined as follows,

$$H_0 : \mu_1 - \mu_2 = 0 \; ; \; H_A : \mu_1 - \mu_2 \neq 0 \qquad (6.18)$$

where, μ_1 = the mean of TFP/ OTE / OSME for period 1995-2005 (pre-TRIPS implementation policy). μ_2 = the mean of TFP/OTE/OSME for period 2006-2016 (post-implementation policy).

Table 6.10: Results of t-Test Comparing Means of TFP, OTE and OSME for Pre- and Post-TRIPS Period in Different Indian Industries at 5% Significance Level

(a) Biotechnology Technology

t-test	**TFP Hypothesis** $H_0: \mu_1 - \mu_2 = 0$ $H_A: \mu_1 - \mu_2 \neq 0$		**OTE Hypothesis** $H_0: \mu_1 - \mu_2 = 0$ $H_A: \mu_1 - \mu_2 \neq 0$		**OSME Hypothesis** $H_0: \mu_1 - \mu_2 = 0$ $H_A: \mu_1 - \mu_2 \neq 0$	
Period	Pre-TRIPS	Post-TRIPS	Pre-TRIPS	Post-TRIPS	Pre-TRIPS	Post-TRIPS
Mean	0.507	0.491	0.845	0.915	0.770	0.684
t stat	10.550		-37.600		57.655	
t-critical value two tail	1.962		1.962		1.962	
Conclusion	Reject the Null Hypothesis		Reject the Null Hypothesis		Reject the Null Hypothesis	

(b) Electronic & Electronic Industry

t-test	**TFP Hypothesis** $H_0: \mu_1 - \mu_2 = 0$ $H_A: \mu_1 - \mu_2 \neq 0$		**OTE Hypothesis** $H_0: \mu_1 - \mu_2 = 0$ $H_A: \mu_1 - \mu_2 \neq 0$		**OSME Hypothesis** $H_0: \mu_1 - \mu_2 = 0$ $H_A: \mu_1 - \mu_2 \neq 0$	
Period	Pre-TRIPS	Post-TRIPS	Pre-TRIPS	Post-TRIPS	Pre-TRIPS	Post-TRIPS
Mean	0.659	0.661	0.913	0.929	0.912	0.843
t stat	-1.426		-7.919		36.350	
t-critical value two tail	1.962		1.962		1.962	
Conclusion	Do not have enough evidence to reject the null hypothesis.		Reject the Null Hypothesis.		Reject the Null Hypothesis.	

(c) Information Technology & Communication Industry

t-test	**TFP Hypothesis** $H_0: \mu_1 - \mu_2 = 0$ $H_A: \mu_1 - \mu_2 \neq 0$		**OTE Hypothesis** $H_0: \mu_1 - \mu_2 = 0$ $H_A: \mu_1 - \mu_2 \neq 0$		**OSME Hypothesis** $H_0: \mu_1 - \mu_2 = 0$ $H_A: \mu_1 - \mu_2 \neq 0$	
Period	Pre-TRIPS	Post-TRIPS	Pre-TRIPS	Post-TRIPS	Pre-TRIPS	Post-TRIPS
Mean	0.722	0.724	0.948	0.931	0.927	0.871
t stat	-1.145		6.856		27.700	
t-critical value two tail	1.963		1.963		1.963	
Conclusion	Do not have enough evidence to reject the null hypothesis		Reject the null hypothesis		Reject the null hypothesis	

(d) Pharmaceutical Industry

t-test	**TFP Hypothesis** $H_0: \mu_1 - \mu_2 = 0$ $H_A: \mu_1 - \mu_2 \neq 0$	**OTE Hypothesis** $H_0: \mu_1 - \mu_2 = 0$ $H_A: \mu_1 - \mu_2 \neq 0$	**OSME Hypothesis** $H_0: \mu_1 - \mu_2 = 0$ $H_A: \mu_1 - \mu_2 \neq 0$

Period	Pre-TRIPS	Post-TRIPS	Pre-TRIPS	Post-TRIPS	Pre-TRIPS	Post-TRIPS
Mean	0.363	0.372	0.687	0.876	0.898	0.861
t stat	11.716		70.995		12.740	
t-critical value two tail	1.961		1.961		1.961	
Conclusion	Reject the null hypothesis		Reject the null hypothesis		Reject the null hypothesis	

Source: Author's calculation from the output of DPIN 3.0 using R (Table 6.10a, 6.10b, 6.10c and 6.10d)

The t-test precisely permits to determine that whether the mean of one condition is truly different from the mean of another condition. Thus, the first t-test performs in this thesis analyses whether the mean of TFP for one pre-TRIPS period is equal to the mean of the post-TRIPS periods. All tests are conducted at the 5% significance level. The results of this test are presented in Appendix 6.1.

The null hypothesis H_0 is rejected for TFP in the pre-TRIPS and post-TRIPS periods, for the biotechnology and pharmaceutical industries, thus suggesting that at the 5% of significance level, the means of TFP are significantly different in pre-TRIPS and post-TRIPS periods. Contrastingly, for the other two industries, the electrical & electronics and IT & communication industries, enough evidence is available to reject the null hypothesis, therefore it suggests that no significant difference was presented in pre-TRIPS and post-TRIPS periods. Besides, the null hypothesis H_0 is rejected for OTE and OSME scores in the pre-TRIPS and post-TRIPS periods for all the four selected sunrise industries. Hence, implies that at the 5% of significance level, the means of OTE and OSME are significantly different in pre-TRIPS and post-TRIPS periods for all the selected manufacturing industries.

6.7 Conclusion

This thesis undertook a more in-depth analysis of the data by examining TFP change and its major drivers for the four industries during the pre-TRIPS implementation period (1995 to 2005) and post-TRIPS implementation period (2006 to 2016). Based on the long-term productivity growth, in the pre-TRIPS period, the four industries can be ranked as follows: electrical and electronics (by 0.7585%), IT and communication (by 0.2243%), biotechnology (by -1.92927%) and pharmaceutical (by -2.40279%) industries. However, the TFP estimates were consistently higher for the IT and communication industry than the electrical and electronic industry. The other two industries also demonstrated steady positive TFP scores. All four industries experienced regressive long-run productivity growth during the post-TRIPS period. The hierarchy can be portrayed as the electrical and electronics (by -1.28048%), IT and communication (by -1.30765%), biotechnology (by -1.89752%) and pharmaceutical (-2.05323%) industries, based on productivity growth.

Interestingly, this study found that technical change was a significant driver for the improvement of TFP scores for the IT and communication industry and electrical and electronics industry. Plausibly, industrial policies, such as relaxation of custom duties or allowance of FDI, enhanced innovation opportunities and eventually induced technical progress. In contrast, overall efficiency drove TFP change for the biotechnology and pharmaceutical industries. The reduction in overall efficiency again derived from the reduction of OSME. In this context, it is justifiable to argue that the existence of a pool of large firms failed to acquire the adequate benefits of the economies of scale. Further, the electrical and electronics industry and IT and communication industry depicted marginal reduction; in contrast, the biotechnology and pharmaceutical industries manifested substantial reduction in productivity growth over the entire sample period (1995 to 2016). Thus, the exclusive attributes of the different industries suggest that firm-level individual characteristics are crucial in determining productivity growth.

Productivity analysis customarily estimates the association between the TFP index and variables that affect or measure a specific economic pursuit (O’Donnell 2014). Hence, the subsequent chapter computes the relationship between TFP growth and the variables associated with the patent protection regime in the context of TRIPS.

Chapter 7: Effect of Patent Reforms on Productivity Growth

7.1 Introduction

The two preceding chapters explained TFP and the associated topics with reference to the selected Indian manufacturing industries. Chapter 5 examined the effects of patent reforms on firm-level productive efficiency. The four-component semiparametric smooth coefficient SPF model developed by Kumbhakar, Sun and Tveterås (2018) was employed for this computation. This model decomposes the inefficiency term further into transient (time-varying) inefficiency and persistent (time-invariant) efficiency. The subsequent Chapter 6 narrated the decomposition of TFP growth into more intrinsic efficiency measurements, such as technical change, efficiency change, TE change and SE change, employing the Färe-Primont productivity index proposed by O'Donnell (2012). The present chapter analyses the effect of the TRIPS patent reform on firms' productivity growth as a continuation of the two previous chapters. The findings in Chapter 5 demonstrated a mixed effect of the patent reform attributes (number of patents, R&D intensity, technology transfer and trade openness) to generate firm-level TE. Consequently, it is pertinent to perform further analysis to examine the relationship between the patent reforms and TFP growth, since TE is one of the sources of TFP.

The WIPO (1995) states that a patent can be granted either in the form of a product or process, and is an exclusive right to an invention. Numerous empirical studies have hypothesised that a stronger patent right triggers economic growth through the invention of new products and innovative technologies (Hudson and Minea 2013; Kanwar and Evenson 2003). However, a contrasting view appears in the case of emerging economies (Park and Ginarte 1997). The empirical debate among scholars relies on two theoretical notions—reward theory and contract theory (Denicolò and Franzoni 2003). Reward theory expresses that patent protection instils invention endeavour through reward via potentially initiating a transitory monopoly. Contract theory argues that patent protection propagates knowledge by publicising information. Numerous studies have estimated the optimal length and scope of patents to accommodate the trade-off between the reward and social welfare loss owing to the monopoly (Arrow 1962; Gabrovski 2017; Nordhaus 1969). Endogenous growth theory argues that patent protection generates economic growth, yet the empirical literature reveals that the economic behaviour of patent reforms varies in promoting economic growth (Gallini 1992; Gilbert et al. 1990; Klemperer 1990; Shin et al. 2016). To help clarify this ambiguity, this chapter investigates the effects of patent reforms (with special reference to TRIPS) on TFP growth, using firm-level data from selected Indian sunrise manufacturing industries, during the period of 1995 to 2016.

This chapter comprises seven sections, structured as follows. Section 7.2 briefly discusses the relationship between the patent protection system and productivity growth. Sections 7.3 and 7.4 discuss the empirical model and estimation method, respectively. The subsequent Section 7.5 discusses the specific empirical model while Section 7.6 presents the data sources and measurement of variables. Section 7.7 reports the results and empirical analysis. Finally, Section 7.8 concludes the chapter.

7.2 Patent Protection and Productivity Growth

Although almost two decades have passed since implementing the WTO's TRIPS agreement, the patent protection system remains disputed. The recent research trend states the contentious nature of the association between patent protection systems and economic development from theoretical and empirical aspects (Acemoglu and Akcigit 2012; Arora et al. 2008; Hall 2007; Hu et al. 2007; Sweet and Eterovic 2015). Thus, it is a pertinent question whether rigid patent protection systems propel or inhibit economic progress. The existing literature has identified several channels for acquiring technology, and stated that excessive dependence on the level of development probably leads to adverse outcomes (Fu and Gong 2011; Jaffe and Lerner 2004; Sweet and Eterovic 2019). Per-capita output relies on the capital–output ratio, human capital per person, research intensity and population of the economy (Fernald and Jones 2014). The latter two components relate to TFP (Sweet and Eterovic 2019); thus, the magnitude of the patent rights system eventually affects TFP. In this context, it is noteworthy to mention the seminal work of Cohen and Levinthal (1990, 128) on absorptive capacity. Absorptive capacity is 'the ability of a firm to recognize the value of new, external information, assimilate it and apply it to commercial ends'. Absorptive capacity is intensely path driven; therefore, to accomplish future progress in technical capability, firms must invest in their arena of expertise (Cohen and Levinthal 1990). Hence, firm-level analysis is appropriate to capture the effect of a stronger patent system on productivity growth.

In general, aggregate-level data, such as country or industry level, were employed in recent empirical studies on TFP (Goldar et al. 2017; Khanna and Sharma 2021; Pal and Das 2018; Sweet and Eterovic 2019; Trivedi et al. 2000; Unel 2003). These studies provided a macro-view and solicited micro-level research (Sweet and Eterovic 2019). Contrastingly, several empirical studies emphasised the relationship between TFP and economic policies for specific industrial areas using firm-level data (Balakrishnan et al. 2000; Das 2004; Goldar and Kumari 2003; Kumar 2004; Mitra 1998). Rationally, the attributes of each firm differ across countries and even within industries; thus, firms may innovate in a diversified manner; however, macro-analyses ignore this significant heterogeneity of a typical economic agent. In contrast, micro-level analysis enables the incorporation of the avenues by which specific firms' knowledge assets influence their productivity. Moreover, micro-level analysis discusses the attributes of individual economic agents and their aptitudes towards the external environment.

7.3 Empirical Model

Numerous studies have revealed that patent regimes foster productivity growth through a few channels. Proponents of endogenous growth theory acknowledge the crucial role of R&D in stimulating TFP through innovation (Griliches 1980; Grossman et al. 1991; Mansfield 1980; Rivera-Batiz et al. 1991; Scherer 1982; Shukla 2017). The existing literature firmly advocates that trade development instils knowledge transfer and eventually innovations (Barro 1997; Eaton and Kortum 1996; Grossman et al. 1990b; Keller 2004; Maskus 1999, 2016; Romer 1986). Besides, empirical researchers proclaim the effects of technology transfers on firm-level productivity (Arora and Gambardella 1990; Sharma 2016; Veugelers and Cassiman 1999) and the combination of technology transfer and R&D is likely to act in either a complementary or substitute role in determining productivity growth (Deolalikar and Evenson 1989; Sharma 2016). Thus, the empirical model regards the patent reform variable as combining the number of patents, R&D intensity, trade openness and technology transfer. To test the effect of patent reforms specifically for the TRIPS agreement on productivity growth, the empirical model can be expressed as:

$$TFP_{jit} = \beta_0 + \beta_1 PAT_{jit} + \varepsilon_{ijt} \tag{7.1}$$

where TFP_{jit} denotes the productivity growth for firm i , j TRIPs periods, at time t. The Färe-Primont productivity index is employed to compute the productivity growth scores. PAT_{jit} denotes the patent variable that comprises the number of patents, R&D intensity, technology transfer and trade-openness variables. MNCs play a crucial role in technology transfer through various avenues, such as, franchising, licensing, management contracts, marketing contracts, and technical service contracts along with establishing subsidiaries in overseas (Blomstrom and Wolff, 1989). Besides, foreign subsidiaries also exhibit spillover efficiency through imposing standards on the local economy. Simultaneously, the study reveals that the TFP growth differs in foreign firms and local firms subject to the developing status of the host country. Another research advocates a positive correlation between the long-run annual rate of TFP growth and full private ownership of a firm (Ehrich et al. 1994, Vukšić, 2016). Thus, it is evident that foreign ownership (FOR), MNC, and private ownership (PVT) aspects influence TFP through technology transfer and spillover effect. The term γ_{it} are firm and industry characteristics that incorporate foreign ownership (FOR), MNC and private ownership (PVT), whilst the TRIPs dummy is denoted as D_j. The ε_{ijt} term depicts the residual term that demonstrates the unobservable effects and can be expressed as,

$$\varepsilon_{ijt} = u_i + v_{it} \tag{7.2}$$

Here, u_i is time-invariant firm-specific effect and v_{it} is time-variant random error. The parameters β_1, β_2, and β_3 to be estimated. The parameter β_3 is the causal effect of interest.

7.4 Estimation Method

This study employed panel data in a dynamic model in the attempt to attain a robust outcome while explaining the intricate relations among patents, R&D and productivity. Substantial studies used macro-level analysis with either cross-sectional or time-series country-level or industry-level data. Customarily, cross-sectional estimates offer weaker conclusions than time-series ones (Crepon et al. 1998). The empirical model in Equation (7.1) was estimated using a panel data framework. The critical advantage of panel data over cross-section or time-series data is that they have higher proximity to modelling the complexity of individualistic behaviour (Arellano 2003; Baltagi and Kao 2001; Hsiao 2007). Hence, the panel data structure enabled this thesis to examine various hypotheses with reference to the diverse channels of patent reform and firm heterogeneities that may align with the aforesaid channels. At first, the within-group fixed-effects model (FEM) and random-effects model (REM) were tested for the four selected manufacturing industries in this thesis. The FEM essentially assumes one true effect size and the heterogeneity among the firms under the same industries are solely random implies that no specific reason creates the firm's heterogeneity. Contrastingly, REM assumes firms' heterogeneity is not correlated with the other influential independent variables. Basically, REM makes some additional assumptions; however, if the assumptions are violated, the result will be biased. Therefore, the Hausman test is performed to ascertain the pertinence of the FEM or REM in the given panel dataset. The null hypothesis of the Hausman test considers that the omission of the fixed-effect component from the econometric modelling will not create any bias. The conventional estimation of a dynamic panel model is pooled OLS; however, it ignores the cross-sectional and time-variant attributes of the data. Consequently, in the presence of individual specific effects using pooled OLS with a single lag in the dependent variable, it is upwards biased (Hsiao 2002). Conversely, in the case of short panel data structure, using a fixed-effects (FE) estimation method shows a downwards bias (Nickell 1981). REM provides consistent estimates in this circumstance, as the estimates remain between the interval of the pooled OLS and FE model (Bond et al. 2001; Roodman 2009). The estimation results of the various models are demonstrated in Table 7.1. The DiD technique is used to assess the effect of patent reforms, especially the TRIPS agreement, for the four selected manufacturing industries in the succeeding section.

7.5 Specific Empirical Model

7.5.1 Static Model

In conjunction with the TRIPS agreement of 1994, product patents had to be legalised in 2005 for the conferred member countries (WTO, 1994). To directly assess the differential effect of the 2005 TRIPS agreement on firm-level productivity, this thesis employed a DiD model. The observed period of 1995 to 2016 was segregated into two sub-periods: 1995 to 2005 and 2005 to 2016, identified as the pre-TRIPS and post-TRIPS periods, respectively. It is conceivable that the firm-level productivity of manufacturing industries positively correlates with foreign ownership, as foreign financing is easily procurable (Bose et al. 2020).

Further, MNC characteristics drive extensive productivity growth in domestic firms and enhance their efficiency (Caves 1996; Görg and Strobl 2001) via the channel of international knowledge diffusion. Besides, complete private ownership leads to extensive long-run productivity growth through rate effect (Ehrich et al. 1994; Vukšić 2016). Thus, this thesis incorporated various expositions of the DiD model, based on a post-TRIPS dummy, along with the Indian ownership dummy (*Indian*), multinational firm dummy (*MNC*), private limited dummy (*private*) and corresponding interaction terms.

DiD fixed effect equations are explained as follows,

$$TFP_{it} = \beta_0 + \beta_1 * post\_TRIPsDummy_t + \beta_2 * Indian\ Dummy_{it} + \beta_3 * post\_TRIPsDummy_t * Indian\ Dummy_{it} + \beta_4 * patent_{it} + \beta_5 * RNDI_{it} + \beta_6 * TO_{it} + \beta_7 * TT_{it} + c_i + \lambda_t + \varepsilon_{it} \quad (7.3)$$

$$TFP_{it} = \beta_0 + \beta_1 * post\_TRIPsDummy_t + \beta_2 * MNC\ Dummy_{it} + \beta_3 * post\_TRIPsDummy_t * MNC\ Dummy_{it} + \beta_4 * patent_{it} + \beta_5 * RNDI_{it} + \beta_6 * TO_{it} + \beta_7 * TT_{it} + c_i + \lambda_t + \varepsilon_{it} \quad (7.4)$$

$$TFP_{it} = \beta_0 + \beta_1 * post\_TRIPsDummy_t + \beta_2 * private\ Dummy_{it} + \beta_3 * post\_TRIPsDummy_t * private\ Dummy_{it} + \beta_4 * patent_{it} + \beta_5 * RNDI_{it} + \beta_6 * TO_{it} + \beta_7 * TT_{it} + c_i + \lambda_t + \varepsilon_{it} \quad (7.5)$$

The $post\_TRIPsDummy_t$ variable is assigned a value of 1 in the post-TRIPs period and 0 in the pre-TRIPs period. The $Indian\ Dummy_{it}$ takes a value of 1 when the ownership of the firm is Indian, and 0 value for foreign firms in equation 7.3. The $post\_TRIPsDummy_t * Indian\ Dummy_{it}$ connotes the interaction effect between the post-TRIPs period and treatment group dummy i.e., $Indian\ Dummy_{it}$.

Likewise, $MNC\ Dummy_{it}$ takes a value of 1 when the firm is a multi-national corporation and 0 otherwise in equation 7.4. The interaction effect denotes as $post\_TRIPsDummy_t * MNC\ Dummy_{it}$ term. In the subsequent equation 7.5 the $private\ Dummy_{it}$ term is assigned the value of 1 for the private limited firm and the value of 0 otherwise. The interaction between the post-TRIPs period and treatment group dummy i.e., $private\ Dummy_{it}$ is expressed through the term $post\_TRIPsDummy_t *$

$private\ Dummy_{it}$. The findings of these three empirical DiD models stated in equation 7.3, 7.4 and 7.5 respectively are presented in Table 7.2.

The comparative analysis of the interaction effect of the firm characteristic variables and post-TRIPS among the selected industries capture through the following DiD fixed effect equation,

$$TFP_{it} = \beta_0 + \beta_1 * post\_TRIPsDummy_t + \beta_2 * Indian\ Dummy_{it} + \beta_3 * post\_TRIPsDummy_t * Indian\ Dummy_{it} + \beta_4 * MNC\ Dummy_{it} + \beta_5 * post\_TRIPsDummy_t * MNC\ Dummy_{it} + \beta_6 * private\ Dummy_{it} + \beta_7 * post\_TRIPsDummy_t * private\ Dummy_{it} + \beta_8 * patent_{it} + \beta_9 * RNDI_{it} + \beta_{10} * TO_{it} + \beta_{11} * TT_{it} + \beta_{12} * patent\ protection + c_i + \lambda_t + \varepsilon_{it} \quad (7.6)$$

7.6 Data

The data used in this thesis were obtained from the Prowess database generated and maintained by the CMIE, as explained in Chapter 5. The environmental variables of patent reforms were also discussed in Chapter 5. The response variable, TFP growth, was estimated using firm-level data, as explained in Chapter 6. The dependent variable, TFP growth, was measured using the Färe-Primont productivity index proposed by O'Donnell (2012) and estimated from firm-level data.

7.7 Analysis of Empirical Findings

7.7.1 Estimation Approach

This section evaluates the empirical results of the estimation of Equation (7.1). The estimation results of the four distinct models are reported in Table 7.1. The pooled OLS and FEM are depicted in the second and third columns in Table 7.1, respectively. The subsequent column portrays the REM. The final column presents the corrected version of REM using the Arellano method. The Hausman test was applied to adopt the appropriate model among the FEM (within) and REM. The lower panel of Table 7.1 presents the Hausman (1978) test, often known as the Durbin-Wu-Hausman test, which constructs the difference of the vectors of coefficients of two different models. The null hypothesis favoured the REM over the FEM, while the FEM was preferred under the alternative hypothesis.

Autocorrelation in linear panel data models biases the standard errors; as a consequence, the results become less effective. Hence, it is imperative to perform a diagnostic test to detect serial correlation in the idiosyncratic error term in a panel data model. This thesis performed the Breusch-Godfrey/Wooldridge test for autocorrelation in panel models. Like autocorrelation, heteroscedasticity also leads to serious bias in standard errors. The Breusch-Pagan test was performed in this study to detect heteroscedasticity. The null hypothesis for the Breusch-Pagan test is homoscedasticity. The Arellano method[22] was used to make the standard error robust in the existence of heteroscedasticity and autocorrelation problems.

[22] The Arellano-Bond test is a test of correlation established on the residuals of the estimation. The computation is performed with the standard covariance matrix of the coefficients by default. The *vcov* argument in the R platform can be performed to obtain a robust estimator of this covariance matrix.

Table 7.1: Estimation Results of Dynamic Model Dependent Variable: TFP, 1995–2016

(a) Biotechnology Industry

Independent variables	**Pooled-OLS (1)**	**FEM (2)**	**REM (3)**	**Corrected model (4)**
Number of Patents (z1)	0.002 (0.001)	0.000 (0.000)	0.000 (0.001)	0.000 (0.002)
R&D intensity(z2)	0.053 (0.052)	0.181 (0.042)***	0.170 (0.041)***	0.170 (0.314)
Trade Openness (z3)	-0.005 (0.002)**	0.000 (0.005)	-0.003 (0.004)	-0.003 (0.008)
Technology Transfer (z4)	0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	0.001 (0.002)
Number of Patents (z1) x R&D intensity(z2)	0.062 (0.024)*	0.039 (0.015)**	0.039 (0.015)**	0.039 (0.025)
Number of Patents (z1) x Trade Openness (z3)	0.000 (0.002)	0.001 (0.001)	0.001 (0.001)	0.001 (0.002)
Number of Patents (z1) x Technology Transfer (z4)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)
R&D intensity(z2) x Trade Openness (z3)	-0.200 (0.056)***	-0.239 (0.042)***	-0.230 (0.040)***	-0.230 (0.303)
R&D intensity(z2) x Technology Transfer (z4)	0.002 (0.008)	-0.008 (0.006)	-0.007 (0.006)	-0.007 (0.021)
Trade Openness (z3) x Technology Transfer (z4)	-0.001 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.002)
Number of Patents (z1)x R&D intensity(z2) x Trade Openness (z3)	-0.102 (0.031)**	-0.060 (0.019)**	-0.060 (0.019) **	-0.060 (0.028) **
Number of Patents (z1) x R&D intensity(z2) x Technology Transfer (z4)	-0.018 (0.006)**	-0.010 (0.004)**	-0.011 (0.004)**	-0.011 (0.005) **

Number of Patents (z1) x Trade Openness (z3) x Technology Transfer (z4)	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.001)
R&D intensity(z2) x Trade Openness (z3) x Technology Transfer (z4)	-0.003 (0.012)	0.004 (0.008)	0.003 (0.008)	0.003 (0.022)
Patent Reform Interaction effect	0.020 (0.006)**	0.011 (0.004)**	0.011 (0.004)**	0.011 (0.005)**
Constant	1.161 (0.003) ***	-----	1.149 (0.008)**	1.1498 (0.013)***
Median Residual	-0.009	0.000	-0.001	
Adjusted R^2	0.049	0.015	0.164	

Hausman test : chi-square = 12.524, p-value = 0.639=> REM

Lagrange Multiplier test - (Breusch-Pagan) : p-value < 0.000 => REM

Breusch-Godfrey/Wooldridge test for serial correlation in panel models to check autocorrelation: p value < 0.000=> existence of serial correlation

Breusch-Pagan test to check heteroskedasticity: p-value = 0.000 =>existence of heteroskedasticity

Heteroscedasticity-Consistent Covariance Matrix Estimation is used to handle the autocorrelation and heteroskedasticity (column 4)

Author's calculation. All values in the parentheses are standard errors and $p < 0.01$, $p < 0.05$ and $p < 0.1$ are denoted by ***, ** and *, respectively.
All the values are standardised to 3 decimal points.

The above Table 7.1 a) reports the different estimation models for the biotechnology industry. The lower panel of the Table shows the Hausman test, and the p-value is depicted as 0.639. This p-value strongly indicates the inability to reject the null hypothesis. Thus, REM is the appropriate model to provide consistent estimates. The Breusch-Godfrey/ Wooldridge test is used for serial correlation in panel models to check autocorrelation. The p-value of the Breusch-Godfrey/Wooldridge test is 0.00. It indicates the presence of autocorrelation. Besides, to check the existence of heteroskedasticity this study performs the Breusch-Pagan test. The p-value of this test is 0.00, which indicates the presence of heteroskedasticity. To overcome the problem of autocorrelation and heteroskedasticity, the estimation of the standard error in the REM is adjusted through the Heteroscedasticity-Consistent Covariance Matrix Estimation. The Appendix 7.1 presents the results.

(b) Electrical equipment and Electronic Industry

Independent variables	Pooled-OLS (1)	FEM (2)	REM (3)	Corrected model (4)
Number of Patents (z1)	-0.003	-0.002	-0.002	-0.002
	(0.002)	(0.001)	(0.001)	(0.003)
R&D intensity(z2)	0.004	-0.024	-0.021	-0.021
	(0.017)	(0.016)	(0.016)	(0.022)
Trade Openness (z3)	0.017	0.015	0.015	0.015
	(0.006)**	(0.010)	(0.009)	(0.015)
Technology Transfer (z4)	0.000	-0.001	0.000	0.000
	(0.000)***	(0.001)	(0.000)	(0.001)
Number of Patents (z1) x R&D intensity(z2)	0.009	0.008	0.008	0.008
	(0.012)	(0.008)	(0.008)	(0.006)
Number of Patents (z1) x Trade Openness (z3)	0.003	0.005	0.005	0.005
	(0.002)	(0.001)***	(0.001)***	(0.004)
Number of Patents (z1) x Technology Transfer (z4)	0.000	0.000	0.000	0.000
	(0.000)	(0.000)***	(0.000)***	(0.000)
R&D intensity(z2) x Trade Openness (z3)	0.070	-0.131	-0.111	-0.111
	(0.061)	(0.064)*	(0.062)	(0.051)*
R&D intensity(z2) x Technology Transfer (z4)	-0.004	0.003	0.001	0.001
	(0.002)**	(0.002)	(0.002)	(0.003)
Trade Openness (z3) x Technology Transfer (z4)	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)
Number of Patents (z1)x R&D intensity (z2) x Trade Openness (z3)	-0.012	-0.010	-0.009	-0.009
	(0.021)	(0.013)	(0.013)	(0.007)
Number of Patents (z1)x R&D intensity(z2) x Technology Transfer (z4)	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)*	(0.000)	(0.001)

Number of Patents (z1) x Trade Openness (z3) x Technology Transfer (z4)	0.000 (0.000)	-0.001 (0.000)***	0.000 (0.000)***	0.000 (0.001)
R&D intensity(z2) x Trade Openness (z3) x Technology Transfer (z4)	-0.005 (0.006)	0.008 (0.006)	0.007 (0.005)	0.007 (0.004)
Patent Reform Interaction effect	0.000 (0.001)	0.001 (0.000)	0.001 (0.001)	0.001 (0.002)
Constant	0.919 (0.003)		0.926 (0.008)	0.926 (0.009)
Median Residual	0.007	0.000	0.001	
Adjusted R^2	0.021	-0.036	0.147	
Hausman test : chi-square =11.485, p-value = 0.718=> REM Breusch-Godfrey/Wooldridge test for serial correlation in panel models to check autocorrelation: p value < 0.000 => existence of serial correlation Breusch-Pagan test to check heteroskedasticity: p-value < 0.000 =>existence of heteroskedasticity Heteroscedasticity-Consistent Covariance Matrix Estimation is used to handle the autocorrelation and heteroskedasticity (column 4)				

Author's calculation. All values in the parentheses are standard errors and $p < 0.01$, $p < 0.05$ and $p < 0.1$ are denoted by ***, ** and *, respectively. All the values are standardised to 3 decimal points.

The Table 7.1 b) presents the four estimation models for the electrical and electronic industry. The lower panel of Table 7.1b) displays that the p-value of the Hausman test is equal to 0.7175. This strongly refers that the estimation model fails to reject the null hypothesis. Therefore, REM is the appropriate model to provide consistent estimates. In order to check the existence of autocorrelation, this thesis performs the Breusch-Godfrey/ Wooldridge test in panel models. The p-value of the Breusch-Godfrey/Wooldridge test is 0.00. Hence, this diagnostic test indicates the presence of autocorrelation. Further, to check the presence of heteroskedasticity, this study performs the Breusch-Pagan test. The presence of heteroskedasticity is revealed as the p-value of this test is 0.00. The estimation of the standard error in the REM is adjusted by using Heteroskedasticity-Consistent Covariance Matrix Estimation to overcome this heteroskedasticity [23] (Appendix 7.2).

[23] A parameter *covariance matrix estimator* that is *consistent* even when the disturbances of a linear regression model are *heteroskedastic* (White 1980).

(c) Information Technology Industry

Independent variables	**Pooled-OLS (1)**	**FEM (2)**	**REM (3)**	**Corrected model (4)**
Number of Patents (z1)	0.004 (0.004)	0.001 (0.002)	0.002 (0.002)	0.002 (0.003)
R&D intensity(z)	-0.138 (0.038)	-0.090 (0.065)	-0.095 (0.058)	-0.095 (0.167)
Trade Openness (z3)	-0.026 (0.006)	-0.067 (0.014)***	-0.056 (0.012)***	-0.056 (0.031)·
Technology Transfer (z4)	-0.000 (0.000)	-0.002 (0.002)	-0.001 (0.000)	-0.001 (0.001)
Number of Patents (z1) x R&D intensity(z2)	0.020 (0.018)	0.006 (0.011)	0.006 (0.011)	0.006 (0.008)
Number of Patents (z1) x Trade Openness (z3)	-0.004 (0.004)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.003)
R&D intensity(z2) x Trade Openness (z3)	0.301 (0.226)	0.147 (0.220)	0.153 (0.215)	0.153 (0.263)
Number of Patents (z1) x Technology Transfer (z4)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)
R&D intensity(z2) x Technology Transfer (z4)	0.001 (0.003)	0.004 (0.004)	0.002 (0.004)	0.002 (0.008)
Trade Openness (z4) x Technology Transfer (z3)	0.001 (0.001)	0.003 (0.001)*	0.002 (0.001)*	0.002 (0.002)
Number of Patents (z1) x R&D intensity(z2) x Trade Openness (z3)	0.092 (0.069)	-0.063 (0.042)	-0.061 (0.042)	-0.061 (0.033)
Number of Patents (z1) x R&D intensity(z2) x Technology Transfer (z4)	0.000 (0.001)	0.000 (0.001)	0.000 (0.001)	0.000 (0.000)

Number of Patents (z1) x Trade Openness (z3) x Technology Transfer (z4)	0.001 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
R&D intensity(z2) x Trade Openness (z3) x Technology Transfer (z4)	-0.017 (0.018)	-0.003 (0.013)	-0.003 (0.013)	-0.003 (0.012)
Patent Reform Interaction effect	-0.006 (0.004)	0.003 (0.002)	0.002 (0.002)	0.002 (0.002)
Constant	0.984 (0.004)		1.001 (0.011)***	1.001 (0.020)
Median Residual	0.006	0.000	0.001	
Adjusted R^2	0.035	-0.042	0.104	

Hausman test : chi-square = 9.867, p-value = 0.828=> REM

Breusch-Godfrey/Wooldridge test for serial correlation in panel models to check autocorrelation: p value <0.000=> existence of serial correlation

Breusch-Pagan test to check heteroskedasticity: p-value < 0.000=>existence of heteroskedasticity

Heteroscedasticity-Consistent Covariance Matrix Estimation is used to handle the autocorrelation and heteroskedasticity (column 4)

Author's calculation. All values in the parentheses are standard errors and $p < 0.01$, $p < 0.05$ and $p < 0.1$ are denoted by ***, ** and *, respectively.
All the values are standardised to 3 decimal points.

The above Table 7.1c) describes the various estimation models for the IT and communication industry. The autocorrelation and heteroskedasticity problem lead to the estimates bias and the model less efficient. The lower panel of the above Table represents the p-value of the Hausman test is equal to 0.828. This p-value strongly suggests that the estimation model fails to reject the null hypothesis. Thus, REM is preferred over FEM as the appropriate model to specify consistent estimates. Likewise, to check the existence of autocorrelation, this thesis performs the Breusch-Godfrey/ Wooldridge test in panel models for this specific industry. The p-value of the Breusch-Godfrey/Wooldridge test is 0.00. Hence, this diagnostic test indicates the presence of autocorrelation (Appendix 7.3).

Further, to check the presence of heteroskedasticity, this study performs the Breusch-Pagan test. The presence of heteroskedasticity is revealed as the p-value of this test is 0.00. The estimates of the standard error in the REM are adjusted by using Heteroskedasticity-Consistent Covariance Matrix Estimation to overcome this heteroskedasticity and autocorrelation.

(d) Pharmaceutical Industry

Independent variables	Pooled-OLS (1)	FEM (2)	REM (3)	Corrected model (4)
Number of Patents (z1)	0.002 (0.002)	-0.001 (0.002)	-0.001 (0.001)	-0.001 (0.002)
R&D intensity(z2)	0.117 (0.054)*	0.258 (0.045)***	0.247 (0.045)	0.247 (3.8453e-01)
Trade Openness (z3)	-0.011 (0.006)	0.011 (0.006)	0.009 (0.006)	0.009 (0.020)
Technology Transfer (z4)	0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.002)
Number of Patents (z1) x R&D intensity(z2)	0.138 (0.028)***	0.109 (0.020)***	0.110 (0.020)***	0.110 (0.034)**
Number of Patents (z1) x Technology Transfer (z4)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)
R&D intensity(z2) x Technology Transfer (z4)	-0.007 (0.008)	-0.010 (0.006)	-0.010 (0.006)	-0.010 (0.026)
Number of Patents (z1) x Trade Openness (z3)	0.001 (0.003)	0.000 (0.002)	-0.003 (0.002)	-0.003 (0.003)
R&D intensity(z2) x Trade Openness (z3)	-0.158 (0.056)**	-0.268 (0.045)***	-0.258 (0.045)***	-0.258 (0.370)
Trade Openness (z3) x Technology Transfer (z4)	0.000 (0.000)	0.000 (0.000)	0.001 (0.001)	0.001 (0.002)
Number of Patents (z1) x R&D intensity(z2) x Technology Transfer (z4)	-0.005 (0.006)	-0.010 (0.004)*	-0.010 (0.004)*	-0.010 (0.003)***
Number of Patents (z1) x R&D intensity(z2) x Trade Openness (z3)	-0.190 (0.035)***	-0.137 (0.025)***	-0.139 (0.025)***	-0.139 (0.037)***
Number of Patents (z1) x Trade Openness (z3) x Technology Transfer (z4)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.001)

R&D intensity(z2) x Trade Openness (z4) x Technology Transfer (z4)	0.006 (0.010)	0.007 (0.009)	0.007 (0.009)	0.007 (0.027)
Patent Reform Interaction effect	0.008 (0.006)	0.011 (0.004)*	0.010 (0.004)*	0.010 (0.003)***
Constant	1.1375 (0.005)	0.000 (0.000)	1.1286 (0.008)	1.1286 (0.017)
Median Residual	0.006		-0.001	
Adjusted R^2	0.046		0.209	

Hausman test : chi-square = 12.746, p-value = 0.622=> REM

Lagrange Multiplier test - (Breusch-Pagan) : p-value < 0.000=> REM

Breusch-Godfrey/Wooldridge test for serial correlation in panel models to check autocorrelation: p value < 0.000 => existence of serial correlation

Breusch-Pagan test to check heteroskedasticity: p-value = 0.000 =>existence of heteroskedasticity

Heteroscedasticity-Consistent Covariance Matrix Estimation is used to handle the autocorrelation and heteroskedasticity (column 4)

Author's calculation. All values in the parentheses are standard errors and $p < 0.01$, $p < 0.05$ and $p < 0.1$ are denoted by ***, ** and *, respectively.
All the values are standardised to 3 decimal points.

Similar to the other sunrise industries, the Hausman test results for the pharmaceutical industry suggested REM. The *p*-value for this test was recorded as 0.6219, thus failing to reject the null hypothesis favouring REM. Next, autocorrelation was detected with the diagnostic Breusch-Godfrey/Wooldridge test. This panel data model constructed from pharmaceutical industry data also checked for the presence of heteroscedasticity. The Breusch-Pagan test was employed, and the corresponding *p*-value was reported as 0.00, detecting the presence of heteroscedasticity. Heteroscedasticity and autocorrelation bias the standard error. Therefore, it was necessary to rectify the problem of serial correlation and heteroscedasticity. The heteroscedasticity-consistent covariance matrix estimation was employed to deal with the autocorrelation and heteroscedasticity (Appendix 6.4).

The patent variables—number of patents, R&D intensity, technology transfer and trade openness—did not reveal a significant individual effect on productivity growth in the four industries constructed with the patented firms. The result is consistent with some previous studies that found no strong association between the effects of product and process innovation output , R&D investment and the productivity performance of the firm (Basant et al. 1996; Mishra et al. 2021; Raut 1995; Sharma 2011). Contrastingly, other research measured R&D intensity as the ratio of in-house R&D expenditure to total sales, and found a positive effect of R&D intensity on firms' productive progress (Chand and Sen 2002; Mitra et al. 2014). The findings of this thesis indicated no significant individual effect of technology diffusion on productivity growth for patented firms in the selected manufacturing industries. One recent study evaluated the magnitude of international technology transfer on productivity growth at the industry level of the manufacturing industry in India via various channels (Sikdar and Mukhopadhyay 2020). It found that technology transfer affected productivity growth only in specific sectors, such as raw materials and capital goods importing sectors. The results of this thesis differ from another recent study estimating the relationship between trade openness and productivity for 17 two-digit organised manufacturing sector industries during 1980 to 2013 (Rijesh 2019). Empirical studies investigating the effect of trade liberalisation on TFP growth in the Indian manufacturing sector demonstrated mixed results. Some studies reported that the liberalisation policies led to productivity growth (Chand and Sen 2002; Driffield and Kambhampati 2003; Unel 2003), while others found that trade reform had no significant or negative effect on TFP growth (Goldar and Kumari 2003; Trivedi et al. 2000).

Interestingly, the joint effect of the patent variables was significant at a 5% level for the biotechnology and pharmaceutical industries; however, the joint effect of the patent variables for the other two sunrise industries was not significant. Despite the significance, no strong correlation was found between the effect of the patent variables and productivity growth. The rationale behind this finding is that Indian patented manufacturing firms are unable to reap the benefits of greater technological inflow. Besides, to procure potential gain from R&D investments, firms require a convenient environment. It is imperative to evaluate the effect of firms' individual attributes in promoting TFP growth in this context. The following section explains the differential effect of the 2005 TRIPS agreement on firm-level productivity.

7.7.2 Differential Effects of 2005 TRIPS Agreement Implementation on Firm-level Productivity Growth

This section evaluates the empirical results of the estimation of Equations (7.3), (7.4) and (7.5). The estimation results of the three DiD models are reported in Table 7.2. The general proposition is that the adaptive capacity may differ in domestic firms and foreign firms. The second column of Table 7.2 presents the differential effect of Indian and foreign firms during the pre-TRIPS and post-TRIPS periods. Simultaneously, another proposition is that MNCs disseminate technological knowhow and transfer technology to their local franchise. Moreover, the local franchise experiences more opportunities to procure benefit by attracting employees with firm-specific knowledge from the foreign affiliate, compared with the domestic firm. In line with this proposition, the third column reports the differential effect of MNC and domestic firms during the pre-TRIPS and post-TRIPS periods. Economic theory postulates that firms' productivity growth under private ownership is better than state or public ownership in general. The rationale behind this is that the formulation and execution of the strategic movement are more convenient for private ownership (Vukšić 2016). The final column of Table 7.2 captures the differential effect for private and non-private firms under the TRIPS condition. The following Tables 7.2 (a), 7.2(b), 7.2(c) and 7.2(d) present the differential effects of the 2005 TRIPS agreement implementation on firm-level productivity growth for all four selected industries.

Table 7.2: Differential Effects of 2005 TRIPS Agreement Implementations on Firm-level Productivity Growth

(a) Biotechnology Industry

Variables	Model I: Indian ownership	Model II: MNC	Model III: Private ownership
	TFP growth	TFP growth	TFP growth
Post-TRIPS dummy	0.017 (0.032)	–0.002 (0.019)	–0.015 (0.020)
Firm ownership dummy	–0.174 (0.029)***	–0.082 (0.027)**	0.371 (0.022)***
Post-TRIPS dummy × firm ownership dummy	–0.005 (0.037)	0.012 (0.034)	0.012 (0.028)
Number of patents	–0.007 (0.001)***	–0.005 (0.001)	–0.003 (0.001)**
R&D intensity	0.002 (0.057)	0.024 (0.058)	–0.007 (0.052)
Trade openness	–0.018 (0.019)	–0.023 (0.019)	–0.036 (0.017)*
Technology transfer	–0.006 (0.001)***	–0.005 (0.001)***	–0.004 (0.001)***
Patent reform interaction effect	–0.001 (0.001)	–0.001 (0.001)	–0.001 (0.001)
Constant	0.273 (0.029)***	0.161 (0.020)***	–0.054 (0.020)**
Median residual	0.046	0.045	–0.001
Adjusted R^2	0.049	0.026	0.220

Author's calculation. All values in the parentheses are standard errors and $p < 0.01$, $p < 0.05$ and $p < 0.1$ are denoted by ***, ** and *, respectively.

(b) Electrical and Electronics Industry

Variables	Model I: Indian ownership	Model II: MNC	Model III: Private ownership
	TFP growth	TFP growth	TFP growth
Post-TRIPS dummy	–0.035 (0.005)***	–0.020 (0.003)***	–0.019 (0.004)***
Firm ownership dummy	–0.006 (0.004)	0.022 (0.003)***	0.003 (0.004)
Post-TRIPS dummy × firm ownership dummy	0.008 (0.005)	–0.031 (0.038)***	–0.013** (0.005)
Number of patents	0.001 (0.000)*	0.001 (0.000)***	0.001 (0.000)*
R&D intensity	–0.011 (0.008)	–0.009 (0.008)	–0.013 (0.008)
Trade openness	–0.001 (0.003)	–0.004 (0.003)	–0.001 (0.003)
Technology transfer	0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***
Patent reform interaction effect	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Constant	0.286 (0.004)***	0.273 (0.003)***	0.279 (0.003)***
Median residual	–0.001	–0.002	–0.001
Adjusted R^2	0.112	0.129	0.115

Author's calculation. All values in the parentheses are standard errors and $p < 0.01$, $p < 0.05$ and $p < 0.1$ are denoted by ***, ** and *, respectively. All the values are standardised to 3 decimal points.

(c) IT and Communication Industry

Variables	Model I: Indian ownership	Model II: MNC	Model III: Private ownership
	TFP growth	TFP growth	TFP growth
Post-TRIPS dummy	0.042 (0.009)***	0.031 (0.005)***	0.046 (0.006)***
Firm ownership dummy	0.015 (0.008)*	0.003 (0.006)	0.020 (0.006)***
Post-TRIPS dummy × firm ownership dummy	-0.015 (0.010)	-0.003 (0.007)	-0.028 (0.008)***
Number of patents	0.001 (0.000)**	0.001 (0.000)**	0.001 (0.000)**
R&D intensity	0.048 (0.017)**	0.049 (0.017)**	0.049 (0.017)**
Trade openness	-0.004(0.004)	-0.005(0.004)	-0.004 (0.004)
Technology transfer	-0.001 (0.000)***	0.001 (0.000)***	0.001 (0.000)***
Patent reform interaction effect	0.000 (0.000)	0.321 (0.005)	0.000 (0.000)
Constant	0.310 (0.008)***	0.000 (0.000)***	0.310 (0.006)***
Median residual	0.003	0.003	0.002
Adjusted R^2	0.065	0.063	0.071

Author's calculation. All values in the parentheses are standard errors and $p < 0.01$, $p < 0.05$ and $p < 0.1$ are denoted by ***, ** and *, respectively. All the values are standardised to 3 decimal points.

(d) Pharmaceutical Industry

Variables	Model I: Indian ownership	Model II: MNC	Model III: Private ownership
	TFP growth	TFP growth	TFP growth
Post-TRIPS dummy	-0.020 (0.026)	0.016 (0.021)	0.023 (0.023)
Firm ownership dummy	-0.028 (0.028)	-0.130 (0.030)***	-0.196 (0.027)***
Post-TRIPS dummy × firm ownership dummy	0.059 (0.035)*	-0.031 (0.038)	-0.016 (0.034)
Number of patents	-0.006 (0.001)***	-0.006 (0.001)***	-0.005 (0.001)***
R&D intensity	0.167 (0.064)**	0.153 (0.064)*	0.149 (0.063)*
Trade openness	-0.014 (0.021)	-0.032 (0.021)	0.014 (0.021)
Technology transfer	-0.008 (0.001)***	-0.007 (0.001)***	-0.008 (0.001)***
Patent reform interaction effect	-0.001 (0.001)	-0.002 (0.001)	-0.001 (0.001)
Constant	0.143 (0.027)***	0.174 (0.023)***	0.198 (0.024)***
Median residual	0.028	0.042	0.005
Adjusted R^2	0.035	0.060	0.090

Author’s calculation. All values in parentheses are standard errors and $p < 0.01$, $p < 0.05$ and $p < 0.1$ are denoted by ***, ** and *, respectively. All the values are standardised to 3 decimal points.

The findings for the biotechnology, electrical and electronics, IT and pharmaceutical industries are described below. The findings of the biotechnology industry indicated that the TFP growth of Indian firms was lower than that of foreign firms by 0.173545, and significant at 1% level. This result is consistent with previous studies (Parameswaran and Prameswaran 2004). The rationale behind this is probably that Indian manufacturing firms are unable to deal with extreme technological intricacy. The productivity growth of MNC firms was lower by 0.082158 than that of non-MNC firms, and significant at 1% level. This finding differs from the general notion that MNC firms more efficiently access the benefits of technology transfer (Dhanora 2021). It is conceivable that the local franchises were unable to absorb the advantages of technology diffusion. Third, private ownership firms reported higher productivity growth by 0.0031509 than non-private firms, significant at 1% level. One of the probable reasons is that private firms can develop and implement strategies more conveniently. The interaction effect of post-TRIPS and firm ownership dummy were insignificant. However, private firms and MNC firms revealed higher TFP growth during the post-TRIPS period. Further, the individual effect of the patent protection variable—number of patents, R&D intensity, technology transfer and trade openness—conferred mixed results for domestic, MNC and private ownership firms.

No significant joint effect of these patent protection estimates in contributing to productivity was obtained. Possibly, a combination of all these variables only creates an environment that stimulates productivity growth. Simultaneously, the electric and electronics industry showed that TFP growth decreased in the overall post-TRIPS period, compared with the pre-TRIPS period. The DiD results of firm characteristic variable MNC and private limited ownership and post-TRIPS year demonstrated negative results. The productivity growth declined in MNC firms and private ownership firms by, on average, 3.06% and 1.26% during the post-TRIPS period, significant at 1% and 5% levels, respectively. The patent protection variables individually and collectively portrayed marginal or no significant effect on TFP growth for domestic, MNC and private ownership firms. Unlike the electrical and electronics industry, the IT and communication industry showed no significant variation in productivity growth either among the domestic and foreign firms or in the MNC and non-MNC firms. In contrast, the private firms exhibited 1.99% higher TFP growth than their counterpart at a 1% level; however, during the post-TRIPS period, there was 2.77% less productivity growth in private firms than non-private firms. The patent protection variable of R&D intensity varied by 4.87% among the private and non-private firms at 5% level. A possible reason for this finding is that private firms can channel their R&D expenditure more conveniently than can non-private firms. In contrast, in the post-TRIPS period, non-private firms may capture more foreign investment and subsequently more advanced technology.

Like the biotechnology industry, the Indian pharmaceutical industry also reported that the productivity growth of MNC firms and privately-owned firms was lower by 12.97% and 19.63%, respectively, than their counterparts, and significant at 1% level. Moreover, the technology transfer variable consistently remained significant for all three models. It was evident that, on average, the domestic firms’ productivity growth was 0.8% lower than that of the foreign firms. Besides, the productivity growth of the MNC firms and privately-owned firms was lower by 0.7% and 0.8%, respectively, than their corresponding counterpart. Simultaneously, the R&D intensity estimates were significant in all three models, as presented in Table 7.1(d). During the sample period, the effect of R&D intensity in generating productivity growth was 16.69% higher in foreign firms. Besides, the private ownership firms and MNC firms demonstrated a higher effect of R&D intensity on substantial TFP growth by 14.89% and 15.31%, respectively. It is logical that, as an emerging manufacturing sector, the Indian pharmaceutical industry, especially the local franchise of MNC firms, has better opportunities for R&D investment. Consistently, domestic pharmaceutical companies of India possess huge potential and market, which entices domestic private firms for higher R&D investment. No significant difference was found when examining the joint effect of the patent protection variables in generating TFP growth.

The efficacy of the procurement of technology is generally evaluated by the stability between imported technology and in-house developed technology (Lowe and Taylor 1998). Firms’ strategy towards technology decisions relies on their own R&D, as well as on technology purchased, thus embodied and disembodied R&D (Basant 1997; Blonigen and Taylor 2000; Hou and Mohnen 2013). Thus, the huge domestic market, difficulty catching up to the advanced knowledge, less opportunities in the export market and dependence on imported technical know-how can be accounted for this scenario.

Table 7.3: DiD Model for Post-TRIPS Period—Comparative Analysis

Variables	Biotechnology industry	Electrical and electronics industry	IT and communication industry	Pharmaceutical industry
	TFP growth	TFP growth	TFP growth	TFP growth
Post-TRIPS dummy	0.009 (0.008)	–0.007(0.009)	–0.066 (0.012)	–0.036 (0.009)
Firm ownership dummy	0.021 (0.007)	–0.013(0.006)	–0.022(0.008)	0.001 (0.006)
Post-TRIPS dummy × firm ownership dummy	0.010 (0.009)	0.009 (0.008)	0.047 (0.010)	–0.005 (0.008)
Firm MNC dummy	0.003 (0.009)	–0.014 (0.005)	–0.013 (0.007)	–0.011 (0.007)
Post-TRIPS dummy × firm MNC dummy	–0.006 (0.011)	–0.005 (0.007)	0.027 (0.008)	0.028 (0.008)
Firm private ownership dummy	0.008 (0.008)	0.011 (0.006)	–0.011(0.007)	–0.015(0.006)
Post-TRIPS dummy × private ownership dummy	–0.035(0.010)	0.007 (0.007)	0.036 (0.008)	0.011 (0.008)
Number of patents	0.001 (0.001)	0.002 (0002)	0.004 (0.004)	0.003 (0.002)
R&D intensity	0.044 (0.051)	0.008 (0.017)	–0.163 (0.038)	0.105 (0.054)
Trade openness	–0.005 (0.002)	0.017 (0.006)	–0.024 (0.006)	–0.009 (0.006)
Technology transfer	0.000 (0.001)	0.002 (0.000)	0.000 (0.000)	0.000 (0.001)
Patent reform interaction effect	0.022 (0.006)	0.000 (0.001)	–0.006 (0.004)	0.007 (0.006)
Constant	1.161 (0.007)	0.923 (0.008)	1.010 (0.010)	1.163 (0.009)
Median residual	–0.009	0.006	0.003	–0.005
Adjusted R^2	0.065	0.045	0.064	0.071

Author’s calculation. All values in the parentheses are standard errors. All the values are standardised to 3 decimal points.

Table 7.3 presents the fixed-effect DiD model estimates of the interaction effect among the firm characteristics' variables and post-TRIPS year dummy on TFP growth. These findings explain Equation (7.6) for the selected four industries. The second column of Table 7.3 reports no substantial productivity growth difference in the post-TRIPS period for domestic firms in the biotechnology industry. Similarly, MNC and private ownership firms of this industry obtained no distinctive change in TFP growth in the post-TRIPS period. The third and fourth columns of the above table summarise the findings of the electrical and electronics and IT and communication industries, respectively. As with the biotechnology industry, the results show no significant difference in productivity growth in domestic firms, MNCs and privately-owned firms in the pre-TRIPS and post-TRIPS periods with their counterparts. The final column demonstrates the DiD model of the pharmaceutical industry. The coefficient of estimates for the interaction effect demonstrates no considerable TFP growth in the post-TRIPS period. These results are almost symmetrical with the results of the primary DiD model in Table 7.1, with only a few exceptions, which confirms the robustness of the findings.

7.8 Conclusion

As a continuation of the two previous chapters, this chapter has evaluated the effects of patent protection on productivity growth in the selected Indian manufacturing industries in the timespan of 1995 to 2016. Patent protection policy is a crucial mechanism that administers rights to innovators to protect their innovation from imitation and enables them to gain profits from it. It channels market forces into technological advances that eventually encourage technology-driven economic growth. The conventional wisdom is that a patent institution is an efficient avenue to boost innovation, expedite technology diffusion, advocate trade and enhance competitiveness. Thus, the three major concepts of R&D, technology diffusion and trade openness were the mainstay of this analysis. Endogenous growth theory spawned the classical controversy regarding whether the spillover effect of innovation, technology diffusion and trade can promote firm-level productivity, which remains pertinent. However, it is evident that the accomplishment of future progress is driven by the absorptive capacity of the firm, and the absorptive capacity of a typical firm relies on the firm's attributes. Thus, this thesis contemplated a set of firm attributes expected to influence productivity growth among Indian domestic firms, MNCs and privately-owned firms. As a conferred member of the WTO, India is required to comply with the product patent regime under the TRIPS agreement (WTO 1994). Therefore, a dummy variable representing post-TRIPS implementation was included in this study. An econometric estimation using either static or dynamic model panel data was employed to address the effective patent protection on productivity growth. The DiD model was applied to analyse the differential effect of the TRIPS agreement.

The empirical findings indicated no significant individual effect of the patent variables—number of patents, R&D intensity, technology transfer and trade openness—on productivity growth for the four industries constructed with the patented firms. Simultaneously, the coefficient of estimates of the combined effect of the patent variables on TFP growth did not exert any strong correlation across all selected sunrise industries. The rationale behind this is that the Indian patented manufacturing firms of these sunrise industries remain incapable of reaping the potential benefit of the more significant technological inflow. This confirms that to procure the prospective gain from R&D investments in the form of both embodied and disembodied R&D investments, firms require supportive and convenient infrastructure. The adaptive capacity of individual firms is imperative in this context, which is extensively based on the firm's heterogeneity characteristics, such as foreign ownership, MNC features and private ownership. The estimation exhibited mixed results. The productivity growth of foreign firms in the biotechnology industry was significantly higher than that of domestic firms.

In contrast, the other three industries did not exert an apparent distinctive effect among the foreign and domestic firms on productivity growth, as the estimation result was not statistically significant. The MNC firms of the biotechnology and pharmaceutical industries showed significantly lower productivity growth. However, the electrical and electronics industry reported marginally higher growth, and the IT industry depicted no distinguishable productivity growth in MNC firms compared with their counterpart. Probably, MNC firms are more interested in promoting their business in the Indian huge consumer market than in investing in innovation activities. Besides, the private ownership of the firms is perceived to be more appropriate than non-private firms for improving firm-level productivity growth, as demonstrated in the biotechnology, electrical and electronics, and IT industries. In contrast, private firms become incompetent to enhance

TFP growth, since they require a colossal innovation cost, as exhibited in the pharmaceutical industry.

The empirical result of the differential effect demonstrated no significant productivity change for the domestic and foreign firms during the post-TRIPS period for the biotechnology, electrical and electronics, or IT industries. In contrast, the domestic firms of the pharmaceutical industry improved their productivity after the implementation of the TRIPS agreement. Substantial domestic demand and local expertise may expand the market for domestic firms. The non-MNC firms in the electrical and electronic industry only showed improvement in productivity during the post-TRIPS regime. The shift of paradigm from process to product patent plausibly encouraged the non-MNC firms of the electrical and electronic industry to strive for self-reliance. In addition, in the post-TRIPS period, productivity declined in private firms of the electrical and electronics and IT industries. Non-private firms were likely to use the greater investment to catch up with the advanced and sophisticated technology that accelerates productivity.

Several relevant policy implications evolved from the above empirical findings. This thesis found that patent institution does not contribute significantly to productivity growth; however, India is obliged to implement the TRIPS agreement. Therefore, the Indian government should give precedence to the patent institution while designing the spatial industrial policy. The comparative analysis provided a diversified scenario for the different industries; thus, instead of a homogeneous industrial policy, the emphasis should be industry specific. The efficacy of the procurement of technology for innovation entails consolidation between in-house R&D, the adaptive capacity of the imported technology and trade. In conclusion, to intensify productivity growth, the government should strive to ensure a supportive and collaborative business environment.

Chapter 8: Conclusion and Policy Implications

8.1 Introduction

The effects of patent protection regimes on firms' productivity growth have gained increasing attention over the past few decades among researchers and policymakers, especially with regard to the productivity benefits for native firms. Many developing countries, including India, have implemented a wide array of incentives to procure spillover gains. Numerous researchers have invested effort to evaluate these precise effects. Endogenous growth theory claims that innovation fosters economic growth, and patents are a pertinent measure of innovation. However, exclusive patent grants stimulate innovation, yet also generate social welfare loss through the creation of a monopoly. Hence, the exhaustive contributions of the patent system in promoting economic development, especially for developing countries with low adaptability of technology level (Basant 1997; Blonigen and Taylor 2000; Hou and Mohnen 2013), are dubious and demand empirical evidence. This thesis developed an empirical framework, built on two productivity analysis approaches, to analyse whether patent reform enhanced the productivity of four selected Indian manufacturing industries. The thesis decomposed productivity growth into three components: technological change, TE change and scale mix efficiency change. Thus, it empirically examined whether the patent institution can influence firms' productivity growth through various sources of productivity growth.

TFP growth has gained growing interest among policymakers and researchers as a measure of productivity growth while analysing the effect of the patent institution on productivity gain. This measure can derive the productivity growth owing to patent protection from technical progress, TE improvement and scale-mix efficiency. However, TE, SE and scale-mix efficiency are frequently overlooked in empirical studies. A number of prior studies conducted at the country and industry level followed a conventional production function. Firms were presumed to be producing at a full efficiency capacity and with CRS, indicating productivity growth generated by the patent institution is exclusively endowed by technical progress. Therefore, technical and scale efficiencies have remained unexplored as the sources of productivity gains at the firm level. Besides, very limited studies (Mahajan 2020, Goldar 2017) have analysed the elements of TE in light of the implementation of the TRIPS agreement.

This thesis contributes to the existing literature on patent protection regimes by investigating these overlooked issues. The significant contributions of this thesis are as follows. First, this thesis investigated patent protection effects on firm-level productive efficiency under a framework of a four-component smooth coefficient SPF approach, which permits decomposition of the inefficiency term into persistence and transient inefficiency. This methodology is relatively new, and this study is one of the first to apply it in a patent reform context. Second, this is one of the first studies from another aspect also, as it employed a decomposition analysis to examine the intrinsic sources of productivity gains from the patent institution in the Indian context. Third, this study estimated patent protection effects on firm productivity in the selected Indian sunrise manufacturing sectors directly affected by the mandatory shift of paradigm from process patent to product patent clause under the TRIPS agreement. Fourth, this study incorporated the period of implementation of the TRIPS agreement along with the transition period to capture the magnitude of the effects of patent protection before and after the TRIPS implementation.

8.2 Major Findings

This thesis undertook an empirical analysis of the effects of patent reform on firm-level productivity efficiency and productivity growth in four selected Indian manufacturing industries. These selected industries were directly affected by the paradigm shift from process patent to product patent under the TRIPS Agreement of the WTO—the biotechnology, electrical and electronics, IT and communication, and pharmaceutical industries. The principal source of data was the annual financial statements of listed and unlisted enterprises and participant companies in the Indian Stock Exchange, compiled by the Prowess database. Further, firm-level patent data were extracted from the database published by the Indian Patent Office, Government of India. Two productivity analysis approaches—the four-component semiparametric smooth coefficient SPF method and the Färe-Primont productivity index method—were used to achieve the primary objectives of this thesis. The DiD approach was applied to assess the differential effect between the pre-TRIPS and post-TRIPS periods.

Several intriguing findings from this study enriched the patent protection literature. Some results are consistent with the established theory and align with similar studies conducted in other countries. However, some new perspectives are provided in this study, which may be valuable for researchers and policymakers in India and other developing countries, as the implementation of TRIPS became mandatory for WTO member countries. The following sections explore these findings.

8.2.1 Effect of Patent Protection on Firm-level Productive Efficiency

The empirical results showed that the effects of patent reform on TE differed across industries (Chapter 5). In general, manufacturing industries of India—such as the pharmaceutical, electrical and electronics, and biotechnology industries—gained technical progress, represented by the positive coefficient of time; however, the IT and communication industry experienced adverse technical progress. Besides, the findings revealed a negative value for the labour input elasticity in the electrical and electronics industry, and capital input elasticity for the IT and communication industry.

The mean marginal effect of the number of patents and R&D intensity on transient inefficiency was lower in the pharmaceutical industry than the electrical and electronics industry. The marginal effects of the number of patent variables on transient inefficiency were always positive, with the mode around zero in the pharmaceutical and electrical and electronic industries. These empirical findings suggest that an increase in the number of patents would never induce a decline in transient inefficiency. The marginal effects of R&D intensity on transient inefficiency were also consistently positive and had a mode around zero in the pharmaceutical and IT and communication industries. Similarly, the electrical and electronics and biotechnology industries revealed that an increase in trade openness would never cause a reduction in transient inefficiency. Besides, the marginal effects of the technology transfer variables on transient inefficiency, along with the mode around zero for the electrical and electronics and IT and communication industries, indicated that trade openness would never decrease transient inefficiencies.

The mean PTE was relatively high in the pharmaceutical and biotechnology industries, signifying that most firms did not suffer from persistent inefficiencies. In contrast, the PTE scores of the other two industries demonstrated the existence of persistence inefficiencies. Moreover, the OTE scores of all three industries, except the pharmaceutical industry, were less than 0.5, indicating room for improvement.

8.2.2 Decomposition of Total Factor Productivity Growth

This thesis evaluated TFP change and its major drivers for the selected four industries during the pre-TRIPS implementation period (1995 to 2005) and post-TRIPS implementation period (2006 to 2016) in Chapter 6. The decomposition analysis was performed using the Färe-Primont productivity index, which allows the decomposition of the TFP into smaller components. The findings showed that all four industries experienced regressive long-run productivity growth during the post-TRIPS period. Interestingly, the study found that technological change was a significant driver for the improvement of TFP scores for the IT and communication and electrical and electronics industries. Contrarily, overall efficiency drove TFP change for the biotechnology and pharmaceutical industries. The reduction of the overall efficiency further relied on the reduction of OSME.

A *t*-test was used to investigate empirically whether the average TFP was significantly different during the pre-TRIPS and post-TRIPS periods. The results of the *t*-test demonstrated a substantial difference in mean TFP pre-TRIPS and post-TRIPS for the biotechnology and pharmaceutical industries. In contrast, no significant difference in mean TFP for the IT and communication and electrical and electronics industries was revealed in this period. Similar results depicted the overall TE across those industries. The average TFP scores may vary between the pre-TRIPS and post-TRIPS periods. Thus, a *t*-test assuming both variance and unequal variance was performed among the two sample sets. These *t*-tests showed a similar result and indicated the robustness of the findings.

8.2.3 Effect of Patent Reform on Productivity Growth

The results from the decomposition of TFP growth revealed a diverse growth trend between the different industries. The estimates of the different components that evolve after the decomposition of productivity growth are presented in Chapter 6. A panel data analysis was performed to evaluate the effect of patent reform on productivity growth in Chapter 7. The empirical results of the analysis showed no strong individual effect of the number of patents, R&D intensity, technology transfer or trade openness (the patent protection variables) on productivity growth for the four industries. Consequently, the coefficient of estimates of the combined effect of the patent variables on TFP growth also revealed no significance across all selected sunrise industries. Further, the magnitudes of the estimates varied among the industries, indicating that the heterogeneous features of the different industries are crucial in determining productivity growth.

The adaptive capacity of individual firms is imperative for innovation, and that substantially relies on firms' heterogeneity characteristics, such as foreign ownership, MNC features and private ownership. This thesis estimated the differential effects of these firm-level characteristics, which revealed mixed results. The productivity growth of foreign firms only in the biotechnology industry was significantly higher than that of domestic firms. Among the industries, the MNC firms of the biotechnology and pharmaceutical industries portrayed significantly lower productivity growth. Privately-owned firms in the biotechnology, electrical and electronics, and IT industries were more productive.

8.3 Policy Implications

Several potential policy implications arise from these empirical findings. First, this study found that the effects of the patent protection regime on TE vary across industries and sub-periods, with the pharmaceutical and biotechnology industries not experiencing severe persistent inefficiency. However, the electrical and electronics and IT and communication industries experienced persistent technical inefficiency. Thus, this study recommends that intense investigation is most important before public spending as different industries portrayed distinctive impacts on efficiency. To some extent, India is dependent on imports for the integral parts of manufacturing products in the electrical and electronics and IT and communication industries. Thus, promoting specific micro-level self-reliance of firms should be a new government resolution. Moreover, focusing on manufacturing electrical and electronics commodities can enhance the exports since those have very low non-tariff barriers. More institutional reforms to obtain the benefit from the trade liberalization and disperse it according to the requirement of the different industries probably improve the efficiency.

Second, on average, an increment of the environmental variables showed a mixed effect on the smooth coefficients. However, overall, trade openness and technology transfers influenced the magnitude of technical progress adversely. As a developing country, India must bear colossal licensing fees, royalty and technology transfer costs. Thus, this result suggests that, as a developing country, the manufacturing policy of India should focus on technology development by building strategies, including the construction of new offices associated with technology transfer. Simultaneously, it could establish specific universities to instil the benefits related to technology transfer that will eventually enhance the adaptive capacity. The empirical findings showed no significant individual effect of the patent variables—number of patents, R&D intensity, technology transfer and trade openness—on productivity growth for the four industries constructed with the patented firms. Simultaneously, the coefficient of estimates of the combined effect of the patent variables on TFP growth did not exert any strong correlation across the selected sunrise industries. The rationale behind this is that the Indian patented manufacturing firms of these sunrise industries remain incapable of reaping the potential benefits of the more significant technological inflow. Thus, to procure the prospective gain from the R&D investments in the form of both embodied and disembodied R&D investments, firms require supportive and convenient infrastructure. Hence, the government should develop adequate and integrated infrastructure and business environments across different firms to generate multiplier effects from development. Simultaneously, the government should promote other potential industries to reduce the inter-industry development gap.

Third, the study found that technical change is a significant driver for the improvement of TFP scores for the IT and communication and electrical and electronics industries. This suggests that industrial policies, such as relaxation of custom duties or allowance of FDI, enhance innovation opportunities and eventually induce technical progress. The 'Make in India' initiative launched in 2014 had two primary visions—(i) to refurbish India into a global design and manufacturing hub and (ii) to entrap FDI inflows—and should be continued. Policies to entice further FDI should also be formulated. In contrast, overall efficiency substantially drives TFP change for the biotechnology and pharmaceutical industries. Besides, the overall efficiency gain is determined by the OSME. Hence, it can be perceived that the existence of a pool of large firms is incapable of acquiring the adequate benefits of economies of scale. Regulation through a set of transparent, consistent and non-discriminatory rules may establish a competitive and dynamic environment in which market players can thrive.

Fourth, this thesis found that patent institution does not contribute significantly to productivity growth across the four selected industries; however, India is obliged to implement the TRIPS agreement. Therefore, the Indian government should give precedence to the patent institution while designing the spatial industrial policy. The comparative analysis provided a diversified scenario for the different industries; thus, instead of a homogeneous industrial policy, the emphasis should be on industry-specific policies. The efficacy of the procurement of technology for innovation entails consolidation between in-house R&D, the adaptive capacity of the imported technology and trade. To intensify productivity growth, the government should strive to ensure a supportive and collaborative business. However, the government should take into account that protection is needed in several industries in the early phases of development, as it brings positive effects in TFP components. For example, in the IT and communication and electrical and electronics industries, where protection increases TP and TE. However, in the biotechnology and pharmaceutical industry, protection increases scale-mix efficiency. Thus, the estimation results signify that the Indian government, especially while formulating national industrial policy, should emphasise the creation of a dynamic and flexible R&D ambience through which firms can achieve more patents that eventually enhance firm output at a micro-level and industry output at a macro-level.

Fifth, the results from the TE and productivity analysis showed a negative relationship between capital intensity, TE and productivity for the IT and communication industry, and labour elasticity in the electrical and electronics industry. The likely cause of this is the rebound effect, which reflects that the beneficial effects of new technology through the cost of capital (such as equipment) or labour (such as training) outweigh these behavioural responses at the initial stage. Therefore, a more dynamic role of the government is required to mobilise resources in physical infrastructure and offer more general policies, such as establishing an excellent institutional environment, spending and motivating effectively to acquire the new technologies.

8.4 Limitations and Focus for Future Research

The empirical findings of this study shed light on aspects of patent protection and productivity growth, and subsequently offer some valuable insight for researchers and policymakers in India. However, this study has some limitations to consider while interpreting the results and pursuing further empirical research. The principal limitation of this thesis was the unavailability of data, which was difficult to overcome. Several significant challenges because of the manufacturing database were encountered, as follows. First, labour is an imperative input of any production practice, yet the Prowess database of the CMIE lists data on the number of employees as zero, despite positive sales and capital in the case of many firms. This inconsistency rendered the data inappropriate for the purpose of this study. Thus, there was a need to identify a proxy variable in the absence of data on the number of employees. The Prowess database also provides data on the cost of labour, including salaries and wages, bonuses and ex-gratia payments, contributions to provident funds, gratuities and superannuation, staff welfare and staff training. This study computed employment data by dividing the cost of labour by the industrial wage rate, assuming industry-wise wages were equal. However, this assumption is narrowly specified, as heterogeneity of wages among firms is usual. Second, despite the Prowess database being a comprehensive database, values of some variables for some periods were unavailable. These missing values were estimated by using a multiple imputation methodology in the R platform.

Third, a holistic view of labour input captures both the quality and quantity of labour. The quality of labour comprises education levels, experience, expertise and so forth. The quantity of labour contains the number of workers, the number of hours worked and so forth. Inclusion of the quality of labour may play an essential role in assessing adaptive capacity. Unfortunately, the Prowess database does not provide qualitative data on labour; therefore, this study relied on quantitative data on labour alone. Thus, this study evaluates the TE and TFP growth only from the quantitative aspects of labour.

Finally, with reference to the methodology applied in the decomposition analysis in Chapter 6 and the generated data used in Chapter 7, this thesis employed DEA methodology to decompose the Färe-Primont productivity index. Despite several contributions of the DEA approach, one of its drawbacks is that it does not contain any statistical noise; therefore, the measurement errors in data are displayed in the estimates of TFP and its components. In this thesis, the measurement error was convoluted, as the decomposition was comprehensive. Thus, if any component of TFP change was computed inadequately, then at least one other component also demonstrated inadequacy. Therefore, this study also did not include any statistical noise while computing the TFP growth. Thus, in the future, using an econometric methodology that allows statistical noise, such as the four-component semiparametric smooth coefficient SPF model, probably demonstrate marginally different results. The four-component semiparametric smooth coefficient SPF model is used in this thesis to compute the technical efficiency. The possibility of lagged correlation between 'transient and persistent' might alter the result in the case of longitudinal data would be preserved for our future work.

Despite these limitations, this thesis provides important contributions to the empirical literature regarding the effects of patent protection on productivity growth, especially for the Indian case, where implementation of the TRIPS agreement is mandatory. This study is one of the first to employ decomposition analysis to explore the effects of patent reform on firms' productivity. Further, this study represents a significant endeavour to analyse the intrinsic components of productivity growth from patent reform in the four selected Indian manufacturing firms. The empirical findings in this study provide valuable areas for future studies and policy prescription in India, especially for policies associated with patent reform and industrial policy formulation.

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Appendices

Appendix Chapter 3

Appendix 3.1 Concepts of Total Factor Productivity

The economic growth literature claims that Quesnay, in his article in 1766, first published the word ‘productivity’ (Larouse Etymological Dictionary 1946–1949). Later, in 1883, a Frenchman Littre addressed productivity as the ‘faculty to produce’. The notion of productivity is fundamentally viewed as the relationship between the amounts of inputs needed to produce a particular amount of output in the economy. Specifically, productivity can be explained by the ratio between outputs and inputs (OECD 2001).[24] The existing literature has theoretical consensus in defining the doctrine of productivity, though it is evident that diversified application of patent ensures neither a distinctive purpose nor a unique measure to address it. Economic theories classify productivity measures in several ways—as single- or partial-factor productivity and total or multi-factor productivity. Although debate regarding the best measure continues, TFP explains long-term productivity trends better than labour productivity or partial productivity (Sargent and Rodriguez 2000). Thus, the study of TFP and its components is frequent in the economic growth literature (Easterly and Levine 2001; Ozane 2001), particularly in the wake of economic reforms.

In his pioneer study, Solow (1956) computed productivity measures with a production function framework and explained economic growth theory as a conjecture of it. In a growth accounting (GA) framework, TFP growth is the residual of output growth that does not evolve through input factors (commonly known as Solow residual). The derivation of TFP growth components is pertinent, as it encapsulates the sources of economic growth those are not captured in the production function. Therefore, it is always interesting for policymakers to explore the determinants of TFP. The microeconomic theory identifies components such as technical progress, technical efficiency, the scale of firm operation and other socio-economic factors as accountable sources of such residual growth. Simultaneously, from the perspective of macroeconomics, education and training, changes in demand, economic restructuring and capital structure are

[24] The OECD is an international organisation that works to establish evidence-based international standards and find solutions to a range of social, economic and environmental challenges.

acknowledged as not part of the production function. Solow (1957) defined technical change as ‘any kind of shift in the aggregate production function’, which is the residual of production function if input variations are omitted from output growth. Solow connoted technical change as ‘manna from heaven’, since he assumed that the marginal rate of substitution among the factors remains unchanged at a given capital–labour ratio, even if there is a shift in the production function. In terms of mathematics, technical change is Hicks-neutral, as total output increases proportionately with the increase in input variables at given input ratios.

A production function demonstrates the maximum output attainable with every feasible input combination that reflect diagrammatically in a boundary or frontier. The neoclassical growth model introduces the mathematical form of the production function, under two crucial assumptions: (i) prevalence of constant returns to scale (CRS) and (ii) perfectly competitive market condition in factor markets:

$$Q = A(t)f(K, L) \tag{3.1}$$

where the multiplicative term represents technical change along with as output, as capital and as labour. Thus, TFP growth can be comprehended as:

$$g_y = \alpha g_k - (1 - \alpha)\, g_l \tag{3.2}$$

where g_y denotes the growth rate of output, g_k is the growth rate of capital, g_l is the growth rate of labour and α is the capital share.

Later, some researchers used parametric estimations of production functions—specifically, the Cobb-Douglas production functions—following Solow’s residual approach. The major assumption of this approach is that all the firms are efficient. Thus, it is unable to distinguish between technological progress and changes in technical efficiency (Danquah et al. 2014). Previous studies (Barro 1991; Benhabib and Spiegel 1994, 2005; Kneller and Stevens 2006; Miller and Upadhyay 2000; Vandenbussche et al. 2006) have argued that the residual approach has not identified the determinants of TFP growth and its components. The assumptions of the Solow model require researchers to redefine the measurement of TFP. Thus, the frontier approach commences where the actual output and potential output may differ because of the existence of technical inefficiency. This infers that TFP growth comprises both technological change and efficiency change. Technological progress entails the upward movement of the production frontier as a consequence of technological improvement and the usage of better equipment. Besides, the catching-up effect describes technical efficiency (Mahadevan 2003).

Farell (1957) initiated a concept of the distance function to separate the technological progress and efficiency change components. The linear programming method of data envelopment analysis (DEA) was introduced by Charnes, Cooper and Rhodes (1978) to estimate the distance function and consequential productivity index in a nonparametric manner. In contrast, stochastic frontier analysis (SFA) was simultaneously introduced by Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977). This parametric technique enables the measurement of distance function with an asymmetrically distributed error term. Further, TFP can be decomposed into several micro-components: technological progress (TP), technical efficiency (TE), scale efficiency (SE) and allocative efficiency (AE). The effect of each component can be calculated in a parametric economic modelling framework (Kumbhakar 2000; Salim 1999).

TP is an additional source of productivity change that emerges upon comparing productivity over time, and is customarily represented as technological change. In an econometric approach, TP entails the upward movement of production as a consequence of technological improvement. The efficiency measurement was instituted by the work of Debreu (1951) and Koopmans (1951) and Farrell (1957) to compute the best suitable measure of firm efficiency that enables to envelop multiple inputs. Farrell (1957) indicated two distinctive components of firm efficiency: (i) TE, which confers, with a given set of inputs, the competency of a firm to acquire the utmost level of output, and (ii) AE, which signifies, with specific production technology and respective input prices, the firm’s aptitude to use the inputs at an optimum level. In an econometric method, TE is depicted through movement towards or away from the frontier. More precisely, it indicates the firm’s position relative to the frontier. Färe, Grosskopf and Roos (1998) defined SE while decomposing productivity change over time; however, Balk (2010) formalised the earlier propositions of TFP and classified three components: TE, AE and SE. SE considers whether a firm might become more efficient by altering its production scale under the ceteris paribus clause, keeping the input proportion constant. Thus, it graphically represents the gap between the outputs of the firm while operating under constant returns and VRS.

Numerous scholars argue about the key features of DEA and SFA methods. Like the standard nonparametric statistical method, the main advantage of DEA is that explicit specification of a functional form and the error term are not prerequisites for this approach (O'Donnell 2011a). Moreover, this approach can handle multiple input–output technologies statistically. In contrast, SFA was one of the first models to separate the inefficiency term from the error term (Aigner et al. 1977; Meeusen and van den Broeck 1977). However, there are not only absolute advantages for these two approaches (Resti 2000). When comparing DEA and SFA techniques, while DEA is more accurate, regression-type models are more stable with estimations (Thanassoulis 1993). The main disadvantage of DEA is that it is unable to distinguish between inefficiency and the error term; thus, it is difficult to compute output elasticities and efficiency scores, it is sensitive to outliers, and the results tend to be biased with a small sample size. In contrast, the major drawbacks of SFA are that the estimated findings are sensitive to the selected functional form, the computed results tend to be unreliable with a small sample size and the endogeneity problem may emerge in the estimation. The parameters of the production frontier generally will appear biased and inconsistent with the existence of endogeneity. Therefore, to solve the endogeneity problem, a more suitable approach—such as the generalised method of moments (GMM)—is essential (O'Donnell 2011a).

Several TFP indexes were introduced to further decompose the TFP change into intricate components, such as technical change, TE change, SE change and mix efficiency change. The Fisher, Törnqvist and Hicks-Moorsteen TFP indexes belong to that class. However, the Malmquist TFP index developed by Caves, Christensen and Diewert (1982) decomposes the TFP indexes only into TP, TE change or SE change (O'Donnell 2010). These indexes can be computed and decomposed in the DEA or SFA framework. Later, O'Donnell (2011) proposed the Färe-Primont index used in constructing productivity. Unlike other indexes, this index contemplates as multiplicative complete as it satisfies the transitivity test (O'Donnell 2012a). Further, this index decomposes the TFP indexes further into mixed efficiency and residual efficiency, along with the conventional TP, TE change and SE change.

The semiparametric approach can be considered a synthesis of the parametric and nonparametric approaches, addressing the limitations of both the parametric and nonparametric approaches. The explanatory part of the model consists of a predetermined production function portion and an unknown form of the production function (O'Donnell 2011a, 2012). A semiparametric smooth coefficient stochastic production frontier model developed by Sun and Kumbhakar (2013) assumes that the inputs are exogenous, and an unknown smooth function of the environmental variables determines the technology parameters. The authors further extended this model in 2018, with the assumption that inputs are endogenous in a production function framework. In addition, the error term comprises four components: two of them are the noise components, containing the persistent and transient noises, and the other two are the time-invariant and time-varying inefficiencies. This thesis adopted the semiparametric approach proposed by Kumbhakar, Sun and Tveterås (2018) to analyse the effect of patent protection on TE, and the Färe-Primont productivity index approach developed by O'Donnell (2011, 2012) for the decomposition of productivity.

Appendix Chapter 4

Appendix 4.1

The four-component model can be expressed as,

$$y_{it} = \beta_0 + f(x_{it};\beta) + \mu_i + v_{it} - \eta_i - u_{it}$$

where, μ_i are random firm effects that capture unobserved time-invariant inputs. Out of this four-components two of which η_i and u_{it} are inefficiency and the rest two are firm effects (μ_i) and noise term (v_{it}). This model conquers persistent inefficiency (PTE) /invariant inefficiency along with heterogeneous firm effect.

This model can be estimated in a single stage Maximum Likelihood (ML) estimation on the basis of the distributional assumptions. However, the simple way of estimation is multi-step procedure. Thus, the above equation can be rewritten as,

$$y_{it} = \beta_0^* + f(x_{it};\beta) + \alpha_i + \varepsilon_{it}$$

where, $\beta_0^* = \beta_0 - E(\eta_i) - E(u_{it})$ and $\varepsilon_{it} = v_{it} - u_{it} + E(u_{it})$

With this specification α_i and ε_{it} have zero mean and constant variance.

The familiar panel data model can be estimated in 3 steps.

Step 1: The standard random effect panel regression is used to estimate $\hat{\beta}$. The predicted values of α_i and ε_{it} can be estimated as, $\widehat{\alpha_i}$ and $\widehat{\varepsilon_{it}}$.

Step 2: By assuming v_{it} is iid N (0, σ_v^2) and u_{it} is iid $N^+(0,\sigma^2)$ that means $E(u_{it})$ = $\sqrt{2/\pi}\ \sigma$ and ignoring the difference between the true and predicted values of ε_{it}.

This procedure gives prediction of the time-varying technical inefficiency components $\widehat{u_{it}}$, the estimator (Jondrow et al. 1982), which can be used to estimate time-varying technical efficiency, Transient Technical Efficiency (TTE) = *exp* (-$\widehat{u_{it}}$).

Step 3: Estimate of η_i can be computed in a similar procedure. Using the standard normal, half-normal Stochastic Frontier model cross-sectionally and obtain estimates of the persistent technical inefficiency component η_i using the procedure stated by Jondrow et al. 1982. So, PTE = *exp* (-$\hat{\eta}_i$), where $\hat{\eta}_i$ is the Jondrow et al. 1982 estimator of η_i.

Then, the overall technical efficiency (OTE) can be obtained as the product of PTE and TTE.

Appendix Chapter 5

Appendix 5.1 Summary Statistics of the Variables - Biotechnology Industry

Symbol	Variable Name	Mean	Sd.	Min.	Max
Y	Output	561886258.3	1092.5	5725.007	970966690185.51
X_1	Capital	192579574	152477.1	1.724592	491014500000000
X_2	Labour	61756513	118217.3	1.105171	178871700000000
X_3	Material	180758058	664.0915	2580.767	49619661830
X_4	Energy	8010424	15157.11	1.0001	211730483801
Z_1	Number of Patent	5.152956	14.19214	1.00	150.00
Z_2	Research & Development Intensity	0.038754	0.126349	0.0001	1.00
Z_3	Trade Openness	0.681218	0.41144	0.0001	1.00
Z_4	Technology Transfers	5.300153	7.425311	0.1	36107952179

t	Time	11.5	6.34428877	1.00	22.00

Appendix 5.2 Summary Statistics of the Variables – Electrical & Electronic Industry

Symbol	Variable Name	Mean	Sd.	Min.	Max
Y	Output	314526921956.45	7319046597760.62	757.1313	278021427175.01
X_1	Capital	3240848251	18743026714	72535.58782	284360082762011
X_2	Labour	8015505086	50356300022	263712.7	716141601369.86
X_3	Material	135387238795.76	1857168158112.81	2042.969	79304194828612.5
X_4	Energy	4964885904	73680582304	1932.061625	3241647297657.26
Z_1	Number of Patent	4.381944	6.860895	1.00	57
Z_2	Research & Development Intensity	0.053308	0.146534	0.00022843	0.996046
Z_3	Trade Openness	0.425162	0.366387	0.000173	1.004913
Z_4	Technology Transfers	716717644.6	360957130	8.33614525	69204244888

t	Time	11.5	6.34428877	1.00	22.00

Appendix 5.3 Summary Statistics of the Variables –Information Technology & Communication Industry

Symbol	Variable Name	Mean	Sd.	Min.	Max
Y	Output	3569138189	2943.713	51090.3	284359386639034.00
X_1	Capital	227809429.1	137.9222	307121.9	278020308464.65
X_2	Labour	19155300.04	19626.52	29411.200	216362266610.13
X_3	Material	1230221412.14	2019.72	56796.5	79304025007794.90
X_4	Energy	14812322.59	3183.790	31837.81	3241638409943.44
Z_1	Number of Patent	16.2	31.77578	1.00	73.00
Z_2	Research & Development Intensity	0.1942572	0.425558	0.000000000	0.955451161
Z_3	Trade Openness	0.4727205	0.4871015	0.0000010	1.0000000
Z_4	Technology Transfers	8.169883	11.53617	0.10000	24.96033
t	Time	1.00	11.4	8.38451	22.0

Appendix 5.4 Summary Statistics of the Variables –Pharmaceutical Industry

Symbol	Variable Name	Mean	Sd.	Min.	Max
Y	Output	25094523697.50	624627653552.15	559.69	69510591812.30
X_1	Capital	1254934100015.32	37484997553534.90	1.724591	1864489492551440
X_2	Labour	79952056101.25	3287990653521.81	44.63469	178872251107190
X_3	Material	323506782125.51	11879046530767.40	2580.768	620417683369943
X_4	Energy	1254934100015.32	2315906242225.30	6927.265	119153012212831
Z_1	Number of Patent	6.361702128	16.56634056	1.00	150.00
Z_2	Research & Development Intensity	0.037460847	0.177681117	0.0001494	4.888888889
Z_3	Trade Openness	0.812994972	0.351951996	0.00	3.188749286
Z_4	Technology Transfers	28941762.72	681776067.48	1.00	36107952237
t	Time	11.5	6.34428877	1.00	22.00

Appendix Chapter 6

Appendix 6.1 Biotechnology Industry

Period	OSE	RME	OSME = OSE x RME = OME x ROSE	OME	ROSE
1995	0.864855	0.952264	0.822477	1	0.822477
1996	0.872114	0.930132	0.810156	1	0.810156
1997	0.878459	0.909865	0.799268	1	0.799268
1998	0.884408	0.892026	0.788914	1	0.788914
1999	0.894536	0.874186	0.781998	1	0.781998
2000	0.899853	0.857473	0.771655	1	0.771655
2001	0.900976	0.84644	0.76273	1	0.76273
2002	0.912491	0.826035	0.753587	1	0.753587
2003	0.912407	0.809852	0.738579	1	0.738579
2004	0.903498	0.807695	0.729432	1	0.729432
2005	0.900913	0.797111	0.718028	1	0.718028
2006	0.898185	0.790066	0.709575	1	0.709575
2007	0.887768	0.795875	0.706441	1	0.706441
2008	0.873798	0.803339	0.701877	1	0.701877
2009	0.864465	0.814314	0.703885	1	0.703885
2010	0.856701	0.824771	0.706327	1	0.706327
2011	0.848048	0.81621	0.691715	1	0.691715

2012	0.839041	0.836779	0.701798	1	0.701798
2013	0.817653	0.851293	0.696048	1	0.696048
2014	0.832218	0.778704	0.648182	1	0.648182
2015	0.917565	0.655808	0.60197	1	0.60197
2016	0.94129	0.70166	0.661111	1	0.661111

Appendix 6.2 Electrical and Electronics Industry

Period	OSE	RME	OSME = OSE x RME = OME x ROSE	OME	OSE
1995	0.957108	0.963126	0.92183	1	0.92183
1996	0.959586	0.957661	0.919267	1	0.919267
1997	0.959897	0.962423	0.923729	1	0.923729
1998	0.959967	0.966869	0.928046	1	0.928046
1999	0.95858	0.947726	0.908232	1	0.908232
2000	0.956952	0.955615	0.914243	1	0.914243
2001	0.959258	0.955259	0.916131	1	0.916131
2002	0.960064	0.918214	0.881097	1	0.881097
2003	0.97239	0.931717	0.905866	1	0.905866
2004	0.982429	0.921184	0.9049	1	0.9049
2005	0.986149	0.925477	0.91245	1	0.91245
2006	0.968678	0.913365	0.884756	1	0.884756
2007	0.968988	0.887863	0.860074	1	0.860074
2008	0.970537	0.87921	0.853423	1	0.853423
2009	0.971897	0.871657	0.847349	1	0.847349

2010	0.982152	0.84533	0.830545	1	0.830545
2011	0.962537	0.885392	0.85289	1	0.85289
2012	0.978413	0.845563	0.828103	1	0.828103
2013	0.978973	0.844621	0.827687	1	0.827687
2014	0.974452	0.846215	0.825492	1	0.825492
2015	0.974754	0.853588	0.832928	1	0.832928
2016	0.981674	0.839425	0.824972	1	0.824972

Appendix 6.3 Information Technology and Communication Industry

Period	OSE	RME	OSME = OSE x RME = OME x ROSE	OME	ROSE
1995	0.955146	0.966853	0.922834	1	0.922834
1996	0.959174	0.969901	0.929775	1	0.929775
1997	0.960986	0.96772	0.929485	1	0.929485
1998	0.965248	0.964346	0.930572	1	0.930572
1999	0.970488	0.970459	0.941596	1	0.941596
2000	0.968565	0.966502	0.935944	1	0.935944
2001	0.970376	0.960129	0.931699	1	0.931699
2002	0.970759	0.946055	0.918484	1	0.918484
2003	0.965836	0.957434	0.924768	1	0.924768
2004	0.975716	0.941339	0.918568	1	0.918568
2005	0.977449	0.932042	0.911154	1	0.911154
2006	0.969816	0.947996	0.919276	1	0.919276
2007	0.967517	0.929562	0.899529	1	0.899529
2008	0.970096	0.913591	0.886536	1	0.886536
2009	0.977819	0.902142	0.882051	1	0.882051

2010	0.971802	0.900555	0.875278	1	0.875278
2011	0.971727	0.893754	0.868673	1	0.868673
2012	0.972215	0.886411	0.862086	1	0.862086
2013	0.969361	0.887392	0.860494	1	0.860494
2014	0.96128	0.884502	0.851021	1	0.851021
2015	0.955802	0.877978	0.840132	1	0.840132
2016	0.954411	0.870313	0.831794	1	0.831794

Appendix 6.4 Pharmaceutical Industry

Period	OSE	RME	OSME = OSE x RME = OME x ROSE	OME	ROSE
1995	0.958595	0.924371	0.887166	1	0.887166
1996	0.959112	0.925185	0.888238	1	0.888238
1997	0.961113	0.927864	0.892597	1	0.892597
1998	0.959575	0.930265	0.893487	1	0.893487
1999	0.961009	0.934628	0.898771	1	0.898771
2000	0.961234	0.938501	0.902604	1	0.902604
2001	0.962551	0.940789	0.906264	1	0.906264
2002	0.963043	0.945841	0.911148	1	0.911148
2003	0.954272	0.938038	0.895604	1	0.895604
2004	0.958114	0.937451	0.898413	1	0.898413
2005	0.960652	0.940001	0.902998	1	0.902998
2006	0.966254	0.952728	0.920573	1	0.920573
2007	0.966254	0.952728	0.920573	1	0.920573
2008	0.964803	0.963429	0.929558	1	0.929558
2009	0.954682	0.965131	0.921576	1	0.921576

2010	0.917989	0.960807	0.88209	1	0.88209
2011	0.896701	0.96646	0.866615	1	0.866615
2012	0.909661	0.972783	0.885277	1	0.885277
2013	0.833566	0.961985	0.802168	1	0.802168
2014	0.850619	0.945909	0.805172	1	0.805172
2015	0.944049	0.828206	0.782499	1	0.782499
2016	0.955905	0.802926	0.768293	1	0.768293

Appendix Chapter 7

Appendix 7.1 Biotechnology Industry

a) Pooling Model

Residual

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.5014303	-0.0376297	-0.0088597	0.0293971	0.8778577
Coefficients	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	1.1612e+00	2.7183e-03	427.1985	< 2.2e-16 ***
z1	1.6410e-03	1.0066e-03	1.6302	0.1031528
z2	5.2987e-02	5.1785e-02	1.0232	0.3062955
z3	-6.4278e-05	5.4619e-04	-0.1177	0.9063261
z4	-5.1488e-03	1.5810e-03	-3.2568	0.0011394 **
z1:z2	6.1756e-02	2.4309e-02	2.5404	0.0111212 *
z1:z3	-1.4976e-04	1.6327e-04	-0.9173	0.3590675
z2:z3	1.7806e-03	8.3438e-03	0.2134	0.8310228
z1:z4	-4.1010e-04	1.9004e-03	-0.2158	0.8291578
z2:z4	-2.0004e-01	5.6235e-02	-3.5571	0.0003807 ***
z3:z4	-7.4614e-04	6.5250e-04	-1.1435	0.2529190
z1:z2:z3	6.3783e-03	-1.7733e-02	-2.7802	0.0054658 **
z1:z2:z4	-1.0229e-01	3.1328e-02	-3.2650	0.0011069 **
z1:z3:z4	8.1382e-05	1.9090e-04	0.4263	0.6699119
z2:z3:z4	-2.8555e-03	1.1668e-02	-0.2447	0.8066877

z1:z2:z3:z4	1.9713e-02	6.4502e-03	3.0561	0.0022618 **

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 31.763
Residual Sum of Squares: 30.07 R-Squared: 0.0533 Adj. R-Squared: 0.048611
F-statistic: 11.3689 on 15 and 3029 DF, p-value: < 2.22e-16

b) Fixed Effect Model

Residuals

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.31998722	-0.01462585	0.00032588	0.01511526	0.62343367
	Estimate	Std. Error	t-value	Pr(>|t|)
z1	1.4137e-04	6.0400e-04	0.2341	0.814959
z2	1.8060e-01	4.1534e-02	4.3483	1.420e-05 ***
z3	1.4169e-03	7.5237e-04	1.8832	0.059774
z4	4.9849e-05	4.9696e-03	0.0100	0.991997
z1:z2	3.9245e-02	1.5085e-02	2.6016	0.009328 **
z1:z3	1.7702e-05	9.3076e-05	0.1902	0.849173
z2:z3	7.5010e-03	5.6539e-03	-1.3267	0.184713
z1:z4	7.0603e-04	1.0633e-03	0.6640	0.506751
z2:z4	-2.3850e-01	4.1641e-02	-5.7276	1.124e-08 ***
z3:z4	-2.1343e-04	5.8203e-04	-0.3667	0.713869

z1:z2:z3	-1.0567e-02	3.8916e-03	-2.7154	0.006660 **
z1:z2:z4	-5.9617e-02	1.9102e-02	-3.1209	0.001821 **
z1:z3:z4	-7.3465e-05	1.0530e-04	-0.6976	0.485458
z2:z3:z4	4.0728e-03	7.9810e-03	0.5103	0.609872
z1:z2:z3:z4	1.1213e-02	3.9453e-03	2.8422	0.004512 **

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Total Sum of Squares: 8.2257
Residual Sum of Squares: 7.8581 R-Squared: 0.044683 Adj. R-Squared: -0.015358
F-statistic: 8.93051 on 15 and 2864 DF, p-value: < 2.22e-16

c) Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data: TFPG ~ z1 + z2 + z3 + z4 + z1 * z2 * z3 * z4
chi square = 1615, df = 7, p-value < 2.2e-16
The null hypothesis is no serial correlation. The alternative hypothesis: serial correlation in idiosyncratic errors

The p-value indicates the presence of serial correlation.

d) Breusch-Pagan test for Heteroscedasticity

data: TFPG ~ z1 + z2 + z3 + z4 + z1 * z2 * z3 * z4

BP = 598.8, df = 15, p-value < 2.2e-16
The null hypothesis for the Breusch-Pagan test is homoskedasticity.
The p-value indicates the presence of Heteroscedasticity.

e) Lagrange Multiplier Test - for unbalanced panels (Panel Effect)

data: TFPG ~ z1 + z2 + z3 + z4 + z1 * z2 * z3 * z4
chi square = 14662, df = 1, p-value < 2.2e-16
The null is no panel effect that is OLS better. The alternative hypothesis: significant effects.

The p-value indicates the presence of Panel Effect.

Appendix 7.2 Electrical and Electronics Industry

a) Pooling Model

Residuals

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.5732024	-0.0254651	0.0069173	0.0384821	0.3006420
Coefficients	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	9.1867e-01	3.1827e-03	288.6491	< 2.2e-16 ***

z1	-2.9450e-03	1.8247e-03	-1.6140	0.106671
z2	3.9124e-03	1.6824e-02	0.2325	0.816135
z3	1.4624e-03	3.4367e-04	4.2552	2.178e-05 ***
z4	1.6787e-02	5.7060e-03	2.9420	0.003296 **
z1:z2	8.9030e-03	1.2742e-04	0.7172	0.473340
z1:z3	4.9912e-05	1.2742e-04	0.3917	0.695316
z2:z3	-4.4938e-03	1.6469e-03	-2.7287	0.006410 **
z1:z4	3.0548e-03	2.1991e-03	1.3891	0.164941
z2:z4	6.9833e-02	6.1374e-02	1.1378	0.255315
z3:z4	-1.1068e-03	5.9023e-04	-1.8752	0.060893 .
z1:z2:z3	-1.2735e-04	6.7230e-04	-0.1894	0.849777
z1:z2:z4	-1.1914e-02	2.0844e-02	-0.5716	0.567663
z1:z3:z4	8.8111e-05	2.1644e-04	0.4071	0.683976
z2:z3:z4	-5.2078e-03	6.2760e-03	-0.8298	0.406743
z1:z2:z3:z4	-2.3785e-04	1.4773e-03	-0.1610	0.872105

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Total Sum of Squares: 11.951
Residual Sum of Squares: 11.615 R-Squared: 0.028071 Adj. R-Squared: 0.021352
F-statistic: 4.1782 on 15 and 2170 DF, p-value: < 1.1529e-07

b) Fixed Effect Model

Residual

	1st Qu.	Median	3rd Qu.	Max.
Min.				
-0.31993782	-0.01218467	0.00028722	0.01204769	0.30191281
	Estimate	Std. Error	t-value	Pr(>|t|)
z1	-1.8785e-03	1.1253e-03	-1.6693	0.0952144 .
z2	-2.3542e-02	1.6254e-02	-1.4484	0.1476714
z3	-5.9929e-04	1.1528e-03	-0.5198	0.6032308
z4	1.5330e-02	9.5931e-03	1.5981	0.1101843
z1:z2	7.6896e-03	7.6731e-03	1.0021	0.3163892
z1:z3	3.7311e-04	8.5683e-05	4.3546	1.399e-05 ***
z2:z3	2.8098e-03	2.3031e-03	1.2200	0.2226170
z1:z4	4.8693e-03	1.3480e-03	3.6122	0.0003108 ***
z2:z4	1.3131e-01	6.3793e-02	-2.0583	0.0396835 *
z3:z4	-8.4267e-04	7.7836e-04	-1.0826	0.2791043
z1:z2:z3	-8.1709e-04	4.1357e-04	-1.9757	0.0483232 *
z1:z2:z4	-9.8626e-03	1.2740e-02	-0.7742	0.4389196
z1:z3:z4	-7.3467e-04	1.4235e-04	-5.1609	2.694e-07 ***
z2:z3:z4	7.9666e-03	5.5122e-03	1.4453	0.1485346
z1:z2:z3:z4	1.3036e-03	9.1279e-04	1.4281	0.1534116

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Total Sum of Squares: 3.3197
Residual Sum of Squares: 3.2374 R-Squared: 0.024763 Adj. R-Squared: -0.036426
F-statistic: 3.48042 on 15 and 2056 DF, p-value: < 6.2906e-06

c) Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data: TFPG ~ z1 + z2 + z3 + z4 + z1 * z2 * z3 * z4
chi square = 1068.5, df = 7, p-value < 2.2e-16
The null hypothesis is no serial correlation. The alternative hypothesis: serial correlation in idiosyncratic errors
The p-value indicates the presence of serial correlation.

d) Breusch-Pagan test for Heteroscedasticity

data: TFPG ~ z1 + z2 + z3 + z4 + z1 * z2 * z3 * z4

BP = 481.85, df = 15, p-value < 2.2e-16
The null hypothesis for the Breusch-Pagan test is homoskedasticity.
The p-value indicates the presence of Heteroscedasticity.

e) Lagrange Multiplier Test - for unbalanced panels (Panel Effect)

data: TFPG ~ z1 + z2 + z3 + z4 + z1 * z2 * z3 * z4
chisq = 9946.2, df = 1, p-value < 2.2e-16
The null is no panel effect that is OLS better. The alternative hypothesis: significant effects

The p-value indicates the presence of Panel Effect.

Appendix 7.3 Information Technology and Communication Industry

a) Pooling Model

Residual

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.4747361	-0.0253239	0.0051316	0.0308456	0.3180241
Coefficients	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	0.98413439	0.00403106	244.1376	< 2.2e-16 ***
z1	0.00357322	0.00421821	0.8471	0.3970691
z2	-0.13784730	0.03803744	-3.6240	0.0002992 ***
z3	-0.00010276	0.00037889	-0.2712	0.7862570
z4	-0.02568855	0.00587106	-4.3755	1.29e-05 ***
z1:z2	0.02040670	0.01775546	1.1493	0.2505963
z1:z3	-0.00038123	0.00024128	-1.5801	0.1142929
z2:z3	0.00115324	0.00270429	0.4264	0.6698391
z1:z4	-0.00441707	0.00426515	-1.0356	0.3005368
z2:z4	0.30140705	0.22614938	1.3328	0.1827946
z3:z4	0.00098926	0.00063672	1.5537	0.1204584.
z1:z2:z3	-0.00044289	0.00093313	-0.4746	0.6351177
z1:z2:z4	0.09246670	0.06865477	1.3468	0.1782242

z1:z3:z4	0.00058816	0.00032631	1.8025	0.0716573 .
z2:z3:z4	-0.01689463	0.01782229	-0.9479	0.3432988
z1:z2:z3:z4	-0.00575859	0.00361270	-1.5940	0.1111372

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Total Sum of Squares: 9.1737
Residual Sum of Squares: 8.7665 R-Squared: 0.044389 Adj. R-Squared: 0.035414
F-statistic: 4.9455on 15 and 1597 DF, p-value: < 1.4072e-09

b) Fixed Effect Model

Residual

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.34454393	-0.01319656	-0.00018304	0.01312285	0.25660182
	Estimate	Std. Error	t-value	Pr(>|t|)
z1	1.4615e-03	2.4428e-03	0.5983	0.54974.
z2	-8.9625e-02	6.5213e-02	-1.3743	0.16954
z3	-2.1704e-03	1.6588e-03	-1.3084	0.19093
z4	-6.6651e-02	1.4158e-02	-4.7077	2.735e-06 ***
z1:z2	6.2143e-03	1.0805e-02	0.5751	0.56528
z1:z3	-6.5244e-05	1.6066e-04	-0.4061	0.68473
z2:z3	3.5738e-03	3.9566e-03	0.9033	0.36653
z1:z4	-7.8942e-04	2.4733e-03	-0.3192	0.74964
z2:z4	1.4676e-01	2.2078e-01	0.6648	0.50631
z3:z4	2.9194e-03	1.1457e-03	2.5481	0.01093 *

z1:z2:z3	-1.8817e-04	5.7633e-04	-0.3265	0.74410
z1:z2:z4	-6.3274e-02	4.1738e-02	-1.5160	0.12973
z1:z3:z4	4.5406e-05	2.3420e-04	0.1939	0.84630
z2:z3:z4	-2.5251e-03	1.3337e-02	-0.1893	0.84985
z1:z2:z3:z4	2.6237e-03	2.1805e-03	1.2032	0.22907

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Total Sum of Squares: 2.5493
Residual Sum of Squares: 2.4939 R-Squared: 0.021733 Adj. R-Squared: -0.042278
F-statistic: 2.24085 on 15 and 1513 DF, p-value: 0.0041477

c) Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data: TFPG ~ z1 + z2 + z3 + z4 + z1 * z2 * z3 * z4 where z1*z2*z3*z4 measures the joint effect.
chisq = 922.61, df = 9, p-value < 2.2e-16
The null hypothesis is no serial correlation. The alternative hypothesis: serial correlation in idiosyncratic errors.

The p-value indicates the presence of serial correlation.

d) Breusch-Pagan test for Heteroscedasticity

data: TFPG ~ z1 + z2 + z3 + z4 + z1 * z2 * z3 * z4

BP = 647.56, df = 15, p-value < 2.2e-16
The null hypothesis for the Breusch-Pagan test is homoskedasticity.
The p-value indicates the presence of Heteroscedasticity.

e) Lagrange Multiplier Test - for unbalanced panels (Panel Effect)

data: TFPG ~ z1 + z2 + z3 + z4 + z1 * z2 * z3 * z4
chi square = 5508.6, df = 1, p-value < 2.2e-16
The null is no panel effect that is OLS better. The alternative hypothesis: significant effects.

The p-value indicates the presence of Panel Effect.

Appendix 7.4 Pharmaceutical Industry

a) Pooling Effect

Residual

Min.	1st Qu.	Median	3rd Qu.	Max.
-0.5479809	-0.0342950	-0.0061179	0.0294432	0.5441381
	Estimate	Std. Error	t-value	Pr(>|t|)
Intercept	1.1375e+00	4.8396e-03	235.0360	< 2.2e-16 ***

z1	2.4379e-03	2.0673e-03	1.1793	0.238393
z2	1.1725e-01	5.3830e-02	2.1781	0.029488 *
z3	-2.9409e-05	5.3415e-04	-0.0551	0.956098
z4	-1.0996e-02	5.9147e-03	-1.8591	0.063122 .
z1:z2	1.3790e-01	2.8188e-02	4.8921	1.058e-06 ***
z1:z3	-9.0332e-05	1.9128e-04	-0.4722	0.636795
z2:z3	-6.9097e-03	7.6322e-03	-0.9053	0.365371
z1:z4	1.0269e-03	2.8685e-03	0.3580	0.720387
z2:z4	-1.5804e-01	5.6423e-02	-2.8009	0.005132 **
z3:z4	7.6519e-04	6.5597e-04	1.1665	0.243518
z1:z2:z3	-4.8793e-03	5.7384e-03	-0.8503	0.395242
z1:z2:z4	-1.9006e-01	3.4972e-02	-5.4345	5.996e-08 ***
z1:z3:z4	-1.2963e-04	2.2236e-04	-0.5830	0.586024
z2:z3:z4	5.6978e-03	1.0461e-02	0.5447	0.586024
z1:z2:z3:z4	7.5294e-03	5.8028e-03	1.2975	0.194557

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Total Sum of Squares: 20.566
Residual Sum of Squares: 19.504 R-Squared: 0.051623 Adj. R-Squared: 0.046246
F-statistic: 9.6019 on 15 and 2646 DF, p-value: < 2.22e-16

b) Fixed Effect Model

Residual

Min.	1st Qu.	Median	3rd Qu.	Max.

-0.35609814	-0.01497011	0.00019543	0.01568782	0.35783653
	Estimate	Std. Error	t-value	Pr(>|t|)
z1	-1.1905e-03	1.5024e-03	-0.7924	0.42818.
z2	2.5839e-01	4.5132e-02	5.7251	1.157e-08 ***
z3	-8.7022e-04	7.9591e-04	-1.0934	0.27434
z4	1.0932e-02	6.2279e-03	1.7553	0.07932 .
z1:z2	1.0886e-01	2.0168e-02	5.3976	7.389e-08 ***
z1:z3	1.6468e-04	1.3645e-04	1.2069	0.22759
z2:z3	-1.0172e-02	6.2037e-03	-1.6396	0.10121
z1:z4	-4.4679e-04	2.0313e-03	-0.2199	0.82593
z2:z4	-2.6777e-01	4.5308e-02	-5.9100	3.886e-09 ***
z3:z4	4.7984e-04	6.6217e-04	0.7246	0.46874 *
z1:z2:z3	-9.9992e-03	4.2649e-03	2.3446	0.01913 *
z1:z2:z4	-1.3692e-01	2.5057e-02	-5.4644	5.105e-08 ***
z1:z3:z4	-7.4478e-05	1.5509e-04	-0.4802	0.63111
z2:z3:z4	7.2114e-03	8.7530e-03	0.8239	0.41009
z1:z2:z3:z4	1.1062e-02	4.3213e-03	2.5599	0.01053 *

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Total Sum of Squares: 8.1752
Residual Sum of Squares: 7.6871 R-Squared: 0.059694 Adj. R-Squared: -0.042278
F-statistic: 10.5933 on 15 and 2503 DF, p-value: < 2.22e-16

c) Breusch-Godfrey/Wooldridge test for serial correlation in panel models

data: TFPG ~ z1 + z2 + z3 + z4 + z1 * z2 * z3 * z4
chi square = 1447.3, df = 7, p-value < 2.2e-16

The null hypothesis is no serial correlation. The alternative hypothesis: serial correlation in idiosyncratic errors.
The p-value indicates the presence of serial correlation.

d) Breusch-Pagan test for Heteroscedasticity

data: TFPG ~ z1 + z2 + z3 + z4 + z1 * z2 * z3 * z4
BP = 964.8, df = 15, p-value < 2. 2e-16
The null hypothesis for the Breusch-Pagan test is homoskedasticity.
The p-value indicates the presence of Heteroscedasticity.

e) Lagrange Multiplier Test - for unbalanced panels (Panel Effect)

data: TFPG ~ z1 + z2 + z3 + z4 + z1 * z2 * z3 * z4
chi square = 7970.5, df = 1, p-value < 2.2e-16
The null is no panel effect that is OLS better. The alternative hypothesis: significant effects
The p-value indicates the presence of Panel Effect.