TECHNOLOGY-PRODUCTIVITY CONUNDRUM IN INDIA'S MANUFACTURING UNDER GLOBALIZATION A PRELIMINARY EXPLORATION USING INNOVATION SYSTEM PERSPECTIVE

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Abstract

Using innovation system perspective, this paper analyses the relative role of science based learning (STI mode) and experience based learning (DUI mode) in determining Total Factor Productivity (TFP). Making use of the firm-level panel data from the Indian manufacturing sector during 2000–2001 to 2016–2017, TFP is estimated using semi-parametric method of Levinsohn–Petrin that accounts for the endogeneity bias in productivity estimation. Our regression results underline the significance of both STI and DUI mode of interactive learning in determining TFP. Further, intra-country interactions within STI mode as represented by R&D, technology purchases and staff training are important factors in determining productivity while only one of the inter-country interactions (FDI) is found having positive influence. While R&D is found relatively more important in low and high-tech industries, intra-country and inter-country interactions through technology purchase are important in case of medium tech industries. Among the interactions within DUI mode, both intra-country interactions (input purchases from domestic suppliers) and inter-country interactions (export intensity and import of inputs) play an important role in determining firm's productivity. The present study, while reconfirming the findings of some of the earlier studies, by using the innovation system perspective, offers a few additional insights. We highlight the role of domestic technology purchases, staff training and managerial experience along with overall institutional architecture and labour market institutions, which were overlooked by the earlier studies.

Introduction

One of the encouraging developments in the developing world under globalization has been an unprecedented increase in GDP growth recorded by select developing countries. Especially notable has been the remarkable growth record of large developing countries like China and India. While China sustained a growth rate of 9.4% since 1980 India is presently considered as one of the fastest growing countries, even surpassing China (IMF 2017)[3]. Analyzing underlying factors, recent empirical analysis (Krishna et al 2017), using the India KLEMS database version 2015, found that the higher output growth in India has been contributed significantly by Total Factor Productivity Growth (TFPG) notwithstanding significant inter-industry variation wherein many industries contributed negatively to aggregate productivity growth. The study further observed that during 2003-2011 TFPG in manufacturing revived significantly, breaking its own past record, and services lost its relative importance significantly in contributing to aggregate TFPG. A comparative analysis of China and India (Wu et al 2017) argued that though China's value added growth was 50 per cent higher than India during 1981-2011, the TFP growth in China was nearly 25 per cent slower than India (0.83% and 1.13% per annum). In sync with these studies, APO (2017) observed that in India, though TFP growth was a drag during the 1970s, there has been acceleration since then which in turn has significantly accounted for a greater proportion of economic growth. Accordingly during 2010–2015,

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[3] IMF World Economic outlook update; http://www.imf.org/external/pubs/ft/weo/2017/update/01/ accessed on 21 April 2018

India achieved TFP growth of 3.5% - highest in the past four decades. It further observed that the recent slowdown in China could be mainly explained by the lower TFP growth (only 2.0%) during 2010–2015.

TFP is generally considered as an indicator of technology, which in turn is the key driver of economic growth. Given this well-established relationship the observed TFP growth needs to be associated with the commonly articulated sources of technological progress/change. From the literature on technological change in developing countries mostly undertaken at the firm/industry level three alternative sources of technological change could be discerned: (a) Technological change through the firm'/industries' own effort like R&D; (b) technology purchased from sources external to the firm/industry (domestic or foreign either in the embodied or disembodied form); and (c) spillovers created by technology generation of other entities especially foreign facilitated by trade and FDI (Basant 2018). However, the higher TFP growth in India has been associated with a much lower R&D intensity as compared to developed countries or even China. The R&D intensity in China is as high as 2.1% where as in India R&D intensity is not even 1%. Similarly, the number of patent applications in China in 2016 stood at 1.3 million as compared to only 46904 in India for the year 2015-16. According to the Enterprise survey of the World Bank (2012), while 18% of the Chinese firms reported technology licensing from foreign companies, the reported percentage in India was only about half of China (9.4% in India). Thus there appears to be an apparent paradox in the observed technology-productivity relationship in India. This apparent paradox, along with the observed inter-industry variation in TFP growth, tends to suggest that, considerable research on the issue of technological change and productivity notwithstanding, an observation by Nelson (1981) in an influential article appears not less relevant even today. To quote "theoretical model underlying most research by economists on productivity growth over time, and across countries, is superficial and to some degree even misleading regarding the following matters: the determinants of productivity at the level of the firm and of inter-firm differences; the processes that generate, screen, and spread new technologies; the influence of macroeconomic conditions and economic institutions on productivity growth". In this context, the present study, even with the reservations on the theoretical foundations of the concept of TFP, intends to explore the sources of TFP growth at the firm level in India's manufacturing sector. We approach this problem from the National Innovation System (NIS) perspective, which adopts a broader approach to innovation and focuses on institutionally governed interactive learning among various actors as central to the process of innovation.

The remainder of the paper is organized as follows. Section 2 presents an overview of related literature and discusses innovation system perspective as an analytical approach of the study. The empirical strategy of the paper wherein estimation procedure, data sources, variable construction for productivity estimation and its determinants are presented in section 3. Section 4 provides the results of the estimated models on the role of mode of learning and interaction in determining TFP along with various combination strategies. The final section highlights the main findings of the study and draws few concluding observations.

Towards an analytical framework

As already indicated, this article is motivated by an apparent paradox in India wherein there has been a remarkable increase in the contribution of TFP to output growth in India without a concomitant change in the factors that are commonly considered as instrumental in technological change. Hence it appears that at the root of this apparent paradox lie the limits of the conceptual foundations of our understanding of the process that contribute towards TFPG which is often considered as technological change. Our understanding of the process of technological change has undergone substantial refinements over time. As per the traditional understanding, technological change was often construed as confined to high-tech firms in developed countries, which gradually diffuse to the developing countries. Given the public good character ascribed to technology, such diffusion was expected to yield relatively quick benefits provided that legal instruments that facilitate easy and costless diffusion are in place such that international diffusion of new technology works as powerful equalizer in the global economy enabling the catch up by developing countries. However, going by the available evidence the expected convergence in technology, productivity and growth is yet to materialize instead, development divides between rich and poor countries have been on the increase (Palma, 2011;Atkinson, Piketty and Saez, 2011; Nayyar 2013).

Inspired by the remarkable performance of select developing countries, especially South Korea, there has been a growing literature on technological capability in developing countries (Dahlman et 1987; Fransman and King 1984; Lall 1992; Kim and Nelson 2000) These studies have conceptualized technological change in developing countries as a process involving technology import from developed countries, own R&D effort, mostly adaptive, leading to incremental rather than radical changes and technology spillovers arising mainly from FDI and trade. There have been a number of studies empirically exploring the bearing of these factors on productivity. Satisfactory results showing a positive association between R&D and productivity has been found for newly industrialized countries such as South Korea (Lee and Kang, 2007), Malaysia (Hegde and Shapira, 2007), Taiwan (Yan Aw et al., 2008), and China (Jefferson et al., 2006). For South Korea, Kim (1986) investigated the impact of indigenous R&D and technology transfer on productivity growth in Korea and found a strong positive effect of total R&D expenditure on productivity growth for the period 1976-82. At the firm level, there is convincing evidence for industrialized countries showing the positive links between R&D, innovation, and productivity (Griffith et al., 2004; Griffith et al., 2006; Mairesse and Monhen, 2010; OECD, 2009). In India Basant and Fikkert (1996) observed that for the industrial sector as a whole there are high, private rates of return to expenditures on both technology purchase and R&D, although the effect of the latter is statistically insignificant in the most general specification in which both fixed effects and time dummies are included. Furthermore, the rate of return to TP exceeds that of R&D by 44% in the most general specification. The study however observed significant difference across scientific and non-scientific firms. In case of scientific firms the return to TP is estimated to be 166%, while the return to R&D falls to only 1% where as in nonscientific group returns to TP was estimated at 95% and 64% for R&D. In contrast, Perez et al. (2005), Chudnovsky et al. (2006) and Benavente (2006) failed to find any significant effect of innovation on firms' productivity (measured as sales per employee) in Argentinean and Mexican firms, respectively. The failure of R&D to correlate significantly with productivity outcomes in developing countries could be explained by the fact that firms in developing countries are too far from the technological frontier and incentives to invest in R&D and innovation are weak or absent (Acemoglu et al., 2006).

Analyzing the link between productivity and R&D Coe and Helpman (1995) suggest that a country's productivity depends not only on its own domestic R&D but also on that of its foreign partner. The most important means by which the foreign partners' R&D gets transmitted is through trade and investment. Hence a number of studies have explored the bearing of trade and FDI on productivity by conceptualizing such impact as spillovers. Following Griliches, 1979, 1992) Parameswarn (2009) made an analytical distinction between rent spillovers (through embodied technology import) and knowledge spillovers (though disembodied technology import and other trade facilitated knowledge spillovers).

It was observed that rent spillovers through embodied technology import have a significant effect on productivity in technology-intensive industries. The effect of trade-facilitated knowledge spillovers is significant in all cases with a greater effect on productivity in technology-intensive industries. However, Rijesh (2015) has a different finding to offer wherein embodied technology was found having positive impact across the board. Goldberg et al. (2010), and Topalova and Khandelwal (2011) also found the positive impact of trade on manufacturing productivity.

Examining the productivity spillovers associated with FDI, Kathuria (2002) showed that after liberalization, productivity of Indian industry, especially the foreign owned firms, has improved. Further under liberalization only 'scientific' non-FDI firms have benefited where as for the 'non-scientific' firms, the impact is found to be productivity depressing. In sync with the findings of earlier studies it was shown that with respect to FDI spillovers only those domestic firms, which invested in R&D to decode the spilled knowledge, could benefit. Siddharthan and Lal (2004) using a more appropriate measure of labour productivity that takes into account the differences in skills also observed the presence of significant spillover effects from FDI. Though the spillover effects were modest during the early years of liberalization, it increased over time Spillovers, however, was not automatic since not all domestic firms gained equally. Domestic firms that possessed higher labour productivities and had lower productivity gaps with MNE were able to enjoy higher spillovers while those with larger productivity gaps could not benefit much indicating that absorptive capacity does matter. Kachoo and Sharma (2016) observed that MNCs are carriers of positive externalities in the recipient country industries, but their effects vary significantly across typologies of industries. The positive impact of MNC investments on innovation is particularly strong for the firms active in supplying industries as opposed to firms operating in the same sector as the MNC. Studies also analyzed the differential impact with respect to vertical and horizontal spillovers. Mondal and Pant (2010) observed that that the productivity growth of Indian firms is adversely affected by various horizontal spillover channels while the vertical linkages are insignificant. Yet another issue attracted the Scholars related the heterogeneity across subsidiaries with respect to the type of technological activity they carry out in the host economy affects spillovers. Marin and Sasidharan (2010) distinguished between two types of technological activities by subsidiaries: 'competence creating' – oriented to the creation of new knowledge assets in the host economy– and 'competence exploiting' – oriented to the exploitation of existing MNC technological assets in the host country. The study found that significant positive spillovers emerge only in association with the technological activities of competence creating subsidiaries. In contrast, subsidiaries mostly oriented to exploitative activities did not generate any effect, or generated even negative effects in some circumstances.

On the whole, it is evident that while the firms' efforts towards technological change, either as part of its deliberate competence building strategy or as the outcome of being the recipients of spillovers effected through liberalization of trade and FDI do influence the productivity performance as measured by TFP or labour productivity. However, the studies have also noted that the bearing these factors do vary across industries/firms and is also governed by the form in which R&D and technology import takes place along with the nature of FDI. Here it needs to be noted that focus has been on technology whereas there is reason to believe that firm level productivity cannot be attributed entirely innovations in the sphere of technology alone. Thus viewed, the apparent paradox calls for a broader perspective on innovation as articulated by Schumpeter (1943)– new product, new process, new raw materials, new market and new organization. No wonder, in countries across the world, including India, the focus of policy has shifted from science to technology and to innovation. If our contention that innovation in its broader sense better explains the productivity performance any search for an appropriate analytical frame would lead us to the door steps of innovation system perspective, which over time has emerged as the most widely used approach in innovation studies (Fagerberg and Sapprasert 2011)

While the historical roots to the concept of NSI is often traced to the work of List (1841), Lundvall (1988) introduced the modern version of this concept in a booklet on user-producer interaction and product innovation. Freeman (1987), while analyzing the economic performance of Japan, brought the concept to an international audience. He defined National Innovation System as "the network of institutions in the public and private sectors whose activities and interactions initiate, import, modify and diffuse new technologies" (p.1). The concept of NSI, as defined by Freeman, highlights the processes and outcomes of innovation. Recognizing knowledge as the key resource in the modern economy and learning as the key process other scholars Lundvall (1992), Nelson (1993), Edquist (1997) articulated the bearing of institutionally governed interactive learning among different actors as the driving force of innovation.

The NIS approach to innovation spells out explicitly the importance of the 'systemic' interactions between the various components of inventions, research, technical change, learning and innovation (Soete et al., 2010). The national systems of innovation also bring to the forefront, the central role of the state as a coordinating agent. An important contribution of the innovation system perspective is towards enhancing our understanding on the link between interactive learning and innovation in contrast to the endogenous growth models that linked technology and economic growth (Lundvall et al., 2011). The interaction as understood in the NSI framework goes beyond the conventional understanding of linkage between industry, academia and the government and encompasses broader user - producer interaction governed by the institutional context (Lundvall, 1992; Lundvall, 1988; Nelson, 1993, 2008).

From the above discussion, it is evident that the central pillar of our analytical frame is the nature and extent of interactive learning among different actors in the innovation system. For any agent involved in innovations, there could be two sources of interactive learning- internal and external sources (Lundvall, 1988; Cohen and Levinthal, 1990). The internal interactions refer to intra-firm interactions; for example, between different departments within a firm. The external interactions could be with actors outside the firm. This may be with actors within the country (intra-country interactions) and/or with those outside the country (inter-country interactions). The intra-country interactions refer to interactions among actors within the region/country like users, suppliers, competitors, research institutes, universities, consultants, government agencies and others. In the current context wherein innovation systems are becoming increasingly global, learning is not confined to interaction among the actors within the country. Interactions with actors outside the country (inter-country) include but not limited to FDI, trade in capital goods and spares, trade in technology/services. In addition, interactions with universities and other actors like customers and suppliers from outside the country (inter-country interactions) are increasingly becoming important under globalization.

From the very beginning innovation system perspective delineated two modes of interactive learning. The first one, often referred to as STI (Science Technology and Innovation) mode of learning (Lundvall 2007; Jenson et al 2007; Lunvall 2017) emanates from science and R&D efforts that leads to codified and scientific knowledge which Asheim and Coenen (2005) refers to as analytic knowledge. Such R&D efforts may be undertaken through in-house R&D units established by the firms – both local and foreign - , public research laboratories, universities and through their collaborative efforts. This is in sync with the analyses of national science systems and national technology policies (Nelson, 1993, Mowery and Oxley, 1995). Jensen et al. (2007) considered STI mode as the most relevant in production based on high R&D expenditures along with investments in highly skilled scientific human resources and advanced technologies and infrastructures. This knowledge output is typically associated with high-technology industries and firms that operate in pharmaceuticals, biotechnology, and nano-materials, among others. STI mode of interaction is shown to have been extremely important especially since the last century wherein the large R&D laboratories in the big private firms have significantly contributed towards technological learning about artifacts and techniques leading economic growth (Freeman, 1982; Mowery and Oxley, 1995).

The second mode of learning discussed in the literature refers to Doing Using and Interacting (DUI) mode. This is based on the premise that not all the important inputs into the process of learning and innovation emanate from science and R&D efforts[4]. In the real world, much of the learning is experience-based that takes place in connection with routine activities in production, distribution and consumption and produces important inputs to the process of innovation (Lundvall 1992 p 9). In the similar vein Nelson (2004: 458) argued that much of engineering design practice involves solutions to problems that professional engineers have learned from 'work' without any particularly sophisticated understanding of why. Asheim and Coenen (2005) argued that such learning activities leads to synthetic knowledge in contrast to the scientific knowledge disused above. Building on to these arguments and the basic tenet of interactive learning from innovation system Lundvall (2007) and Jenson et al (2007) articulated Doing Using and Interacting (DUI) mode of learning. Thus this mode of learning also includes the learning from both formal and informal interactions internal to the firm, but also interactions with suppliers, customers and competitors (Fitjar and Rodriguez-Pose, 2013)[5]. In the context of global production network driven by globalisation, trade could be an important means of international interactions facilitating the DUI mode of learning.

Reflecting on the relative role of STI and DUI mode of learning using firm-level empirical evidence from Denmark, Jenson et al (2007) observed that firms adopt primarily either DUI or STI learning strategies. Further, the firms that combine a strong version of STI mode with a strong version of DUI mode excel in product innovation. Characterizing STI mode as supply driven and DUI mode as demand driven, Isaksen and Nilsson (2013), combined mode of learning with innovation policies and analysed the innovation performance in Sweden and Norway. They argue that STI mode of learning enables building more research competence within firms, and DUI mode facilitates competence building in industrialization and commercialization within firms. Fitjar and Rodríguez-Pose (2013) demonstrated that engagement with external agents is closely related to firm innovation and that both STI and DUI-modes of interaction matter. However, they also shows that DUI modes of interaction outside the supply-chain tend to be irrelevant for innovation, with frequent exchanges with competitors being associated with lower levels of innovation. Collaboration with extra-regional agents is much more conducive to innovation than collaboration with local partners, especially within the DUI mode. Another study, based on the empirical evidence from Spain (Parrilli and Heras 2016), has shown that while the STI mode has a stronger effect on technological innovations, non-technological innovations are mostly driven by DUI mode of learning. Further, the combined STI and DUI mode of interactions generate the greatest impact on all types of innovations. In line with above studies, firm level analysis by Thoma (2017) showed the significant role of DUI mode of learning along with STI

[4] A strategy paper on Towards a more innovative and inclusive India prepared by the office of Advisor to the Prime Minister states that, while we do need to increased R&D investment and efforts, this view of innovation is myopic since innovations are increasingly going beyond R&D and patentable technologies.

[5] Parrilli and Heras (2016) argue that in general firms in Sweden, Finland, Japan, and the US, among others, tend to focus on the STI mode, whereas Denmark, Norway, Italy, and Spain traditionally tend to follow the DUI route to learning and innovation.

mode in contributing towards innovation activity in Germany. In the light of these findings it may be hypothesized that the inter-firm variation in productivity is attributed to the firms knowledge generation behavior through STI and DUI mode of learning through intra-firm, intra-country and inter country interactions.

While the propositions based on interactive learning for knowledge generation appears impressive, its empirical verification is rather difficult. While the community innovation surveys undertaken in most of the OECD countries and select developing countries enables such an exploration, in case of India in the absence of such innovation surveys the required data in not available. In what follows we shall make use of the firm level data obtained from PROWESS, which could be construed as an outcome of the interactive learning behavior of firms. To that extent our results may be considered at best as indicative. We consider R&D expenditure by the firm as an indicator of STI mode of learning, which is an outcome of the intra-firm interaction. It implies that firms' decision to invest in R&D and its magnitude is not an autonomous decision of R&D department, instead governed by the integrations among production, marketing, R&D and other relevant departments within the firm. As Bell and Pavitt (1993) have pointed out, most firms in developing countries innovate on the basis of a broad range of capabilities. These are, they argue, typically concentrated in the departments of maintenance, engineering or quality control (rather than in, say, a R&D department). We consider domestic payment of royalty and technical fee as an indicator of intra-country interaction within the STI mode to indicate learning by firms through their interaction with other knowledge generating entities like universities and research laboratories within the country that has attracted much attention in the literature (Resenberg and Nelson (1994; Cohen and Levinthal 1990; Nelson and walsh 2002). To the extent that STI mode of learning possibilities exists through interaction with knowledge generating entities outside the country, which has attracted substantial attention of scholars in India, we consider royalty payment abroad as an indicator of inter-country interactions in STI mode. Finally, within the STI mode we consider FDI, which is often recognized as depositories of knowledge as an indicator of inter-country interaction with in the STI mode. When it comes to DUI mode of interaction, we consider purchase of raw materials and spares from sources within the country as an indicator of learning through user-producer interactions, which takes form of intra-country interactions. Similarly import of raw materials and spares and export are considered as an indicator of DUI mode of learning through user producer interactions facilitated by the participation in global production network, which takes the form of inter-country interactions. Two other indicators of knowledge and learning at the firm level relates to staff training and managerial expertise. Expenses incurred by the firm on staff training indicate the former while the latter is captured by the share of salary bill for the managerial staff in wages and salaries.

Empirical strategy

Estimation procedure

We capture the impact of STI and DUI mode of interactions and combination of these two learning strategies in three-step procedure. First, we estimate a Cobb-Douglas production function.

$$\log Y_{ijt} = \propto + \beta_l logL_{ijt} + \beta_k logK_{ijt} + \beta_m logM_{ijt} + \beta_e logE_{ijt} + \beta_s logS_{ijt} + \omega_{ijt} + \mu_{ijt} \quad (1)$$

Where i, j, and t refer to firm, industry, and time respectively and Y, K, L, M, E, S, ω and μ are output, capital stock, labour, raw material, energy, services, productivity, and the measurement error in output, respectively, to obtain Total Factor Productivity (TFP) estimates for firm as residual. In the second stage, we regress the estimated TFP on a set of STI and DUI interactions along with the institutional factors and other firm specific controls. The second state equation may be specified as follows.

$$\log TFP_{ijt} = \propto + \beta_1 RDI_{ijt} + \beta_2 IDETI_{ijt} + \beta_3 DDETI_{ijt} + \beta_4 FFIRMDUMMY_{ijt} + \beta_5 STAFFDUMMY_{ijt} + \beta_6 EXPIN_{ijt} + \beta_7 IRMSI_{ijt} + \beta_8 DRMSI_{ijt} + \beta_9 EXEDIRDUMMY_{ijt} + \beta_{10} TARIFF_{jt} + \beta_{11} LABLAWSDUMMY + \beta_{12} AGE + \beta_{13} AGESQUARED + \Omega_j + \mathcal{E}_t + \mu_{ijt} \quad (2)$$

Where Ω_j and $\mathcal{E}_t$ are industry and time fixed effects respectively (see Table 1 for description of variables). With a view to capture the effect of combination of different learning strategies, we divide both STI and DUI learning strategies in four mutually exclusive categories. In equation 2, we represented four STI interactions and four DUI interactions. Based on the four modes of learning in each category of interaction, we categorised a firm as strong STI firm if a firm participates in three or more interaction and weak otherwise. Similarly, we categorised a firm as strong DUI firm if a firm participates in three or more interactions and weak DUI otherwise. Based on these categories we created four mutually exclusive combinations of learning strategies. (1) Strong STI combined with strong DUI, (2) strong STI combined with weak DUI, (3) weak STI combined with strong DUI and (4) weak STI combined with weak DUI. We estimate the combination of learning strategies in equation 3.

$$\log TFP_{ijt} = \propto + \beta_1 strongSTI * weakDUI_{ijt} + \beta_2 weakSTI * strongDUI_{ijt} + \beta_3 strongSTI * strongDUI_{ijt} + \beta_{12} AGE + \beta_{13} AGESQUARED + \Omega_j + \mathcal{E}_t + \mu_{ijt} \quad (3)$$

Given the panel structure of the data, studies have employed fixed or random effects models to estimate the determinants of the TFP as mentioned in equation (2) and (3). However, the fixed effects model assumes the entity characteristics do not vary over time. In our case, we have a few variables that do not vary over time and is dropped in the fixed effect models. Hence, we estimated pooled OLS regression controlling for time and industry fixed effects. In the OLS estimation, heteroscedasticity and serial correlation are always potential problems and their presence leads to a bias in the estimated of the model. In this paper, we use cluster sample methods to obtain robust variance matrix estimator to address the issue of heteroscedasticity.

Data

Like many other studies, which have addressed the issues relating to productivity at the firm level, for the empirical analysis, we obtain firm-level information from the Prowess database provided by the Centre for Monitoring the Indian Economy. Prowess contains information primarily from the income statements and balance sheets of publicly listed companies. The companies in the database account for more than 70% of the economic activity in the organized industrial sector of India. We have collected data on 16,915 firms during 2000-01 to 2016-17. The database provides firm-level information where firms are classified into various industries according to the national industrial classification (NIC) 2008. Since our analysis is restricted to the manufacturing sector, we drop firms with NIC code that does not fall under manufacturing sector. For example, we exclude the following industries from analysis: NIC 34 (diversified), NIC 35 (electricity), NIC 42 (civil engineering), NIC 68 (real estate) and NIC 98 (Undifferentiated goods). In our sample, we have considered firms which have reported sales for at least five years. Hence, we dropped all the newly incorporated firms as well as firms for which data is available for less than five years did. We also dropped firms, which reported zero sales, capital stock, wages and salaries, raw material cost, and energy. We therefore use an unbalanced panel of companies for estimation purposes and verify the robustness of the results by conducting the analysis using only the subset of companies whose information is available for all years. In the final sample, after dropping a few outliers the total number of observations in our sample is 67,103 representing about 4 to 5 thousand firms every year. In the sample that we have considered, firms did not report any information on variables such as research and development, purchase of technology licences, equity ownership, exports etc. Though it is possible that non-reporting of the variable might not indicate zero values, we have converted the non-reporting as zeros in order to prevent loss of number of observations for the empirical analysis.

This study also draws data from other sources. We build wage rate data using the Annual Survey of industries. The data on tariffs across three digit industries using HS-88 is obtained from UN-COMTRADE through WITS. We have concorded NIC 2008 classification in prowess into NIC-2004 to be able to merge industry wise tariff and wage rage with the firm level data. We have also built industry wise WPI drawn from economic advisory industry and WPI on capital formation from CSO.

Construction of variables for TFP estimation

All the variables in the production function are in 2004-05 prices, obtained by deflating values reported in current prices using appropriate price indices collected from the "Index Numbers of Wholesale Prices in India, base 2004-05 = 100" published by the Economic Adviser, Ministry of Commerce and Industry, Government of India. The specific details on the construction of each variable are given below.

Output (Y)

Following many of the previous studies, output at the firm level is obtained by adding plus changes in stocks to sales. Next, we deflate nominal output using 3-digit industry-level price deflators, constructed from the Wholesale Price Index (WPI) series obtained from the Office of the Economic Advisor, Ministry of Commerce and Industry. If the appropriate deflator is not available, the deflator corresponding to the nearest product group is selected. The WPI is collected from the office of Economic Advisor, Government of India.

Labour (L)

One of the serious drawbacks in using Prowess data for TFP estimation is lack of data on number of persons engaged. A very few firms report number employees and the information is most of discontinuous. Therefore, we follow the standard practice in the literature. Prowess provides data on wages and salaries given to employees. We arrive at firm level employment figure in our study by making use of emoluments and total persons engaged data from Annual Survey of Industries (ASI), Central Statistics Office, Government of India. First, for each three-digit industry in ASI (according to National Industrial Classification, NIC), we calculate the average industrial wage rate by dividing total emoluments with total employees. Next, we match each three-digit ASI industry to NIC in Prowess using concordances. This gives us the average industrial wage-rate for each firm in our panel. Lastly, we divide wages and salaries reported by each firm in Prowess with its corresponding average wage-rate to get firm-level labour. The ASI data was available only up to 2015–2016. We have extrapolated the values for the remaining years in our study.

Capital (K)

The estimation of capital stock has been a core issue of concern in the productivity literature. There are two broad approaches to estimate real capital stock. Many studies that estimated TFP using either

ASI data (at industry level) or Prowess (firm level) have used perpetual inventory method, following Srivastava (1996). Some studies have used 'blanket deflation method' (Haider, 2012; Goldar and Banga, 2015). In this study, following Goldar and Banga (2015), we use the blanket deflation method, despite its known limitations. To construct real capital stock, we first collect data on net fixed assets for each firm in our panel, using the Prowess dataset, and then deflate it using the implicit deflator for fixed capital formation in manufacturing, computed using National Accounts Statistics with base year 2004-05 (combined with the new series on National Accounts).

Material (M)
The raw material expenses include the value of raw materials consumed. The nominal value of the raw material cost was deflated using raw material price indices, base 2004–05=100. The raw material price indices were constructed using weights obtained from the Input–output transaction table, published by the CSO and appropriate price indices from the WPI.

Energy (E)
We first calculate the nominal energy input for a firm as the sum of its expenses on power and fuel, in current prices, obtained from Prowess. To construct the energy deflator, we use price indices of coal, petroleum products, natural gas and electricity for industrial use from the official WPI series and other sources. We combine the price series with 1994/94 as the base year with series using base prices 2004/05, and splice and rebase the combined series to 2004-05.

Services (S)
We arrive at total services consumed by a firm by summing up its expenses on heterogeneous services comprising of rent and lease, repair and maintenance, outsourced manufacturing jobs, outsourced professional jobs, insurance, selling, distribution expenses, and financial services (Banga and Goldar, 2015).

The detailed description of the construction of variables for our second stage estimation as specified equation (2) is mentioned in Table 1.

Table 1: Construction of variables used in the second stage regression analysis

Mode of learning	Type of interaction	Proxy	Construction of the variables	Source
STI Mode	Intra-firm interactions	RDI	R&D expenditure as a proportion of sales	Prowess
	Global STI	IDETI	Purchase on royalties and licences from foreign entities as a proportion of sales	Prowess
	Domestic STI	DDETI	Purchase on royalties and licences from domestic entities as a proportion of sales	Prowess
	Global STI	FFIRMDUMMY	The value takes 1 if foreign equity share holding is more than 10 per cent and 0 otherwise	Prowess
	Global STI	MINORITY	The value takes 1 if foreign equity share holding is more than 10 and less than 50 per cent and 0 otherwise	Prowess
	Global STI	MAJORITY	The value takes 1 if foreign equity share holding is more than 50 per cent and 0 otherwise	Prowess
	Domestic STI	STAFFD	The value takes 1 if a firm reports staff training expenses and 0 otherwise.	Prowess
DUI Mode	Global DUI	EXPIN	Exports of goods as a proportion of sales	Prowess
	Global DUI	IRMNSI	Import of raw materials, stores and spares as a proportion of sales	Prowess
	Domestic DUI	DOMIRMNSI	Domestic raw materials, stores and spares as a proportion of sales	Prowess
	Domestic DUI	EXDIRDUMMY	The value takes 1 if the share of executive directors remuneration in total compensation is greater than the industry average and zero otherwise	Prowess
Institutions	Trade orientation	TARIFF	Average weighted tariff at three digit industry classification	COMTRADE
	Labour market institutions	LABLAWSDUMMY	0=pro worker states 1=pro employer states 2=neutral states	Besley and Burges (2004)
Controls	Firm specific controls	AGE	Reporting year – year of incorporation	Prowess
	Firm specific controls	AGE Squared	Square root of Age	Prowess

Estimation of TFP

There are various methodological approaches to estimate total factor productivity. We use the residual from a production function estimated at firm level as a proxy to measure TFP. It is well acknowledged that an estimation of the production function using ordinary least squares (OLS) gives inconsistent and biased estimates of explanatory variables (Malik, 2014). There are likely to be a host of firm, industry, time, and region-specific influences that are unobservable to the econometrician but are known to the firm. These unobservables might influence the usage of production inputs, making them endogenously determined. Since the OLS technique assumes production inputs are uncorrelated with omitted unobservable variables, it fails to address this endogeneity issue, resulting in inconsistent and biased estimates of the production function.

Marschak and Andrews (1944) and Griliches and Mairesse (1995), among others, have explored the potential correlation between input levels and firm-specific productivity shocks in estimating the production function. Olley and Pakes (1996) have outlined a semi-parametric method to handle the simultaneity problem. They use investment as a proxy to control the correlation between input levels and unobserved firm-specific productivity shocks in the estimation of the production function. This methodology is applicable if plants report non-zero investment. Unfortunately, many plants in developing countries do not report positive levels of investment. There are zero investment values in sample of our study. The sample of the study needs to be truncated if we employ the Olley–Pakes' approach to estimate the production function. Levinsohn and Petrin (2003) however propose an alternative method to estimate the production function. They, instead, use intermediate inputs such as electricity or energy to address the simultaneity problem. The method allows the analysis to proceed without reducing the sample size. Another benefit of this method compared to the use of an investment proxy is its applicability to non-convex adjustment costs. "If adjustment costs lead to kink points in the investment demand function, plants may not entirely respond to some productivity shocks, and correlation between the regressors and error can remain. If it is less costly to adjust the intermediate input, it may respond more fully to the entire productivity term." (Levinsohn and Petrin 2003: 318).

For our study, we use the Levinsohn and Petrin (LP) methodology to estimate the production function (1). It is explained below. Writing the production function as,

$$y_t = \propto + \beta_l l_t + \beta_k k_t + \beta_m m_t + \beta_e e_t + \beta_s s_t + \omega_t + \mu_t \tag{4}$$

where y_t , k_t , l_t , m_t , s_t and et are the logarithm of output, capital stock, labour, raw materials, energy and services of the firm respectively, ω_t denotes productivity of the firm and μ_t stands for the measurement error in output, which is uncorrelated with input choices. In most of the existing studies using LP method, used material inputs or energy consumed as a proxy to take care of endogeneity problem arising out of unobserved shocks. In this paper, we take energy and services as a proxy. Given that LP assumes that firm's intermediate inputs demand function, is monotonically increasing in productivity given its capital stock, the unobservable productivity term ω depends solely on three observed inputs, e_t, s_t, and k_t. Hence, we can re-write the equation 4 as follows.

$$y_t = \beta_l l_t + \beta_m m_t + \beta_e e_t + \Phi\ (k_t, e_t, s_t) + \omega_t + \mu_t$$

Where $\Phi\ (k_t, e_t, s_t) = \propto + \beta_k k_t + \beta_e e_t + \beta_s s_t + \omega_t(k_t, e_t, s_t) + \mu_t$ and the error term μ_t is not correlated with inputs. This allows us to calculate productivity of manufacturing firms by taking the difference between actual and predicted output which can be written as

$$TFP_{ijt} = y_{ijt} - \beta_k k_t - \beta_l l_t - \beta_m m_t - \beta_e e_t - \beta_s s_t \quad (5)$$

The estimated coefficients of the of the production function equation are presented in Table 2.

Table 2: Production function estimates using Energy and Services as Proxy

VARIABLES	(1) LP
lnLabor	0.119***
	(0.00386)
lnRRM	0.151***
	(0.0126)
lnNFA	0.416***
	(0.0161)
Observations	64,190

Note: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Empirical Results

With a view to discern the bearing of interactive learning on firm's innovation as represented by TFP, we have estimated four models. Model 1 presents the basic STI and DUI interactions. In model 2, we account for the extent of inter country interactions through FDI by considering different levels of foreign equity ownership. In model 3 we incorporate two institutional factors as represented by trade liberalization and labour market institutions. In model 4 we add the firm characteristics such as age of the firm. In all the models, we controlled for potential time, industry, and firm fixed effects. In what follows we shall focus on the model 4 with all the controls.

Table 3: The effect of mode of learning and type interaction on TFP

VARIABLES	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4
RDI	3.303***	3.250***	3.249***	3.192***
	(0.606)	(0.598)	(0.598)	(0.577)
IDETI	1.948	1.408	1.413	1.763
	(1.946)	(1.782)	(1.783)	(1.877)
DDETI	1.842***	1.798***	1.765***	1.927***
	(0.480)	(0.467)	(0.467)	(0.470)
STAFFTD	0.227***	0.224***	0.224***	0.226***
	(0.0127)	(0.0127)	(0.0126)	(0.0125)
Base: DOMESTIC FIRMS				
FFIRMDUMMY	0.359***			
	(0.0129)			
BASE: NO FOREIGN SHARES				
MINORITY SHARES		0.160***	0.160***	0.137***
		(0.0143)	(0.0143)	(0.0141)
MAJORITY SHARES		0.562***	0.562***	0.522***
		(0.0183)	(0.0183)	(0.0184)
EXPIN	0.0913***	0.0946***	0.0948***	0.0971***
	(0.0148)	(0.0147)	(0.0147)	(0.0147)
IRMNSI	1.503***	1.503***	1.502***	1.560***
	(0.0347)	(0.0346)	(0.0346)	(0.0350)
DOMRMSPI	0.639***	0.651***	0.651***	0.710***

	(0.0203)	(0.0203)	(0.0203)	(0.0208)
EXDIRDUMMY	0.149***	0.150***	0.150***	0.143***
	(0.00681)	(0.00679)	(0.00679)	(0.00678)
TARIFF			-0.00146***	-0.00138**
			(0.000555)	(0.000559)
BASE: WORKER FRIENDLY STATES				
EMPLOYER FRIENDLY STATES			0.246**	0.183
			(0.124)	(0.124)
NEUTRAL STATES			0.197	0.157
			(0.130)	(0.131)
AGE				0.00541***
				(0.000476)
AGE SQUARED				-2.05e-05***
				(4.97e-06)
Constant	2.127***	2.120***	2.230***	2.151***
	(0.125)	(0.125)	(0.133)	(0.134)
Observations	65,651	65,651	65,651	65,651
R-squared	0.260	0.263	0.263	0.269
Firm FE	YES	YES	YES	YES
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

The estimated coefficients indicate that all the variables representing STI model of learning except inter-country interactions with knowledge generating entities abroad indicated by import of royalty and licenses abroad are positive and statistically significant at one per cent level. Earlier studies (Basant and Fikkert, 1996; Parameswaran, 2009; Rijesh, 2015) without controlling for many of the factors and for different time periods have reported the positive role of dis-embodied technology import. The coefficient of RDI representing intra-firm interaction is positive and statically significant, indicating firms that translate the feedback from various departments within a firm in its R&D agenda with greater interaction among various departments leading to higher productivity. The innovation system literature has highlighted the crucial role of interactions among firms and other knowledge generating entities like universities and research laboratories as an influential factor in promoting innovation. However, the earlier studies in the Indian context have hardly dealt with the impact of domestic technology purchases. The value of domestic disembodied technology intensity coefficient is positive and significant 1 per cent level, which provides empirical support to the importance of domestic inter-firm STI interactions in enhancing productivity. This finding may be viewed in the context of heightened international competition wherein firms consider domestic sources as important means of technology and knowledge. Yet another factor indicating the knowledge base of the firm indicated by staff training, which has not been considered by the earlier studies, is also positive and statistically significant. Finally, it is evident that firms with foreign equity shares are found to be more innovative and productive as compared to domestic firms. The value of the estimated coefficient further indicates that firms with majority equity participation are more productive as compared to firms with minority equity shares.

When it comes to the variables representing DUI mode of interaction, the results indicate the positive role of all the indicators considered. The positive coefficient of export intensity indicates that firms with greater export orientation have greater opportunities to interact with customers and suppliers abroad which in turn contributes to their innovation and productivity. Similarly, firms do enhance their productivity through interactions with suppliers of raw materials and spares whether they are within the country or abroad. Finally, measure of accumulated knowledge base of the managerial staff is also found having its positive impact on productivity. The firm specific factor represented by the age of the firm is found to have non-linear relationship indicating an inverted 'U' shape. This suggests that productivity increases as the age of the firm increases and starts to decline thereafter.

Innovation system postulates that the institutions govern interactive learning and knowledge generation. In the estimated model, we have considered two types of institutions- trade liberalization represented by tariffs and labor market institutions. The tariff coefficient is negative and statistically significant indicating a positive influence of trade liberalization on productivity. With respect labour we observed that flexible labour market is conducive for productivity (Nelson, 1982).

Table 4: The effect of mode of learning and type interaction on TFP across technology classification

VARIABLES	(1) Low Tech	(2) Medium Tech	(3) High Tech
Dependent variable: ln TFP			
RDI	4.455**	-0.734	3.693***
	(2.262)	(0.759)	(0.699)
IDETI	2.093	6.801***	1.000
	(2.622)	(1.342)	(2.091)
DDETI	-0.245	9.832***	2.886*
	(0.443)	(1.727)	(1.510)
STAFFTD	0.242***	0.203***	0.224***
	(0.0282)	(0.0228)	(0.0174)
BASE: NO FOREIGN SHARES			
MINORITY SHARES	0.149***	0.101***	0.127***
	(0.0343)	(0.0222)	(0.0205)
MAJORITY SHARES	0.655***	0.466***	0.467***
	(0.0429)	(0.0269)	(0.0243)
EXPIN	0.241***	0.0531**	-0.0797***
	(0.0223)	(0.0258)	(0.0275)
IRMNSI	1.666***	1.637***	1.375***
	(0.0677)	(0.0643)	(0.0534)
DOMRMSPI	0.842***	0.468***	0.730***
	(0.0326)	(0.0377)	(0.0396)
EXDIRDUMMY	0.190***	0.114***	0.116***
	(0.0116)	(0.0112)	(0.0121)
TARIFF	-0.00192***	0.00454**	0.00599*
	(0.000625)	(0.00226)	(0.00309)
BASE: WORKER FRIENDLY STATES			
EMPLOYER FRIENDLY STATES	0.620***	-0.0873	-0.129***
	(0.125)	(0.0683)	(0.0309)
NEUTRAL STATES	0.968***	-0.0603	-0.479***
	(0.132)	(0.0848)	(0.109)
AGE	0.00130	0.00709***	0.00425***
	(0.000794)	(0.000870)	(0.000863)
AGESQUARED	-9.32e-06	-8.01e-06	1.64e-05*
	(7.61e-06)	(1.09e-05)	(9.23e-06)
Constant	1.771***	1.642***	1.344***

	(0.136)	(0.106)	(0.103)
Observations	21,628	22,981	21,042
R-squared	0.315	0.267	0.258
Firm FE	YES	YES	YES
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

In literature on productivity and technological change, much attention has been given to the observed variation in this relationship across industries with different levels of technology intensity. Table 4 presents results of the estimated model for the low, medium and high tech industries following the OECD classification (see Appendix 2 for the list of industries). The estimated model reveals considerable variation with respect to different indicators of STI mode of learning across industries with different levels of technological intensity. It is evident that in house R&D is found having positive and statistically significant relation relationship at one per cent level is observed only in case of high technology industries. When it comes to low technology industries the estimated coefficient is significant only at 10% whereas in medium technology industries intra-firm interaction in STI mode does not have any significant bearing. In medium technology industries though R&D is not significant interactions with technology suppliers both foreign and local are found having a positive influence. Similar finding has been reported by Rijesh (2015). But, when it comes to high technology industries firms scientific learning is driven by interactions with local technology generating entities. Finally, the other two indicators of STI mode of learning – staff training and FDI – are found positive influence in all the three kinds of industries.

When it comes to DUI mode of learning, it is found that interactions with customers abroad through exports while have a positive influence on interactive learning and innovation in case of low and medium technology industries, it is found have a negative influence in case of high technology industries. The negative influence in case of high technology industries wherein India lacks comparative advantage trends to suggest that interactive learning is also contingent on the industries' comparative advantage. Further it is also evident that interactions with suppliers, both foreign and local are of much significance in promoting learning and innovation for enhanced productivity. Finally the estimates of the model also indicate that the managerial expertise as an indicator of accumulated experience based learning is having a positive and significant bearing on innovation and productivity. With respect to firm specific characteristics (age) it is observed that age of the firm has a positive bearing in case of medium and high tech industries whereas it doesn't matter in low-tech industries indicating that the role of experience increases with technological intensity.

In case of institutional factors we observe that while the tariff barriers could be instrumental in productivity enhancement through innovation in medium and high tech industries its effect could be adverse in case of low technology industries, which are known for price/cost based comparative advantage. Finally, it is observed that while flexible labour market could be helpful in fostering productivity through innovation n case of low-tech industries, it could act as a dampener in case of medium and high tech industries. While the existing literature makes the case for across the broad flexibility in the labour market for facilitating the manufacturing growth, the present analysis makes the case for more nuanced approach calling for further empirical exploration.

Table 5: Combination of learning strategies and TFP

VARIABLES	(1) Total	(2) Low Tech	(4) Medium Tech	(6) High Tech
Dependent variable: *ln* TFP				
Stong STI & DUI	0.942***	1.055***	0.896***	0.920***
	(0.0177)	(0.0479)	(0.0348)	(0.0224)
Strong STI & Weak DUI	0.621***	0.780***	0.538***	0.654***
	(0.0541)	(0.279)	(0.104)	(0.0589)
Weak STI & Strong DUI	0.466***	0.473***	0.406***	0.509***
	(0.00630)	(0.0112)	(0.00989)	(0.0116)
Age	0.000778*	-0.00281***	0.00425***	-0.00197**
	(0.000472)	(0.000793)	(0.000885)	(0.000851)
Age squared	3.96e-06	1.11e-05	6.75e-06	5.41e-05***
	(5.03e-06)	(7.68e-06)	(1.12e-05)	(9.34e-06)
Constant	2.462***	2.083***	1.946***	1.737***
	(0.106)	(0.146)	(0.0733)	(0.0333)
Observations	65,651	21,628	22,981	21,042
R-squared	0.269	0.291	0.258	0.279
Firm FE	YES	YES	YES	YES
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Let us now turn to the final empirical issue often discussed in the innovation system literature, which relates to the relative role of combined STI and combined DUI on the innovation by firms. We have estimated the bearing of four different combination strategies (A) strong STI combined with strong DUI b) strong STI combined with weak DUI, C) weak STI combined with strong DUI and finally D) weak STI and weak DUI) for total manufacturing, low tech, medium tech and high-tech industries. In the estimated model we have considered weak STI and weak DUI as the comparison group. The estimates of the model tends to suggest that for the manufacturing sector as a whole and its three sub-categories, productivity could be enhanced either using strong STI strategy or strong DUI strategy. Under the current context, there appears to be a choice for the firm to between STI or DUI mode of learning as a conduit for enhancing productivity. To the extent that firms, could manage to achieve higher productivity adopting a strong DUI mode without corresponding attempts in STI learning explain the apparent paradox wherein indian industry recording higher productivity without concomitant increase in indicators representing technological change. Having said this, it may also be noted that the estimated differences in estimated t statistics consider point towards the greater relevance of STI mode of learning in high-tech industries and a strong DUI mode of learning in low-tech industries. From the above evidence, we are inclined to infer the increasing role of DUI mode of learning building static comparative advantage. In this context, the relevance of building dynamic comparative advantage with a greater focus on STI mode as articulated by Stiglitz and Greenwald (2014) and Lee (2015) drawing from the experience of South Korea cannot be over emphasized in the Indian context.

Conclusion

Recent empirical evidence tends to suggest that higher GDP growth in India is associated with turnaround in Total Factor Productivity Growth. While TFP growth is generally attributed to technological progress, there has not been any marked increase in any of the commonly used indicators of technological progress. The present paper is an attempt to explore this apparent paradox by using the innovation system perspective. Viewed from the lens of innovation system perspective, knowledge is the key resource in the modern economy and learning is the key process leading to innovation, which is an outcome of the interaction among different actors and governed by the institutional context in which they operate.

Empirical analysis within the innovation system perspective in India severely constrained in the absence of community innovation surveys. Nonetheless, the present study made use of the available firm level data to analyze the bearing of the different modes of interactive learning on innovation at the firm level as indicated by TFP. The analysis has been undertaken at three different levels. To begin with we have analysed the influence of various indicators representing the STI mode of learning that represent the scientific and codified knowledge and DUI mode of learning indicating experience based tacit knowledge on TFP for the manufacturing sector as a whole. At the second stage, we analysed the role of these indicators of interactive learning based knowledge on productivity across industries with varying levels of technological intensity. Finally, we analyzed the relative role of combined STI and DUI mode of learning on TFP by dividing the STI and DUI mode of learning strategies into four mutually exclusive categories; (a) strong STI combined with strong DUI, (b) strong STI combined with weak DUI, (c) weak STI combined with strong DUI and (d) weak STI and weak DUI for total manufacturing, low tech, medium tech and high-tech industries.

Analysis of the indicators of STI mode of learning and DUI mode of learning highlighted the contribution of intra-firm interaction as indicated by R&D, interaction with technology suppliers and producers abroad indicated by disembodied technology and FDI along with learning from suppliers abroad represented by dis-embodied technology import. In general these findings are in sync with that of the studies undertaken earlier. The use of innovation system perspective however enabled us to offer additional insights by locating highlighting certain other factors that are instrumental in promoting interactive learning, innovation and productivity but neglected by the earlier studies. It was shown productivity performance at the firm level is positively influenced by their interaction with domestic knowledge generation entities like universities and research laboratories. Further, interaction with domestic suppliers along with staff training and managerial expertise also could be instrumental in promoting innovation and productivity.

The study also observes that the influence of DUI and STI mode of learning, however, is contingent on the technology intensity of the industry concerned. The productivity performance of the high technology industries, in contrast to the low technology industries, is driven mostly STI mode of interaction indicated by R&D, interactions with local technology generating entities along with FDI and staff training. Staff training and FDI (both majority and minority) are found having their positive influence in all three kinds of industries. Further, it is evident that the DUI mode of learning plays a decisive role in innovation and productivity all three types of industries with the only exception being the negative impact of export on high technology industries. Regarding the role of combined STI and combined DUI mode of learning innovation and productivity it is observed that for the manufacturing sector as a whole and its three sub-categories, productivity could be enhanced either using strong STI strategy or strong DUI strategy. Since the firms could manage to achieve higher productivity adopting a strong DUI mode without corresponding attempts in STI learning explain the apparent paradox wherein Indian industry recording higher productivity without concomitant increase in any of the indicators representing technological change. The present study thus point towards certain new areas wherein innovation policy should focus for making the India's manufacturing sector more innovative and productive. At the same time, given the increasing role of DUI mode of learning towards building static comparative advantage the study also makes the case for dynamic comparative advantage with a greater focus on STI mode of learning as articulated by Stiglitz and Greenwald (2014) and Lee (2015).

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Appendix 1

Table A1: Descritptive Statistics of Production function variables

Variable	Obs	Mean	Std. Dev.	Min	Max
lnoutput	67,103	6.33	1.89	-2.03	14.99
lnLabor	67,103	5.50	1.84	-1.22	12.80
lnRRM	65,683	5.63	2.07	-3.08	14.58
lnRenergy	65,202	2.81	2.06	-2.85	11.17
lnservices	67,103	6.28	2.00	-2.30	15.12
lnGFA	67,065	5.57	1.86	-2.82	14.39

Table A2: Mean TFP across different industry classification

	TFP	Low Tech	Medium Tech	High Tech	Domestic	Foreign	Minority	Majority
2001	15.18	16.52	15.86	13.14	14.94	17.04	14.64	19.56
2002	14.29	14.88	15.09	12.83	13.99	16.73	14.51	19.28
2003	13.77	13.79	14.67	12.81	13.37	17.65	15.56	20.03
2004	13.86	13.50	14.65	13.39	13.44	18.47	15.75	21.65
2005	15.30	13.86	16.79	15.20	14.86	20.78	18.38	24.29
2006	15.54	14.15	16.01	16.55	15.07	21.86	18.11	25.99
2007	16.83	15.20	16.86	18.62	16.32	24.49	19.82	28.65
2008	17.44	15.57	17.25	19.76	16.88	26.13	21.39	30.24
2009	17.63	15.07	18.27	19.71	17.09	26.23	21.66	30.76
2010	17.76	16.00	17.30	20.23	17.21	26.68	22.67	30.67
2011	19.07	17.17	18.03	22.30	18.44	29.05	24.61	32.70
2012	20.16	18.02	19.31	23.30	19.51	30.56	25.30	35.04
2013	21.35	20.08	19.99	24.08	20.72	30.89	25.42	35.75
2014	22.73	22.97	20.86	24.44	22.19	30.95	25.67	35.65
2015	23.95	25.43	21.26	25.35	23.43	31.03	24.77	36.32
2016	24.38	25.23	20.59	27.30	23.65	33.08	25.02	39.59
2017	25.33	25.23	21.54	29.37	24.30	34.54	26.14	40.98

Table A3: Summary statistics of the determinants of TFP

Variable	Obs	Mean	Std. Dev.	Min	Max
lntfpoutput	65,651	2.54	0.88	-3.25	7.31
RDI	67,103	0.00	0.02	0	2.09
IDETI	67,103	0.00	0.01	0	0.93
DDETI	67,103	0.00	0.01	0	1.38
staffTD	67,103	0.04	0.21	0	1
ffirmdummy	67,103	0.07	0.26	0	1
expin	67,103	0.12	0.23	0	1
IRMNSI	67,103	0.07	0.13	0	1.97
domRMSPI	67,103	0.45	0.24	0	1.99
exdirdummy	67,103	0.61	0.49	0	1
tariff	67,103	19.88	19.64	0.01	148.91
lablawsdummy	67,103	0.67	0.68	0	2

Appendix 2

Table 2A.1 OECD Technology Classification

NIC	Industry Type
	High Tech Industries
24	Chemicals and Products
29	Machinery
30	Computing Machinery
31	Electrical Machinery
32	Radio, Television
33	Medical, Precision and Optical Instruments, Watches and Clocks
34	Motor Vehicles,
35	Transport Equipment
	Medium Tech Industries
20	Plating Materials
23	Petroleum Products
25	Rubber and Plastic Products
26	Non-Metallic Mineral Products
27	Basic Metals
28	Fabricated Metal Products
	Low Tech Industries
15	Food Products
16	Tobacco Products
17	Textiles
18	Garments
19	Leather and Footwear
21	Paper and Paper Products
22	Printing
36	Furniture

Source: Compiled based on OECD Technology classification.