Innovation System meets Solow Residual
Mode of Learning and Productivity in India's Manufacturing Sector

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Abstract

Using the innovation system perspective that highlights the role of interactive learning, we explored the role of STI (Science Technology and Innovation) and DUI (Doing Using and Interacting) mode of learning in contributing to TFP. Making use of the firm-level panel data from the Indian manufacturing sector during 2001–2002 to 2016–2017, TFP has been estimated using semi-parametric method of Levinsohn–Petrin that accounts for the endogeneity bias in productivity estimation. Analysing the firm's combination of learning strategies, this paper shows that a strong STI mode of learning coupled with strong DUI mode of learning is associated with highest productivity performance. However, a large proportion of firms combine a strong version of DUI along with weak or no STI. Further, our regression analysis indicated the positive effect of all the elements in STI and DUI mode of interaction in determining firms' TFP. Our paper, using the innovation system perspective, highlights the role of DUI mode of learning especially in a developing country and makes a case for an innovation policy that strategically exploits the DUI collaborations along with standard STI policies.

Keywords: Total Factor Productivity, Mode of Learning, Innovation systems and Institutions

1. Introduction

The seminal contribution of Solow (1957) on Total Factor Productivity (TFP), as the key driver of economic growth, continues to engage the economists of different persuasions (Griliches and Jorenson, 1966; Jorenson and Yip, 2001; Acemoglu and Dell, 2010, among others). The research on productivity focussed on among others on A) on the precise measurement of inputs and outputs given that TFP is a 'residual'. Thanks to the significant improvements in the production of data, the scholars have been able to squeeze out TFP in a more precise manner. B) on the 'determinants of TFP' and its differences. Since TFP is generally considered as an outcome of technological change, a large body of empirical research highlighted the significant role of innovation (measured in terms of R&D and patents) and human capital in determining TFP in developed and developing countries. Another strand of literature focussing on innovation outcomes in terms of patents using the knowledge function approach wherein R&D and human capital have been articulated as the key inputs (Griliches, 1979, Griliches and Pakes 1980; Griliches and Lichtenberg 1984). Extending this approach further, using the World Bank Enterprise Survey, Crespi and Zuniga (2012) analysed innovation productivity relationship in Latin American countries which gave rise many studies such studies using the similar empirical approach (Crowley, and McCann, 2018; Morris, 2018; De Feutes et al, 2020, among others)

Simultaneously our understanding on the process of Science, Technology and Innovation (STI) has also undergone a major change. The latest in this direction within the innovation system perspective is the articulation of the role of different modes of learning and resulting knowledge in innovation. The seminal contribution by Jenson et al (2007) have shown that both STI and DUI mode of learning play an important role in innovation performance of firms and the combined mode of interaction. Subsequent studies have taken this agenda forward and made important contribution with respect to understanding mode of learning in different developed countries (Fitjar and Rodríguez-Pose, 2013; Isaksen and Nilsson, 2013; Parrilli and Heras 2016; Thoma, 2017). While these studies have primarily aimed at analysing the inter-relation between different modes of learning and innovative outcomes, the bearing of the mode of learning on productivity seems to have not received the attention that it deserves.

Against this background, this study aims at analysing the role of different modes of learning on the productivity performance at the firm level. The contribution of the present study to the literature includes it provides the empirical evidence on the contribution of different modes of learning especially that of DUI mode to the productivity performance of the firms in a developing country. In doing so, it contributes to the growing number of studies that provide empirical support to innovation system perspective especially from a developing country perspective. Thirdly, it brings out new insights for firm level knowledge management strategy for productivity enhancement while contributing towards informed innovation policy making in developing countries.

The remainder of the paper is organized as follows. Section 2 deals with different modes of interactive learning as articulated in innovation system by way of providing analytical framework of the study. Data is presented in section 3. The empirical strategy of the paper wherein estimation procedure, variable construction for productivity estimation and its determinants are presented in section 4. Section 5 provides the results of the estimated models on the role of mode of learning and interaction in determining TFP. The final section highlights the main findings of the study and draws few concluding observations.

2. Analytical background

Surveying the voluminous literature on TFP, Syverson (2011) concluded that though we know more about what causes the measured differences in productivity, there is still plenty to be learned and there is no sign that the rate at which researchers accumulate knowledge in this area is slowing. Yet, the concerns raised by Nelson (1981) in an influential paper, to quote "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", still hold especially in developing countries, *albeit* with reduced intensity. Against this background, relevance of studies on the determinants of firm level productivity cannot be over emphasized especially in developing countries.

Studies on technological change in developing countries often conceptualized it as an outcome of own R&D, mostly adaptive, technology import from developed countries, and technology spillovers arising mainly from FDI and trade (Katz, 1987; Bell, 1984 2006; Kim 1987, 1997; Dahlman et al 1987; Fransman and King 1984; Lall 1992; Kim and Nelson 2000, among others). In line with these analytical arguments, the empirical studies analyzing the determinants of TFPG could be broadly categorized as follows. First, technology purchases both in the form of embodied and disembodied technology along with own R&D is associated with high private rate of returns in the form of increased productivity (Coe and Helpman, 1995; Basant and Fikkert, 1996; Rijesh, 2015). Considering the important role of FDI in transmitting foreign partners' R&D, a number of studies have explored the bearing of FDI on productivity by conceptualizing such impact as spillovers - horizontal or vertical. While some of the scholars highlight the positive spillover effects of FDI in developing countries (Eden et al 1997; Kokko et al 1996; Buckley et al 2002; Fu, 2008; Kathuria, 2002; Siddharthan and Lal, 2004; Malik, 2014; Marin and Sasidharan, 2015.) others have indicated negative effects on technological upgrading in the domestic firms.

The studies cited above focused mainly on the factors in the realm of technology that primarily emanate from formal scientific research through investment in R&D, leading to knowledge which is science based and codified. However, economists beginning with Adam Smith who described division of labour as the key source of productivity growth, recognised the role of non-technological factors. Thus viewed, there is reason to believe that along with technological innovation resulting from formal R&D and codified knowledge, experience-based knowledge which is often tacit and non-codified could be equally important in determining productivity.[1] If TFP is a progeny of scientific and non-scientific knowledge, analysis of its level and variation calls for an understanding of the process involved in the production of knowledge. To the extent that knowledge production is an outcome of learning process, any such enquiry would lead us to the doorsteps of innovation system perspective which has over time evolved as the most widely used approach in innovation studies. The IS approach considers knowledge as the key resource in the modern economy and is an outcome of interactive learning among different actors in the innovation system governed by the institutional context (Lundvall, 1992; Lundvall, 1988; Nelson, 1993, 2008). This approach towards innovation is beyond the conventional understanding of linkage between industry, academia and the government and encompasses broader user - producer interactions and other informal interactive learning that give rise to experience-based learning (Lundvall, 1992; Lundvall, 1988; Nelson, 1993, 2008). In a seminal paper, Jenson et al (2007) explicitly articulated two broad modes of interactive learning - Science Technology and Innovation (STI) mode of learning and Doing Using and Interacting (DUI) mode of learning- and highlighted their differential impact on innovation.

STI mode of learning

The STI mode of learning (Lundvall 2007; Jenson et al 2007; Lundvall 2017) emanates from science and R&D efforts that lead to codified scientific 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 (Nelson, 1993, Mowery and Oxley, 1995). In addition to R&D investments, STI mode of learning also takes place through technology licensing from actors that include universities, research laboratories and other firms. Knowledge generating actors could be either

[1] Neglect of such non-R&D based innovation in developing countries presumably has induced scholars to articulate innovation paradox (Ciera and Malony, 2017). They argued that very high potential return for R&D investment in developing countries notwithstanding, they invest much less in R&D.

domestic or foreign. International collaboration and technology licensing has been considered as a crucial aspect of technological capability building in developing countries (Lall, 1992, Basant, and Fikkert, 1996; Evenson and Joseph, 1999; Siddharthan; 1988). Since technology licensing both domestic and foreign involves payment in the form of royalty, technical fee and others, payments made by firm the firms could be an indicator of such STI mode of learning. The STI mode of learning with its crucial bearing on the innovation process, is shown to be most important in high technology industries such as pharmaceuticals, biotechnology, and nanomaterials (Freeman, 1982; Mowery and Oxley, 1995). The studies on innovation both in the developing and developed countries with their focus on R&D, patenting and such other organized forms of scientific knowledge generation have articulated innovation as an outcome of STI mode of learning. Accordingly, investment in R&D and other means of generating scientific knowledge have been at the core of S&T policy both in developing and developed countries. However, when it comes to developing countries, considering the role that technology import plays in building technological capability technology licensing have also been an important aspect of S&T policy.

DUI mode of learning

The analytical foundations of DUI mode of learning could be traced to the concept of tacit knowledge introduced by Polanyi (1967) and further articulated in the context of evolutionary economics by Nelson and Winter (1982). They have argued that much of the technological knowledge is not codified and that they are tacit and learned through experience. Thus viewed, in the production and research, much of engineering design practice involves solutions to problems that professional engineers have learned from 'work' without any particularly sophisticated understanding of why (Nelson (2004: 458). Such knowledge is confined to its owners and not easily accessible to others because their transfer and application is difficult. Hence the mastery of a technology may require a close and continuous interaction between the user and the producer of such knowledge (Giuliani et al 2005). Thus viewed, not all the important inputs into the process of innovation does not emanate from science and R&D efforts[2]. 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). 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 not only includes the learning from both formal and informal interactions internal to the firm, but also interactions with suppliers, customers and competitors outside the firm (Fitjar and Rodriguez-Pose, 2013)[3]. The literature on global value chains (Gereffi, 1999; Gereffi & Kaplinsky, 2001among others) highlight avenues open to local producers to learn from the global leaders to help upgrading or innovation (Giuliani et al 2005; Pietrobeli and Rabelloti 2011). Apart from Global Value Chains (GVCs), DUI mode of learning is also facilitated by foreign direct investment (Dunning, 1994; Lall, 1992; Eden et al 1997; Kokko et al 1996; Buckley et al 2002 among others). Considering the growing trend in the OFDI from developing countries including India (Sauvant 2008; Cantwell and Bernard 2008 among others) and its potential for interactive learning, one could consider such investment as conduit for DUI mode of learning. Yet another aspect of DUI learning is related to widely prevalent firm level strategy of staff training. While such trainings are primarily oriented towards enhancing workers efficiency and their productivity, this could lead to stock of experience-based knowledge mostly arising out of workers interaction with their counterparts elsewhere. Among the constituents of DUI mode of learning discussed above FDI and staff training could be considered as purposive and explicitly aimed at building firm’s core competence and knowledge. On the other hand, participation in GVC and import of capital goods are undertaken as part of the business routine and such interaction may be weakly related to knowledge generation (Fitjar and Rodríguez-Pose, 2013).

[2] 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.

[3]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 of Learning and Innovation Performance

Analyzing the relative role of STI and DUI mode of learning using the firm-level data from Denmark, Jenson et al (2007) found that firms combining a strong version of STI mode with a strong version of DUI mode excel in product innovation while weak STI and weak DUI mode contributes to process innovations. Characterizing STI mode as supply driven and DUI mode as demand driven, Isaksen and Nilsson (2013) observed that combined mode of learning with innovation policies and analysed the innovation performance in Sweden and Norway. While STI mode of learning enables building more research competence, 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. Further, they have also made distinction between different types of interaction within DUI mode and their differential impact on innovation. 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, a firm level analysis by Thoma (2017) showed the significant role of DUI mode of learning along with STI mode in contributing towards innovation activity in Germany.

Overall, there is reason to believe that the growing number of studies dissecting the mode of learning has contributed significantly to our understand on the differential impact of modes of learning on different types of innovation outcomes. It is also evident that these studies have provided with details on different forms of innovation and the underlying mode of learning. Though the nexus between productivity and innovation has been widely acknowledged in the literature, in the light above finding the question arises does the mode of learning matters in productivity – the major point of enquiry of this paper. Above discussion also suggest that the relative role of different modes of learning will be contingent on the industry characteristics. Hence, another point of enquiry by the present study is the differential impact of mode of learning on the productivity of industries with varying technological intensity.

3. Data

All the previous studies on mode of learning and innovation are based on data gathered through primary survey. In our study, we have made use of firm-level information from the Prowess[4] database provided by the Centre for Monitoring the Indian Economy and proxied the available the indicators of different modes of learning. 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. In our sample, we have considered firms in the manufacturing sector 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. We also dropped firms, which did not report 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, there were firms that did not report any information on variables such as research and development, purchase of technology, 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 the loss 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 (ASI). The data on tariffs across three-digit industries using HS-88 is obtained from UN-COMTRADE through WITS. We have concorded NIC 2008

[4]Prowess contains information primarily from the income statements and balance sheets of publicly listed companies.

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 constructed industry wise WPI drawn from economic advisory industry and WPI on capital formation from Central SO.

4. **Empirical strategy:**

We capture the impact of interactive learning in the form of STI and DUI mode on TFP in two-step procedure. First, we estimate total factor productivity (TFP) using a semi-parametric approach developed by Levinsohn and Petrin (2003). Second, we estimate the relative role of STI and DUI mode of learning in determining TFP. The details of the empirical methods are as follows.

4.1 Estimation of TFP

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.

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 use 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, but most plants in developing countries do not report positive levels of investment. There are zero investment values in the sample of our study. The sample of the study needs to be truncated if we employ the Olley–Pakes' approach to estimating 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).

$$y_t = \propto + \beta_l l_t + \beta_k k_t + \beta_m m_t + \beta_e e_t + \beta_s s_t + \omega_t + \mu_t \qquad (4)$$

where y_t , k_t ,l_t , m_t , $e_t$and s_t 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. Subscripts the firm and industry are not used for the notational convenience. 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 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.

4.2 Mode of Learning and Total Factor Productivity

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 stage equation may be specified as follows.

$$\log TFP_{ijt} = \propto + \beta_1 RDDUMMY_{ijt} + \beta_2 IDETD_{ijt} + \beta_3 DDETD_{ijt} + \beta_4 FEQUITY_{ijt} + \beta_5 STAFFDUMMY_{ijt} + \beta_6 ICGI_{ijt} + \beta_7 OFDI_{ijt} + \beta_8 GVC_{ijt} + \beta_9 TARIFF_{jt} + \beta_{10} LMRDUMMY_{ijt} + \beta_{11} AGE_{ijt} + \beta_{12} AGESQUARED_{ijt} + \Omega_j + \mathcal{E}_t + \mu_{ijt} \quad (2)$$

Where Ω_j and $\mathcal{E}_t$ are industry and time fixed effects respectively (see Table 1 for description of variables). Since the focus of this paper is to analyse the impact of firm's learning capabilities on TFP, the major concern in the analysis is to address the problem of endogeneity. The unobserved firm characteristics may affect both TFP and some of our regressors like R&D, technology purchases, participation in GVC, leading to spurious correlation between the two. Endogeneity and biased results may also arise when unobservable time-invariant firm effects are correlated with regressors in the empirical model. Most important concern in our specification is reverse causality or simultaneity bias. In our specified model, we are concerned about the reverse causality between TFP and R&D, OFDI, technology purchases and imports, participation in GVC and training workers. In such cases, the endogenous variables are likely to be correlated with the error term, generating inefficient estimators. The other potential problems could be the correlation of time invariant fixed effects with the independent variables and the autocorrelation as the past values of the dependent variable and are expected to have a significant effect on current values. This is simply because firm's TFP today would be influenced by their past. In order to address these econometric problems, this paper employs the dynamic panel data model based on the system GMM method initiated by

Arellano and Bover (1995) and fully developed by Blundell and Bond (1998). The GMM estimators, by using more information on data, provide consistent and efficient estimators as compared to the method of instrumental variables and solves the problem of autocorrelation, heteroscedasticity, specification errors, etc. While the dynamic panel model and fist-differencing can solve the serial correlation problem, the system GMM can control the issue of endogeneity by including lagged versions of repressors as instruments. The presence of autocorrelation problem and validity of instruments are tested by applying the Arellano-Bond (1991) test for auto-covariance and the Sargan test (1958) of over-identifying restrictions respectively. The system GMM model in our case can be specified as follows.

$$\Delta \log TFP_{ijt} = \alpha + \beta_1 \Delta \log TFP_{ijt-1} + \beta_2 \Delta RDDUMMY_{ijt} + \beta_3\ \Delta IDETD_{ijt} + \beta_4 \Delta DDETD_{ijt} + \beta_5\ \Delta STAFFDUMMY_{ijt} + \beta_6 \Delta FEQUITY_{ijt} + \beta_7 \Delta ICGI_{ijt} + \beta_8 \Delta OFDI_{ijt} + \beta_9\ \Delta GVC_{ijt} + \beta_{10} \Delta TARIFF_{jt} + \beta_{11} \Delta LMRDUMMY_{ijt} + \beta_{12} \Delta AGE_{ijt} + \beta_{13}\ \Delta AGESQUARED_{ijt} + \Delta \mathcal{E}_t + \Delta \mu_{it} \qquad (3)$$

In the initial dynamic panel data model, developed by Arellano-Bond (1991) includes lagged values as instruments for the endogenous variables, which are considered as poor instruments for first differenced variables. In the system GMM, as propounded by Arellano and Bover (1995) and Blundell and Bond (1998), the estimators include lagged levels as well as lagged differences. While lagged differences of endogenous variables are used as instruments in the level equation, lagged levels of the endogenous variables are used as instruments in the first differenced equation thereby controlling the endogeneity of explanatory variables. Thus, the Arellano-Bover/Blundell-Bond estimators augment the Arellano-Bond estimators by making an additional assumption, that the first differences of instruments are uncorrelated with the fixed effects (Roodman, 2006). It is argued that the introduction of more instruments improves efficiency of the estimators considerably. In our analysis, the lagged logTFP as well as RDI, IDETD, DDETD, STAFFDUMMY, OFDI, and GVC are considered as endogenous variables. The two-step estimators with robust standard errors, clustered at the firm-level are used for testing specification and overall significance of the estimated model as they yield standard errors that are asymptotically robust to both heteroscedasticity and autocorrelation. We also use the 'orthog' option (Arellano and Bover, 1995) which preserves the sample size in unbalanced panels by subtracting the average of all available future observations, rather than subtracting the previous observation from the current one. In our model, inclusion of one-year lagged value of the dependent variable as one of the explanatory variables accounts for the dynamic effects. Two-year lagged values of the dependent variable and two lagged values of the endogenous variables are used as the instruments to control the endogeneity problem. We include time dummies in all our models since the assumption of no correlation across individuals in the idiosyncratic disturbances, as made by the AR test and robust estimates, is more likely to hold if time effects are included. In system GMM, we can include time-invariant regressors, such as industry dummies, which cannot be included in difference-GMM. Asymptotically excluding them does not affect the coefficient estimates of other regressors because all instruments for the levels equations are assumed to be orthogonal to fixed effects. The system GMM estimates are considered robust subject to satisfying some tests on the validity of instruments and serial correlation problem. First, we must ensure that the instruments used in the analysis to control for the endogeneity are jointly valid using the Hansen test of overidentification. Secondly, the first order autocorrelation of the residuals (AR 1 test) needs to be rejected; and the second order autocorrelation (AR 2 test) needs to be accepted. Towards estimating the model specified in equation 3 using the system GMM method, we use *xtabond2* in STATA as developed by Roodman (2006).

5 Empirical Results and discussion

To recap, the main concerns of the paper are the bearing of mode of learning on firm level productivity performance and inter industry variation therein. The pioneering study (Jenson et al, 2007) on mode of learning and innovation in the case of a developed country using logistic regression has shown that while a strong version either STI or DUI contributes to innovation, mixed strategy of combining two mode tend to perform significantly better than those relying predominately on either mode. Table 1 presents a mapping of nine different combination of learning strategies. The combination of learning strategies is defined as follows. A firm could adopt no STI, weak STI or strong STI and no

DUI, weak DUI or strong DUI. In this article, we define no STI and no DUI if a firm is not investing in any of the elements STI and DUI mode of learning. Similarly, weak STI and weak DUI refers to firms which are investing in at least one element in STI mode and one element in DUI mode. Finally, strong STI and strong DUI refers to firms investing in at least two elements in STI mode and DUI mode. Using these three combinations, we arrive at nine combinations of learning strategies (see, Table 3).

Table 1: Variable Construction

Type of interaction	**Proxy**	**Construction of the variables**	**Source**
STI	RDDUMMY	Value 1 if firm invests in R&D and 0 otherwise	Prowess
STI	IDETD	Purchase on royalties and licences from foreign entities as a proportion of sales	Prowess
STI	DDETD	Purchase on royalties and licences from domestic entities as a proportion of sales	Prowess
DUI	STAFFD	The value takes 1 if a firm reports staff training expenses and 0 otherwise.	Prowess
DUI	GVA	Value is 1 if a firm imports raw-materials and spares and exports simultaneously	Prowess
DUI	ICGI	Import of capital goods as a percentage of sales	
DUI	FFIRMDUMMY	The value takes 1 if foreign equity share holding is more than 10 per cent and 0 otherwise	Prowess
DUI	MINORITY	The value takes 1 if foreign equity share holding is more than 10 and less than 50 per cent and 0 otherwise	Prowess
DUI	MAJORITY	The value takes 1 if foreign equity share holding is more than 50 per cent and 0 otherwise	Prowess
DUI	OFDI	Value 1 if a firm invests in outward foreign direct investment	Prowess
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	Gupta et al (2009)
Firm specific controls	AGE	Reporting year – year of incorporation	Prowess
Firm specific controls	AGE Squared	Square root of Age	Prowess

It is evident that the mode of learning and innovation behavior of firms in India's manufacturing sector broadly in sync with finding of Jenson et al (2007). Our findings indicate that the firms that combine a strong version STI and a strong version DUI record the highest productivity performance. However, it is important to note that firms that adopt such a learning strategy are found to be very small proportion in our sample. The predominant learning strategies are a) no STI and weak DUI, b) no STI and strong DUI and c) weak STI and strong DUI. Looking at the estimated mean TFP values of firms belonging to above three categories, it could be inferred that with strong DUI (b & c) firms are able to record mean TFP of 2.6 and 2.8 respectively which is only marginally lower than firms resorting to strong STI. This finding that finding that firms could record high TFP performance is in accordance with the finding of Jenson et al (2007) and Fitjar and Rodríguez-Pose (2013)

Our finding that firms in Indian manufacturing sector by and large resort to DUI mode of learning and firm that invest in STI are small in number is also in tune with the argument of Cirera and Maloney (2017). They observed that developing countries invest less in R&D despite high returns associated with R&D investments and articulated this pattern as innovation paradox. Our analysis using innovation system perspective could provide a credible explanation for this paradox based on the learning productivity performance of firms. If the firms could achieve high productivity simply adopting a strong DUI and weak or no STI mode of learning, there is no reason why profit motivated firms invest in STI mode of learning which is shown to be risky. This, however, needs further empirical verification and a definite conclusion is not warranted.

Table 2: Summary Statistics of Combination of Learning Strategies

Learning Strategy	**Observations**	**Mean TFP**	**Std. Dev.**	**Min**	**Max**
No STI No DUI	73	20.38	14.54	-01.9	56.8
No STI Weak DUI	20,984	21.66	09.64	-32.5	73.1
No STI Strong DUI	**19,098**	**26.12**	**07.50**	**-06.5**	**68.4**
Weak STI No DUI	5	08.51	13.02	-12.3	23.7
Weak STI Weak DUI	5,999	25.38	08.66	-10.7	57.4
Weak STI strong DUI	**16,619**	**28.20**	**07.01**	**-06.4**	**61.1**
Strong STI No DUI	0	00.00	00.00	00.0	0.00
Strong STI Weak DUI	**173**	**31.45**	**08.41**	**12.4**	**53.3**
Strong STI Strong DUI	2,700	32.68	06.82	11.3	58.7

As already shown firm's learning strategy has a crucial bearing on productivity. As articulated in the literature, the combination of learning strategy is contingent on the industry wherein it operates especially the technological intensity. Thus viewed, mode of learning as part of the knowledge management strategy that the firm adopts will vary from high-tech to low-tech industries. Analysis of the TFP performance across different categories revealed that not only with respect to levels but also with respect growth of TFP high tech industries display a better performance in comparison with low-tech and medium-tech industries (Table 3).

Table 3: Mean TFP across different industry classification

	Total Manufacturing	Low Tech	Medium Tech	High Tech
2001	15.18	16.52	15.86	13.14
2002	14.29	14.88	15.09	12.83
2003	13.77	13.79	14.67	12.81
2004	13.86	13.50	14.65	13.39
2005	15.30	13.86	16.79	15.20
2006	15.54	14.15	16.01	16.55
2007	16.83	15.20	16.86	18.62
2008	17.44	15.57	17.25	19.76
2009	17.63	15.07	18.27	19.71
2010	17.76	16.00	17.30	20.23
2011	19.07	17.17	18.03	22.30
2012	20.16	18.02	19.31	23.30
2013	21.35	20.08	19.99	24.08
2014	22.73	22.97	20.86	24.44
2015	23.95	25.43	21.26	25.35
2016	24.38	25.23	20.59	27.30
2017	25.33	25.23	21.54	29.37
Average Annual Growth	3.34	2.89	2.06	5.25

Let us now turn to the results of the econometric analysis on the relative role of different modes of learning on firm's productivity. One of the common findings of the literature dealing with mode of learning and innovation is the role of STI and DUI mode of learning in the firm's knowledge management strategy to be innovative (Jensen et al., 2007; Aslesen et al., 2011; Chen et al., 2011; Isaksen and Karlsen, 2012; Isaksen and Nilsson, 2013;

Apanasovich, 2014). More importantly the studies have noted that the combined STI&DUI mode is the most beneficial in all types of innovation, including technological, radical and non- technological innovation (Parelli and Heras, 2016). Results of model 1 which pertains to the manufacturing sector as a whole is in conformity with the findings of earlier studies. The results highlight the significant impact of both STI and DUI mode of learning. All the elements in the STI mode and DUI mode are found to be positive and statistically significant. This finding underlines the need for innovation and policy agenda that goes beyond the narrow linear approach with emphasis on R&D and patenting to a broader approach that recognize relevance of DUI mode of learning.

With respect inter-industry variation in the observed firm level knowledge management strategy through mode of learning and its impact on productivity, earlier studies have shown that STI mode of learning contributes more towards technological innovation in knowledge intensive industries. Whereas DUI mode of learning contributes more towards non-technological innovation. Our results for industry groups with varying technological intensity shows that STI mode of learning is instrumental in productivity growth in high technology and medium technology industries with all the STI variables are found to be positive and statistically significant. In contrast when it comes to low tech industries, none of the STI variables are found to be statistically significant tending to suggest that knowledge management strategy of firms in low tech industries focus mainly on DUI mode of learning for attaining high productivity. Whether such learning strategy results in technological or non-technological innovation is an issue that needs separate enquiry.

Table 4: System-GMM estimates of determinants of TFP

VARIABLES	(1) Total Manufacturing	(2) Low Tech	(3) Medium Tech	(4) High Tech
L.LNTFPOUTPUT	0.853***	0.900***	0.793***	0.847***
	(0.0116)	(0.0180)	(0.0222)	(0.0146)
RDDUMMY	0.0315***	0.0146	0.0347***	0.0503***
	(0.00609)	(0.0113)	(0.0121)	(0.0103)
IDETD	0.0275***	0.00860	0.0503***	0.0387***
	(0.00956)	(0.0201)	(0.0146)	(0.0138)
DDETD	0.0272***	0.0125	0.0298***	0.0267***
	(0.00703)	(0.0129)	(0.0106)	(0.00972)

ICGI	0.729***	0.279	-0.148	0.909*
	(0.267)	(0.259)	(0.452)	(0.495)
STAFFTD	0.258*	0.612***	-0.0250	-0.0522
	(0.141)	(0.195)	(0.122)	(0.123)
BASE: NO FOREIGN SHARES				
MINORITY SHARES	0.0119	0.0175	0.00900	0.00271
	(0.0163)	(0.0291)	(0.0341)	(0.0280)
MAJORITY SHARES	0.0695***	0.0113	0.0782**	0.0550*
	(0.0179)	(0.0441)	(0.0359)	(0.0281)
OFDIDUMMY	0.0302***	0.0123	0.0505***	0.0307**
	(0.00871)	(0.0134)	(0.0149)	(0.0137)
GVC	0.0148**	0.0239**	0.0555***	0.0274***
	(0.00641)	(0.0103)	(0.0114)	(0.00972)
AGE	-0.0119***	-0.00197	-0.0167***	-0.0125***
	(0.00163)	(0.00240)	(0.00286)	(0.00317)
AGESQUARED	0.000130***	9.95e-06	0.000206***	0.000146***
	(1.98e-05)	(2.60e-05)	(3.94e-05)	(4.35e-05)
TARIFF	-0.00284***	0.000364	-0.00338***	-0.00482***
	(0.000348)	(0.000447)	(0.000489)	(0.000613)
BASE: WORKER FRIENDLY STATES				
EMPLOYER FRIENDLY STATES	-0.0506	-0.0618*	4.08e-05	0.0153
	(0.0362)	(0.0367)	(0.0348)	(0.0260)
NEUTRAL STATES	-0.0682	-0.0739	-0.0316	0.0335
	(0.0644)	(0.0565)	(0.0574)	(0.0504)
Constant	0.510***	0.243***	0.801***	0.642***
	(0.0544)	(0.0567)	(0.0797)	(0.117)
Observations	56,343	18,329	19,792	18,222
Wald Statistic	14027.18	11942.82	5486.54	14027.18
	(0.00)	(0.00)	(0.00)	(0.00)
Arellano-Bond test for AR(1)	-29.60	-16.13	-17.85	-16.20
	(0.000)	(0.000)	(0.000)	(0.000)
Arellano-Bond test for AR(2)	-1.39	-0.08	-0.14	-1.26
	(0.166)	(0.934)	(0.891)	(0.18)
Lag Structure	(2, 2)	(2, 2)	(2, 2)	(2, 2)
Standard errors	Two-step robust clustered on firms	Two-step robust clustered on firms	Two-step robust clustered on firms	Two-step robust clustered on firms
Number of firms	6,175	2,094	2,146	1,935
Firm FE	YES	YES	YES	YES
Year FE	Yes	Yes	Yes	Yes

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

6 Conclusion and policy implications

Differences in productivity performance within across countries has been an issue that attracted much scholarly attention. There is a consensus that productivity is a progeny of innovation. Empirical literature within the National Innovation System perspective, analyzing the knowledge management strategy of firms as manifested in their choice of their mode of learning and its influence on the innovation outcomes is gaining prominence. Taking que from this literature, the present study analysed the bearing of STI mode of learning and DUI mode of learning on the firm level productivity performance. The study also analyzed variation in the firm level learning strategies across industries.

The present study made use of firm level data from India's manufacturing sector. The analysis has been undertaken at three different levels. To begin with we have estimated TFP using the Levinson and Patrin (2003) method that controls for endogeneity. Secondly, we 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. Thirdly, we analysed the role of these indicators of interactive learning-based knowledge on productivity across industries with varying levels of technological intensity.

The contributions of the study could be seen from both analytical and policy perspective. Analytically, this is the first attempt towards understanding the productivity performance using innovation system perspective. The study highlights that a knowledge management strategy of a firm involving a strong version of both STI and DUI mode of learning is associated with highest productivity performance. The analysis thus validates the hypothesis that both STI and DUI-modes of interaction matter for productivity. Yet, the most predominant learning strategies for productivity enhancement involves the adoption of combination of strong DUI with either weak or no STI. The study also highlights the importance of non-scientific interactions which comes under DUI mode in enhancing the productivity performance. The study tends to suggest that the firms focusing on developing their science and technology base are reaping much dividend by resorting to learning strategies under DUI mode. By highlighting the key role of DUI mode of learning in productivity performance in all types of industries, the present study is able to provide some insights in addressing the productivity paradox in developing countries articulated by Maloney and Ciera (2017). Based on this study it could be argued that firms tend to invest much less in R&D not withstanding the high return from such investment because the firms could manage to achieve high productivity a strong DUI mode of learning with coupled with weak STI or no STI.

The empirical studies on mode of learning and innovation has provided much insights towards policy making in the case of developed countries like Sweden (, Norway(, Germany and Denmark. The findings of this study are also of much relevance for informed policy making in India and other developing countries. Going by the findings of the present study, it could be argued that the focus of innovation policy shall not be premised on the linear approach with its emphasis on R&D, patenting and such other scientific knowledge generating processes since its outcomes could be suboptimal. If the national innovation policies were to be informed by the firm's learning strategy to increase their productivity, the policy need to have greater focus on promoting DUI mode.

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Appendix

A1. 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 the lack of data on a 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 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).

A.2 Descriptive Statistics

Table A1: Descriptive Statistics of Production function variables					
Variable	Observations	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: Production function estimates using Energy and Services as Proxy	
	(1)
VARIABLES	LP
lnLabor	0.119***
	(0.00386)
lnRRM	0.151***
	(0.0126)
lnNFA	0.416***
	(0.0161)
Observations	64,190

Table A3: Summary statistics of the determinants of TFP					
Variable	Observations	Mean	Std. Dev.	Min	Max
LNTFP	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
GVA	67,103	0.12	0.23	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