Does patenting influence firm's efficiency and productivity? : Evidence from Indian high and medium-tech firms

Abstract

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The aim of the paper is to study the impact of patenting on productivity of 489 high and medium-technology firms in India using firm level data for the period 1995-2010. For calculating the efficiency and productivity of firms, we employ the frontier non-parametric estimation method. We apply the Data Envelopment Analysis (DEA) based Malmquist productivity index (MPI) to measure the productivity change that consists of efficiency change and technical change. This index helps in understanding whether the improvement in firms is attained through the adoption of new technologies (technical change) or catching up with the efficient one (efficiency change). The study employs relatively new source of data particularly in the context of India, firm level patent granted, that has not been explored earlier. The study finds that majority of Indian firms are suboptimal and their efficiency levels have improved during the study period. We also find an evidence of impact of patenting on firms productivity whereas R&D have a little impact.

Keywords: Innovation, R&D, Patent, and productivity.

1. Introduction

Innovation is regarded as an output, resulting from inputs, where physical capital, human capital, R&D, and economies of scale all play major roles (Mokyr, J. 2010). The fraction of productivity growth that cannot be explained through labour and capital is attributed to technical change that results from innovation. Various studies investigate the link between innovation and productivity of firms due to increase in availability of firm level data as well as the methodological improvements (Bartelsman and Doms 2000). Existing literature on firm level productivity used two measures of innovative activity: R&D spending and patent counts (Hall 2011). Researchers who express their views regarding a direct link between

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R&D and productivity argue that investment in knowledge capital contribute positively to the performance of firms (Mansfield 1984; Griliches and Mairesse 1984; Raut 1995). The second category of researchers believe that it is not innovation input but output that lead to higher performance of firms (Deolalikar and Roller 1989; Eaton and Kortum 1996; Crepon et al. 1998). Though there are many studies that examine the link between both aspects of productivity, studies associate with patent and productivity are scarce especially in the Indian context (Deolalikar and Roller 1989 is an exception and their study preliminary based on 1974-79 data). Therefore, the present study considers India as a research context to examine the relationship between productivity and patenting by high and medium technology firms during 2000-2010.

Studies on efficiency and productivity on Indian firms generally used three digit industry level aggregate panel data (Raut 1995) as well as firm level data (Golder 1986; Deolalikar and Roller 1989; Sharma 2010 & 2011). Many of the studies do not examine the relationship between patent and productivity of firms. Patents are considered as a measure of inventive output (Griliches 1990). Moreover, the endogenity theory of economic growth discussed in Romer (1986, 1990) and Aghion and Howitt (1992) show that accumulation of knowledge leads to economic growth and monopoly rights emerges through patents incentivize knowledge creation. Therefore, we intend to study the influence of patenting on the efficiency levels of firm. In this paper, we use a panel of 489 firms for high and medium technology sectors to estimate the technical efficiency and changes in productivity of firms due to patenting. The study finds that patenting by firms has an influence on their efficiency levels whereas R&D is insignificant. Further, majority of Indian firms are suboptimal and there is an indication of overall efficiency improvement of the firms in the industry.

The rest of the study is organized into 5 sections. Section 2 provides some theoretical linkages and empirical evidence of the study. Section 3 provides an overview of the research methodology applied in the study. Subsection 3.1 and 3.2 provide the brief introduction of DEA and Tobit analysis respectively. Section 4 focuses on description on data and variable used in the study. Section 5 presents the results and analysis. Section 6 offers some concluding remarks.

2. The theoretical linkage and empirical evidence

Technical efficiency, the ratio of the actual output to the maximum producible output and productivity, the ratio of volume of output produced to the quantities of input are the most commonly used and easily understood measures of the firm’s performance. Theories on technological innovation at the firm level consider both research input in the form of R&D investment and output in the form of patent contribute the higher performance (Kamien and Schwartz 1982: Griliches 1987; Crepon et al. 1998). One argument is that, accumulation of knowledge through R&D investment directly influences the productivity of firms (Mansfield 1984; Griliches and Mairesse 1984; Cuneo and Mairesse 1984; Coe and Helpman 1993; Doraszelski and Jaumandreu 2011). In case of R&D –productivity relationship, Mansfield (1984) shows that both domestic and overseas R&D increases the productivity of U.S. firms whereas the study of Griliches and Mairesse 1984 prove that the relationship between R&D and productivity hold only in cross sectional dimension, not over a period of time. As a companion study to that of Griliches and Mairesse (1984), Cuneo and Mairesse (1984) uses similar framework to test the hypothesis in the French manufacturing industry during 1972-77. The authors have arrived at a similar conclusion that the result is valid only in cross sectional dimensions. Coe and Helpman (1993) have concluded that there is a convincing empirical evidence of the influence of cumulative R&D in determining the TFP. Doraszelski and Jaumandreu (2011) estimate the link between R&D and productivity in the context of uncertainty, nonlinearity and heterogeneity. This study uses data from 1800 Spanish manufacturing firms in nine industries during 1990s shows the key role of R&D expenditure in determining the differences in productivity across firms.

Another set of studies establish a structural relationship between R&D investment and patenting where R&D leads to innovation in the form of patenting and the patents further contribute to the productivity (Deolalikar and Roller 1989; Crepon et al. 1998; Griffith et al. 2006; Benavente 2006). As a first study in Indian context, Deolalikar and Roller (1989) study clearly distinguishes between inventive inputs and inventive outputs while looking at the impact of innovation on firm performance. The study argues that patenting has a significant impact on productivity growth across firms even though there was a limited scope of patent protection. In a cross country analysis, Eaton and Kortum (1996) find that the relative productivity of a country is determined by its ability to make use of a new invention. This implies that the innovation output leads to better performance of a unit. The study of Crepon et al. (1998) also finds that firm's productivity positively correlates with the number of patent application. Similarly, Griffith et al. (2006) also formulates a structural model where they assume that investment in R&D leads to innovation in the form of product and process. The study further shows that innovation contributes to improve the productivity of firms but vary between countries. The estimated coefficients of process innovation are significant only in one country while the product innovation is significant in three out of four countries. As a contrary to the previous studies, Benavente (2006) find that neither research expenditure nor innovation has a significant impact on firm's productivity in Chile. Santarelli and Lotti (2008) based on 58 Italian biotechnology firms during 1990s show that productivity is positively influenced by innovation output measured through patent.

The empirical evidence explained above is quite ambiguous in terms of influence of R&D and patenting on firms productivity. Researchers produce several reasons for differences in the impact of R&D and patenting on productivity (Atella and Quintieri 2001). The measurement and definition of TFP may itself lead to certain biases as some models like growth accounting put forth some strong assumptions which are not representative of the real world. The models consider perfect competition, absence of scale economies and short- run flexibilities are some of the assumptions. Secondly, biases may arise when a researcher adopts unique production function for different sectors. Normally, the manufacturing sector is disaggregated into several industries and an analysis based on the data representing the whole manufacturing sector may lead to biases. While keeping in mind the above discussion, the present study estimates the influence of patenting by firms on their productivity. Initially, we have estimated technical efficiency of each firm through non parametric data envelopment analysis (DEA). The study then estimate the determinants of technical efficiency where innovative variable like R&D spending, patenting by firms and other firm specific as well as industry specific variables consider as major explanatory variables (Jackson and Fethi 2000; Fethi et al.2000). These determinants help to identify the impact of innovation on firm productivity.

3. Research methodology

Akin to Luoma et al. (1998) and Fethi et al. (2000) the present study follows a two-stage approach, in which the first stage involves the specification and estimation of technical efficiency and in the second stage we use Tobit regression model to explain the technical efficiencies. In the first stage, we rely on Data Envelopment Analysis (DEA) to estimate technical efficiency. Further, we estimate DEA based Malmquist productivity index to understand the sources of TFP. DEA is a frontier non- parametric analytical tool that empirically measures the relative efficiency of a decision making units (DMUs)[1].The frontier approach assumes that, there exists a best practice production function corresponding to the set of maximum attainable output levels for a given combination of inputs. Aigner, Lovell and Schmidt (1977) and Meeusen and Van- den Broeck (1997) have independently contributed to the econometric modeling of the frontier production function and paved the way for theoretical research and empirical application of the model to many different industries. Stochastic frontier approach is the other way to estimate the productivity under frontier analysis[2].

We select DEA as an appropriate method for the present study due to the following reason. First, it does not require any functional specification as it looks for a best practice frontier within the data rather than considering the average path through the middle points of a series of data. Second, as stated by Beveren (2010) DEA is preferable to other models when the measurement errors are small, technology is heterogeneous and returns to scale are not constant. Third, DEA is appropriated when the relative importance of various inputs and output cannot be defined. In our case, absence of available market prices limits allotting the respective weights to various inputs in the production process. DEA however, overcome this problem by allowing each DMU to choose the vectors of input and output weights, which maximizes its own ratio of weighted output to weighted inputs subject to the constraints. Fourth, DEA does not require any specific functional form. It is useful in our case as we do not know the precise interrelationships between inputs and outputs. Finally, literatures consider no approach is superior to others while calculating TFP (Lovell 1993; Kathuria et al. 2013). The decision to choose frontier or the non frontier approach depends on the research question. If the intention of a researcher is to estimate the contribution made by each factor of production to productivity, the non frontier approach is considered as superior to frontier analysis. On the contrary, if the researcher would like to estimate the best practice output

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[1] Farell (1957) originally developed the idea of measuring efficiency as a relative distance from frontier through a non parametric approach. Later, Charnes, Cooper and Rhodes (1978) extended the frame work and gave the name DEA.

[2] In the frame work of frontier and non-frontier approaches, researchers and policy makers employed parametric, semi-parametric and non-parametric method to analyze the productivity and efficiency of different Decision Making Units (DMUs). Mahadevan (2003) and Kathuria et al. (2013) provides a detailed explanation of these approaches.

level frontier analysis is considered as the best method. Lastly, DEA method helps us to identify the sources of TFP growth.

The above explained special features of DEA have acquired attraction from many researchers (Korhonen et al.2001; Wang and Huang 2007). In Indian context, productivity measurement studies have been popularized even before the introduction of new economic reform in 1991 (Goldar 1986; Ahluwalia 1991) while the DEA method was popularized after Ray (2002) who used the method to estimate the technical efficiency of firms after the reform period. Since then, there are numerous studies that employ DEA technique to estimate the efficiency and productivity growth in Indian manufacturing (Kumar 2005; Marjit and Kar 2009; Raj 2011; Raj and Babu 2011). These studies however, deal with productivity of either Indian states or organized/unorganized sector as a research context.

3.1. An illustration of Data Envelopment Analysis

Firms normally seek to increase their market share which enables them to acquire some degree of monopoly power. Therefore, the present study considers output maximization as a firm's objective. We consider the conventional DEA framework where labour and capital are the two inputs and deflated sale is the output for the study. DEA constructs an efficient frontier composed of those firms that produces as much output as possible from given the input levels. Firms at the frontier are efficient while those below are inefficient. Further, the efficiency score depends on how well a DMU performs over other firms[3].

3.2. Two-limit Tobit estimation

In the second stage studies follow censored regression model (Tobit model) since the dependent variable is limited in between 0 and 1 (Luoma et al.1996; Gillen and Lall 1997). In this stage, these estimated efficiency scores are explained through a set of variables those are expected to influence the performance of firms. Corroborating with earlier studies, the present study also conducts Tobit estimation for explaining the efficiency of Indian high and medium-high tech firms. Tobit model is a censored normal regression model, censoring from below at zero (Cameron and Trivedi 2010). The underlying model is:

$$y^* = X^! \beta + \varepsilon \qquad (11)$$

[3] A brief illustration of DEA algebraic formulation for one output and multiple inputs is given in Appendix 1.

Where y* is a continuous latent variable ranging between 0 and 1, X is a matrix of explanatory variables, β is a vector of coefficients to be estimated and ε is vector of error terms which is normally distributed with mean 0 and variance σ^2. Since our dependent variable is censored from both below and above we apply a two-limit Tobit model (Cameron and Trivedi 2010). Hence, our model will become:

$$\begin{aligned} y &= 0 && \text{if } y^* \leq 0 \\ y &= y^* && \text{if } 0 < y^* < 1 \\ y &= 1 && \text{if } y^* \geq 1 \end{aligned} \tag{12}$$

4. Data and variable description

The research setting of the study is the firms from medium and high- technology industries in India, the relative research intensive sectors. Particularly, we focus on firms which are producing consistent data on input and output variables. The main source of data for our study is the website of Controller General of Design, Trademark and Patent (CGDTP). All patent data used in this study are based on patent granted to each firm at the Indian Patent office (IPO). We arrange all the patents based on the application date on the assumption that there is no time lag between patent application and completed invention. Center for Monitoring Indian Economy (CMIE) prowess data base is used to collect all firm level information and all firms' variables are deflated with appropriate deflators. Sales data is deflated by industry specific Whole Sale Price (WPI) index. The index is obtained from the website of Office of economic advisor (OEA), the Ministry of Commerce and Industry. The capital data is deflated by the capital deflator and index number of industrial production is obtained from Handbook of Statistics on Indian Economy (RBI).

4.1. Input and output variables

In this study, similar to Mahadevan (2001) one output and two input variables are used. Deflated net sale, sales net of indirect taxes, is the output variable for DEA. The argument in favor of net sale is that indirect taxes are imposed by government and therefore not reflected in the productive capacity or the operation of the company. We consider two conventional inputs namely, labour and capital for the DEA. For capital we do consider Net fixed asset (NFA) akin to the previous study (Sharma 2011). NFA comprise of net of tangible assets, land and buildings, plant and machinery, transport and communications, furniture and other fixed assets. The advantage of using NFA as a capital is that the value is given in stock format and allowed for normal depreciation[4]. Since we do not have direct information of labours, we constructed the labours information as follows by (Sharma 2010). We obtain average wage rate (wages for the workers/number of workers) of each industry from the Annual Survey of Industries (ASI) database and each firm's salaries and wages divided by the average wage rate obtained from ASI, which provides the number of labour employed by firm.

4.2. Determinants of productivity and efficiency

The technical efficiency scores obtained from the first stage regression are explained through relevant variables includes the factors other than labor and capital that are likely to affect the efficiency levels across the DMUs. Based on the extensive literature survey, we identified the variables that can explain the productivity of manufacturing firms. Similar to Deolalikar and Roller (1989) and Crepon et al. (1998) we consider patenting by firms as the major determinant of firms differences in efficiency. Chang et al. (2013) find that the level of patenting has a significant effect on TFP growth. The study considers stock of patent as a measure of countries knowledge stock. In our study, we adapt the concept from Chang et al (2013) to construct the firm level knowledge stock (PAT) through their grated patent. Firms invest in R&D activities by expecting the product, process or organizational innovation, all of which together contribute in increasing the productivity. Hence we consider R&D stock (RDS) as one of the explanatory variables that determines the level of efficiency of firms[5&6].

Many researchers consider the impact of foreign ownership (FOS) on the level of efficiency. Aitkin and Harrison (1999) and Arnold and Javorick (2005) have find that foreign ownership leads to a significant improvements in productivity. Age (AGE) and size (SIZE) of a firm also has an influence on efficiency level. Mengistae (1995) finds that the efficiency of a firm positively influenced by its age implies the impact of firms experience on firm's efficiency improvement. Contrary to the finding, Ahmed and Ahmed (2013) argue that big size and old age is a source of inefficiency of firms. In case of market concentration, there is no

[4] The depreciation rate applied to the assets when creating the accounts at the end of each financial year though depends on the discretion of the company but should comply with the prescriptive rates given in the companies act. Further, companies need to comply with Income Tax Act while depreciating their assets. Since NFA comprises of many components, the depreciation rates are different for each of these components.

[5] R&D stock has been constructed through perpetual inventory method, the process outlined by Levinsohn and Petrin (2003). Specifically, we calculate R&D stock as $R_t = I_t + (1-\delta)R_{t-1}$

Where R_t =stock of R&D, I_t R&D investment made at time *t* and δ is the 15% depreciation rate .

[6] In order to check the likely occurrence of multicollinearity in between R&D and patents, we introduce these variables separately in the model.

unanimous opinion among the researchers. Several studies attempt to clarify the relationship between concentration and innovation but studies have found some positive (Scherer 1967; Angelmar 1985), negative (Connolly and Hirschey 1984) and modest (Scherer 1965; Levin et al.1985) relationship. Therefore, the present study uses Herfindahl Hirschman Index (HHI) as a concentration variable. Further, we use market growth rate (MGR) and export intensity (EXPI) as control variables because if reflect market condition in each industry.

5. Results and analysis

5.1. DEA results

Table 1 reports the frequency distribution of TE calculated annually for each sector. The first column represents number of firms in each sector along with the group name. Considering TE, we categories the firm as optimal, suboptimal and least efficient depending upon the efficiency score equal to 1, between 0.99-0.75 and less that 0.74 respectively. The analysis shows that most firm for all sectors are in the range of 0.99-0.75, reflecting that inefficient firm may not sustain for long in the industry. This result should be understood in view of the data cleaning process that we followed where we removed all loss making units. The medical and motor sectors are the most efficient with 62.5% and 60% of firms respectively in the suboptimal category in 2000. However, we will not use data on motor and medical sectors for further analysis as the number of firms in this case is small. In case, the minimum number of firms chosen for DEA is less than 3 times of total number of inputs and outputs, the probability of an inefficient firm being declare as efficient increases. Therefore, it is not desirable to compare the efficiency levels of firms across industries as the number of firms in each sector vary between 5 and 159. However, a comparison of industries over the years is possible as the number of firms remain constant. The analysis shows efficiency improvement in chemical sector where the number of efficient firms doubles in 2010 compared to 2000. Similarly, firms in pharma sector have also improved their efficiency during the same period. One positive sign in all the sectors is that the firms with the efficiency level below 0 .75 has been reduced significantly during the study period. The study further investigates the efficiency differential of the foreign and domestic firms but does not find any significant difference. Only foreign firms from pharma and chemical sectors are technically efficient than the domestic firms (Table 4).

Table 1: Frequency distribution VRS TE

I	Range of firms	Year										
		2000	01	02	03	04	05	06	07	08	09	2010
Pharma	1	**7**	**11**	**11**	**9**	**10**	**8**	**8**	**9**	**7**	**7**	**11**
(83)	0.75-0.99	56	55	62	59	57	57	58	57	58	60	62
	<0.74	20	17	10	15	16	18	17	17	18	16	10
RTC	1	**8**	**9**	**9**	**7**	**7**	**10**	**12**	**11**	**7**	**7**	**7**
(19)	0.75-0.99	10	8	8	9	10	8	7	7	10	11	11
	<0.74	1	2	2	3	2	1	0	1	2	1	1
Medical	1	**5**	**5**	**5**	**5**	**4**	**4**	**4**	**6**	**4**	**3**	**3**
(8)	0.75-0.99	3	3	3	3	4	4	4	2	4	5	5
Electrical	1	**11**	**11**	**8**	**8**	**7**	**7**	**8**	**11**	**10**	**9**	**10**
(42)	0.75-0.99	27	28	32	31	31	30	30	26	30	33	28
	<0.74	4	3	2	3	4	5	4	5	2	0	4
Motor	1	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**	**3**
(5)	0.75-0.99	2	2	2	2	2	2	2	2	2	2	2
Chemical	1	**6**	**8**	**9**	**12**	**11**	**14**	**13**	**14**	**12**	**12**	**12**
(159)	0.75-0.99	117	122	117	126	129	133	132	132	135	137	135
	<0.74	36	29	33	21	19	12	14	13	12	10	12
Rail	1	**6**	**6**	**10**	**11**	**8**	**8**	**7**	**4**	**7**	**6**	**7**
(86)	0.75-0.99	76	76	76	75	77	78	78	81	77	78	78
	<0.74	4	4	0	0	1	0	1	1	2	2	1
Machinery	1	**7**	**7**	**9**	**10**	**10**	**7**	**8**	**8**	**8**	**10**	**7**
(87)	0.75-0.99	55	55	56	60	68	68	65	61	64	67	71
	<0.74	25	25	22	17	9	12	14	18	15	10	9

Note: Number in parenthesis represent total number of firms in each sector.

Table 2 reports annual average TEs and total factor productivity changes (TFPCs) of various sectors during 2000-2010. The overview shows that Indian medium and high -tech firms are technically in- efficient at the 13% level (Mean of Column VII). Their overall efficiency level of 87 % implies that, if they would have been technically efficient, they can produce 13% of more output from the given level of inputs. Among the sectors R.T.C. is the highest efficient as they are able to realize 95 % of their potential output from the given inputs (in the year 2005 and 2006), while pharma is the least efficient with 83% and 84% realization of their potential output during the same years. One probable reason to the highest efficiency of RTC is the small number of firms in that group. Since DEA is a relative measurement of efficiency, variation in number of firms in each category may lead to biases in the calculation of efficiency. When we compare the years 2000 and 2010, it is observed that TEs of all the sectors have increased.

When we look at the total factor productivity changes, we can see that chemical sector is the best performer among them as the sector grows at an annual average rate of 3% per annum, followed by R.T.C. where the sector grows at the rate of 2% per annum, on average. It is interesting to see that none of our high tech sectors are in declining trend while the growth of rail road sector is constant. During the study year (2000-2010), the total factor productivity of all other sectors has increased at the rate of 1% per annum. While considering all sectors and average TFP changes (Column VIII), the year 2008 appears to be good for them, produces highest productivity rate (3 % per annum). This growth figure mainly attributed to the best performance of chemical sector that grow at an average rate of 14% per annum. Sectors like machinery, pharma and R.T.C also grows at an average rate of 6% per annum. All the sectors except machinery, shows an improvement over their performance during the years with a great performance of pharma at the rate of 7 % per annum in 2010.

Table 3 summarizes the components of the Malmquist productivity index and decomposes TFPC in to technical change (TECH) and technical efficiency change (EFFCH). The table also provides sources of efficiency changes into pure efficiency (pech) and scale efficiency changes (sech). For MPI, the first year of the study (2000) has been taken as the reference period. For a better comparison we are reproducing TFPC of each sector for the years 2001, 2005 and 2010. In 2001, the average of CRS-VRS based TFPC index of R.T.C. is 1.01, imply a slight improvement in TFP (1%) while remaining other sectors have either regressed in productivity (Pharma and machinery by 1%, rail road by 2% and chemical sector by 3%) or constant (electrical). But in the year of 2005, only the rail road sector productivity reduced by 1%. Rest of the sectors are either showing an improvement (pharma and chemical by 2%, electrical by 1%) or remain constant (RTC and Machinery). Further, a movement from 2005 to 2010 shows that except machinery (a regress of productivity by 3%), remaining sectors show an improvement in their productivity over the years with an exceptional performance of pharma sector by 7%. Therefore, in terms of productivity, we can conclude that productivity of firms in India has improved during the study period.

The improvement in productivity may be due to either technical change or efficiency change. In 2001, both R.T.C and electrical show technical progress at the rate of 8% and 1% respectively, while others show a technical regress with a maximum of 5 percent by chemical sector. In 2005, however, pharma, machinery and chemical sectors technically progress at the rate of 6%, 5% and 2% respectively while other sectors regress. One remarkable feature during the last year of the study is that, all sectors except machinery shows technical progress with an outstanding performance of pharma and chemical sectors by 25% and 16% respectively. Finally, the source of efficiency is decomposed into pure efficiency change and scale efficiency change. The result shows that scale efficiency has considerably declined in the sectors like pharma, chemical and railroad sectors while R.T.C and machinery shows an improvement during the study period. Pure efficiency change, the residual of technical efficiency after scale efficiency change also shows a declining trend.

The comparative statistics of the components of MPI between foreign and domestic firms are given in Table 4. The study does not provide any clear differences between foreign and domestic firms in terms of changes in productivity and technical efficiency level. However, a close examination shows that only pharma sector exhibits some efficiency differences between the two (0.83 and 0.91 for domestic and foreign firms respectively). Similarly, in case of TFPC, there exists some productivity differential among the two categories as the domestic firms grows at an average rate of 2% per annum while foreign grows at an average of 4 % during the study period. There could not find any difference in SECH as both group performs alike.

5.2. Tobit estimation result

As we are dealing with panel data, the issues like heteroskedasticity and endogenity emerge and we have addressed these issues in our modeling. The results of the tests confirm the problem of heteroskedasticity, but show no endogenity (Appendix II). By applying bootstrap standard errors we can minimize the problem of heteroskedasticity. For best approximation, we use the fixed effect one sided censoring Tobit estimation developed by Honore (1992)[7]. The semi parametric estimator for fixed effect Tobit model unspecified the distribution of error term

7 Many of the software packages provide only random effect panel data Tobit estimation technique. Though we are applying Honore (1992) fixed effect model, we reports the results obtained from random effect panel Tobit estimation also.

Table 2: Technical Efficiency and Total Factor Productivity Change (Annual and sectoral average)

	I		II		III		IV		V		VI		VII	VIII
	Chemical		Electrical		Machinery		Pharma		Railroad		R.T.C			
Year	TE@	TFPC#	TE	TFPC	TE	TFPC	TE	TFPC	TE	TFPC	TE	TFPC	ATE	ATFPC
2000	0.82	-	0.90	-	0.81	-	0.82	-	0.85	-	0.91	-	**0.85**	-
2001	0.83	0.97	0.89	1.00	0.81	0.99	0.84	0.99	0.85	0.98	0.90	1.01	**0.85**	**0.99**
2002	0.82	1.00	0.89	1.03	0.82	1.03	0.86	0.98	0.90	1.02	0.91	1.02	**0.87**	**1.01**
2003	0.85	1.02	0.88	1.03	0.84	1.02	0.84	1.01	0.90	1.02	0.90	0.99	**0.87**	**1.02**
2004	0.85	1.04	0.89	1.03	0.85	1.03	0.85	1.02	0.89	0.99	0.91	1.03	**0.87**	**1.02**
2005	0.86	1.02	0.88	1.01	0.84	1.00	0.83	1.02	0.89	0.99	0.95	1.00	**0.87**	**1.01**
2006	0.87	1.02	0.90	0.98	0.84	1.01	0.84	1.02	0.90	0.98	0.95	1.04	**0.88**	**1.01**
2007	0.87	1.03	0.91	1.02	0.84	1.01	0.84	0.99	0.90	1.03	0.94	1.04	**0.88**	**1.02**
2008	0.85	1.14	0.90	0.93	0.85	1.06	0.85	1.06	0.89	0.95	0.91	1.06	**0.87**	**1.03**
2009	0.87	0.99	0.89	1.01	0.85	1.00	0.85	0.98	0.89	1.02	0.90	0.99	**0.88**	**1.00**
2010	0.87	1.04	0.89	1.02	0.86	0.97	0.86	1.07	0.89	1.01	0.92	1.03	**0.88**	**1.02**
Mean	**0.85**	**1.03**	**0.89**	**1.01**	**0.84**	**1.01**	**0.84**	**1.01**	**0.88**	**1**	**0.92**	**1.02**	**0.87**	**1.01**

Note. ATE and ATFPC indicate average technical efficiency and average total factor productivity changes respectively.@ and # indicate average for all the firms in the industry

Table 3: Components of MPI: Total factor productivity change, Technical change and sources of Efficiency change

	2001					2005					2010				
	TECHCH	EFFCH	pech	sech	TFPC	TECHCH	EFFCH	pech	sech	TFPC	TECHCH	EFFCH	pech	sech	TFPC
Pharma	0.91	1.11	1.04	1.07	0.99	1.06	0.97	0.98	0.99	1.02	1.25	0.88	1.02	0.86	1.07
RTC	1.08	0.95	0.98	0.97	1.01	0.96	1.05	1.04	1.01	1.00	1.00	1.04	1.02	1.02	1.03
Electrical	1.01	1.00	1.00	1.00	1.00	0.98	1.03	1.00	1.04	1.01	1.03	1.00	1.00	1.00	1.02
Chemical	0.95	1.02	1.01	1.01	0.97	1.02	1.01	1.01	1.00	1.02	1.16	0.90	0.99	0.91	1.04
Railroad	0.96	1.03	1.01	1.02	0.98	0.99	1.00	1.00	0.99	0.99	1.11	0.91	1.01	0.91	1.01
Machinery	0.98	1.02	1.01	1.01	0.99	1.05	0.96	0.98	0.98	1.00	0.93	1.05	1.01	1.04	0.97

Note: each value indicate average for all the firms in the industry

Table 4: Distance summary and MI summary: Foreign versus domestic firms

	Pharma.		RTC.		Electrical.		Chemicals.		Railroad.		Machinery.	
Variable	D	F	D	F	D	F	D	F	D	F	D	F
TE	0.83	0.91	0.92	0.91	0.89	0.91	0.85	0.88	0.88	0.91	0.84	0.82
EFFCH	0.99	0.98	1.00	1.02	1.03	1.02	1.00	0.99	1.00	1.00	1.00	1.00
TECCH	1.06	1.08	1.03	1.03	0.99	1.01	1.09	1.09	1.01	1.02	1.03	1.03
PECH	1.01	1.01	1.00	1.02	1.00	1.00	1.01	1.01	1.01	1.01	1.01	1.01
SECH	0.98	0.97	1.00	1.01	1.02	1.02	0.99	0.98	0.99	0.99	0.99	0.99
TFPC	1.01	1.02	1.02	1.04	1.00	1.01	1.03	1.03	1.00	1.00	1.01	1.01

Results of panel Tobit estimation as suggested by Honore (1992) are given in Table 5 through column I-III. We employ three different equations to estimate the R&D and Patenting productivity. In column I & II we use RDS and PAT as an innovation variable separately to check for multicollinearity whereas in column III both RDS and PAT variable use simultaneously. The results indicate a significant but small impact of patenting on efficiency differential among the firms but there is no evidence of R&D impact on productivity. Therefore, our results corroborate with earlier findings like Deolalikar and Roller (1989) and Crepon et al (1998). Since the panel analysis produce little evidence of innovative activities on productivity there are likely some cross sectional impact as suggested by Griliches and Mairesse (1984). Therefore, the results need to be tested against short run shift in demand that is being met by these firms through utilization of labour and capital (or cross section). Among the control variables, firm's size and age have a significant impact on productivity. This implies that firms experience and benefits of scale operation arising from their big size do matter for productivity. Alternatively, we produce the results of random effect Tobit results through column IV-VI. We got the same result for age and size, but the significance level of PAT and RDS has been interchanged.

Table 5. Results of panel Tobit estimation with fixed effect and Random effect. Dependent variable is TE

	I	II	III	IV	V	VI
PAT	0.0138		0.0145	0.0132		0.0156
	(1.6)***		(1.68)***	(1.55)		(1.51)
RDS		0.0007	0.0008		0.0057	0.0058
		(1.19)	(1.35)		(3.29)*	(3.83)*
SIZE	0.0095	0.0094	0.0094	0.0102	0.0097	0.0097
	(4.09)*	(4.06)*	(4.05)*	(4.17)*	(3.23)*	(3.75)*
HHI	0.0155	0.0143	0.0155	0.0295	0.0293	0.0308
	(0.41)	(0.38)	(0.41)	(0.62)	(0.62)	(0.75)
FOS	0.0101	0.0099	0.0100	0.0105	0.0104	0.0104
	(1.56)	(1.52)	(1.55)	(1.97)	(1.64)	(1.52)
MGR	0.0001	0.0001	0.0001	-0.0001	-0.0001	-0.0001
	(-0.01)	(0.02)	(-0.02)	(-0.43)	(-0.54)	(-0.62)
EXPI	-0.0015	-0.0015	-0.0015	-0.0019	-0.0020	-0.0021
	(-0.93)	(-0.94)	(-0.94)	(-1.19)	(-1.28)	(-1.27)
AGE	0.0975	0.0955	0.0978	0.0751	0.0744	0.0759
	(3.78)*	(3.78)*	(3.79)*	(4.05)*	(4.13)*	(4.63)*
Constant				0.7453	0.7426	0.7403
				(29.08)*	(26.4)*	(28.31)*
Chi2	31.3	31.09	29.47			
Observation	4284	4284	4284	4284	4284	4284

Note: *,*** represent variables are significant at 1% and 10% level of significant.

6. Conclusion

In this study, we estimate efficiency scores and productivity changes of high and medium technology sectors during the year 2000-2010. DEA based Malmquist productivity index have been used to estimate TE and the components of productivity changes. These estimated efficiency scores are further use to explain the influence of patenting on the productivity with the help of panel fixed effect Tobit estimation. We have a clear indication that majority of firms in Indian high tech sectors are suboptimal. Among the firms on average, 10 % are found to be optimal during the study period. Remaining are either 'suboptimal' (70%) or 'less efficient' (20%). But as an indication to the performance up gradation, firms under the category of less efficient is reduced to 8% and that of optimal firms have increased to 12 %.

We find the evidence of productivity improvement of firms through patenting, but there is little evidence of R&D influence. The result is interesting in the sense that the importance of patent as an instrument to promote research, innovation and growth has been increased recently. Why R&D becomes insignificant for productivity improvement coincides with the theory of Chor and Lai (2013). They argue that when patent protection increases R&D may actually decline. Further, the lack of truly innovative R&D investment may also be liable for the insignificant coefficient of RDS. In the context of India we can observe that most of the R&D is carried out by firms as a way to tax evasion. In future, we plan to study the influence of patenting on profitability of the firms to capture another performance related variable.

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Appendix I

3.1.1. DEA optimization problem: An algebraic formulation for 1 output and N number of inputs)

Let y^k be the output and x_i^k (where i=1, 2,..n) be the inputs of the firm k (where k =1, 2 …m). We wish to measure the technical efficiency of firm E. The linear programming problem for the DEA would be;

$$\begin{aligned} & \max(\varphi), \textit{the objective function} \\ s.t. \quad & \sum_{k=1}^{m} \lambda_k x_{ik} \leq x_{iE} \;\; (i = 1,2,....n) \\ & \sum_{k=1}^{m} \lambda_k y_k \geq \varphi y_E \qquad\qquad (5) \\ & \sum_{k=1}^{m} \lambda_k = 1; \lambda_k \geq 0 \,(k = 1,2,...m); \varphi \end{aligned}$$

The technical efficiency of firm E would be

$$\tau_E = \frac{1}{\varphi^*} \qquad (6)$$

Where, φ^* is the optimal solution for the linear programming problem.

Based on Fare et al. (1994) popularly known as FGNZ model, we also use DEA to measure Malmquist productivity indices (MPI)[8]. The MPI decomposes in to technical change and changes in technical efficiency. Technical change measures the shift in the technology frontier between two time periods that might occur through adoption of new technology. This component measures how much the frontier shift that indicates whether the best practice firm relative to the evaluated one improves, stagnates or decline. Efficiency change on the other hand, shows how much closer (or farther away) *a firm* from the frontier made up of best practice firm. This also indicates that capability of a firm in catching up with those efficient ones. This component may greater than (improves), equal to (stagnate) or less than (declines) unity. The efficiency change further factored in to pure efficiency change and scale efficiency change.

[8] The use of Constant Returns to Scale (CRS) specification will result in measures of TE which are confounded by scale efficiencies (SE). The model of Banker, Charnes and Cooper (1984) proposes an extension of CRS specification in to Variable Returns to Scale (VRS) specification which permits calculation of TE devoid of SE.

Based on caves et al. (1982), MPI the geometric mean of two Malmquist productivity indexes states as follows.

$$M(X^{t_2},Y^{t_2},X^{t_1},Y^{t_1}) = \left[\frac{D^{t_1}(X^{t_2},Y^{t_2})D^{t_2}(X^{t_2},Y^{t_2})}{D^{t_1}(X^{t_1},Y^{t_1})D^{t_2}(X^{t_1},Y^{t_1})}\right]^{1/2} \tag{7}$$

Where, t_1 and t_2 are the time periods such that $t_1 < t_2$. The above equation stands for the productivity of the production point (X^{t_2},Y^{t_2}) relative to the production point (X^{t_1},Y^{t_1}) at two different technology levels. A value greater than 1 indicates positive TFP growth in period t_2. As we discussed above, the index can be further decomposed in to technical change and efficiency change as follows;

$$M(X^{t_2},Y^{t_2},X^{t_1},Y^{t_1}) = \frac{D^{t_2}(X^{t_2},Y^{t_2})}{D^{t_1}(X^{t_1},Y^{t_1})}\left[\frac{D^{t_1}(X^{t_2},Y^{t_2})D^{t_1}(X^{t_1},Y^{t_1})}{D^{t_2}(X^{t_2},Y^{t_2})D^{t_2}(X^{t_1},Y^{t_1})}\right]^{1/2} \tag{8}$$

Term outside the bracket in the right hand side of equation 4 implies efficiency change and the term inside the bracket indicate technical change. MPI given by equation (3) and (4) can be defined through DEA distance function. As said earlier, by utilizing both CRS and VRS DEA frontiers, the technical efficiency is factored in to scale efficiency and pure efficiency. The scale efficiency change is expressed through equation (5);

$$SECH = \left[\frac{D^{t_2}_{vrs}(X^{t_2},Y^{t_2})/D^{t_2}_{crs}(X^{t_2},Y^{t_2})}{D^{t_2}_{vrs}(X^{t_1},Y^{t_1})/D^{t_2}_{crs}(X^{t_1},Y^{t_1})}\cdot\frac{D^{t_1}_{vrs}(X^{t_2},Y^{t_2})/D^{t_1}_{crs}(X^{t_2},Y^{t_2})}{D^{t_1}_{vrs}(X^{t_1},Y^{t_1})/D^{t_1}_{crs}(X^{t_1},Y^{t_1})}\right]^{1/2} \tag{9}$$

And the pure efficiency change can be defined through equation (6);

$$PECH = \frac{D^{t_2}_{vrs}(X^{t_2},Y^{t_2})}{D^{t_1}_{crs}(X^{t_1},Y^{t_1})} \tag{10}$$

Appendix II

Table A2: Test for endogenity

	Huasman-taylor	OLS
TV exogenous		
dsale	0.028(0)	0.030(0)
hhi	0.040(0.175)	0.049(0.096)
fos	0.006(0.163)	0.005(0.188)
mgr	0.000(0.005)	0.000(0.007)
expi	-0.001(0.532)	-0.001(0.39)
age	0.053(0)	0.045(0)
TV endogenous		
gpatstock	0.008(0.248)	0.011(0.062)
rds	0.000(0.872)	0.000(0.537)
TI exogenous		
secdum	-0.002(0.168)	-0.002(0.157)
cons	0.711(0)	0.716(0)
sigma_u	0.082581	
sigma_e	0.045691	
rho	0.765625	

Note: TV indicate time variant and TI indicate time invariant