Indigenous RD Effectiveness and Technology Transfer on Productivity Growth: Evidence from the Hi-Tech Industry of China

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Indigenous R&D Effectiveness and Technology Transfer on Productivity Growth: Evidence from the Hi-Tech Industry of China

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Abstract

The study employs the panel data of 15 hi-tech industries over the period of 2000-2010 in order to examine the effectiveness of R&D with respect to productivity change and indentify the significant contributing factors with intensity in the Chinese hi-tech sector. The Malmquist Productivity Indexes are calculated by using the non-parametric programming technique and censored regression model is applied to conduct the empirical investigation. We find that on average, the sector is confronting productivity deterioration which is mainly due to the technical inefficiency. The Office Equipments industry has the highest productivity gain in our sample at the rate of, on average, 3.7% per year and all of which is caused by technical change. Furthermore, the electronic components industry is found to be the most efficient industry in the sector that drives an industry to have productivity progress on average, of 1.7% per year over the study period. At last, Tobit results indicate that spillovers through FDI and technology import are having significant and positive effect on the productivity progress.

JEL: C34, C61, D24

Keywords: Productivity Growth;DEA;Tobit Model

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1. Introduction

The Industrial policy of 1990's for the hi-tech sector of China paid great significance to the technological advancement and bloom quality workforce, the key driving forces of rapid economic growth. Therefore, it was emphasized on the commercialization of the results of scientific research (Liu and White, 2001). Later on, several plans related to science and technology were developed and implemented successfully. Presently, China has been trying to fold herself completely with the technology which directly or indirectly getting into virtually all departments of the nation's economy. Moreover, the prospective long-term growth track and to ascertain economic prosperity of the metropolitan cities of the China could be connected with the hi-tech sector. Almost all industrialized nations including China are getting comparative advantage from vintage in advancing and producing hi-tech products.

The hi-tech manufacturing industries have dominated position over the other manufacturing sector as far as the productivity is concerned. The growing ratio of hi-tech industrial value added to manufacturing value added from 9.5% in 2001 to 12.7% in 2007 is one of the important indicators reflecting the successfully implemented innovative policies in hi-tech sector of China. Furthermore, growth in the full-time equivalent R&D personnel, rising investments, increasing revenue from new products and growing inventive patents are considerable variables which show that the hi-tech industries have became the significant contributor in economic growth of China (Z.Y.Lie & L. Liang, 2008). It has also been observing the rising trend in spending on the R&D, new products development and development of S&T institutes in order to boost the productivity growth by encouraging the hi-tech industrial product and process innovations (H.C. Wu, 2008).

The theorists have been emphasizing on the technological advancement achieved through the R&D because it gives the consistent technological progress. In an empirical study, positive linear relationship has also been seen between the R&D and industrial output of hi-tech sector of China (X.D. Zhang & Z. X Wang, 2008). Moreover, R&D doesn't only enhance the innovation but it also plays the role of recognition, absorption and utilization of outdoor knowledge. For this reason, several studies conducted to identify the impact of R&D and technology spillovers through FDI and imports (X.Xu, Q. Chen, B.Y. Zhen, 2008 and L.P. Wang, S.N. Zheng, 2008).

Despite the fact that hi-tech sector of China has been performing well but still this sector is encountering many challenges and problems such as short of full-time hi-tech personnel, lame innovative capacity, meager R&D expenditure and low-level innovative efficiency (F.Wei, & Y.L. Zhao, 2008). The output elasticity with respect to R&D is found to be insignificant if we would have a comparative look over this sector with other developed nations. The empirical evidences on technology spillovers through FDI and technology import are vague (Aitken & Harrison 1999 and Liu, 2002). Furthermore, the intensity of FDI and technology import to affect productivity is also very in the short and long run periods.

The past studies related to hi-tech sector of China are mainly focused on the impact of fresh R&D investments and technological spillover effects on the output. However, the productivity trend and technical efficiency as a result from R&D inputs are less explored for this sector. Moreover, the measurement of intensity coefficient related to technology imports in the presences of rising structure of absorbing capacity is barely observed. Hence, this paper undertakes to extend the existing literature by analyzing the effectiveness of R&D to productivity enhancement for the hi-tech sector of China, as well as to examine the determining variables of the productivity growth.

The rest of the paper is organized as follows. The literature regarding productivity measurement is presented in section 2. After that, section 3 reveals the adopted methods and procedure in order to execute the research and then description of the variables and data used in our research are showed in section 4. The research results are exhibited and explained in Section 5 and then section 6 concludes the paper.

2. Total Factor Productivity

Total Factor Productivity is one of the sources of economic growth besides the primary factors of production (labour and Capital). Productivity improvement leads an economy (industry or firm) to achieve better than before with the unchanged inputs in the production process. According to the Paul Schreyer (2001), total factor productivity is generally defined as a ratio of a volume measure of output to a volume measure of input use.

Solow (1957) presented to measure the Hicksian neutral shift parameter in the production function by using the non-parametric index number approach. He interpreted the shift parameter as the costless increment of output to input ratio. The growth in output which cannot be expressed besides the primary inputs is attributed to the residual. Practically, this residual named "measure of our ignorance" by the Abamovitz (1956). Further, he divided the measure of our ignorance as the effects of technical and organizational innovation which are under the category of wanted and as measurement error, aggregation bias and model misspecification which are categorized as unwanted. The researchers are off course, more interested to measure the effects of technical change, organizational innovation and technical efficiencies by minimizing the other measurement errors.

The consistency of the TFP measurement depends on the careful selection and quality of output and inputs used. By realization of this notation, this paper is an effort to obtain quality output and input variables with respect to hi-tech industries of China.

2.1 Methods to measure TFP

There is a consensus over the view in the literature that productivity could be measure in different ways according to its purpose and availability of data. There are four significant productivity measurement approaches namely, growth accounting, index number, a distance function and the econometric approaches (Mawson et al., 2003).

Assumptions based, growth accounting approach determine the TFP growth residually. It means, by subtraction of observable income share of inputs (labour and Capital) from output growth leads to the TFP growth. Furthermore, growth accounting needs a specification of production function. It also enables to decompose the output growth into different inputs growth and total factor productivity growth. The growth accounting methodology was extensively widen since 1957 (Solow) and applied on a great scale in empirical researches such as, of Griliches (1960, 1963), Denison (1962) and Kendrick (1973, 1976, 1977).

Econometric approach doesn't demand the relationship between the production elasticities and income shares; it is only based on the observations of volume outputs and inputs. The literature regarding the econometric approach could be found in Morrison (1986) or Nadiri and Prucha (2001).

This study employs DEA-Malmquist Productivity Index (distance function approach) to measure the productivity changes over time and to get insight sources of its changes. The Malmquist Productivity Index based on the DEA (Data Envelop Analysis) developed by the Fare et al (1992, 1994). The DEA is a linear programming tool available to DMU (Decision Making Units) to evaluate the performance based on the multiple outputs and inputs and the methodology was originated by Charnes et al (1978) based on the frontier line which was developed by Farell (1957).

The Malmquist Index was first proposed by Sten Malmquist by constructing the quantity indexes for the consumption analysis purpose as ratios of distance functions (Malmquist, 1953). Later, the Fare et al (1992) merged the two ideas, the efficiency measurement presented by the Farrell (1957) and the measurement of productivity presented by the Caves at el (1982) to develop the Malmquist productivity index which is directly measured from the data of input and output by using the DEA.

There are number of captivating features to use DEA Malmquist Productivity Index approach. It is a non-parametric approach which means it doesn't require any functional form and it also shows the best practicing frontier. Secondly, its nature is non-statistical which suggests that the result from DEA doesn't produce any standard errors. On account of Malmquist Index, it is based on simple calculation as showed by Fare, Grosskopf and Roos (1995). The index can be related to the superlative Tornqvist and Fisher Ideal quantity indexes, under certain conditions as showed by Caves, Christensen and Diewert (1982) and Fare & Grosskopf (1992).

Fare et al (1992) developed the DEA-based Malmquist productivity index as the geometric mean of two Malmquist productivity indexes of Caves et al (1982). Therefore, Malmquist Index can be decomposed into two components, the efficiency change and technical change and the values of these components can be the evidences of the productivity change sources.

3. Methods and Procedure

3.1 Malmquist Productivity Index

In the first phase of the study, we employ the Malmquist productivity index to measure the productivity changes and its components.

It is assume that there are k=1, …. K number of hi-tech industries which are using n=1….N number of inputs at each time period t=1….T and yield m=1, ….M number of outputs. In our studies, output-oriented approach has been adopted because of industries have goal to maximize outputs at the given level of inputs.

Following the Fare et al (1994), the output-oriented Malmquist productivity index between the period t and t+1 can be define as,

$$M_0\,(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{D_o^{t+1}\,(x^{t+1}, y^{t+1})}{D_o^t\,(x^t, y^t)} \times \left[\left(\frac{(D_o^t\,(x^{t+1}, y^{t+1})}{D_o^{t+1}\,(x^{t+1}, y^{t+1})}\right)\left(\frac{(D_o^t\,(x^t, y^t)}{D_o^{t+1}\,(x^t, y^t)}\right)\right]^{1/2}$$

Where, $D_o^t\,(x^{t+1}, y^{t+1})$ shows the distance from the period t+1 observations to the period t technology.

The first component of an index $TEC_o = D_o^{t+1}\,(x^{t+1}, y^{t+1})/D_o^t\,(x^t, y^t)$ measures the relative technical efficiency changes at the period t and t+1. The component shows the score of changes in efficiency over the time which reflects catching up effect of DMU to the frontier. The second component

$FS_o = \left[\left(\frac{(D_o^t\ (x^{t+1},y^{t+1})}{D_o^{t+1}\ (x^{t+1},y^{t+1})}\right)\left(\frac{(D_o^t\ (x^t,y^t)}{D_o^{t+1}\ (x^t,y^t)}\right)\right]^{1/2}$ measures the shift in technology (frontier) between the time period t and t+1. If the score of FS ***o*** is greater than unity suggests the positive shift in the frontier, less than unity represents the negative shift or technical deterioration and equal to unity indicates that there is no change in the technology frontier (Fare et al 1992, 1994).

The Malmquist index is the product of TEC***o*** and FS***o*** components. The improved productivity performance could be evidence if the score of Malmquist index represents greater than unity, if it comes less than unity which indicates productivity regress.

In order to calculate the said two components of Malmquist index, we have to solve four different linear programming problems under the constant returns to scale. The efficiency change can be further decomposed into the scale change and pure-efficiency change under the variable returns to scale; therefore it requires calculation of two more additional linear programming (Fare et al 1994). Linear programming equations can be written as follows;

$$[d_0^t(y_t,x_t)]^{-1} = max_{\emptyset,\gamma,}\ \emptyset \qquad \ldots\ldots \quad (1)$$

$$st \qquad -\emptyset y_{it} + Y_t\gamma \geq 0,$$

$$x_{it} - X_t\gamma \geq 0,$$

$$\gamma \geq 0,$$

$$[d_0^s(y_s,x_s)]^{-1} = max_{\emptyset,\gamma,}\ \emptyset \qquad \ldots\ldots \quad (2)$$

$$st \qquad -\emptyset y_{is} + Y_s\gamma \geq 0,$$

$$x_{is} - X_s\gamma \geq 0,$$

$$\gamma \geq 0,$$

$$[d_0^t(y_s,x_s)]^{-1} = max_{\emptyset,\gamma,}\ \emptyset \qquad \ldots\ldots \quad (3)$$

$$st \qquad -\emptyset y_{is} + Y_t\gamma \geq 0,$$

$$x_{is} - X_t\gamma \geq 0,$$

$$\gamma \geq 0,$$

$$
\begin{aligned}
[\boldsymbol{d_0^s}(\boldsymbol{y_t}, \boldsymbol{x_t})]^{-1} &= \boldsymbol{max}_{\emptyset,\boldsymbol{\gamma},}\ \emptyset \qquad \ldots\ldots \quad (4)\\
st \qquad & -\emptyset y_{it} + Y_s\gamma \geq 0,\\
& x_{it} - X_s\gamma \geq 0,\\
& \gamma \geq 0,
\end{aligned}
$$

3.2 Tobit Regression Model

In the second phase of our data analysis, we are going to use latent dependent variable model also called censored regression model proposed by James Tobin (1958). The structure of the model believes that there is unobservable variable and the values of the sample are testifying at a certain threshold instead of at the actual values. The vector of the independent variables determines the latent variable and normally distributed error term is there to capture the impact of this association. The model is also further expanded with the information of cross sectional units analyzed over the time, known as panel Tobit model. The model can be expressed as follows:

$$Y_{it}^* = \alpha_i + \beta' x_{it} + u_{it} \qquad i = 1, 2 \ldots\ldots\ldots. N$$

$$t = 1, 2 \ldots\ldots\ldots. T$$

and observable variable comply with for certain threshold a.

$$\begin{cases} y = y^* & if\ \ y^* > a \\ y = a & if\ \ y^* \leq a \end{cases}$$

Where, Y_{it}^* is a latent variable implying the productivity progress rate related to the *i*th hi-tech industry at time t, α_i captures the unobserved heterogeneity among industries that is assumed to be same over the period of time, βx_{it} vector of estimated coefficients and independent variables and u_{it} is an error term which is assumed to be $u_{it} \sim IID\ (0, \sigma^2)$. The latent variable (Y_{it}^*) would take value 0 if the productivity performance of hi-tech industry is deteriorated in year t and otherwise 1 if a productivity performance is progressive. The estimated parameters of Tobit model don't have the same interpretation as we usually do in the normal linear regression models as a marginal effect of the independent variable on the dependent. Therefore, in Tobit models, the marginal change has been interpreted in two distinct ways, firstly, the marginal effect on the mean of, when it is observed and a marginal effect on the likelihood of being observed (Mc Donald and Moffitt, 1980). For this reason, the expected values (conditional and unconditional) of dependent variable in the Tobit panel model could be expressed as follows:

Conditional Tobit Marginal Effect = $\frac{\partial E[y_{it} / x_{it},\ y \leq 0]}{\partial x_{it}}$ …... (5)

Unconditional Tobit Marginal Effect = $\frac{\partial E[y_{it}^{*} \ / \ x_{it},\ y>0]}{\partial x_{it}}$ ….. (6)

Total Tobit marginal effect = $\frac{\partial E[y_{it} / x_{it},\ y \leq 0]}{\partial x_{it}} + \frac{\partial E[y_{it}^{*} \ / \ x_{it},\ y>0]}{\partial x_{it}}$ ….. (7)

The estimation of regression could be carried out by pooling the observations all together and run the normal pooled Tobit model and by employing a specification of random effect of the Tobit panel data model (Wooldridge, 2002). Thus, the likelihood-ratio (LR) test, which is the test of goodness of fit of the model, would be conducted in order to choose the pre-eminent model for the study of the results. It would be preferable to use panel random effect model over the pool data model, if we reject the null hypothesis of rho=0 that decision could be made on the rho test $\rho = \sigma_v^2(\sigma_v^2 + \sigma_u^2)$.

4. Data and Variables

In our study, the panel data of 15 hi-tech industries (see Table-1) have been selected over the period of 2000-2010, which makes the sample of 165 observations and data comes from China Statistical Yearbook on Hi-tech Industry. An effort has been incorporated in order to careful selection of variables with respect to hi-tech sector. With the purpose of measure the productivity, technical and efficiency change, two outputs and two inputs have chosen. The outputs, namely, Industrial output value from new products (Y_1) in 10000 RMB which is price deflated at the end of each year and Patents (Y_2) in units which are granted under the three classifications, invention, utility model and designs. And the two inputs contain, firstly, R&D Expenditure (X_1) in 10000 RMB that is adjusted by the price at the end of year and measured under the perpetual inventory method by assuming 15% of depreciation rate and in the second place, R&D personnel (X_2) in persons is used, which is measured by the sum of full-time persons and the full-time equivalent of part-time persons converted by workload.

At the second stage of data analysis, Tobit regression would be arranged with the following independent variables (see equation-8). Firstly, in order to capture the power of externalities, the personnel for Scientific & Technological (S&T) activities in Joint Ventures (in persons) is used as a proxy of *FDI*. Diffusion of imported technology plays a significant role and contribution to the domestic productivity enhancement, for this purpose, Technology Import *(TI)* is utilized, the variable is measured in 10000 RMB and deflated with the price at the end of each year. Furthermore, it is generally observe that the expenditure on R&D and innovation is quite tough to finance, therefore, the index for financing *(Loan)* is used to measure its effects on productivity progress which is measured as loans from financial institutions for the funding on scientific and technological activities in 10000 RMB and deflated with the price deflator. And finally, the expenditure on technology absorption *(Abso)*, in 10000 RMB, is operated in a Tobit regression equation because it is noticed that at the first period, technology is adapt by the organization and then, in the second period, it is diffused and realized by the local industry.

The productivity scores are regressed on the industries other significant factors using Tobit regression model. As a result, the model for study the association between each productivity measure and others significant factors in this paper can be developed as follows:

$$TFP_{it} = f\ (FDI_{it},\ TI_{it}, Loan_{it},\ Abso_{it}) \qquad ….. (8)$$

Table-1
Taxonomy of the hi-tech Industry of China

No	Industry
1	Chemical Medicines
2	Traditional Chinese Medicines
3	Biological & Biochemical Products
4	Repairing of Airplanes
5	Spacecrafts
6	Communication Equipments
7	Radar and Peripheral Equipments
8	Broadcast and Television Equipments
9	Electronic Appliances
10	Electronic Components
11	Domestic TV sets and Radio Receivers
12	Entire Computer
13	Computer Peripheral Equipments
14	Office Equipments
15	Measuring Instruments

5. Results and Discussion

Table-2 describing the core features of the collected data of inputs, outputs and productivity determining variables. The low standard deviation figures indicate that the pool data points are very close to their mean which could be interpreted that the average variables show some degree of consistency over the number of years. On the other hand, the figures related to skewness and kurtosis illustrate the normality of the observed data for analysis.

Table-2
Descriptive statistics of variables

Statistic	Y_1	Y_2	X_1	X_2	***FDI***	***TI***	***Loan***	***Abso***
Mean	25.298	50.765	20.834	8.764	7.229	9.114	9.204	7.211
Median	25.48	50.965	20.970	8.870	8.108	9.974	9.378	7.906
Maximum	27.72	183	24.140	11.50	10.666	12.887	12.587	12.025
Minimum	21.88	1	16.540	5.220	0.0000	0.000	5.298	0.0000
Std. Dev.	1.5691	9.656	1.5165	1.287	3.195	3.083	1.562	2.569
Skewness	-0.485	1.768	-0.368	-0.295	-1.394	-1.522	-0.402	-0.951
Kurtosis	2.297124	3.987	2.7607	2.663	3.789	5.193	2.469	3.588
Observations	165	165	165	165	165	165	165	165

Sources: Authors' calculation.
Note: All values are converted into natural logarithm form.

The DEA applied to measure the result of Malmquist index and its components (table-4). The results obtained by applying the output-oriented with CRS (Constant Returns to Scale) model.

The Table-4 shows the annual mean values of the efficiency change, pure efficiency change, scale efficiency change, technical change and total factor productivity change over the period of 2000-2010. By looking at, on average figures of the study period, it can be concluded that the industry are exposing productivity deterioration which is mainly due to the technical inefficiency of the sector as the technical change, on average, progresses. Furthermore, the technical efficiency change is the product of pure technical efficiency and scale efficiency change therefore; in our case the relative sources of inefficiency are both these indices.

If we would look at the result on the year to year basis, the industry has enjoyed the consecutive productivity improvement from the year 2004 to 2009. The highest productivity growth took place in the year of 2004 at around 2.9% which was only supported by the technical change (innovation) in the industry. These results somehow support many public finance programs introduced by the Chinese government in order to provide subsidized R&D activities.

Instead of showing the separated results for each industry and year, we move to the summarized results in the form of averages, of each industry over the study period. The table-5 exhibits the mean changes of technical efficiency, technology, pure technical efficiency, scale efficiency and Malmquist productivity Index of 15 hi-tech tech industries from the year 2000 to 2010. The Malmquist Index score shows that, on average, the industries in our sample are experiencing productivity improvement for the study period. Furthermore, the productivity index changes, on average, less than 1 percent per year for the whole selected sample of our study. And, on average, that rise in productivity is because of innovation (technical change) instead of the technical efficiency improvement of the hi-tech sector.

If we would look at the industry-by-industry results, we could clearly see that the industry related to Office Equipments has the highest productivity change in our sample at the rate of, on average, 3.7 percent per year. Furthermore, innovation or technical change is the only reason behind the productivity change of the Office equipments industry. Whereas, Electronic Components industry is the only technically efficient industry in hi-tech sector, which implied that industry is good at catching up the frontier. The rate of change, on average, of productivity growth is 1.7 percent per year which is the second highest in the sector. Additionally, the scale efficiency has been indentified behind the technical efficiency improvement in the electronic components industry.

Two out of fifteen industries namely Electronic Appliances and Domestic TV sets and Radio Receivers are found to be deteriorated in productivity performance as their Malmquist index is less than unity. The reasons behind of productivity deterioration in case of electronic appliances industry are the inefficiency as well as lame technical change; it means the industry has been struggling to move herself towards the frontier and unable to do innovation in order to move the frontier. Whereas, Domestic TV sets and Radio receivers industry is confronting technical inefficiency which makes it difficult for the industry to do productivity improvement. Furthermore, both pure inefficiency and scale inefficiency contributed to the overall technical inefficiency of this industry.

Table-3
Annual Means for DEA Model from 2000 to 2010

* Year	EC	PEC	SEC	TC	MI
2001	1.025	1.013	1.012	0.964	0.988
2002	0.914	0.982	0.931	1.117	1.021
2003	1.028	1.006	1.022	0.883	0.908
2004	0.973	0.999	0.974	1.058	1.029
2005	1.017	1.006	1.011	0.995	1.012
2006	1.025	1.001	1.024	0.976	1.000
2007	0.978	1.001	0.977	1.050	1.027
2008	0.985	0.994	0.991	1.017	1.002
2009	0.996	0.996	1.000	1.008	1.004
2010	1.000	0.998	1.002	0.975	0.975
Mean	0.9941	0.9996	0.9944	1.0043	0.9966

Sources: Authors' calculation
Note: The figures are rounding off to 3 digits
*2001 describe the change from 2000 to 2001 and continuing in the same way.

Table-4
Annual mean change of technical efficiency, technology, pure technical efficiency, scale efficiency, and total factor productivity from 2000 to 2010

No	TEC	PEC	SEC	TC	MI
1	0.994	1.001	0.993	1.009	1.003
2	0.993	0.999	0.994	1.010	1.003
3	0.991	0.997	0.994	1.009	1.000
4	0.993	1.001	0.992	1.009	1.002
5	0.994	0.999	0.995	1.009	1.003
6	0.992	1.000	0.992	1.009	1.001
7	0.991	0.997	0.994	1.009	1.000
8	0.995	1.002	0.993	1.017	1.012
9	0.995	0.999	0.996	0.98	0.975
10	1.002	1.000	1.002	1.015	1.017
11	0.992	1.002	0.99	1.000	0.992
12	0.994	1.000	0.994	1.006	1.000
13	0.993	1.000	0.993	1.016	1.009
14	1.000	1.000	1.000	1.037	1.037
15	0.992	0.998	0.994	1.008	1.000
Mean	0.9941	0.9996	0.9944	1.0095	1.0036

Source: Authors' calculation
Note: The figures are rounding off to 3 digits

The above mean results related to technical change are in expressive form, it does not clearly indicate that which industries are actually cause to move the frontier over time. The results reported in table-6 show the measured coefficients of constant and time trends variable by running simple linear regression model for total factor productivity, technical change and technical efficiency change. It is observed that time trend variable is statistically significant in case of technical and efficiency change whereas, the coefficient of TFP is found to be statistically positive but insignificant.

Table-5
Time Trends in TFP, TECH, EFF

	Dependent Variable		
Variables	**TFP**	**TECH**	**EFF**
C	0.987944 (112.6943)***	0.967861 (105.4538)***	1.022575 (182.5599)***
@ Trend	0.002066 (1.258371)	0.004775 (2.777503)***	-0.003035 (-2.892356)***
R-Square	0.010586	0.049543	0.053501

Note: The figures in parenthesis are t-statistics. *** shows 1% level of significance

So as to obtain the impact of carefully chosen independent variables on the TFP growth (considered to be the latent variable) in hi-tech industries, we employed Tobit regression model for panel data. At first, test for data poolability is conducted with the rho (ρ) and chi-square (χ^2) tests.

Table-7
Poolability Test Result

Model	**rho (ρ)**	**Std. Er. P**	**chi-square (χ^2)**	**Sig χ^2**	**Choice Made**
Tobit	3.06	7.73	0.00	1.00	Pooled

Source: Authors Calculation

The rho and chi-square tests result are presented in table-7 which shows the preference of using the pooled tobit model over the random-effects model as the null hypothesis of rho=0 cannot be rejected at the required level of significance. In this regard, pooled Tobit regression model is going to be use so that we could estimate the intensity of significant contributors for productivity improvement in hi-tech sector of China.

The Productivity change is a latent variable under our Tobit model which is censored at the lower limit with zero and upper limit with 100%. This could be explained in this way, productivity change is considered to be perceived for hi-tech industry with any progressive change but it would not be considered with negative or deteriorated change.

Table-8
Estimated Results of Pooled Tobit Model

Variables	**TFP**	**Marginal Effects**		
	Estimated Coefficients	**Conditional**	**Unconditional**	**Total**
c	0.965215*** (0.030373)			
FDI	0.002028** (0.002396)	0.0073871	0.0110807	0.0184679
TI	0.006175*** (0.002025)	0.0085438	0.0119398	0.020484
LOAN	0.007766 (0.004857)	0.0173200	0.022474	0.039794
ABSO	0.000300* (0.003128)	0.0028486	0.0036964	0.006545
σ	0.055752*** (0.003219)			
Log likelihood	220.1851			
R - Squared	0.79			

Notes: the figures in parentheses are standard errors. ***,** and * indicate 1%, 5% and 10% significance level of the estimated coefficients. σ represents the standard deviation of residuals of the model.

Table-8 reports the Tobit model results of productivity scores on the hi-tech industry on the other environmental variables according to the relationship in Equation (8). It is observed that the estimated coefficients of each of the single selected variables are statistically significant except for loans in S&T activities and reveal that model fits well in a set of observations. Moreover, R-Squared value is reasonably high i.e. 0.79 which suggest that explanatory strength of the model is significant. The estimated results exhibit that FDI has positive effect on TFP at the 5% level of significance. That propose, FDI has been performing significant part in the productivity progress through building the productive dimension, by offering the advanced technology and by providing the industrial competency in hi-tech sector of China. The current findings about FDI is not surprising if we would observe the encouraging policies associated with FDI in hi-tech sector, such as, foreign firms would have more approach to financing and urge to be the part in mergers. On the other hand, technology import and absorptive capacity individually as well as combined are statistically significant at 1% & 10% level and contribute positively to TFP. That suggest, the trade policy related to importing capital-intensive goods is considered to be good enough to enhancement of the domestic productivity growth and at the same time adequate spending on account of constitution the absorbing capacity by training and educating the labor force would be the helping-hand in order to immediate and sustainable technological progress and hence for productivity improvement. Finally, the loan for S&T activities is not significant. It means, the financial institutes are not importantly contributing their role in favor of product and process innovation financing in this sector of an economy. Furthermore, it suggests that the most of the S&T activities conducted by hi-tech sector may be the large scale industries or government controlled industries that can afford to finance the S&T activities by themselves or may be foreign funded industries.

Marginal Effects of explanatory variables under pooled Tobit model

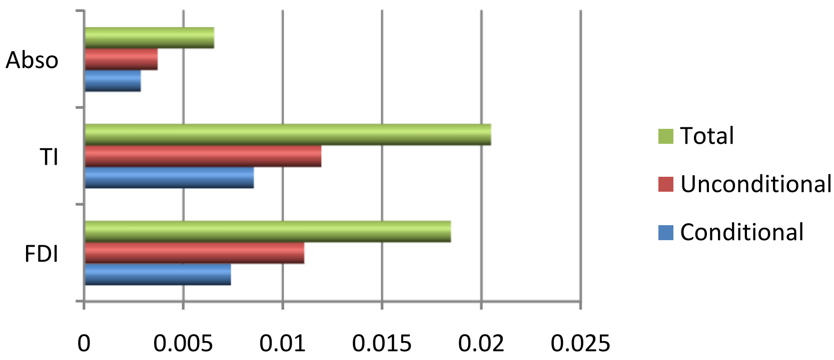

Figure 1

The figure-1 shows significant factors' marginal effects of the censored regression model calculated under the equation 5, 6 and 7 environments. It is observed that the intensity of both variables FDI and Technology Imports and under either situation conditional or unconditional, are having higher intensities to influence the productivity performance compare to the building of absorbing capacity. The industry which attracts FDI has expected number of productivity progressive changes that is 1.84 % more than the one that don't obtain FDI. Similarly, the industry which importing advanced technology has expected number of productivity improvements changes which is 3.97% higher than others. And at the last, the industry which is spending on absorbing the technology has expected number of productivity advancements changes which is 0.65% more than the industry which are not interested to spend in the same.

6. Conclusion

The aim of this study is to analyze the effectiveness of R&D in productivity progress and to estimate & evaluate the determining factors contributing to the improvement in productivity performance in 15 hi-tech industries of China from the year 2000 to 2010. At the first stage, we measure the Malmquist Productivity Index by employing output distance functions. That approach permits us to decompose productivity growth into variations in technical efficiency and transferences in technology over time. These two factors provide the recognition of catching up the frontier and the recognition of innovation.

The results show that on average, hi-tech sector is confronting productivity deterioration over the study period. The sector has been challenged with the overall technical inefficiency, which proposes that the industry is striving in order to catching up the frontier. However, on average, the industry is doing well with the innovation that increased on average, 0.43% per year over the complete time period. These results urge to investigate the determining variables of the technical efficiency in this sector. The results place an attention on the mobility of R&D personnel between sectors and collaborated R&D activities in order to maximize the R&D efficiency. Furthermore, it is recommended to advance the R&D financing efficiency, enhance management level and put more emphasis on the development of R&D human capital stock with consideration of regional disparities in order to deal successfully with the technical inefficiency in the this sector.

The industry-by-industry results in table-4 show that Office Equipments industry has been enjoying the highest productivity gain in our sample at the rate of, on average, 3.7% per year. And this productivity improvement is supported by the consistent progression in technical change or innovation in the industry. Whereas, electronic component industry is found to be the most efficient industry with respect to catching-up the frontier that drive an industry to have productivity progress on average, 1.7% per year.

At the second stage, we conducted empirical study by using the censored regression model so as to realize the spillover effects, the role of absorption capacity and the functions of the funding for S&T activities. It is found that the spillovers through FDI and technology imports contributed significantly with higher intensities compare to other variables in this sector. It is recommended that the sector should improve technological capacity, develop strong infrastructure and produce attracting policy settings in order to get benefits from spillovers more efficiently. On the other hand, variable of funding for S&T activities isn't contribute significantly, in this reason an innovative policy should be develop which could improve the access to acquire finance at the encouraging conditions for the funding of small as well as medium innovation projects.

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