國立政治大學應用經濟與社會發展

英語碩士學位學程

International Master’s Program of

Applied Economics and Social Development

College of Social Sciences

National Chengchi University

碩士論文

Master’s Thesis

創新對企業生產績效之影響

–以中國高新技術產業為例

Innovation and Firm Performance - Firm Level Evidence from High-tech Industries in China

Student:鄭林譽 Lin-Yu Cheng

Advisor:胡偉民 Wei-Min Hu

中華民國 106 年 6 月

Acknowledgement

I would first like to thank my thesis advisor associate professor Wei-Min Hu of Public Finance department at NCCU. I met professor Hu when I studied a bachelor degree in department of Public Finance. He is a very kind professor and always willing to help me for my difficulty toward study as well as life. For my thesis, professor Hu also provided great help and suggestion so that I can complete it in time perfectly. It's my pressure to have professor Hu as my thesis advisor.

I would also like to thank associate professor Chang-Ching Lin of Economics department at NCKU and professor Hsien-Ming Lien of Public Finance department at NCCU. I really appreciate that professor Lin and professor Lien, as my Oral Defense Commissioners, provided advice and comment to make my thesis better. It's very helpful.

I would also like to acknowledge my partners Che-Hsu Chang and Meng-Ping Huang. You helped me a lot for my thesis and kept telling me that we can graduate together. Finally, we made it. I will never forget those days that we buried ourselves in thesis together at the research room.

At last, I would like to thank my family, especially my parents. I appreciate their support and I know it's really difficult to raise a child and afford a huge amount of money for education. Without my parents, I won't be able to finish this master degree.

Author

Lin-Yu Cheng

Abstract

Purpose – China has started a Torch program and invested huge amount of money in high-tech industries since 1989. During last three decades, China's economy also rapidly grows. According to above conditions, this study aims to create a reliable estimation for confirming the relationship between innovation and firm performance from the evidence of China's high-tech industries.

Design/Methodology/Approach – By building a sample composed of the patent stock and firm-level performance data from China's National Bureau of Statistics (NBS), we apply Olley and Pakes method to estimate the productivity and use the regression model for panel data to do the empirical study.

Findings – Both the total patent stock and the patent stock of three different categories maintain a positive and significant relationship toward firm performance such as output, productivity and exports. On the other hand, the finding also implies a negative effect of firm dynamics on the relationship between patent stock and firm performance.

Value – The researches related to innovation and firm performance in the past are usually conducted with the sample of whole manufacturing industries' data and report an overall estimation. However, this study focuses on high-tech industries to provide a more detailed evaluation for China's innovative efforts of Torch program and carves out a direction for future research on high-tech industries.

關鍵詞 – 創新、生產力、Olley and Pakes 生產力模型、高新技術產業

Keywords – Innovation, Productivity, Olley and Pakes Method, High-tech Industries

Table of Contents

Index of Figures

Index of Tables

1 Introduction

Since the reform and opening-up, China has transformed to a manufacturing and exporting hub with 10% annually economic growth in average during 2000 to 2007. The manufacturing industry in China undergoes a rapidly growth. Because of cheap labor force, easily access to land and massive domestic demand, China has attracted many foreign companies to invest in the manufacturing industry and become the second largest economy in the world. In the beginning, those companies only set up factories in China and leave R&D sectors in home country. However, for the efficiency purpose, the supply chain gradually moves to China including R&D sectors. It provides China an opportunity to acquire new skill as well as technology and bring innovation into the manufacturing industry.

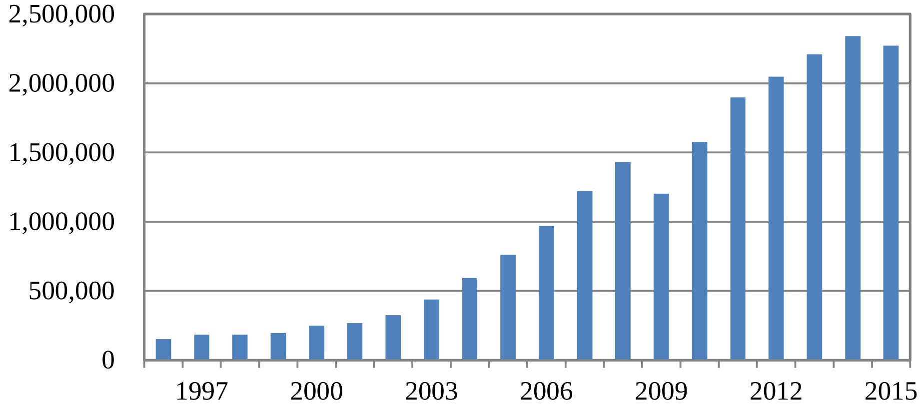
In 1988, Chinese Ministry of Science and Technology started a Torch program which aims at reinforcing innovative environment and promoting high-tech industrialization. Since that, Chinese government set up many national high-tech industrial development zones. It has been more than 150 zones until 2017. These zones are knowledge intensive and opened to other countries to attract foreign fund as well as to imitate foreign high technology and management skills. China aims at turning intangible innovation into real productivity.

However, fast growing as of these zones, China government pointed out some worries. The fundamental development may not be well. The weak industrial cluster and similar industrial structure may lead to a lack of self-characteristic. They consider whether the resource put into these zones really contributes more on the productivity or just a waste.

1.1 The Manufacturing Industries in China

With the fast growing of manufacturing industries, China was named "The world's factory." From the figure 1.1, we can see that the main trend of China's export has been continuously increasing since 1985. The most rapidly growing period is from 2000 to 2011. Although there was a financial crisis in 2008 which strikes the world economy seriously, the influence on China only lasted for few years. The exports just dropped for a while after 2008 and then resumed to the increasing trend again.

Figure 1.1 : China's Exports (Million USD)

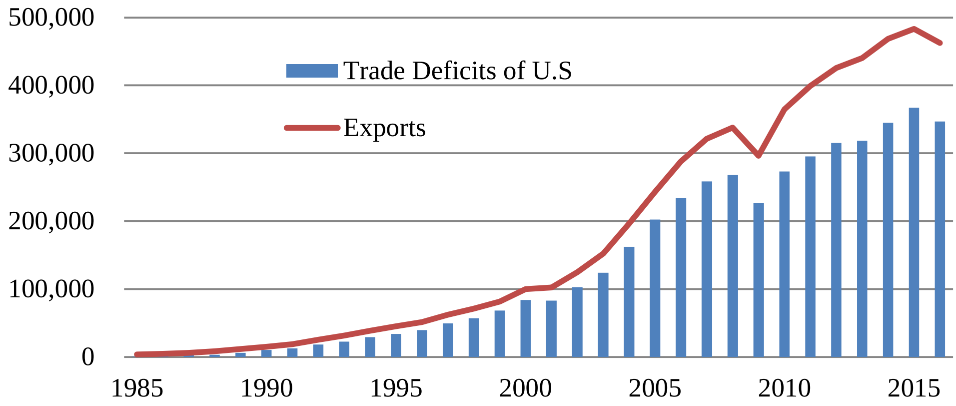


Source: National Bureau of Statistics of China

The main partners trading with China are United States, Japan, Korea as well as Taiwan. Between all of the partners, United States is the largest one. From the figure 1.2, it is quite clear that the trend of exports from China to United States keeps increasing. In 2001, the president Clinton and the U.S. congress permitted China for a permanent normal trade relations status which provides China an entry into World Trade Organization (WTO). The president Clinton at that time believed it was a great opportunity for United States to export cars made in America with a low tariff and invest in the telecommunications. However, the story afterwards implies a totally inverse situation. From the figure 1.2, United States has continued running a trade deficit to China and the amount increases every year. In the end, most of products in America are made in China.

It shows how strong the China's manufacturing industries are and the support from the government since reform and opening-up led to a continuously trade surplus to America.

Figure 1.2 : Exports from China to U.S (Million USD)

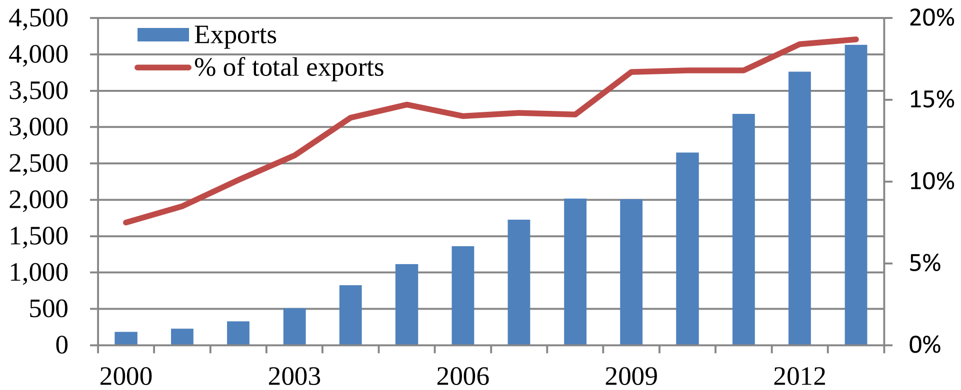


Source: Census Bureau of United States.

1.2 High-Tech Industrial Development Zone and Manufacturing

Although the manufacturing industries in China rapidly developed in early 1980s, the government still worried that the growth of manufacturing industries with low technology would not last for a long time. This thought ends up with the appearance of Torch Program. In order to encourage innovation activities, China's government set up many high-tech industrial development zones such as Zhongguancun Science Park, Nangjing High-tech Zone and Chengdu High-tech Zone. These high-tech zones contribute to the continuous economic growth and the innovation reform after 1990s.

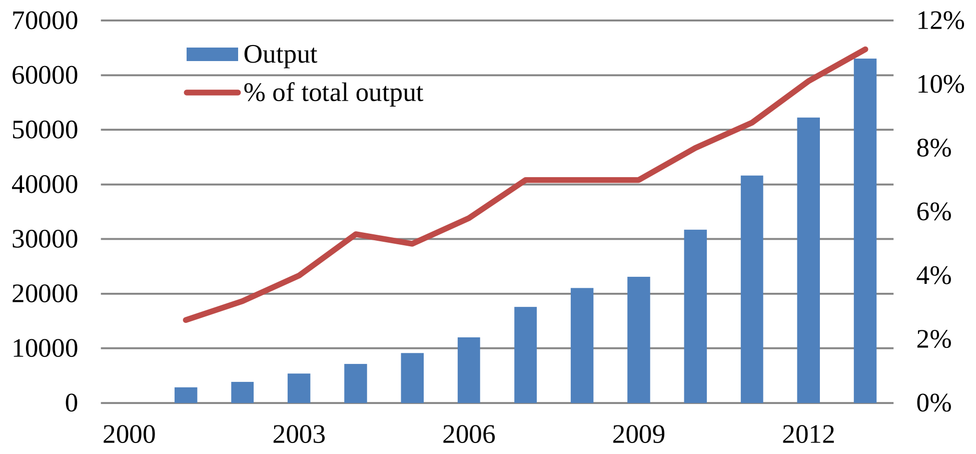
Figure 1.3 : Exports of High-tech Zones (Hundred Million USD)



Source: National Bureau of Statistics of China

The figure 1.3 is the exports trend only considering the high-tech zones. It grows every year except for 2008 and the share of exports from high-tech zones also increases which implies the role of high-tech zones becomes more important. Moreover, for the output, it shows the same trend in the figure 1.4.

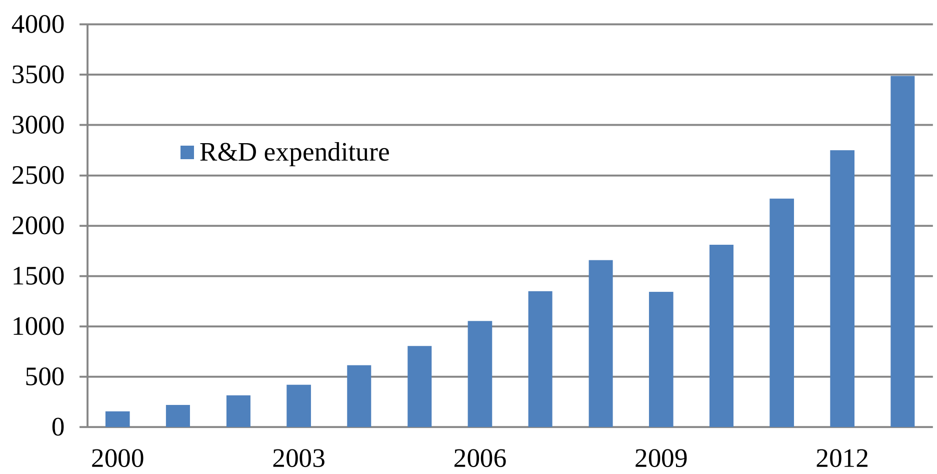
Figure 1.4 : Output of High-tech Zones (Hundred Million USD)



Source: National Bureau of Statistics of China

The firms in high-tech zones are highly innovation-intensive. They invest more on R&D as well as innovation activities compared to firms outside the zones. That can be seen in figure 1.5. Innovation is a key point that the improvement of technology can raise the productivity more than just production.

Figure 1.5: R&D Expenditure of High-tech Zones(Hundred Million USD)



Source: National Bureau of Statistics of China

Owing to the difficulty of distinguishing whether the firm is in the high-tech zone or not, this study use high-tech industries during 2000 to 2007. Following the new categories from National Bureau of Statistics of China in 2013, the high-tech manufacturing industries are (1) Medical manufacturing (2) Aviation, spacecraft and equipment manufacturing (3) Electronic and communications equipment manufacturing (4) Computer and office equipment manufacturing (5) Medical equipment and instrumentation manufacturing (6) Electronic chemicals manufacturing. China refers to the method from OECD for the classification of high-tech manufacturing industries. All these six industries maintain a high R&D intensity which is the ratio of R&D expenditure to prime operating revenue. This study will mainly use these six industries in China to estimate the effects of innovation on firm's performance.

1.3 The Patent System of China

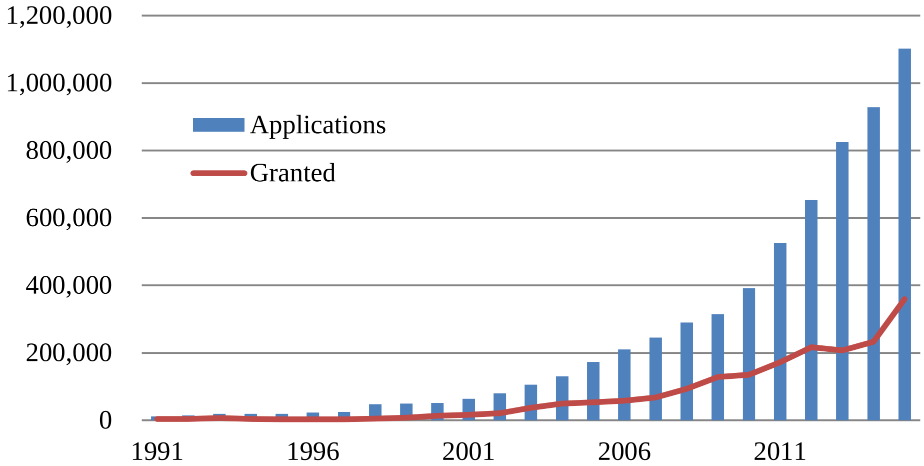
In 1984, the Standing Committee of National People's Congress (NPC) issued the China's Patent Law. On the first day of implementation of the Patent Law, the State Intellectual Property Office (SIPO) received almost 3,500 applications for patent which leaves a record in the patent history. This phenomenon shows that China, as one of a world's top three economies, gathers much energy for innovation and technology improvement. In order to accelerate the economic growth, China makes great efforts on independent innovation. Until 2017, the China's Patent Law has undergone three times amendments. Although the recent controversial issue is about the prohibition and penalty for patent infringement, the government has already created a huge space for innovation activities.

There are three types of patents in China: Invention, Utility Model and Design. The category is the same as Germany, Japan and Korea while America, the UK and Netherlands contain only Invention and Design. In most of countries, the patent law only protects Invention patents. The others two types of patents are under a protection from other specific law. However, China contains these three types of patents in one Patent Law which is a unique characteristic.

The Invention patent and Utility Model patent usually protect those creative works created with natural idea and aims at improving the function of product, technology, manufacturing process or convenience. However, the Invention patent covers more than Utility Model such as products with certain form, materials without certain form, biological materials, method and use. The Utility Model covers only the creation of shape, structure and combination. Owing to the complexity of examination, Invention patent requires more time for the office to finish the prosecution. The Design patent covers the shape, pattern, color or combination for the whole piece or part of the goods. It focuses more on the visual effect instead of skill improvement.

The rapidly increase of total patent applications in China since 2000 implies a more innovative environment for China's industries. From the gradually larger gap in figure 1.6 between applications and granted, we can infer that the patent examination is more strict to guarantee patent's quality. All these efforts made China's patent system more complete and SIPO became one of the top five patent offices.

Figure 1.6: Patent Applications and Granted



Source: World Intellectual Property Office

2 Literature Review

Nowadays innovation is a very important issue for firm's production performance. If only counting on capital stock and labor, there will be a limitation once the saving rate and depreciation rate reach a steady state. To handle this problem, the Solow growth model (1957) introduces the concept of technology improvement. Without innovation, investing in capital stock does not provide much help to economic growth when facing economic stagnation. Thus, firms have to consider investing in improving technology and skills. Since that, more and more either macroeconomics or microeconomics research such as Griliches (1979, 1988), Coe and Helpman (1995) that analyzed the relationship between innovation and productivity. The positive and significant effect of innovation on productivity is confirmed. However, the elasticity of productivity to innovation is quite different owing to research method. Later we split it into two parts for further discussion.

2.1 Innovation

Although firms want to innovate, it is really difficult to measure whether it is worthwhile to invest. If there was no actual achievement, the investment would become the sunk cost. That's also a key point to decide how to measure innovation. Innovation is an intangible concept, but cannot be omitted. Most of the empirical studies use the R&D expenditure or patent stock as a measurement of innovation. However, the outcome is quite different since R&D expenditure is an input but the patent is the output of the investment.

Since the relationship between R&D expenditure and patent stock is input and output, the causality should be examined first in order to do the further estimation. Pakes and Griliches (1984) confirmed a positive and significant relationship between R&D expenditure and patent stock. Griliches and Hausman (1986) continued the work using firm level data of U.S. manufacturing sector during the 1970's and confirmed the same relationship even controlled the firm size, permanent patent policy and the effect of R&D history. In short, if the firm can successfully become more innovative from the R&D investment, they should have a higher productivity as expected.

After affirming the causality, the further question is to decide using R&D expenditure or patent stock as an indicator of innovation. Most of studies during 1970s and 1980s used R&D expenditure to indicate innovation. Griliches (1980) tried to use the slowdown of R&D expenditure growth to explain the slowdown of productivity growth. Piekarz (1983) discussed that whether the government's policy of increasing R&D expenditure really contributed to the growth of productivity and pointed out other concerns toward R&D-related policy. Sterlacchini (1989) applied previous studies' result for R&D and productivity to analyze British cross-industrial manufacturing.

However, the concept of innovation does not only include R&D efforts but also other activities related to innovation. (Smith et al., 2004). The firm can purchase new equipments or software such as patent, unpublished patent and license to embodying technological innovation. In other words, the firms can directly turn to the output of innovation and prevent from the risk of investment in R&D. The R&D expenditure has been substituted with budget for purchasing patents or licenses. In this situation, low R&D expenditure may not stand for low innovation and the result may be biased using R&D expenditure.

Crépon et al. (1998) constructed a model summarizing the procedure from firm's decision to engage in R&D to the use of innovations in the practical production activities. They introduced a fact that it is not innovation input (R&D, R&D capital intensity) but innovation output (patent numbers) that increases productivity. The probability of firm engaging in R&D increases with firm size, market share, diversification and other technology improve indicators. The innovation output rises with the efforts in R&D either directly or indirectly. At last, firm productivity is positively related to innovation output. Ambrammal and Sharma (2016) estimated the impact of innovation on firm's performance with both R&D expenditure data and patent data. The result shows a much lower coefficient of R&D expenditure compared to patenting although the relationship between R&D expenditure and firm's performance is not significant. Stern et al. (2000) is also one of the early studies using aggregated patent data to analyze the effects of innovation and the relationship between innovation and total factor productivity growth. Nowadays, more and more studies following previous research foundation on innovation use patent stock as an indicator for innovation.

2.2 Productivity

When it comes to the estimation of productivity, most of studies in the past tended to measure the production function first and then calculate the productivity from the coefficient of the residual value which cannot be explained by the input factors. Massimo et al. (2010) provided an overview for currently major methods estimating productivity. The methods can be separated into deterministic methodologies and econometric methodologies. For the econometric part that we are interested in, it can further be split into three categories according to being frontier or not and parameter as Table 2.1 shows. Other than the above factors, we should also consider the research is about microeconomics or macroeconomics. Microeconomics focuses on individual firm's productivity while Macroeconomics pays attention to aggregate productivity of an area, an industry or a country. From the past productivity researches in China, the focus was gradually moved from Macroeconomics to Microeconomics owing to the completeness of statistical data.

Table 2.1: Econometric Method for Productivity

	Parametric	Semi-parametric
Frontier	Stochastic frontier analysis (Micro-Macro)	—
Non-frontier	Growth regressions (Macro)	Proxy-variables (Micro)

Frontier model allows inefficiency while Non-frontier model assumes fully efficiency. Frontier model implies that the observed output is different from the potential output because of inefficiency. This assumption allows SFA method to separate productivity change into two parts: technical efficiency that pursues frontier and technical progress that improves frontier.

The Growth regressions methodology is an extension to traditional Solow growth model. It is used in macroeconomics filed for aggregate studies such as difference economic performance across countries.

For microeconomics estimating individual firms, most of the studies started with a Cobb-Douglas production function. Traditional estimation only considered balanced panel data which only included continuously existing firms and it is obviously that the sample is not random selected. As many studies for firm's productivity faced before, the main difficulties are two: the selection bias caused by firm dynamics (entry and exit) and simultaneity. The selection bias was firstly found in the research of Wedervang (1965). The low productivity firms would choose to exit the market and it leads to overestimation of productivity with an unbalanced panel data. Marschak and Andrews (1944) mentioned that the level of inputs is potentially correlated to unobserved productivity shock and it caused simultaneity and endogeneity of input choice.

The researchers in the past tried to use fixed effect model to deal with simultaneity issue and use balanced panel data to deal with selection bias. However, it was difficult to fix the endowgeneity and the non-random sample would cause more bias. Olley and Pakes (1996) offered a proxy variables method mentioned in Table 2.1 as a better solution for these two difficulties which is further discussed in next chapter.

3 Methodology

3.1 Olley and Pakes Productivity Estimator

First we assume a Cobb-Douglas production function:

(1) $$Y = TFP \cdot A^{\beta a} K^{\beta k} L^{\beta l} M^{\beta m}$$

Then we take a logarithmic form of equation (1):

(2) $$y_{it} = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_t t + \omega_{it} + \eta_{it}$$

In the equation (2), Y_{it} is the log of value added, a_{it} is the age, k_{it} is the log of capital stock, l_{it} is the log of employment and m_{it} is the log of intermediate inputs from firm *i* at time *t*. The coefficient β_a is the marginal effect of age to the value added. $\beta_k, \beta_l, \beta_m$ are the marginal effect of capital stock, employment, intermediate inputs to the value added. For total factor productivity, it can be separate into three parts: $\beta_t t$ is the trend that TFP varies as time goes by. ω_{it} is the productivity that this study is unable to observe. η_{it} is the measurement error or unexpected shocks which is not correlated with a_{it}, k_{it}, l_{it} and m_{it}.

According to Solow residuals, the constant term and the error term are the productivity that we are going to measure. However, if we directly apply OLS estimator to analyze, endogeneity bias happens between error term and the input variables. The firm has to decide the input demands according to ω_{it} which is the productivity that only firm knows. Thus, there will be an overestimate for coefficients of input variables because the OLS method fails to take this unobserved productivity into consideration.

There would also be selection bias owing to exit behavior of firms. The traditional method of accounting for exit and entry only allows balanced panel which means there are only continuously existing firms during the whole sample period in the data. The decision of firms for exiting the market usually depends on their expectation for future productivity and their future productivity is partially on current productivity. In this way, the balanced panel would exclude those firms with lower productivity and lead to overestimate for productivity.

In order to deal with simultaneity and selection bias if using OLS estimator, this study applies three steps semiparemetric productivity measurement from Olley and Pakes (1996).

3.1.1 The First Step: To Eliminate the Simultaneity

In order to estimate β_l and β_m , we have to eliminate the simultaneity.

First we assume generally investment is positive correlated to productivity that only firm can observe.

(3) $$i_t = i_t(\omega_t, a_t, k_t)$$

To do the estimation, Olley and Pakes method assumes monotone increasing between i_t and ω_t according to Pakes(1994). Given the fixed k_t, we can use inverse function of equation (3) to rewrite the unobserved ω_t with i_t that we can observe.

(4) $$\omega_t = h_t(i_t, a_t, k_t)$$

Then, we replace ω_t with $h_t(i_t, a_t, k_t)$ in the equation (2) and rearrange.

(5) $$Y_{it} = \beta_l l_{it} + \beta_m m_{it} + \Phi(i_{it}, a_{it}, k_{it}) + \eta_{it}$$

where

(6) $$\Phi(i_{it}, a_{it}, k_{it}) = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + h_t(i_{it}, a_{it}, k_{it})$$

In the equation (5), l_{it}, m_{it} and η_{it} are independent. Thus we can directly use OLS to estimate the coefficient β_l and β_m.

3.1.2 The Second Step: To Fix the Selection Bias

To fix the selection bias, Olley and Pakes (1996) introduce a concept of survival probability into the estimation.

The accumulation equations for capital and age are as follows:

(7) $$k_{t+1} = (1-\delta)k_t + i_t \; and \; a_{t+1} = a_t + 1$$

The firm in the beginning of every period has to consider whether to continue running or exit the market. If the firm decides to continue, it has to choose the amount of labor and investment which determine the future capital stock.

(8) $$V_t(\omega_t, a_t, k_t) = max\left\{ \Phi, \sup_{i_t \geq 0} \pi_t(\omega_t, a_t, k_t) - c(i_t) + \beta E[V_{t+1}(\omega_{t+1}, a_{t+1}, k_{t+1}) | J_t] \right\}$$

The firm is expected to maximize the sell-off value Φ or profit as equation (4) shows. $\pi_t(\cdot)$ is the current profit function consisted of state variables. $c(i_t)$ is the cost of current investment. β is the current discount factor. $E[\cdot]$ is the expected profit function at time t+1 based on current information J_t . The firm has to consider whether it's worth to continue and decide an optimal investment level or just exits the market and receive sell-off value Φ. Then, the solution to this problem is an exit rule and an investment demand function. The function X_t equals to 0 when the firm choose to exit.

(9) $$X_t = \begin{cases} 1 & if\ \omega_t \geq \omega_t(a_t, k_t), \\ 0 & otherwise, \end{cases}.$$

Because k_t is correlated to k_{t-1}, i_{t-1} and ω_{t-1}, we can estimate survival probabilities by applying a probit estimation for X_t using a polynominal series in (i_t, a_t, k_t) in the regression. In this way, we can acquire the survival probability as follows:

(10) $$\begin{aligned} &\Pr\{X_{t+1} = 1 | \underline{\omega}_{t+1}(k_{t+1}, a_{t+1}), J_t\} \\ &= \Pr\{\omega_{t+1} \geq \underline{\omega}_{t+1}(k_{t+1}, a_{t+1}) | \underline{\omega}_{t+1}(k_{t+1}, a_{t+1}), \omega_t\} \\ &= \mathrm{F}\{\underline{\omega}_{t+1}(k_{t+1}, a_{t+1}), \omega_t\} \\ &= \mathrm{F}(i_t, a_t, k_t) \\ &= \mathrm{P_t} \end{aligned}$$

3.1.3 The Third Step: Estimate $\boldsymbol{\beta_a}, \boldsymbol{\beta_k}, \boldsymbol{\beta_t}$ and TFP

Currently we have solved simultaneity and selection bias. Next, we need to estimate the following series estimator with a forth order polynominal expansion in (P_t, h_t) which is derived with β_l, β_m, Φ_t and P_t.

(11) $$y_{t+1} - \hat{\beta}_l l_{t+1} - \hat{\beta}_m m_{t+1}$$

$$= \beta_0 + \beta_a a_{t+1} + \beta_k k_{t+1} + \beta_t t + \sum_{j=0}^{4-m} \sum_{m=0}^{4} \beta_{mj} \hat{h}_t^m \hat{P}_t^j + e_t$$

Where

(12) $$\hat{h}_t = \hat{\Phi}_t - \beta_a a_t - \beta_k k_t$$

Finally, we use nonlinear least squares to estimate the series estimator and acquire the coefficients $\hat{\beta}_a, \hat{\beta}_k$ and $\hat{\beta}_t$. With $\hat{\beta}_l, \hat{\beta}_m, \hat{\beta}_a, \hat{\beta}_k$ and $\hat{\beta}_t$, the total factor productivity can be obtained:

(13) $$\mathrm{P_{it}} = \exp(y_{it} - \hat{\beta}_a a_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it})$$

4 Empirical Result

4.1 Data Description

The patent data and firm-level data come from China's National Bureau of Statistics (NBS). The patent data includes three different kind of patent stock: Invention, Utility Model and Design. This firm-level data is the most complete one and often used in recent studies about China's industry. It includes state-owned and nonstate-owned firms whose annual revenue is higher than 5 million RMB.

To come up with the complete and clean panel data, this study follows the procedures from Brandt et al. (2012) as well as Cai and Liu(2009). The firm-level data then combined with patent data using a unique firm ID and we have an unbalanced panel data from 2001 to 2007. In order to prevent from some measurement error, the observations would be dropped from the sample under following conditions:

(1) There are key variables such as output, total assets, net fixed assets, revenue, value-added missing.

(2) Firms contain less than 10 employees.

(3) Number of total assets is smaller than number of total fixed assets or net fixed assets.

(4) Observations with extreme values (larger than 99.5 percentile or smaller than 0.5 percentile.)

(5) Firms without founded time.

In addition to these conditions, firms with less than three consecutive years of data are also deleted to maintain a proper sample for panel analysis. After all these procedures, we select 6 high-tech industries defined by NBS as previously mentioned:

(1) Pharmaceutical manufacturing.

(2) Aviation, spacecraft and equipment manufacturing.

(3) Electronic and communication equipment manufacturing.

(4) Computer and office equipment manufacturing.

(5) Medical equipment and instrumentation manufacturing.

(6) Electronic chemicals manufacturing.

Table 4.1: Patent-related Variables (Overall Panel)

Variable	Obs	Mean	Std. Dev.	Min	Max
Total Patent	55,353	0.6698	31.7202	0	5166
Invention	55,353	0.3720	29.4558	0	4790
Utility Model	55,353	0.1407	1.8548	0	190
Design	55,353	0.1571	1.9755	0	227

Table 4.2: Patent-related Variables (Balanced Panel)

Variable	Obs	Mean	Std. Dev.	Min	Max
Total Patent	16,752	1.3991	57.3011	0	5166
Invention	16,752	0.9364	53.3287	0	4790
Utility Model	16,752	0.2154	2.8395	0	190
Design	16,752	0.2473	3.0220	0	227

After the procedure of organizing a clean panel data, we provide some descriptive statistics about our sample. The unbalanced panel data contains 55,353 observations. The table 4.1 shows the mean, minimum as well as maximum values and standard deviation for the patent numbers. Invention seems to take up much more proportion of total patent. Considering the firm dynamics issue, we then construct a balanced panel data that only includes continuously existing firms during the sample period. There are 16,752 observations in the balanced panel data. Compared to unbalanced one, the mean values are much larger. However, the Maximum values still remain the same which may implies that the patent stock is related to firm dynamics.

Table 4.3: Firm Performance-related Variables (Overall Panel)

Variable	Obs	Mean	Std. Dev.	Min	Max
Size					
Output	55,353	199619.6	1270216	1.1198	84300000
Value Added	55,353	67300.84	396489.7	0.1688	28000000
Capital Stock	55,353	45942.28	227461.3	0.7839	13300000
Employment	55,353	423.75	1172.042	10	82067
Productivity					
TFP	55,353	4.3974	65.7458	0.00031	8437
Others					
New Product	55,353	49324.53	762481.2	0	84900000
Exports	55,353	98448.66	866947.8	0	54900000

Table 4.4: Firm Performance-related Variables (Balanced Panel)

Variable	Obs	Mean	Std. Dev.	Min	Max
Size					
Output	16,752	348157.1	1979195	169.1332	84300000
Value Added	16,752	110739.7	579454.7	55.8273	28000000
Capital Stock	16,752	67822.54	251578.5	0.9891	9307209
Employment	16,752	598.41	1349.402	10	55632
Productivity					
TFP	16,752	3.0068	11.9118	0.00342	1290
Others					
New Product	16,752	111922.9	1311981	0	84900000
Exports	16,752	177657.8	1276071	0	54900000

Table 4.3 and 4.4 are the descriptive statistics about the firm performance. The unit of this firm-level data is thousand RMB. This study includes some important variables such as Output, Capital Stock, Employment, Total Factor Productivity, New Product and Exports for firm performance. The mean values of the balanced panel data are still larger than unbalanced one except TFP. On the other hand, for the maximum value of TFP, the unbalanced one is larger. It is conflicted with previous studies that the exclusion of firm dynamics may lead to higher productivity because the firms

which exit the market are usually with lower productivity. For this issue, we will do further estimation and discussion later in empirical results.

4.2 Estimation of Productivity

Finally there are 14,451 firms in the sample from 2000 to 2007. However, this is an unbalanced panel because exit and entry happened during this period. The analysis in later section will consider the sample without exit and entry issue.

Table 4.5: Productivity-related Variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Investment	55,353	7383.815	56911.83	0	4718576
Age	55,353	10.38131	11.31322	0	217
Capital Stock	55,353	45942.28	227461.3	0.783945	13300000
Employment	55,353	423.75	1172.042	10	82067
Intermediate Inputs	55,353	136727.7	935615.8	0.586655	65900000

Table 4.6: Productivity Estimation

Variables	β	(s.e.)
Age	0.0019	(0.0011)
Capital Stock	0.1358***	(0.0193)
Employment	0.1309***	(0.0092)
Intermediate Inputs	0.6777***	(0.0105)
Time	0.0708***	(0.0024)
Number of obs	55,353	

Standard errors in parentheses * p<0.05 ** p<0.01 *** p<0.001

The Table 4.6 shows the result of OP method estimating productivity. We put the intermediate inputs into the equation which the original OP method did not because the characteristic of China’s manufacturing industries is highly relying on raw materials. Moreover, raw materials take up most of parts in intermediate inputs. As the result shows, the coefficient of intermediate inputs is much larger compared to capital stock and employment. Thus, according to equation (13), there would be an overestimation of productivity if we ignored the intermediate inputs.

4.3 Total Patent Stock and Firm Performance

Table 4.7: Patent Stock and Firm Performance

	Patent Stock			
	Overall Panel		**Balanced Panel**	
	ln(S)	(s.e.)	ln(S)	(s.e.)
Size				
Output	0.2173***	(0.0151)	0.2498***	(0.0193)
Value added	0.2608***	(0.0206)	0.3144***	(0.0243)
Capital stock	0.1993***	(0.0191)	0.2361***	(0.0216)
Employment	0.1337***	(0.0127)	0.1446***	(0.0141)
Productivity				
TFP	0.0882***	(0.0164)	0.1177***	(0.0190)
Other				
New product	0.5899***	(0.1006)	0.8695***	(0.1013)
Export	0.3858***	(0.0713)	0.4761***	(0.0787)
Number of obs	55,353		16,752	

Standard errors in parentheses * p<0.05 ** p<0.01 *** p<0.001

Table 4.7 shows the relationship between Patent Stock and firm performance including Output, Value Added, Capital Stock, Employment, Total Factor Productivity, New Product Share and Export. The number of observations is 55,353.

Here we run the fixed-effect regression of following equation:

(14) $$lnY_{it} = \alpha lnS_{it} + \tau_i + \varepsilon_{it}$$

Y_{it} is the dependant variables, such as value added, total factor productivity and export for firm *i* at time *t*. S_{it} is the patent stock. τ_i is the firm fixed effect. For the overall panel, the patent stock is positively and significantly related to all of the outcome variables.

A 10% increase in patent stock contributes to almost 2.2% increase in output. A 10% increase in patent stock contributes to about 2.6% increase in value added. This is the most intuitive firm performance and the results fit those studies confirmed in the past research. For capital stock, the effect is also positive and significant. A 10% increase in patent stock means about 2% increase in capital stock.

The magazine Economist once raised a question on February 11, 1995 that whether the technology has created more jobs than it has destroyed or not. Many studies confirmed the positive relationship between innovation and job generation such as Regev (1998). In this study, we surmise the same relationship that a 10% increase in patent stock contributes 1.3% in employment.

For total factor productivity, the result is positive and significant which fits our expectation following previous studies. This is the most concerned part in the research. Productivity is a multiplier to other inputs and it's the key to examine whether the investment in innovation really carries out actual interest for firms. A 10% increase in patent stock implies almost 0.9% increase in productivity. The coefficient is much higher than other country-scale studies because this study isolates the high-tech industries in China which is more innovation intensive.

Besides the previous variables we have discussed, new product is also very important. The innovation may not only be revealed in the productivity and output improvement but also the share of new product. It is the final good that will be on consumer's hand which means the output of whole production line of the manufacturing industry. A 10% increase in patent stock raises 5.9% increase in share of new product and it is still significant. Compared to the result from Fang et al. (2016)

conducted with whole manufacturing industries sample in China, the coefficient is smaller. The reasonable explanation is the higher technical threshold for new product of high-tech industries. It takes more time and investment to come up with a high quality new product for high-tech industries while other industries produce relatively low technology products fast and cheap. For export, the relationship is still positive and significant. A 10% increase in patent stock contributes 3.8% increase in export.

The findings above are based on the overall panel without dealing with the issue of firm's entry and exit behavior. However, the dynamics of firms may easily twist the relationship between patent stock and output variables. Considering this bias, we then further construct a balanced panel which only contains those firms continuously existing during the sample period. That leaves a sample with 16,752 observations. Interestingly, all of the outcome variables still perfectly remain positive and significant. Moreover, the magnitude of the coefficient is even stronger then the result from the unbalanced panel. From this finding, we can infer that the firm dynamics would negatively affect the relationship between innovation and firm performance.

The new entrants are generally above average productivity level of incumbent firms' while the exiting firms are below (Masso et al., 2004). Usually the exiting of firms implies low productivity. Thus, the smaller coefficient of unbalanced panel compared to the balanced one is owing to the larger effect of exiting firm leading to lower firm performance.

4.4 Different Patent Stock and Firm Performance

Table 4.8: Different Type Patent Stock and Firm Performance

	Invention		**Utility Model**		**Design**	
	α	(s.e.)	α	(s.e.)	α	(s.e.)
Size						
Output	0.1961***	(0.0171)	0.1787***	(0.0191)	0.0963***	(0.0171)
Value added	0.2520***	(0.0215)	0.2216***	(0.0240)	0.1290***	(0.0215)
Capital stock	0.2120***	(0.0191)	0.1378***	(0.0214)	0.0920***	(0.0191)
Employment	0.1255***	(0.0124)	0.0932***	(0.0139)	0.0490***	(0.0124)
Productivity						
TFP	0.0923***	(0.0168)	0.0912***	(0.0187)	0.0550***	(0.0167)
Other						
New product	0.7033***	(0.0895)	0.5559***	(0.0999)	0.2647***	(0.0893)
Export	0.2952***	(0.0696)	0.4188***	(0.0775)	0.2058***	(0.0693)
Number of obs	16,752		16,752		16,752	

Standard errors in parentheses * p<0.05 ** p<0.01 *** p<0.001

After the analysis of the relationship between the patent stock and the firm performance, this study further estimates whether the result varies with different types of patent. Not every patent are generated with same quality. Many related researches use the citation data or granted patent data to distinguish the quality. However, we are not able to get the data and put it into our study. We then separate the patent stock into Invention, Utility Model and Design according to China’s patent system.

From the definition of three different patents, Invention usually tends to contain higher innovation values while the other two are for practical use. Here we re-estimate the equation (14) with a balanced panel which can provide a more precise estimation.

The outcome seems to be similar with previous estimation. All types of patent stock remain positive and significant toward the firm performance. It is noteworthy that the coefficients of Invention are larger than the other two types. The result is as our expectation for high-tech industries. This is very intuitive that the Invention patent should contribute more to firm performance.

However, it is different from the one from Fang et al. (2016) that the coefficients of Invention are relatively smaller than the other two. Fang et al. (2016) found that the state-owned enterprises tend to be better at associating new patents with firm performance growth than private-own enterprises but they are more successful for lower quality patents such as Utility Model and Design. In this study, the high-tech industries contain lower portion of SOEs and exclude the sample of relatively low-innovative SOEs. This argument provides a possible explanation for the different result.

5 Conclusion

5.1 Discussion

For last three decades, China's government focused on the development of high-tech industrial zones as well as high-tech industries. No matter state-owned enterprises or private owned enterprises invest huge amount in R&D. Are these efforts worthwhile or just becoming a sunk cost? From the empirical study result in this paper, we can offer a positive answer with a dataset including patent stock information and firm performance information. The result shows that for high-tech industries in China, the relationship is positive and significant between patent stock and firm productivity as well as firm performance including output, value added, capital stock, employment, share of new product and exports.

Considering the issue of exit and entry behaviors may affect the analysis, we then construct a panel data only includes continuously existing firms during the sample period. The result still remains positive and significant as unbalanced panel data. More interestingly, the magnitude of all coefficients becomes larger. From this finding we can speculate that the firm dynamics negatively affect the relationship between innovation and firm performance.

Furthermore, we separate the patent stock into three categories to see their individual effect on the firm performance. No matter it is Invention patent, Utility Model patent or Design patent, the relationship with firm performance is positive and significant. However, in contrast to previous research conducted by Fang et al. (2016) with dataset including all industries, the Invention patent contributes more than the other two to firm performance instead of Utility Model patent. This shows the investment in R&D is worthwhile because Invention patent contains higher innovation and technology than other two.

5.2 Limitations and Recommendations for Future Research

This study analyzes the high-tech industries in China to see how their innovation affects firm performance. However, as we know, China government's plan of country development is according to area. Also the Torch program focuses not only on the development of high-tech industries but also the high-tech zones. Our data only contains some cities information about the firms so that we cannot make sure the precise location of those firms. As a result, this study can only provide an overall view on the high-tech industries.

For future research, if the location information is available that whether the firm is in the high-tech zones or not, the further analysis can be done for the difference of firm performance between firms inside high-tech zones and firms outside. That can provide a more detailed evaluation of the efforts of high-tech zones to eliminate the worries from China government. Also, for the future development of high-tech zones, the further research can introduce the innovation-related issue such as knowledge spillover effect or absorptive capacity to estimate the innovative relationship and firm performance between these high-tech zones.

6 Reference

Ambrammal, S. K., & Sharma, R. (2016), "Impact of Patenting on Firms' Performance: an Empirical Investigation Based on Manufacturing Firms in India," *Economics of Innovation and New Technology*, 25(1), 14-32.

Brandt, L., Van Biesebroeck, J., & Zhang, Y. (2012), "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing," *Journal of Development Economics*, 97(2), 339-351.

Cai, H., & Liu, Q. (2009), "Competition and Corporate Tax Avoidance: Evidence from Chinese Industrial Firms," *The Economic Journal*, 119(537), 764-795.

Coe, D. T., & Helpman, E. (1995), "International R&D Spillovers," *European Economic Review*, 39(5), 859-887.

Crépon, B., Duguet, E., & Mairesse, J. (1998), "Research, Innovation and Productivity: an Econometric Analysis at the Firm Level," *Economics of Innovation and New Technology*, 7(2), 115-158.

Del Gatto, M., Di Liberto, A., & Petraglia, C. (2011), "Measuring Productivity," *Journal of Economic Surveys*, 25(5), 952-1008.

Fang, J., He, H., & Li, N. (2016), "China's Rising IQ (Innovation Quotient) and Growth: Firm-level Evidence," Unpublished paper, IMF.

Griliches, Z. (1979), "Issues in Assessing the Contribution of Research and Development to Productivity Growth," *The Bell Journal of Economics*, 92-116.

Griliches, Z. (1980), "R&D and the Productivity Slowdown," *The American Economic Review*, 70(2), 343-348.

Griliches, Z. (1988), "Productivity Puzzles and R&D: Another Nonexplanation," *The Journal of Economic Perspectives*, 2(4), 9-21.

Hall, B. H., Griliches, Z., & Hausman, J. A. (1986), "Patents and R and D: Is There a Lag?" *International Economic Review*, 265-283.

Marschak, J., & Andrews, W. H. (1944), “Random Simultaneous Equations and the Theory of Production,” Econometrica, *Journal of the Econometric Society*, 143-205.

Masso, J., Eamets, R., & Philips, K. (2004), “Creative Destruction and Transition: The Effects of Firm Entry and Exit on Productivity Growth in Estonia,” (No. 1243) Institute for the Study of Labor (IZA).

Olley, G. S., & Pakes, A. (1996), “The Dynamics of Productivity in the Telecommunications Equipment Industry,” *Econometrica*, 64(6), 1263-1297.

Pakes, A., & Griliches, Z. (1984), “Patents and R&D at the Firm Level: a First Look,” R&D, Patents, and Productivity (pp. 55-72), University of Chicago Press.

Pakes, S. P., & Gerrity, L. W. (1994), “Protozoal Diseases,” *The Biology of the Laboratory Rabbit*, 205-30.

Piekarz, R. (1983), “R&D and Productivity Growth: Policy Studies and Issues,” *The American Economic Review*, 73(2), 210-214.

Regev, H. (1998), “Innovation, Skilled Labour, Technology and Performance in Israeli Industrial Firms,” *Economics of Innovation and New Technology*, 5(2-4), 301-324.

Smith, V., Dilling-Hansen, M., Eriksson, T., & Madsen, E. S. (2004), “R&D and Productivity in Danish Firms: Some Empirical Evidence,” *Applied Economics*, 36(16), 1797-1806.

Solow, R. M. (1957), “Technical Change and the Aggregate Production Function,” *The Review of Economics and Statistics*, 312-320.

Sterlacchini, A. (1989), “R&D, Innovations, and Total Factor Productivity Growth in British Manufacturing,” *Applied Economics*, 21(11), 1549-1562.

Stern, S., Porter, M. E., & Furman, J. L. (2000), “The Determinants of National Innovative Capacity,” (No. w7876) National bureau of economic research.

Wedervang, F. (1965), “Development of a Population of Industrial Firms: the

Structure of Manufacturing Industries in Norway,"1930-1948 (Vol. 141, No. 4), Universitetsforlaget.