Quantitative Assessment on Frictions in Technology Market

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Abstract

In this paper, I first document several novel stylized facts from Chinese patent transaction data matched with manufacturing firm data. A key finding is that Chinese patent market is significantly less developed than the U.S. To understand the causes and consequences, I build a model that endogenizes firm R&D investment, patent trading decision and productivity growth. I structurally estimate the model and find the following two main results. First, Chinese patent market plays a small role in growth. It only accounts for 5% of China's GDP growth rate, as opposed to 17% in the U.S. Second, I evaluate the importance of three frictions calibrated to Chinese patent market: search cost, fixed transaction cost and information asymmetry. Search cost turns out to be the main friction to explain the gap of patent market size. If search cost was reduced to the US level, China's productivity growth would increase by 0.16 percentage points.

Keywords: Under-developed Patent Market, patent quality, search cost, fixed cost, information asymmetry

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1 Introduction

Akcigit et al. (2016) show that technology market can improve welfare by 1.2% in an economy calibrated to the U.S.. However, technology market is not immune to frictions that prevail in the goods and factor markets and can be more severe in developing economies. In contrast to the fast-growing literature that measures various frictions in the goods and factor markets, there are few quantitative assessments on technology market frictions. This paper aims to fill the blank by conducting the following analysis. First, I document a set of stylized facts for the Chinese patent market and contrast them with those for the US patent market. Second, I extend the model in Akcigit et al. (2016), where the meeting probability between seller and buyer in the patent market is the only friction that reduces the market efficiency. I highlight three types of frictions that may explain the differences between the Chinese and U.S. patent market. Third, I use the extended model to estimate the magnitude of each friction in the Chinese patent market and to evaluate their welfare implications.

The stylized facts are from two data sources: China's patent registration data and transaction data. The Chinese patent market is an ideal laboratory for quantitative assessment on frictions in technology market [1] for two reasons. On the one hand, China has accumulated sufficient technology thanks to its fast-growing R&D expenditure and patents granted over the past two decades. As Figure 1 shows, the gap of annual granted patents number between China and U.S. was narrowing sharply from 2000 to 2010. On the other hand, there is no evidence that China's technology market is more developed than its factor markets, which have been found to be highly distortionary.

This leads to our first stylized fact. The narrowing gap of granted patents between China and U.S. does not narrow the gap of the fraction of traded patents between those two countries as shown in Figure 1.

In the Chinese patent market, only 4.4% of domestic patents applied and granted between 1998 and 2013 are traded during this period, only a quarter of the proportion of 14.6% traded in the U.S. in the same period. My second stylized fact is that the proportion of traded patents is higher for high-quality patents in both countries. I measure

[1] By Chinese technology market annual report 2019, 42.67% technology transfer are made secretly, which generates data limitation for research. However, the patents transfers are recorded and opened to the public, which accounts for 10.51% among all the technology transfer contracts turnover in 2019. Without regard to the transfer happens secretly, if we leave out the price effect, patent right transfers number is almost 2 times than the number of patent license, which is shown in Figure B4.

patent quality by forward citation numbers, controlling for patent's technology class and granted year, and then group all the patents into high- and low-quality. I find that the fraction of high-quality patent sold is higher than low-quality sold. In China, the fraction of low- and high-quality patent sold is 4.1% and 4.6%, respectively. In the U.S., the fraction is 12.5% and 17.2%, respectively.

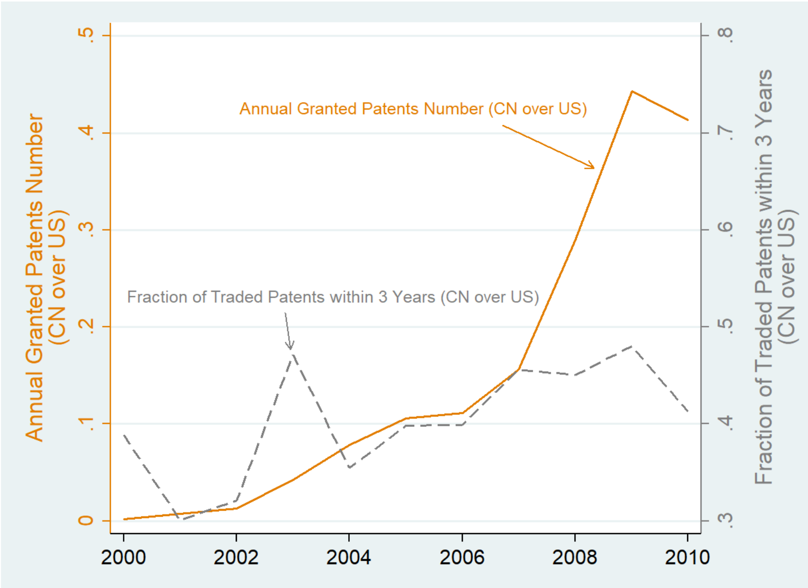


Figure 1: YEARLY GRANTED PATENT NUMBER AND FRACTION OF TRADED PATENTS: CHINA OVER U.S.

Note: (1) "US" indicates U.S.; "CN" indicates China. (2) The U.S. granted patents include all U.S.-firm-inventing patents filed and granted between 2000 and 2010. The Chinese granted patents include all Chinese-firm-inventing patents filed and granted between 2000 and 2010. I define the nationality of patent according to the assignee's type and nationality variables in database. (3) Yearly granted patents number is the number of patents granted in t year in each country, and in the graph, the ratio equals to this value in China over in U.S.. (4) The fraction of granted patents sold within 3 years [2]$= \frac{The\ number\ of\ t-year\ granted\ patents\ sold\ between\ t\ and\ t+3\ year}{The\ number\ of\ patents\ granted\ in\ t\ year}$, and the ratio value in this graph indicates the gap of the fraction of traded patents between China and U.S. as well.

I argue that the facts can be explained by technology market frictions originating from the same source for the frictions in the goods and factor markets, such as search cost in labor market (Pissarides, 2000), information asymmetry in market for used cars (Akerlof, 1978), or fixed transaction cost in housing market (Kaplan and Violante, 2014). Following Akcigit et al. (2016), I built a firm in-house R&D model in the spirit of Klette and Kortum (2004) and Lentz and Mortensen (2008). The model embeds a patent mar-

[2]The reason why I choose 3 years is that as the patent may wait for a long time to be sold, counting the number of patent sold within 3 years after getting granted makes the fractions of patents sold in different years comparable. With my patent data truncates in 2013, I only calculate the fraction of traded patents for the patent granted between 2000 and 2010.

ket that can reduce the patent-firm mismatch [3]. Firm with heterogeneous R&D capacity can do in-house R&D or buy the patent invented by others to improve productivity. I introduce two features that extend the model in Akcigit et al. (2016). First, I endogenize firm's search efforts in the patent market. The search cost measures quantitatively the search frictions that prolong the process of finding a patent in patent market. The search cost implies an intertemporal trade-off between consuming more today and search more for future productivity growth, which does not exist in Akcigit et al. (2016). Second, motivated by the second fact, I introduce patent quality heterogeneity and two alternative frictions related to patent quality: (1) information asymmetry conditional on patent quality and (2) fixed transaction cost. The former friction hinders the trading of high-quality patents more than the trading of low-quality patents and the later friction works in opposite direction.

Next, I structurally estimate the model by simulated method of moments, matching key moments of data from the Chinese patent market basic facts and the Annual Survey of Industrial Firms, e.g., the fraction of traded patents in all patents, the fraction of high-quality traded patents in all patents, the percentage of the firm as the buyer, the share of firms as the buyer ratio (large firm over small firm; up 75 percentile firm over 50-75 percentile firm), variance of sales growth, average R&D-sales ratio, large firm's R&D-sales ratio, R&D-sales ratio (75 percentile), the share of firms as the inventor ratio (large firms over small firms). I use the estimated model to evaluate the impact of patent market on the aggregate economy.

I then conduct several counterfactual exercises. I first evaluate the contribution of the patent market to long-run productivity growth. Shutting down the patent market will reduce the BGP productivity growth, which is 1.4% in the estimated economy, by about 5% (i.e., 0.1 percentage points). Next, I quantify the different implications of reductions of three types of friction. Removing the search cost friction can increase the fraction of traded patent from 4.4% to 34.2%. This will improve the steady-state aggregate welfare by 3.34% and increase the steady-state productivity growth by 29%. The effects of fixed transaction cost are also quantitatively sizable. Removing it can increase the fraction of traded patent to 17.6% and improve the aggregate welfare by 1.68%; The

[3] Many inventions are generated in other fields' research accidentally but every firm has its' specialization and adept fields. This kind of uncertainty could cause the mismatch between the inventor and the inventions. In literature, the patent and firm's matching level is measured by patent-firm similarity. Akcigit et al. (2016) depicts the patent market as an platform to adjust this mismatch problem by translating patent to the firm, where patent-buyer firm's similarity is higher than patent-seller firm's.

effects of information asymmetry are smaller. Removing information asymmetry can only increase the fraction of traded patents by 0.5 percentage points. Its effect on the aggregate welfare is negligible (0.12%). In a frictionless Chinese patent market, the fraction of traded patent can reach to 68.5%, and the aggregate welfare will increase by 6.43%.

Thirdly, I employ this framework to see which frictions can explain most for the large gap of patent market size between China and U.S.. To do this, I re-estimate the parameters correlated with patent market to target the U.S. patent market moments. The results tell us that compared with frictions value in China, in U.S., the search cost is 90% lower; the fixed cost is 2% higher and the information asymmetry on patent quality is 87% lower. Search cost gap can explain 78% of large gap of fraction of traded patent between China and U.S..

Lastly, to take robust check and include other potential factors that may affect the efficiency of the patent market, I also take the patent quality increment and directed search in patent market into consideration. I find that increase the patent market by 50%, the fraction of traded patent will increase from 4.4% to 6.1%. This will improve the steady-state aggregate welfare by 9.57% and increase the steady-state productivity growth by 81.34%. If I change the random search in Chinese patent market to directed search, which means firm can always meet the patent suitable for it, the fraction of patent sold can reach to 21.4%. The aggregate welfare can increase by 25.92% and the steady state productivity growth will increase by 25.92%.

My research suggests that to build a good market and intellectual property right (IPR hereafter) protection institutions to encourage patent market development is vital to an economy. Actually, IPR protection seeps into all aspects of frictions in this paper. My welfare analysis discovers that although search cost and fixed cost 's impact on patent market are both relatively larger than information asymmetry, search cost is the main reason for the large gap of patent market size between China and U.S.. We should put lowering the search cost into the first place in an under-developed patent market. Strengthening the IPR protection can facilitate search cost decrease. For example, well IPR protection encourages patent inventor to disclose detailed information about patents and guarantee that the firm can locate the patent they need quickly and lower the search cost. By policy experiment, the optimal R&D subsidy with lump sum tax is 58%. the aggregate welfare increases 1.6% at largest compared with no subsidy.

The optimal search cost subsidy is 84% which means the government takes lump-sum tax from firms and pay 84% search cost for firms. This will lead to about 1.6% welfare increase compared with no subsidy.

Related Literature This paper relates to several branches of endogenous growth literature. First, I build closely on the seminal contributions of Klette and Kortum (2004) and Lentz and Mortensen (2008). In the nascent endogenous growth model, knowledge production is by-product of capital accumulation or comes from learning-by-doing (Romer, 1986; Stokey, 1988). Aghion and Howitt (1992) embodies Schumpeter's idea of creative destruction in model where production of new idea can bring profit. However, Klette and Kortum (2004), for the first time, add flesh of firm endogenous R&D activities to the bones of an aggregate model of technological change. Firm's entry, exit, size distributions are linked with its' R&D choice, productivity changes, patenting. Lentz and Mortensen (2008)'s paper develops a tractable model to quantitative estimate this framework. This paper is built on the framework of these, extending a new way to get new ideas, purchasing patent from others.

Vast of papers have discussed the mechanisms of the knowledge dissemination and its' aggregate growth effect. In Lucas and Moll (2014), knowledge learning is not the by-product of capital accumulation anymore, the trade-off for the agent is that whether allocating more time to learn from others, improving the productivity to get more profits, or producing more good and getting more profits directly. Another kind of knowledge diffusion paper discuss the choice between innovate and imitate (Jovanovic and MacDonald, 1994; Acemoglu et al., 2006; König et al., 2016; Perla and Tonetti, 2014). In those models, the firms meet randomly with each other, the life cycle of certain industry, the distance to the technology frontier, the shape of the productivity distribution tail have impact on firms' choice between innovation and imitation as well as firms' search behavior while imitating. Except for the knowledge diffusion between firms, Luttmer et al. (2014) embeds knowledge teaching between between managers and workers into growth model. Akcigit et al. (2018) employs big data of European inventors to explicitly describe the knowledge diffusion among inventors. My paper contributes to discussing a special type of knowledge diffusion: transactions in the patent market, where the learner needs to pay and shedding light on factors which hinders the knowledge diffusion in developing country.

As this paper mainly talks about transactions in patent market, where heterogeneous firms are connected in this market, it is also related with the firm-to-firm literature, which is a hot topic recently. Several papers delve into the framework to document the establishment of firms' endogenous linkage in production (Tintelnot et al., 2018; Antras et al., 2017). Lim et al. (2017) develops a structural model of trade between heterogeneous firms in which the network of firm-level input-output linkages are determined both dramatically and endogenously. In this paper, the firms are connected with each other because of the patent transactions, the driven force for the successful transaction is that the present value of surplus of transaction is larger than the value of waiting for next period to sell the patent, which is similar with the criterion in David (2017). However, the problem here is a infinite period question addressed by Bellman equation, not same with the myopic settings in David (2017).

For the explosion of Chinese firms' innovation activities, large quantities of paper concentrate on the innovation in China. König et al. (2020) introduce heterogeneity in productivity and in distortion to the imitation-innovation model. In their work, the comparison between Chinese firms and Taiwan firms unearth the inefficient r&D investment in China. This paper investigate on the institutional efficiency through the lens of patent market.

The paper is organized as follows. Section 2 describes the key empirical facts in Chinese patent market. Section 3 develops the model. Section 4 is the structural estimation results and evaluation of the aggregate implications. Section 5 does some counterfactual exercises. Section 6 makes some policy experiments. Details of data work, robustness check are provided in the Appendix.

2 Empirical Patterns in Chinese Patent Transaction Market

In this section, I combine patent transaction and firm-level operating data to establish a host of facts on Chinese patent transaction activities and firms' participation in patent market. To exhibit how is the patent market in China, I use U.S. patent market as a benchmark. The key empirical findings are as follows:

For patent market: (1) Compared with 14.62% of patents sold in U.S., between 1998 and 2013, Chinese patent market has only 4.40% of patents sold in the same period. (2) Calculating the fraction of high-quality patent sold and low-quality patent sold respectively, I find that the fraction of traded patents ratio (high-quality over low-quality) is larger than 1, and is steeper in U.S. than in China; (3) In line with Akcigit et al. (2016), when new patent is born, there exists uncertainty that the patent's technology field does not match with the inventing firm, so those patents will be sold, and patent market is established in China;

For Firm's participation in Chinese patent market: (1) On seller side, the share of larger firms to be the sellers is much higher than small firms; and within all firms which have patents, the larger firms' sell-invention ratio [4] is lower than small firms'. (2) In China, large firms join the patent market as buyers more actively in the extensive margin. Namely, larger firms are more likely to be the buyer. In the intensive margin, within firms which have bought patents, while large firms' absolute patent purchase number is larger than small firm's, the buy-own ratio [5] is negatively correlated with firm size. (3) Taking control of the firm's accumulated patents number, the patents with higher quality and similarity with the firm raise firm's sales significantly. This increase is higher for larger firms.

2.1 Institutional Background

Compared with other countries, Chinese intellectual property (hereafter IP) system is relative young. China lacked IP law system until reform and opening up policy initiated in 1978. To attract more FDI and import technologies, China joined Word Intellectual Property Organization (WIPO) in 1980 and the first version of Patent Law is born in 1984. It has experienced three times revisions to provide basic protection for patents, and the current Patent Law is the version enacted in 2008. Besides patent, trademark [6], copyright [7], these two kinds of IP are protected by law as well.

As for the technology transaction, the following laws or regulations are built to regularize it. First, for the technology created by universities or research institutes and funded by government, the Law on Promoting the Transformation of Scientific

[4]It equals to the number of patents sold over the number of patents the firm invented.

[5]It equals to the number of patents purchased over the number of patents own

[6]Trademark Law is enacted in 1982, and revised in 1993, 2001 and 2013.

[7]Copyright Law is enacted in 1990,and revised in 2001.

and Technological Achievements issued in 1996 and revised in 2016, and the Law on Technological Progress revised in 2007 obey the spirit of Bayh–Dole Act [8], in which university or research institute has the right to apply for and sell the patent even for the inventions made in the government fund supported project. However, the articles in those two laws are quite vague. For instance, the allocation of patent profit between university, inventor and the government are not defined clearly, which makes the law hard to put into practice (Guo et al., 2007). Second, for the patents invented by firms, Contract Law (effective in 1999), Administration of the Recognition and Registration of Technology Contracts Procedures (effective in 2000) [9] provide a law framework for firms to sell their patents. Chinese government employs some subsidies to encourage patent transactions. For example, if the patent transaction contract is certificated and recorded by local technology contract registration institution, both of assignor and assignee can enjoy corporate income tax exemption in trading year if transaction turnover is lower than 5 million RMB, and for the transaction turnover higher than 5 million RMB part, only half of the corporate income tax is collected.

In regard to patent market participants, firms contributes largest proportion in both seller and buyer side [10]. To stimulate the patent transaction, in 1993, Shanghai government and Ministry of Science and Technology jointly set up Shanghai technology exchange, which is the first exchange for technology in China. Up to 2018, there are 45,685 technology exchanges in China. In early years, even more than half of the technology transfers are completed with the help of those national level exchanges, however, in recent years, as Figure B6 in Appendix B.1.1 shows, more transactions happen without the help of the exchange.

2.2 The data

I develop a sample of 284,639 assignor-assignee-patent transactions between 1985 and 2016. Patent transaction data is from the China National Intellectual Property Ad-

[8] Administrative Measures for Scientific Research Projects by the State Ethnic Affairs Commission which is jointly issued by the Ministry of Science and Technology and the Ministry of Finance in 2002 are often called as the "Chinese Bayh-Dole Act".

[9] Issued by Ministry of Science and Technology and Ministry of Finance and State Administration of Taxation.

[10] The Figure B5 in Appendix B.1.1 shows the share of contract turnover correlated with firms from the perspective of seller side and buyer side, and the firms can account for about 80% on average, which is increasing with the time

ministration (hereafter CNIPA). CNIPA is a comprehensive source of data on Chinese patents, covering all applied and filed patents' detailed information with application and grant date, publication date, patents' inventors, patents' reassignment records and etc. CNIPA transaction data involves the patent transaction date, the transacted patent application number, the assignee and the assignor. The CNIPA records all of the transactions if only the transaction patent is filed and granted between 1985 to 2016 in China[11].

However, as technology may be transferred within a group of companies, namely, from parent firm to subsidiaries, from corporate R&D center to manufacturing firm, or staff like these. By enterprise registration data collected by China State Administration for Industry and Commerce (hereafter SAIC) [12], I restrict the sample to transactions which are between two firms without shareholding relationships [13]. Additionally, I exclude the transactions correlated with patent agents which account for less than 1.5% among all the transactions. As I concentrate on the Chinese patent market, especially the firms' patent trade, and transactions between oversea firms and Chinese domestic firms are not too much in data [14], I only keep the transactions between domestic firms and domestic firms. The information of datasets and sample constructions are described thoroughly in appendix A.

All of the patent characteristics information, like application number, patent application and granted data, forward citation and backward citation and so on, come from CNIPA patent database as well [15]. As Chinese patent takes three years on average to get granted after application as shown in Figure D17 , and the first patent right transfer in my data happens in 1998 [16], I set my patent data period starting from 1998 and ending in 2013, which means I mainly focus on the patent filed and granted between 1998 and

[11]The structure of original data is in the appendix A. The original transaction record is based on patent. In other words, for every patent, the reassignment information is recorded, and I do some works to translate it into the form of assignor-assignee-patent.

[12]SAIC database archives SAIC registered firm's information, including the name, set-up year, shareholders and shareholding ratio, registration location, etc. Almost all variables in this database can be found in https://www.qixin.com/.

[13]If firm A is the shareholder of firm B, or firm B is the shareholder of firm A, or both A and B are subsidiaries of firm C, the patent transaction between firm A and B is not counted into my sample.

[14]Tabel A2 in Appendix A shows descriptive statistics of the nationality types of assignor and assignee.

[15]All variables in this database can be found in http://cpquery.sipo.gov.cn/index.jsp?language=en_us.

[15]My CNIPA data records the patent applied and granted from 1985 to 2016, so, this data truncation problem may lead to the phenomenon that the number of patent applied from 2013 to 2016 decreases a lot, because most of patents applied in this period cannot get granted before 2016 and are not included in database. Figure D16 shows this.

[16]The transacted patent is CN98107411.1, and it is between 韦巴斯托-基克特布斯图恩有限公司 and 工业设备制造股份公司.

2013.

In Akcigit et al. (2016), it documents U.S. patent market from 1976 to 2006. In this paper, I take the U.S. patent market as a benchmark to study why Chinese patent market is underdeveloped. Hence, to make two countries comparable, I update U.S. patent transactions and patent characteristics data to 2013. All the restrictions are analogous to what I do in CNIPA as aforementioned. The U.S. patent data comes from Patentview database, and patent transaction data comes from USPTO official publication. The detailed data work are described in Appendix A.

To compare the characteristics of the sold patents and non-sold patents within a firm, transacting firms and population of firms, the firm owning patent and not owning patent, and other features related with patent transactions, I obtain Chinese manufacturing firm's data (hereafter NBS) which includes firm's basic information and operating variables from 2001 to 2013 [17]. Then I match CNIPA database with NBS database to explore the above questions [18].

2.3 Transaction Size and Patent Features

2.3.1 Patent Market Size in China and U.S.

Table 1 reports the summary statistics of firm's patent and transaction numbers. To show how large the Chinese patent market is, I compare the fraction of traded patents in China with U.S.. Specifically, I define the fraction of traded patents in one period as share of patents invented by domestic firms in that period, which are also sold to other domestic firms in the same period.

[17] I miss the NBS data from 2008 to 2010.

[18] The matching method is in the appendix A.3.

Table 1: Patent Market Statistics: 1998-2013

		Patent Number	Patent Sold	Duration Mean	Duration Std
China	All Domestic Firms 1998-2013	322,632	4.40%	4.47	2.62
	Listed Firms 1998-2013	46,657	1.61%	7.05	2.84
U.S.	All Domestic Firms 1998-2013	975,284	14.62%	4.76	3.61
	Listed Firms 1998-2013	42,125	10.84%	5.75	3.75
	All Firms 1976-2006 (Akcigit et al. (2016))	3,210,361	16%	5.48	4.58

Note: The duration in first two columns is the time lag between the patent sold year and application year; However, the duration equals to sold year minus the granted year in Akcigit et al. (2016)'s paper.

In China, Chinese firms have 318,482 patents applied and granted from 1998 to 2013. Within those patents, 4.40% of patents were sold to other Chinese firms from 1998 to 2013. The patent sold fraction in U.S. in the same period is 11.95 percentage higher than in China. For manufacturing firms in China, the number of patents invented by manufacturing firms sold to other firms over the number of patents invented by manufacturing firms [19] is 1.85%, which is close the the fraction among all firms [20]. As a robust check, merged with 1998-2013 listed firms data from CSMAR (China) [21] and WRDS (U.S.) [22] , I compare the fraction of traded patents for listed firms between those two countries [23]. As in Table 1, this gap is 9.85 percentage. All of the statistics of fraction of traded patents in U.S. are close to the value in Akcigit et al. (2016) [24]. The gap between U.S. and China is significantly large and robust.

[19] The number of patents applied and granted between 1998 and 2013 is 205,639.

[20] As I do not have U.S. manufacturing firms data, I cannot tell the gap between China and U.S. for the manufacturing firms.

[21] http://cn.gtadata.com/#/index

[22] https://wrds-www.wharton.upenn.edu/

[23] One thing to be noted here is that as quantity of transactions within listed firms is too little, I define the number of patent sold for listed firm as the number of patents invented by listed firm sold to any other domestic firms.

[24] My calculation of the fraction of traded patents is a little bit different with Akcigit et al. (2016) in following categories. First, I calculate the fraction of traded patents in different period, and as the Table 1 shows, the fluctuation is not dramatic; Second, to be consistent with the definition of the fraction of traded patents in China, I restrict the samples to the transactions between domestic firms and the patents invented by domestic firms, but in Akcigit et al. (2016), they restrict the samples to the transactions between firms and the patents in NBER 1976-2006 database. However, the value of fraction of traded patents does not change a lot, which means that other types of transactions, e.g. between individuals and firms, between different countries' firms and etc are not the main force in patent market; Fourth, I include all types of transactions including transfer of application right, in which the transaction year is before the patent granted year. In Akcigit et al. (2016), they delete the transactions before the granted year.

Then, I group patents by their technology class [25] and granted year. I divide patents into two types: one is low-quality patent, of which the forward citation number is lower than the median value within the technology class - granted year group, and the other is high-quality patent. I define the fraction of traded patents ratio as the fraction of high-quality patent sold over low-quality patent sold, which is the slope of the line in Figure 2, and this line is steeper in U.S. than in China.

The lines in Figure 2 raise two problems. One is why the fraction of traded patents ratio is larger than one? As high-quality patent can argue for a higher price, the fraction of traded patents for high-quality patent should be same with low-quality patent. The second question is that which factor can control the slope of this line? In another words, what makes the line in China is flatter? I will incorporate fixed cost and information asymmetry in the model later to provide an explanation for this figure, and show how important this slop gap is between U.S. and China.

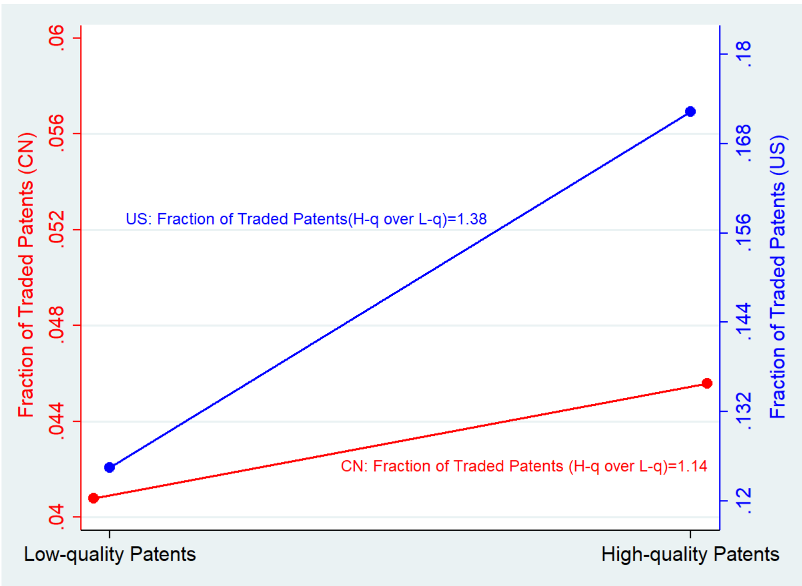


Figure 2: fraction of traded patents within High-quality Patents and Low-quality Patents

Note: The technology class in this figure is the sector level OST classification. I have also tried the field level OST classification, and the result is almost the same with this figure.

[25] Here, I use the OST technology classification, the advantage of it is listed in Appendix A.4.

2.3.2 Patent-firm Similarity

In this paper, patent-firm similarity measurement is constructed same with Akcigit et al. (2016), which is Jaccard similarity coefficient. This measurement shows how distant the patent's technology class is from the firm's technology class. The higher the similarity is, the more valuable the patent means to the firm.

$$D(X,Y) = 1 - \frac{Num(X \cap Y)}{Num(X \cup Y)} \tag{1}$$

$D(X,Y)$ is the distance between X technology class and Y technology class [26]; $Num(X \cap Y)$ designates the number of patents that cite class X and Y simultaneously; and $Num(X \cup Y)$ designates the number of patents that cite either class X or class Y. In an extreme case that if all patents citing patents in class X cites patents in class Y at the same time, and vice versa, the distance between class X and Y is zero. Based on distance between technology class, I calculate the $d(p,f)$, patent-firm specific distance between patent p and firm f. In Equation (2), $\mathcal{P}_f$ represents the patent package of firm f, and $d(X_p, Y'_p)$ indicates the distance between patent p's class and patent p''s class in $\mathcal{P}_f$. Based on distance, $1 - d(p,f)$ indicates the similarity between patent p and firm f.

$$d(p,f) = \left[\frac{1}{||\mathcal{P}_f||} \sum_{p' \in \mathcal{P}_f} d(X_p, Y'_p)^{\iota} \right]^{\frac{1}{\iota}}, \quad \iota = \frac{2}{3} \tag{2}$$

I make two adjustments to make the firm-patent similarity distribution comparable between countries. One is that as the citation intensity and norm are distinctive between two countries, and $D(X,Y)$ distance matrices are different as well [27]. For concordance, I use U.S. distance matrix in two countries to calculate patent-firm distance and similarity [28]. The other is that as patent-firm similarity is built based on firm's knowledge scope, and the different knowledge scope distribution will have large impact on the patent-firm similarity distributions in two countries [29]. To control this, firstly, I calculate sim-

[26] Here, I use IPC 3-digit level (IPC main section + class category) code to define the technology class the patent belongs to. The patent's IPC code in CNIPA is original. The detailed information about IPC classification is described in Appendix A.4.

[27] The Pearson correlation coefficient of distance matrices of U.S. and China is 0.6769.

[28] I also use the Chinese distance matrix to calculate the patent-firm distance in China as well, the result is almost same.

[29] In U.S., for firms which ever had invented patent from 1998 to 2013, the average knowledge scope is 1.75, which is lightly larger than 1.66 in China. The 99th percentile of knowledge scope is 11 in U.S.,

ilarity distribution conditional on firm scope. Secondly, based on Chinese firms' scope distribution, I proportionally add these conditional similarity distribution together in U.S.. So the similarity distribution in U.S. is a weighted similarity distribution by Chinese firms' knowledge scope distribution [30]. The empirical similarity distribution of new-born patent and its' inventing firm is shown in Figure 3. The probabilities in zero and one are fatter in China. Nonetheless, two countries' distribution are pretty same with each other, and this margin does not play an important role to explain why the patent market in China is so small.

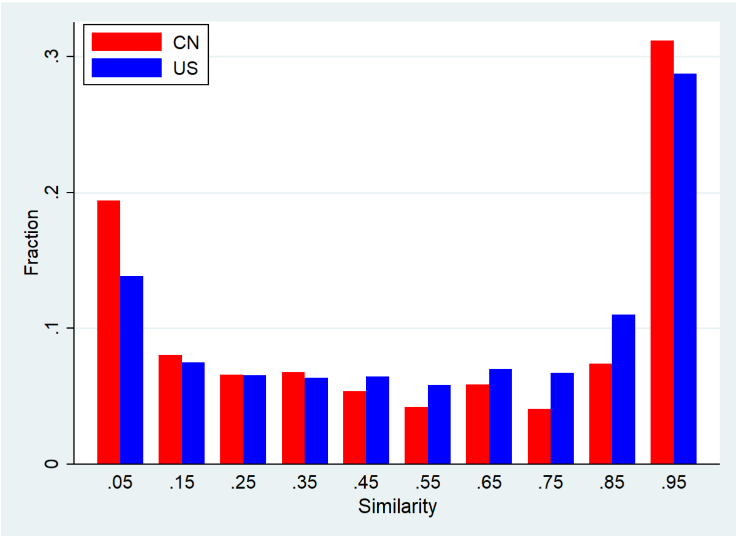


Figure 3: Similarity Distribution between New-born Patent and Knowledge Stock Adjusted by Knowledge Scope

Note: (1) The samples of patents are patents filed and granted from 1998 to 2013. (2) Because every firm's first patent's similarity with the firm is absolutely zero, I drop the observations of patents which are the firm's first applied patents.

2.3.3 Which Patent to be Sold

After measuring patent-firm similarity, now, the question is that do firm sell the patent of which the patent-firm similarity is low? To delve into this question, I set whether the patent to be sold (sell=1) or not (sell=0) to be the dependent variable and run the regression like Equation (3) to see which factors determines firm's sold decision

which is 9 in China.

[30]The unweighted distribution comparison is in appendix B.2 Figure **??**. As the firms' average knowledge is larger in U.S., after adjustment, the patent-firm similarity distribution difference between two countries is much smaller.

on patent.

$$sell_{pist} = \beta_0 + \beta_1 similarity_{pi} + \beta_2 quality_p + \delta_{scope,t} + \delta_s + \delta_t + \delta_i \quad (3)$$

In the equation above, more specifically, $sell_{pist}$ indicates that whether the patent p invented by firm i in t period belonging to technology class s [31] is sold $(= 1)$ or not $(= 0)$; $similarity_{pi}$ is the patent-firm specific similarity which is calculated between patent p and all the patents firm i owns (the patents invented by firm i before t year or the patents bought by firm$i$ before t year); $quality_p$ is patent p's quality. As patent-firm similarity is strictly correlated with firm's knowledge scope, inventing firm's knowledge scope in t year, $\delta_{scope,t}$ [32], is controlled as fixed effect; $\delta_s, \delta_t, \delta_i$ are technology class fixed effect, invention year fixed effect and firm fixed effect respectively. The empirical results are shown in Table 2.

Table 2: Firm's Selling Decision: Whether Sell or Not

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All Sample				NBS Sample			
	Sell=1	Sell=1	Sell=1	Sell=1	Sell=1	Sell=1	Sell=1	Sell=1
Similarity	-0.2450***	-0.1930**	-0.2372***	-0.2838***	-0.2393***	-0.1681*	-0.2923***	-0.4374***
	(0.0783)	(0.0783)	(0.0634)	(0.0712)	(0.0887)	(0.0886)	(0.0746)	(0.0882)
Quality	0.0274**	0.0107	0.0343***	0.0336***	0.0598***	0.0429***	0.0386***	0.0396***
	(0.0134)	(0.0134)	(0.0102)	(0.0102)	(0.0152)	(0.0152)	(0.0130)	(0.0130)
Scope FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IPC FE	Yes	Yes		Yes	Yes	Yes		Yes
Year FE		Yes	Yes	Yes		Yes	Yes	Yes
Firm FE			Yes	Yes			Yes	Yes
N	326332	326332	317754	317754	187678	187678	183411	183411
r2	0.0093	0.0128	0.5787	0.5793	0.0099	0.0145	0.4652	0.4667

Note: As regression in Akcigit et al. (2016), the dependent variable is multiplied by 100 for clarity. Standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; *** denotes significance at the 10% level.

In Table 2, I do the same regressions for all patents invented by Chinese firms and the patents invented by NBS firms severally. From column (1) to (4), I take control of

[31] Here, I control for IPC 3-digit level class

[32] The knowledge scope here is the number of IPC 3-digit classes the firm i in t year belonging to. For a firm's first patent, its' patent-firm similarity equals to 1 for sure, so the obervations like these are deleted in my regression equation (3).

several fixed effects gradually. The coefficient of similarity suggests that when I control the patent quality, within a firm, firm always chooses to sell the patent which is mismatched with the firm.

2.4 Manufacturing Firms in Chinese Patent Market

2.4.1 Firms Participation in Patent Market

I will show how Chinese manufacturing firms join the patent market from the perspective of firm's sell decision and purchase decision respectively.

Sell Decision: For the NBS firms in 2001-2013 balanced data, I divided firms into four groups in terms of their size in 2001 [33]. I define the seller as the firm which had sold patent between 2001 to 2013. Then I calculate the share of seller within every firm size group [34]. It is intuitive that in that large firms are the main force in patent production. In the extensive margin, large firm possesses higher possibility to be a seller than small firms in the patent market as shown in left hand side of Figure 4. It is intelligible that Within all the patents applied from 2001 to 2013, large firms make 93% contributions of it, even for the contributions weighted by the patent quality. Large firms are the main force in patent production.

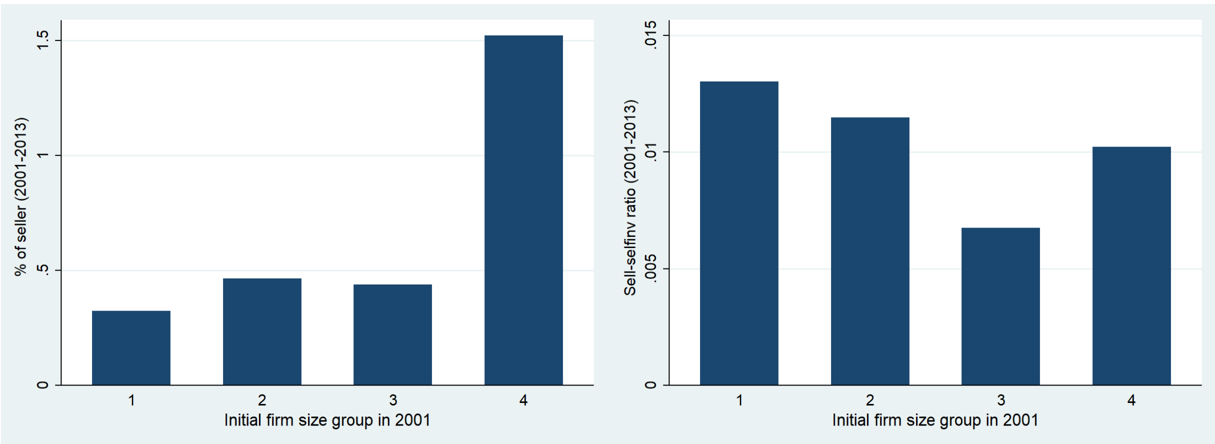


Figure 4: Firm's Sell Decision: Extensive Margin and Intensive Margin

[33] I use firm's sales in 2001 to measure the firm size. I calculate the 25 percentile, 50 percentile and 75 percentile of firms' sales within each industry, and then group firms into 4 groups according to their sales within every industry. The industry is classified by Industrial classification for national economic activities. I use the 4-digit code in this classification.

[34] To control for industry fixed effect, I also calculate the share of seller within ever firm size group and industry and then take the weighted average of seller share based on firm number across industry. The results are robust with this figure.

In the intensive margin, for firm which does in-house R&D and invents patent successfully, who sells more? I define sell-invention ratio as the number of patents the firm sold over patents the firm invented between 2001 and 2013 [35]. Only the firm which had invention in this period has this value. I calculate this ratio within every firm size group, and I present the result in right hand side of Figure 4. It indicates two facts: firstly, as a whole, compared with smaller firm, large firm will sell less proportion of inventions. One explanation for it is that large firm may make better use of the patent than small firm, and when the patent market is inefficient, it would keep the patent for own use. Secondly, I discover that the sell-invention ratio in the largest firm group is relative higher than the third firm size group. In largest firms, because of stragetic patenting behavior, for one technology, more patents will be applied for prohibiting the new entry (Abrams et al., 2013), so if buyer purchases one technology from a large firm, a large package of patents should be bought.

Except for the stragetic patenting behavior in large firm, if large firm will invent patent with higher quality or similarity, this will affect it sell decision as well. I have compared the quality and similarity of patents in large firms and small firms. As illustrated in Figure D18-D19 in Appendix D, the patents generated by large firms are not significantly better than small firms in perspective of their quality and similarity with the firms.

Purchase Decision: Similar with firm's sell decision, I present NBS firm's purchase decision from the extensive margin and intensive margin by share of buyers and buy-own ratio in every firm size group respectively. Condition on the firm that had ever had patents between 2001 and 2013, the buy-own ratio is number of firm's patents that are purchased over the number of firm's patents that had been owned.

In the extensive margin, larger firm participates in this market more intensively than the smaller firm. It manifest that larger firm can obtain larger surplus from this market and join more intensively. In the intensive margin, for those firms which had had patents between 2001-2013, buy-own ratio is lower in larger firms. There are two factors affecting this ratio. Large firm may purchased more patents than small firm. However, it may do more self-inventions than small firm. And if the latter factor dominate the former factor, the buy-own ratio may be lower in large firm.

[35] The sold patent must invented between 2001 and 2013 as well.

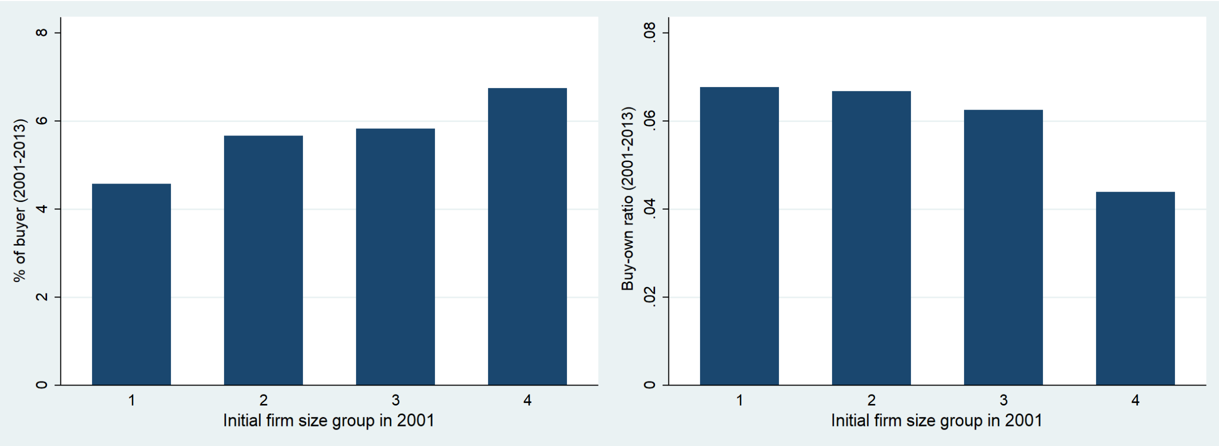


Figure 5: Firm's Purchase Decision: Extensive Margin and Intensive Margin

I also do some regression works to control firm fixed effect, firm age, industry-year fixed effect to check the correlation between firm size and its purchase decision in intensive margin and extensive margin as robust checks. The results [36] are constant with the figure above.

I document the sell and purchase decisions of U.S. listed firms belonging to 2001-2013 balanced panel in Figure D20 and D21 in Appendix D as well. The basic facts that large firms join the patent market more intensively as buyer and seller in extensive margin, and sell-invention ratio and buy-own ratio are lower in large firms are similar with Chinese NBS firms. However, the largest firms (for the upper 75 percentile firm size group) show great participation in patent market in both of extensive and intensive margin. The rise of super star firm and market concentrations (Autor et al., 2020) in U.S. may attribute to this phenomenon .

2.4.2 Revenue Gain from Patents

How much the firm can gain from the increasing number of patents? Analogous to Akcigit et al. (2016), in this part, I regress firm's revenue on accumulated patents weighted by quality and similarity with firm and industry-year fixed effect controlled. Additionally, the correlations between annualized TFP or revenue growth rate and patent increment are checked as well. Column (1)-(4) in Table 3 demonstrate the results of the former in which I use logarithm of sales as the proxy for firm's revenue, and logarithm of accumulated patents number adjusted by similarity and logarithm of accumu-

[36] The results are shown in Table D6-D9 in Appendix D

lated patents number adjusted by quality [37] measure the firm's patent stock. Column (1) to (3) gradually control firm's labor, capital and age using 2001-2013 unbalanced NBS firm-level data. As the firm's capital may complementary with the technology it use, controlling for fixed asset in column (2) decreases the coefficient of accumulated patents adjusted by similarity and quality. The regression in column (4) contains firms in 2001-2013 balanced panel. More accumulated patents with higher quality and higher similarity increase firm's revenue, however, compared with patent quality, patent-firm matching level, similarity exerts bigger influence on firm's revenue.

I have done some robustness check for the regressions in Table 3 in three dimensions. First, for the independent variables, I construct the accumulated patent number adjusted by quality and similarity simultaneously, and divide the patents invented by firm itself and purchased as well; Second, for the dependent variables, I replace the sales with value added; Third, for control variables, I use different measurements to measure the value of firm's labor and capital; Lastly, as large proportion of firms do not have any patents from 2001 to 2013, I restrict the regression sample to be innovative firms or patented firms. The results are in Table D10 in Appendix D10 which are robust with the above results.

How about the firm's growth? In Table 3 from column (5) to (8), the TFP, value added and sales annualized growth rate [38] are depend variables respectively. The independent variable, patent number here are the summation of firm's patents increment in regression periods. The column (5)-(8) are cross-section OLS regressions with 4-digits industry fixed effect, ownership fixed effect and province fixed effect controlled. The higher quality and similarity patents obtained by firms contribute to the higher growth rate of the firm's TFP as well as revenue. It is not surprising that the coefficients of initial value of TFP and revenue in 2001 are negative, which is in compliance with the stylized fact 8 in Klette and Kortum (2004) that the small firms that survive tend to grow faster

[37] Firstly, accumulated patents number adjusted by similarity equals to $\sum_{p \in P_f} Similarity_{pf}$, and accumulated patents number adjusted by quality equals to $\sum_{p \in P_f} Quality_p$, where p is the patent p belong to firm f, P_f is the firm f's patent package; $Similarity_{pf}$ is the similarity between firm f and patent p, and $Quality_p$ is the quality of patent p. Secondly, as the patent data merged with NBS firm level data, I only calculate the accumulated patent number beginning from 2001. That is, accumulated patent number in t year is the summation of patent invented from 2001 to t year.

[38] As the NBS data are missing between 2008 and 2010, the data from 2001 to 2013 is with gap. To ensure the consistence, I only calculate the TFP based on LP and OP method from 2001 to 2007; The value added is not required to report after 2007, so the growth rate of va in column 7 in Table 3 is the annualized growth rate between 2001 and 2007; However, as sales value are reported in every year from 2001 to 2007 and 2011 to 2013, the growth rate of sales is the the annualized growth rate between 2001 to 2013

Table 3: Firm's Revenue, Growth and Patent Stock

	(1) Lnsales	(2) Lnsales	(3) Lnsales	(4) Lnsales	(5) Gr_tfplp	(6) Gr_tfpop	(7) Gr_va	(8) Gr_sales
Lnpat_sim_adj	0.0598***	0.0395***	0.0469***	0.0733***	0.0445***	0.0171***	0.0506***	0.0282***
	(0.0038)	(0.0037)	(0.0037)	(0.0062)	(0.0053)	(0.0047)	(0.0035)	(0.0016)
Lnpat_quality_adj	0.0280***	0.0220***	0.0261***	0.0275***	0.0248***	0.0081**	0.0266***	0.0153***
	(0.0030)	(0.0030)	(0.0029)	(0.0049)	(0.0042)	(0.0037)	(0.0028)	(0.0013)
Lnlabor	0.3538***	0.3227***	0.3094***	0.2896***				
	(0.0008)	(0.0008)	(0.0008)	(0.0018)				
Lnfixasset		0.1247***	0.1200***	0.1885***				
		(0.0004)	(0.0004)	(0.0012)				
Lnage			0.1921***					
			(0.0012)					
Lntfp2001					-0.0793***	-0.0833***		
					(0.0007)	(0.0007)		
Lnva2001							-0.0867***	
							(0.0009)	
Lnsales2001								-0.0468***
								(0.0004)
Firm FE	Yes	Yes	Yes	Yes				
Ind_year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE					Yes	Yes	Yes	Yes
Prov FE					Yes	Yes	Yes	Yes
N	2486713	2466114	2463954	309480	61172	61167	34810	36884
r2	0.8966	0.9019	0.9034	0.8972	0.2104	0.2593	0.2708	0.3354

Note: (1) For large numbers of zero-value in variables related with patent stock, I add one to them first and then take logarithm; (2) tfp2001, va2001 and sales2001 are the values of firm's TFP, value added and sales in 2001; (3) All the fixed effect definitions are same with the definitions in Table **??**; (4) Standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; *** denotes significance at the 10% level.

than larger firms.

Is there any difference between small firm and large firm in the utilization efficiency of the patent. Larger firm may have larger market before and abundant advertising experience or expenditures to promote the new production supported by the new-born patent, which makes the surplus of new-born patent in larger firm to be larger (Arkolakis, 2010). I have also checked the heterogeneous compacts the patents have on firms' revenue and growth rate, which are correlated with firm size. The basic results are exhibited in Table D11, and it shows that after controlling the firm fixed effect and industry year fixed effect and given the same patent value to the owner firms, one more accumulated patent in a large firm increases the revenue and TFP more largely than in a small firm.

3 Model

To quantitatively explain the reasons for under-developed Chinese patent market, I build a structural R&D model with patent market to highlight three types of frictions within the patent market: **search cost**, **fixed transaction cost** and **information asymmetry on patent quality**. There are two features in this model. First, to match with the stylized facts that the fractions of traded high-quality and low-quality patents are different, I introduce patent quality heterogeneity which does not exist in Akcigit et al. (2016)'s model, and the fixed transaction cost and information asymmetry on patent quality can explain why fractions of traded patents differs in high-quality patents group and low-quality patents group. Second, to match the firm's heterogeneous participation in patent market and R&D activity in NBS firms, I introduce firm heterogeneity in its R&D capacity and let the step size of productivity increment correlated with firm size. Naturally, buyer firms can endogenously choose its search effort in patent market.

3.1 Economy Environment

There exists a measure N_t of incumbent firms at the beginning of every period $t = 1, 2, ...$, and every firm merely locates on a certain technology class j on a circle with radius $\frac{1}{\pi}$ forever. The density of firms on the circle is thus $\frac{N_t}{2}$.

Every patent locates on a point on the circle of technology class as well. Because of uncertainty about innovation outcomes, the patent's technology class may be different from its inventor's, as shown in figure below. x is the similarity between firm's technology class j and the new patent's technology class j', which measures this distance and is drawn randomly according to a distribution $X(x)$ with support $[0, 1]$. The introduction of invention uncertainty captures that in reality, every firm has its' specialization and adept fields, but many inventions are generated in other fields accidentally. This kind of uncertainty could cause the mismatch between the inventing firm and the patent. For example, the first patent related with microwave oven was born in a radar test in Raytheon Company, a major U.S. defense contractor but Tappan, an appliance maker, is the one who introduced microwave ovens widely for home use after 10 years. Patent markets are thus needed to adjust the mismatch between patents and inventing firms.

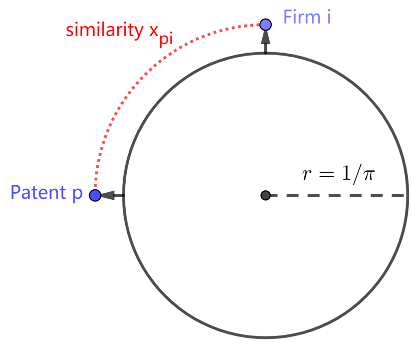


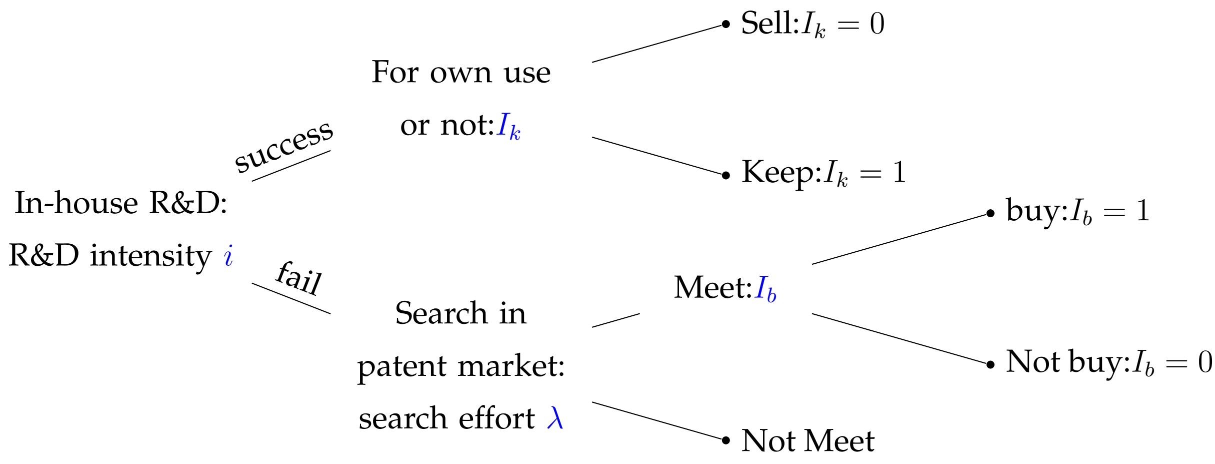
Figure 6: TECHNOLOGY CLASS CIRCLE: MISMATCH BETWEEN PATENT AND FIRM

The timing of this model is as follows:

- **Step1. Exogenous entry and exit:** At the beginning of every period, all incumbents face an exogenous exit rate δ. A fixed number of new entrants will enter simultaneously.[39]

- **Step2. Innovation Activity (In-house R&D or Patent Market Search):** To gain a productivity process, firm can first do in-house R&D. All firms will endogenously decide the optimal R&D intensity, which determines the birth probability of new patent. If a new patent is innovated successfully, the firm will decide whether to keep or sell it. If firms fail to do in-house R&D, it can go to the patent market and decide the optimal search effort in this market, randomly meeting with potential seller, and make a choice between buying or non-buying.

[39] I assume exogenous entry and exit in this paper just to prevent the superstar firm's size explosion and get the stationary firm productivity distribution. As the new entrant's productivity and type draws from the incumbent's productivity and type distribution, this entry and exit doesn't change the firm distribution.



- **Step3. Production:** If the firm gets new patent (in-house invention or purchased patent), the firm's productivity rises. If not, the firm produces without productivity increments. After production, the firm sells good and gets profit.

3.2 Production Function and Law of Motion for Firm's Productivity

At the beginning of every period t, the CDF of firm's productivity distribution is $P_t(z)$. The average productivity of incumbents at the beginning of every period is:

$$\tilde{z}_t = \int_z z \cdot P_t(z) \tag{4}$$

I assume that at the end of each period, firm j produces a homogeneous final good using labor with its productivity z'_t as follows:

$$Y_t = z'^{\alpha}_t l_t^{1-\alpha} \tag{5}$$

Firm hires labor with wage rate w. There is one unit of labor available in the economy. Observe that there are diminishing returns in labor. Hence, there are prots from producing. The equilibrium wage rate is increasing with the firm's productivity. The firm hires labor $l^* = (\frac{1-\alpha}{w})^{\frac{1}{\alpha}} z'$, at the wage rate w to maximize its profit:

$$\Pi(z', \tilde{z}') = \max_l z'^{\alpha} l_i^{1-\alpha} - wl; \tag{6}$$

The profit function could be written as Equation (7) [40], where it is clear that firm has incentive to improve its productivity.

$$\Pi(z';\tilde{z}') = \alpha \cdot (\frac{1-\alpha}{w})^{\frac{1-\alpha}{\alpha}} \cdot z' \tag{7}$$

In every period, no matter where the patent comes from, in-house R&D or patent purchase, the successful inflow of j's technology class patent to a firm with technology class j will lead to a productivity increment:

$$z' = L(z, \gamma, x; \tilde{z}) = z + \gamma x z^{\beta} \tilde{z}^{1-\beta}, \qquad \gamma = \{\gamma_h, \gamma_l\} \quad and \quad x \in [0, 1] \tag{8}$$

where z′ is the productivity of the firm at the end of period t. The parameter γ is the patent quality measurement, that conditional on the firm-patent similarity level, firm's productivity and the economy average productivity, γ is the slope of productivity increments to one more patent. γ_h represents the high-quality patent which means a larger step size. The patent quality is patent specific and determined at the birth of it. I assume that there are h share of patents are born with high quality [41]. I introduce the patent quality heterogeneity here to match the fact that fraction of traded patents are different in high-quality and low-quality patents group.

x represents the other patent heterogeneity, patent-firm similarity. Therefore, a patent's value is firm-specific based on how similar the patent's technology class is with the technology class the firm mainly focuses on.

z^{β} allows for the productivity increment step size varying with firm's initial size [42], because in empirical parts, as Table D11 indicates, the revenue gain varies across large firms and small firms [43].

$\tilde{z}$ is the economy-wide baseline level of productivity. The step size is correlated with the economy average productivity, which indicates the knowledge externality. $\tilde{z}^{-\beta}$

[40] Firm's revenue is $(\frac{1-\alpha}{w})^{\frac{1-\alpha}{\alpha}} z'$, which is linear with firm's productivity at the wage rate w. So larger firm size just means higher firm's productivity.

[41] Patent's quality does not correlates with firm size. The quality distributions of the patents born in large firm and small firm don's show too much difference (refer to Figure D19 in Appendix D)

[42] In this model, the optimal labor hired is linear with firm productivity, so the firm size is linear with firm's productivity.

[43] This is also motivated by the existing literature that has shown that larger firm may have larger markets and abundant advertising experience, which increases the surplus of new-born patents (Arkolakis, 2010). If $\beta \in (0, 1]$, once obtaining a new patent, the large firm's productivity increment is larger than a smaller firm.

is the adjustment of firms' productivity, which is the denominator for z and required to ensure the existence of a balanced growth path.

3.3 Cost of Innovation Activity

At the outset of every period, in order to garner higher productivity for production, the firm can adopt two approaches. One is in-house invention; the other is entering patent market to buy a new patent when the firm fails to innovate successfully. In this model, both of doing in-house R&D and searching for the patent are included in the firm's innovation activity. In this part, I will show the cost of doing in-house R&D and searching in the patent market.

In-house Invention Cost

Firms differ in their in-house R&D capacity $\theta = \{\theta_H, \theta_L\}$. At entry the firm instantly learns its type θ, which is a realization of the random variable $P(\theta = \theta_H) = I_p$, $P(\theta = \theta_L) = 1 - I_p$, where $I_p \in [0,1]$ and $\theta_H > \theta_L > 0$. The in-house invention rate is $\theta \cdot i$, in which i is the endogenous R&D intensity. Firm's in-house invention cost function is as follows:

$$C(i; \tilde{z}) = \chi \cdot \frac{i^{1+\rho}}{1+\rho} \cdot \tilde{z}^{\alpha} \tag{9}$$

In line with (Klette and Kortum, 2004; Lentz and Mortensen, 2008), the R&D cost function is a convex using the final good as input [44]. The price of final good is normalized to 1.

Search Cost in Patent Market

Even if the firm fails in doing in-house invention, it still can go to patent market to buy a patent.

There are three participants joining in the patent market, the potential seller, patent agent [45] and the potential buyer. Every time, the successful inventor can sell its' new-

[44] We can imagine that in this economy, there exists bank and firms can borrow money from the bank. And firm just need to repay the money to this bank without any interest rate at the end of every period. There is no financial friction here.

[45] Introducing the patent agent is learned from Akcigit et al. (2016), which can simplify the question in two dimensions. One is that the introduction of patent agent decreases the complexity of solving the

born patent to the patent agent, who is the potential seller in this market. The potential buyers, all the firms, meet with patent agents and decide whether to buy patent or not.

There are three assumptions here. First, once a new patent invented and its' inventor decides to sell it, there will be always a patent agent paying q to take it from the original inventor. Second, the patent agent can only hold one patent and meet one buyer at one period. Third, the agent can wait for the next period to sell the patent to other buyers.

Suppose that there are n_a patent agents and n_b potential buyers in this market. The potential buyers make $\lambda_\theta(z;\tilde{z})$ efforts to search for the proper patent to improve productivity. Patent agents just wait for being searched [46]. The search cost function is defined as follows (David, 2017):

$$B(\lambda;\tilde{z}) = \eta \cdot \frac{\lambda^\mu}{\mu} \cdot \tilde{z}^\alpha, \quad B'(\lambda) > 0, B''(\lambda) > 0 \tag{10}$$

The scale parameter η can be estimated by the aggregate patent buying rate in the market. When η goes to ∞, it means the friction of patent market is too high and the patent market shuts down.

Define the tightness of buyer side and seller side at one period as T_b, T_a. $Q(\theta, z)$ is R&D capacity type and productivity joint distribution of the firms which entry into the patent market.

$$T_b = min\left(\frac{n_a}{n_b \cdot \int \lambda_\theta(z;\tilde{z})\, dQ(\theta, z)}, 1\right) \qquad T_a = min\left(\frac{1}{T_b}, 1\right) \tag{11}$$

So the rate for a patent agent meets with a potential buyer (θ, z) is that

$$m_a = T_a \cdot \frac{\lambda_\theta(z;\tilde{z})dQ(\theta, z)}{\int \lambda_\theta(z;\tilde{z})\, dQ(\theta, z)} = T_a \cdot \Gamma_\theta(z;\tilde{z}); \tag{12}$$

match problem, transferring a firm-to-firm $N \cdot N$ dimensions' solution to a N dimension's solution. In firm-to-firm trade, the patent price depends on the selling firms and buying firms characteristics, but in patent agent-to-firm trade, as for homogeneous patent agent, the patent price mainly depends on buyer's characteristics. Second, unlike the inventor hold the patent to be sold, the sell decision may change with the firm's patent package's change across periods. It is so hard to disentangle the problem that the patent to be sold can wait for the next time to be sold. As patent agent only holds one patent in hand, the patent can wait for the next period to be sold sold, which matches the reality much well.

[46] Because I assume that there is no heterogeneity between patent agents, which means search efforts are homogeneous among patent agents. It equals that I standardize the patent agents search effort to be 1

The rate for a potential buyer meeting with a patent agent is that

$$m_b\left(\frac{n_a}{n_b}, \frac{\lambda_b}{\bar{\lambda_b}}\right) = \lambda_\theta(z;\tilde{z})T_b \tag{13}$$

Where $\bar{\lambda_b} = \int \lambda_\theta(z;\tilde{z})\, dQ(\theta, z)$ is the average search effort in this economy.

3.4 Firm Dynamics: Buying, Selling and in-house Invention Decision

In the sequence of innovation activity, firm will do R&D decision first. Then, if firm successes in in-house R&D, it need to do keep-or-not decision on the new patent; if not, firm need to do search effort decision, and upon meeting a patent in market, the firm need to do buy-or-not decision. In this part, I will use backward deduction to solve the equilibrium solution for this economy.

3.5 Conditional on Successful Invention: Keep-or-not Decision

For the successful inventing-patent firm, it chooses whether to sell the new-born patent or not. The trade-off in this choice is that how much the firm can get from selling the patent and how valuable the patent is for the inventor.

Let $V_\theta(z;\tilde{z}')$ designates the expected present value of θ-type firm with productivity z at the beginning of t period. Here I omit the subscript t.

$V_\theta^{inn,k}(z + \gamma x z^\beta \tilde{z}^{1-\beta};\tilde{z})$ is the expected value of firm which invents a new patent in this period and keeps it. Keeping patent lead to productivity increment and profit increase. In equation below, r is the discount factor and $(1-\delta)$ is the probability of surviving in the next period.

$$V_\theta^{inn,k}(z + \gamma x z^\beta \tilde{z}^{1-\beta};\tilde{z}) = \Pi(L(z,\gamma,x;\tilde{z});\tilde{z}) + r\cdot(1-\delta)\cdot V_\theta(L(z,\gamma,x;\tilde{z});\tilde{z}') \tag{14}$$

$V_\theta^{inn,s}(z;\tilde{z})$ is the expected value of firm which invents a new patent in this period and sells it. q_γ is the revenue of selling the patent. σ is the patent surviving rate. In reality, every patent has validity of term, in China it is 20 years. There exists possibility that the patent will die before going to patent market.

$$V_\theta^{inn,s}(z;\tilde{z}) = \Pi(L(z,0,0;\tilde{z});\tilde{z}) + \sigma q_\gamma + r\cdot(1-\delta)\cdot V_\theta(z;\tilde{z}') \tag{15}$$

Denote the indication function $I^k_\theta(z,\gamma,x;\tilde{z})$ as the indicator for the decision of keeping or selling the new patent of θ-type firm with productivity z.

$$I^k_\theta(z,\gamma,x;\tilde{z}) = \begin{cases} 1(keep) & if \quad V^{inn,k}_\theta(z+\gamma x z^\beta \tilde{z}^{1-\beta};\tilde{z}) > V^{inn,s}_\theta(z;\tilde{z}) \\ 0(sell) & otherwise \end{cases} \tag{16}$$

So the expectation value for a firm which innovates successfully is $V^{inn}_\theta(z;\tilde{z})$:

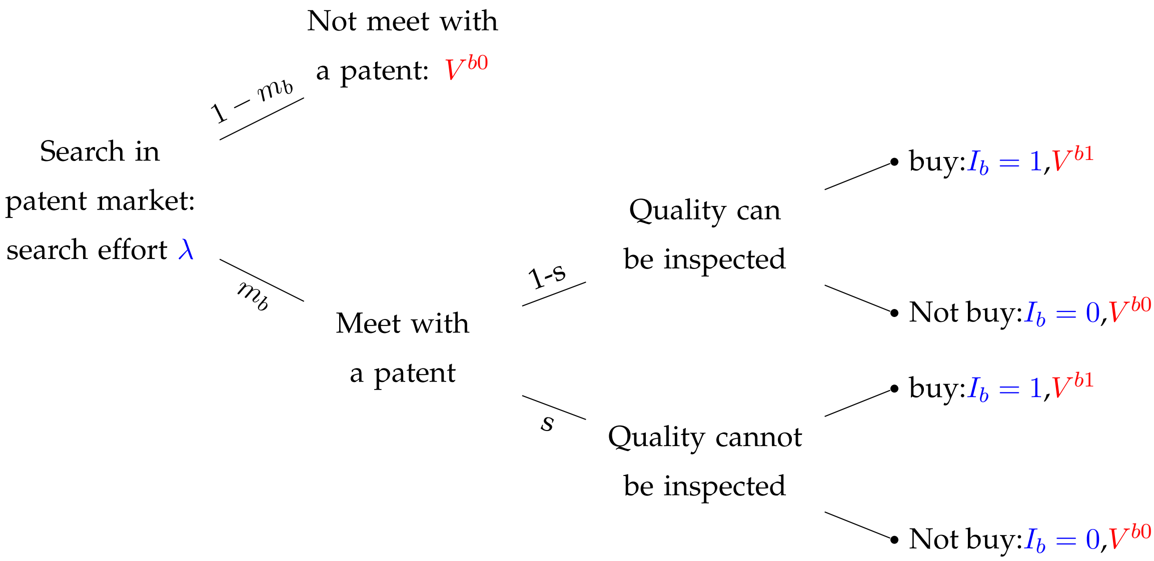
$$V^{inn}_\theta(z;\tilde{z}) = \mathbb{E}_{\gamma,x}\max\{V^{inn,k}_\theta(z+\gamma x z^\beta \tilde{z}^{1-\beta};\tilde{z}), V^{inn,s}_\theta(z;\tilde{z})\} \tag{17}$$

3.6 Patent Market: Buy-or-not Decision

The firm can go to the patent market to meet with patent agent randomly in every period. The choices in patent market for potential buyers are that, first, how much effort to spend in patent market to find patent agent: λ_b; second, when meeting with a patent, whether to buy the patent or not: $I^b_\theta(z,\gamma,x;\tilde{z})$.

The sequence of choices are shown in the tree map below. Within the patent market, there are three types of frictions. First, before meeting, potential buyers need to pay **cost of search**. Second, When patent agent and potential buyer meet with each other in every period, it is very hard to identify or verify a patent's quality before putting it into production for the potential buyer [47]. I call it as the **Information asymmetry on patent quality**. Following the signal setting in labor search literature (Menzio and Shi, 2011; Donovan et al., 2018), upon meeting, the potential buyer draws a signal which equals to the true quality of patent with probability $1-s$ and is a i.i.d. draw from H_m, which is endogenous patent quality distribution in patent market with probability s. In the limit case, s=0 corresponds to match as *inspection goods*, where patent's quality can be verified totally in the meeting; while s=1 corresponds to match as *experience goods*, where patent's quality can only be learned in the production. Finally, if the firm want to buy the patent, it needs to pay the fixed transaction cost of purchase that patent, which is $B\cdot\tilde{z}^\alpha$.

[47] In the seller side, the inventor knows the true quality type of the patent completely. To guarantee the neutrality of the patent agent in the model, the agent also knows the true type of the patent and as an intermediate, it cannot choose whether to be the agent for high-quality or low-quality patent.



When getting out of the patent market, the firm has two types of outcome, one is that firm does not get a patent eventually. I denote it as

$$V_\theta^{b0}(z;\tilde{z}) = \Pi(L(z,0,0;\tilde{z});\tilde{z}) + r\cdot(1-\delta)\cdot V_\theta(z;\tilde{z}') \tag{18}$$

The other is that the firm successfully get a patent in this market.

$$V_\theta^{b1}(z+\gamma x z^\beta \tilde{z}^{1-\beta};\tilde{z}) = \Pi(L(z,\gamma,x;\tilde{z});\tilde{z}) + r\cdot(1-\delta)\cdot V_\theta(L(z,\gamma,x;\tilde{z});\tilde{z}') \tag{19}$$

Then, let's calculate the firm's optimal buy-or-not solution. First, the transaction price is determined by Nash bargaining and the bargaining power for potential buyer is ω. The solution is weighted average of surplus of potential seller and buyer. If patent quality can be inspected, when patent with features (γ, x) meets with firm with features (θ, z), the price $P_\theta^{ins}(z,\gamma,x;\tilde{z})$:

$$P_\theta^{ins}(z,\gamma,x;\tilde{z}) = \omega[V_\theta^{b1}(z+\gamma x z^\beta \tilde{z}^{1-\beta};\tilde{z}) - V_\theta^{b0}(z;\tilde{z}) - B\tilde{z}^\alpha] + (1-\omega)\cdot r\sigma A(\gamma,\tilde{z}') \tag{20}$$

Where $A(\gamma,\tilde{z}')$ is the value function of patent agent. However, if patent quality cannot be inspected, at this time, potential buyer is only willing to pay price based on the expected surplus.

$$P_\theta^{exp}(z,x;\tilde{z}) = \omega\mathbb{E}_\gamma[V_\theta^{b1}(z+\gamma x z^\beta \tilde{z}^{1-\beta};\tilde{z}) - V_\theta^{b0}(z;\tilde{z}) - B\tilde{z}^\alpha] + (1-\omega)\cdot r\sigma A(\gamma,\tilde{z}') \tag{21}$$

To ensure successful transaction, the Price P should be no less than the net gain of potential buyer as well as the seller. Accordingly, In the circumstance that patent is inspection good, the condition of the successful transaction is like below,

$$V_\theta^{b1}(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}) - V_\theta^{b0}(z; \tilde{z}) - B\tilde{z}^\alpha \geq r\sigma A(\gamma, \tilde{z}') \tag{22}$$

the patent is experience goods, and the firm can only knows the value of patent by using it into the production. So the condition of the successful transaction is like below:

$$\mathbb{E}_\gamma V_\theta^{b1}(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}) - V_\theta^{b0}(z; \tilde{z}) - B\tilde{z}^\alpha \geq r\sigma A(\gamma, \tilde{z}') \tag{23}$$

The patent agent value function can be written as:

$$\begin{aligned} A(\gamma; \tilde{z}) =& T_a \cdot \begin{Bmatrix} \mathbb{E}_{\theta,z,x} \Gamma_\theta(z; \tilde{z}) \cdot (1-s) \cdot \max\{P_\theta^{ins}(z, \gamma, x; \tilde{z}), r\sigma A(\tilde{z}')\} \\ \mathbb{E}_{\theta,z,x} \Gamma_\theta(z; \tilde{z}) \cdot s \cdot \max\{P_\theta^{exp}(z, x; \tilde{z}), r\sigma A(\tilde{z}')\} \end{Bmatrix} \\ &+ (1 - T_a) r\sigma A(\tilde{z}') \end{aligned} \tag{24}$$

By the free entry condition of patent agent, in equilibrium, $q(\gamma) = A(\gamma; \tilde{z})$.

Therefore, the value function for the firm that goes to patent market is:

$$\begin{aligned} V_\theta^{buy}(z; \tilde{z}) =& m_b\left(\frac{n_a}{n_b}, \frac{\lambda_b}{\bar{\lambda}_b}\right) \cdot \begin{Bmatrix} \mathbb{E}_{\gamma,x}(1-s) \cdot \max\{V_\theta^{b1}(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}) - P_\theta^{ins}(z, \gamma, x; \tilde{z}); \tilde{z}) - B \cdot \tilde{z}^\alpha, V_\theta^{b0}(z; \tilde{z})\} \\ \mathbb{E}_x s \cdot \max\{\mathbb{E}_\gamma \left[V_\theta^{b1}(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z})\right] - P_\theta^{exp}(z, x; \tilde{z}); \tilde{z}) - B \cdot \tilde{z}^\alpha, V_\theta^{b0}(z; \tilde{z})\} \end{Bmatrix} \\ &+ \left(1 - m_b\left(\frac{n_a}{n_b}, \frac{\lambda_b}{\bar{\lambda}_b}\right)\right) r V_\theta^{b0}(z; \tilde{z})\} - B(\lambda; \tilde{z}) \end{aligned} \tag{25}$$

The more the search effort the firm spends, the higher possibility the firm has to meet with a patent (higher $m_b\left(\frac{n_a}{n_b}, \frac{\lambda_b}{\bar{\lambda}_b}\right)$) and furtherly, get more profits because of the productivity increment. Yet, the convex search cost function leads to the increasing marginal cost of search. so the optimal search effort of potential buyer is the solution for the first-order condition for $V_\theta^{buy}(z; \tilde{z})$.

3.7 R&D Decision

Then firm's in-house R&D choice (R&D intensity i) can be solved. The firm has θi possibility to make an invention and $(1 - \theta i)$ possibility to fail to have a new patent in t period and come to patent market to find a patent. Hence, the expected value of firm is,

$$V_\theta(z;\tilde{z}) = \max_i \theta i \cdot V_\theta^{inn}(z;\tilde{z}) + (1-\theta i)\cdot V_\theta^{buy}(z;\tilde{z}) - C(i;\tilde{z}) \tag{26}$$

3.8 Balanced Growth Path

3.8.1 Labor Market Clearing

I postulate that in this economy, the population equals to 1 without growth. The wage rate is determined by labor market clearing condition:

$$N \cdot \int (l_i^*)\, di = N \cdot \int (\frac{1-\alpha}{w})^{\frac{1}{\alpha}} z_i\, di = 1 \tag{27}$$

The wage rate is

$$w = (1-\alpha)(N\cdot\tilde{z})^{\alpha} \tag{28}$$

Here, N is the number of firms which attend the good production in this period, which is a constant number in balanced growth path; $\tilde{z}$ is average productivity of firms which attend the good production at this period, which grows at the rate of g in balanced growth path.

3.8.2 Aggregation

Stationary Firm Size Distribution $\hat{P}_{\theta,t}(\hat{z} = \frac{z}{\tilde{z}})$ is the firm relative productivity distribution contingent on its' type at the very beginning of period t. The dynamics of relative productivity distribution is illustrated in Appendix C.1. In the steady state, the firm relative productivity distribution will converge to to a stationary distribution.

Balanced Growth Path the BGP growth rate is defined as

$$g \equiv \frac{\int z\, dP_{t+1}(z)}{\int z\, dP_t(z)} \tag{29}$$

Definition A stationary equilibrium of this economy is a tuple

$$\left\{ l_i, V_\theta, i_\theta, \hat{P}_\theta(\hat{z}), w, g \right\}$$

such that

(i) labor demand of firm l_i maximize profits as in (6);

(ii) V_θ is given by the value function in (26);

(iv) i_θ is given by the optimal R&D policy, which is the solution of function in (26);

(vi) $\hat{P}_\theta(\hat{z})$ is evolved according to (34) and goes to a stationary distribution;

(vii) w is consistent with labor market clearing condition in (28);

(vii) g is determined by all the R&D decisions, patent market decisions in (29)

Welfare Analysis The representative consumer's utility function is CRRA form.

$$U = \sum r^{t-1} \frac{C(t)^{1-\zeta}}{1-\zeta} \tag{30}$$

Every period, the good market clearing condition is

$$Y(t) = C(t) + C_{rd,t} + B_{search,t} + F_{search,t} \tag{31}$$

$C_{rd,t}$ is the total cost of R&D for the firms doing in-house R&D. $B_{search,t}$ is the total search cost of potential buyer. $F_{search,t}$ is the total fixed cost in patents transactions.

4 Structural Estimation

4.1 Computational Algorithms

In this model, if the productivity difference parameter β goes to 1, as the the firm can do in-house R&D and patent purchase simultaneously in one period, I cannot get a stationary equilibrium with the large firms grows unboundedly. So the restriction on β is needed to get stationary distribution of relative productivity. By contraction mapping theory, I can prove that there exists a balanced growth path for this model.

I solve the model computationally as a fixed point of the following vector of five aggregate aggregate variables:

$$\left\{T_{a|b}, A(\tilde{z}), g_{BGP}, V_\theta(z;\tilde{z})\right\} \tag{32}$$

The first two variables are patent market tightness and patent agent value in every period; the third one is the growth of aggregate TFP in balanced growth path; the last is the values of firm with R&D capacity θ and productivity z.

I can solve for the stationary equilibrium by first posting a conjecture for (32), then solve for firm's optimal decision in R&D and patent market. Firm with different R&D capacity θ and relative productivity $\hat{z}$ makes different choices. I initiate firm's productivity to be Pareto distribution from 1 to 200 [48] with shape parameter 1.1. Specifically, using the initial distribution of firm's productivity and the guess for variables in (32):

(i) I compute the individual firm's patent keep-or-not decision I^k when firm successes in in-house R&D, optimal patent market search effort (λ), patent buy-or-not decision and optimal R&D intensity i based on equation (16), (22),(23),(25) and (26).

(ii) Using firm's patent market decision and R&D decision, I calculate the number of potential buyer and seller weighted by their search efforts in patent market and update the $T_{a|b}$ and $A(\tilde{z})$.

(iii) I update the value function of firm $V_\theta(z; \tilde{z})$ afterwards.

(iv) The firm distribution changes according to equation (34) and the productivity growth g_{BGP} in balance growth path is defined as (29).

This procedure gives us (32) as a fixed point and also generates stationary equilibrium distribution of relative productivity.

4.2 Simulated Method of Moments

In the full-blown model, there are three kinds of frictions in patent market. By the theoretical model, the search costs (η) hurts high-quality and low-quality patents equally, but fixed cost (B) in patent purchase and information asymmetry on patent quality (s) affect high-quality and low-quality patents differently. What's more, the fixed cost (B) can exclude the small firm which cannot get enough expected surplus from the patent purchase from the patent market. I can use the aggregate the fraction of traded patents, the fraction of traded patents ratio (high-quality patent over low-quality patent)

[48] In NBS data, the lowest 1% quantile of firm's labor is 20 and the upper 99% quantile is 4000.

and several firm's patent market participation features to identify all the frictions in model.

some values of parameters are predetermined as follows:

Table 4: Pre-determined Parameters

Parameters	Definition	Value
α	Labor share	0.50
ω	Bargaining power	0.50
ρ	R&D cost elasticity	3.00
r	Discount factor	0.96
σ	Patent survive rate	0.95
δ	Exogenous exit rate	0.075
h	The probability to invent a high-quality patent	0.40
γ_{gap}	Step size gap between high-quality and low-quality patent	1.16

The R&D elasticity is estimated by the R&D production function, in which I regress logarithm of quality-adjusted patents on the R&D intensity by the manufacturing firms operating data. However, as the small firms' R&D intensity data may be biased or misreported, I restrict the regression samples on the large firms.

In China, the term of patent is 20 years. Accordingly, $\sigma = 1 - 1/(1 + 20)$.

The exogenous exit rate δ is the average exit rate of top 1% firms in NBS database from 2001 to 2013.

For the high-quality patents' share h and high-quality, low-quality patent productivity gap $\gamma_{gap} = \frac{\gamma_h}{\gamma_l}$, as aforementioned in empirical part, I define the patent of which the forward citation number is higher than median within its technology class and grant year as the high-quality patent, and vice versa. I calibrate h with the share of high-quality patent in my data, which is 40% in both of China and U.S. [49]. The forward citation number gap (high-quality patent over low-quality patent) is about 9 in both countries. I regress logarithm of firm's sales on the accumulated patent adjusted by forward citation number to calibrate the elasticity between forward citation number and firm's revenue, which is about 0.069 [50] in Appendix D. So I set the $\gamma_{gap} = exp(0.069 * ln(9)) \simeq 1.16$ in estimation.

[49]Table D4 in Appendix D shows the explicit proportions of high-quality patents and low-quality patents in U.S. and China.

[50]The regression coefficients for U.S. are from 0.0559 to 0.0816, and for China are from 0.0579 to 0.0869. I take the average of those value. The regressions are in Table D5.

What's more, the patent-inventing firm similarity distribution is calibrated by the real distribution of patent-inventing firms' similarity distribution as shown in Figure 3.

The remaining 10 parameters, which are listed in Table 5, are estimated with SMM. Computing the model-implied moments from the simulation strategy described above and comparing them to the data-generated moments, I choose the optimal set of parameters to minimize the problem below.

$$\hat{\Omega} = \underset{\Omega}{\operatorname{argmin}}\, G(\Omega)'\hat{W}G(\Omega) \tag{33}$$

where Ω here refers to the parameters. I index each moment by i. $G_i(\Omega) = \frac{|model(i)-data(i)|}{\frac{1}{2}|model(i)|+\frac{1}{2}|data(i)|}$. SMM iteratively searches repeatedly across sets of parameter values in the model until the model's moments are as close as possible to the empirical moments.

$\hat{W}$ is the optimal weighting matrix, calculated by bootstrapping 1000 times. I draw samples of equal size to samples from 2001 to 2013 NBS balanced data, which is 14803 innovative firms, at every time. Afterwards, I get the variance-covariance matrix of simulated moments, $\hat{S}$, and $\hat{W} = \hat{S}^{-1}$. The standard errors of the parameter estimates are the diagonal elements in $\hat{V} = \hat{D}'\hat{W}\hat{D}$, where $\hat{D}'$ is a gradient matrix equals to $\frac{\partial G(\Omega)}{\partial \Omega}|_{\Omega=\hat{\Omega}}$.

Table 5: Parameter Estimates

Parameter	Description	Value	Standard error
β	Productivity difference	0.094	0.0002
γ	Step size	0.504	0.0007
χ	Cost of R&D	6.356	0.0784
I_p	High-type firms proportion	0.049	0.0004
θ_h	High-type R&D capacity	1.466	0.0016
θ_{gap}	R&D capacity gap	0.132	0.0006
η	Cost of search	49.9997	0.845
μ	Search cost elasticity	2.699	0.0027
B	Fixed cost	0.114	0.0003
s	Information asymmetry	0.598	0.0058

My SMM procedure targets the 13 moments outlined in Table 6. These moments center on firm's sales growth rates, R&D-sales ratio, firms' participation in patent market as buyer in extensive margin and aggregate patent sold fraction, and its ratio.

Standard deviation of the sales growth rate In the NBS 2001-2013 balanced data, the innovative firms' sales growth rate standard deviation is 0.1769. It represents the dispersion of firm sales growth rate. Intuitively, the two parameters in productivity motion equation (8) may be the driven force for this moment. In the extreme case, if the β equals to 1, there is no difference of sales growth rate between small firm and large firm upon getting a new-born patent. Hence, β is negatively correlated with this moment. While γ enlarges the difference of sales growth rate between small firm and large firm upon getting a new-born patent.

Correlation coefficient between firm size and growth rate of sales The firm size is measured with firm's sales in one year's before. To control the industry and year fixed effect, I calculate the correlation coefficient within each industry and year group, and take the average weighted by the number of firms in each industry and year group. The average value is -0.028 in Chinese firm. Which parameter influences this correlation coefficient? Again, parameter β and γ are important. They decrease this correlation because in extensive margin, as the surplus for larger firms of one more patent rises with β and γ, larger firm will spend more effort on R&D and patent market; in intensive margin, upon getting new patent, larger firm will benefit more from it.

The ratio of R&D expenditure over sales In Chinese NBS firms, the total expenditure on research and development is about 1.19% [51] of total sales. This value mainly contains the information in R&D cost function. The higher the cost of R&D χ is, the lower R&D intensity will be chosen by firm. At the same time, the higher step size in productivity γ upon getting a new patent will stimulate firm's incentive to do R&D as the expectation gain increases.

Standard deviation of R&D-sales ratio In NBS innovative firm, this value is 0.0067. This moment reflects the variance of firm's optimal R&D choice. The parameters β and γ affect the expected surplus difference of R&D among firms, and the parameter θ_{gap} indicates the R&D capacity difference among firms. Those parameters will have impacts on the dispersion of R&D-sales ratio among firms.

[51] By world bank database, Chinese R&D expenditure over GDP ratio is 1.45%. Here, I only calculate the the RD expenditure of firm in the year when the firm has RD expenditure record in database.

Table 6: Model and Data Moments

Moments	Description	Data	Model
1. $Std(g\_sales)$	Standard deviation of growth rate of sales	0.177	0.126
2. $Corr(firmsize, g\_sales)$	Correlation coefficient between firm size and growth rate of sales	-0.028	-0.026
3. $\frac{TotalR\&D}{TotalSales}$	Ratio of R&D expenditure to Sales	0.012	0.017
4. $Std(R\&D - SalesRatio)$	Standard deviation of firms' R&D-sales ratio	0.007	0.009
5. $Avg(LargefirmR\&D - SalesRatio)$	Large firm's R&D intensity (firm size larger than 50 percentile firm size)	0.010	0.011
6. $90pc(R\&D - SalesRatio)$	90 percentile R&D-sales ratio	0.032	0.029
7. $\frac{\%ofinventor_{large}}{\%ofinventor_{small}}$	Share of large firms as the inventor over share of small firms as the inventor	1.731	1.725
8. $\frac{Pat\_traded}{Pat\_inv}$	fraction of traded patents	0.044	0.044
9. $\frac{Num(buyer)}{Num(firm)}$	The share of firms to be buyer	0.003	0.002
10. $Std(I\_b)$	Standard deviation of (buyer=1)	0.048	0.047
11. $\frac{\%ofbuyer_{large}}{\%ofbuyer_{small}}$	Share of large firms as the buyer over small firms as the buyer	1.654	1.672
12. $\frac{\%ofbuyer_{up75pc}}{\%ofbuyer_{50-75pc}}$	Share of upper 75 percentile firms as the buyer over 50-75 percentile firms as the buyer	1.487	1.301
13. $\frac{Frac\_of\_patsold_{Hq}}{Frac\_of\_patsold_{Lq}}$	fraction of traded patents ratio (high-quality patent over low-quality patent)	1.114	1.115

Large firms' R&D-sales ratio, 90 percentile of R&D-sales ratio The Large firm's R&D-sales ratio is 1.02%, and 75 percentile of R&D-sales ratio is 3.18%. In general, they are affected by same parameters, χ as same with the third moment, the ratio of R&D expenditure over sales. What's more, to what extend the high type firm's R&D capacity θ_h is and the proportion of high-type firm I_p positively correlate with this moment as well.

Share of firms as the inventor (large firms over small firms) The parameter β, θ_{gap} associated with the heterogeneity among large firm and small firm will affect this ratio. The larger difference between large firm and smaller firm in of surplus of invention and capacity in R&D is, the higher value this ratio will be.

The share of firms as the buyer and standard deviation of buyers From 2001 to 2013, there are approximately 0.3% manufacturing firms to be the buyer in patent market in each year. And if I define an indication function $I_b(buyer = 1)$ as an indicator for whether the firm is a buyer or not, the standard deviation is 0.0484. Same as fraction of traded patents, The parameters governing the matching function, η and μ, are important to this moment. And the parameters connected with firms' heterogeneity, β, θ_{gap}, I_p are significant to the variance of whether to be the buyer or not.

The share of firms as the buyer ratio The ratios of buyers' share (large firm over small firm, upper 75 percentile firm over 50-75 percentile firm) reflect the curvature of the search effort distribution among all firms. I compare the share of buyer in large firm group with small firm group, and firms of which the size is upper 75 percentile and between 50 and 75 percentile. The search cost elasticity μ and fixed cost B directly affects these two ratios.

Fraction of traded patents and its ratio (high-quality over low-quality patents) For patents applied and granted from 1998 to 2013 by Chinese firms, 4.40% were sold to other Chinese firms, as catalogued in Table 1. The parameters governing the matching function, η and μ, control how easy it is to sell the patent. Its ratio is governed by fixed cost parameter B. Let us postulate an extreme case, where B goes to infinity, only the highest-quality patent will be bought. As high B can stop lower quality patent to be sold, it can affect the fraction of traded patents as well. Additionally, s affects this ratio as well.

Table D12 in Appendix D shows the elasticity between estimated parameters and targeted moments. By the estimated parameters, in the balanced path, the long-run productivity growth rate is 1.38%, within which patent market contributes 9%. If I shut down the patent market, the long-run productivity growth rate is 1.32%, which means the patent market explains 5% of Chinese productivity growth [52]. The patent market affects the growth in two ways. Firstly, it directly provides a platform to make full use of the sleeping patents. As there exists uncertainty in innovation, even if the patent is not valuable for its' inventor, the inventor can sell it, which means the patent market raises the expectation value of R&D. Secondly, it increases the innovation incentive of firms indirectly.

[52] Later, in counterfactual exercise part, I have estimate the patent market parameters in U.S. By shutting down patent market in U.S., the patent market can explain 17% of productivity growth.

4.3 Goodness of Fit and Nontargeted Moments

The method of moments approach infers the model parameters using an informative set of moments that capture key aspects of the data. Here, I show that the estimates are consistent with the broad set of NBS firms' sales growth and R&D patterns and empirical patterns documented in Section 2, i.e. the growth rate of sales ratio (small firm over large firm), share of firm with high R&D intensity, firm's participation in patent market on seller side (extensive margin and intensive margin), and sales duration patterns.

Growth rate ratio between small firm and large firm Conditional on successful innovation, The first row in Table 7 shows the sales growth rate ratio in data and model. The small firm's sales growth rate is larger than large firm's. However, this moment in model is a little bit larger than data. This may be because that the only way to increase firm's sales is to do innovation. Imitation is not considered. What's more, more than one patent being obtained in one period is not allowed. Lack of these, if large firm does more imitation or invents more quantities of patents in one period than small firm, our model will get a higher value of sales growth ratio than data.

Table 7: Nontargeted Moments

Non-target Moments	Description	Data	Model
1. $\frac{g\_sales_{s,pat=1}}{g\_sales_{l,pat=1}}$	Sales growth rate ratio while having new patent (small firm over large firm)	2.199	2.750
2. $\frac{TotalR\&D}{TotalSales} > 0.03$	Share of firms of which R&D-sales ratio is larger than 0.03	0.024	0.023
3. $\frac{\%ofseller_{large}}{\%ofseller_{small}}$	Share of firms as the seller (large firm over small firm)	2.489	1.548
4. $\frac{sell-invratio_{large}}{sell-invratio_{small}}$	Sell-invention ratio (large firm over small firm)	0.771	0.872
5. $\frac{buy-ownratio_{large}}{buy-ownratio_{small}}$	Buy-own ratio (large firm over small firm)	0.763	0.867
6. $Avg(duration)$	Average of duration	4.440	4.944
7. $Std(duration)$	Standard deviation of duration	2.820	4.399

R&D-sales ratio The share of firms of which the R&D-sales ratio is larger than 3%, this moment predicted by my model fits well with the data.

Firms participation on seller side The model in this paper is not firm-to-firm patent transaction model, I mainly match the moments on buyer side, especially the extensive margin of buyer side. However, in row 3 and 4 in Table 7, I check the fitness of this model regarding the firm's participation patterns on seller side. In the extensive margin, as the Section 2 presents, the share of firms as the seller in large firm group is higher than in small firm group. In the intensive margin, for the sell-invention ratio, our model predicts that as large firm can generate more surplus conditional on patent's quality and similarity, the proportion of invention to be sold in large firm is lower than in small firms, which is consistent with the data.

Intensive margin on buyer side In the structural estimation, I mainly match the moments of buyer side in extensive margin. Here, I check the buyer side pattern in intensive margin (row 5 in Table 7). As shown by Section 2, the buyer-own ratio is lower in larger firm. My model predicts the same result, because large firm accounts for much higher proportion of inventors than small firm, even the purchase number of it is higher than small firm, but the market is small in China. As a result, the buy-own ratio (large firm over small firm) is smaller than 1.

Sales Duration The sales duration of patent equals to the year when patent is sold less the year when the patent is filed. It takes 4.44 years on average for a patent to be sold in China, and the value my model predicts is 4.944. I also document the sales duration distribution of data and my model, which is depicted in Figure D22.

5 Counterfactual Exercises

In this section, the counterfactual and experiments I have done can be divided into three parts. Firstly, I test the impact of three frictions on the fraction of traded patents and other economy implications. Secondly, I target the U.S. patent market moments to re-estimate the parameters correlated with patent market and estimate the frictions differences between U.S. and China. Thirdly, there exists criticism on the low quality of Chinese patents. I test how patent quality increment can affect the patent market. Besides patent quality increase experiment, I also change the random search into directed search and analyze the impact of it on the economy.

5.1 Frictions Descend

In Table 8, I try to decrease or remove search cost, fixed cost and information asymmetry in the baseline economy. If I decrease η to 0, the fraction of traded patents in

China can reach to 34.2% [53], and the productivity growth rate will increase by 29.3% (i.e., 0.4 percentage) and the welfare will increase by 3.3%.

Table 8: Counterfactual Exercises: Frictions Descend

Friction parameters		g_{BGP}	i^*	$\bar{\lambda}$	$\frac{Patnum_{Hq}}{Patnum}$	$\frac{Pat\_traded}{Pat\_inv}$	g_{market}	Welfare
Basline economy		1.379%	0.154	0.006	0.404	0.044	0.089	100.000
$\eta_{baseline} = 50$	↓ 50% $\eta = 25$	1.424% (3.27%)	0.154 (0.32%)	0.009 (53.71%)	0.474 (12.16%)	0.072 (59.36%)	0.132 (48.85%)	100.415 (0.42%)
	↓ 100% $\eta = 0$	1.783% (29.26%)	0.157 (2.29%)	2.458 (43436.65%)	0.392 -(3.02%)	0.342 (1151.30%)	0.302 (239.66%)	103.336 (3.34%)
$B_{baseline} = 0.114$	↑ 2.4% $B = 0.116$	1.383% (0.29%)	0.154 (0.29%)	0.006 -(1.40%)	0.413 (2.16%)	0.044 -(2.40%)	0.087 -(2.36%)	100.026 (0.03%)
	↓ 100.0% $B = 0$	1.563% (13.33%)	0.159 (3.09%)	0.013 (125.26%)	0.384 -(4.98%)	0.176 (545.86%)	0.277 (211.00%)	101.683 (1.68%)
$s_{baseline} = 0.598$	↓ 100% $s = 0$	1.392% (0.95%)	0.154 (0.07%)	0.006 (8.62%)	0.707 (74.71%)	0.052 (16.84%)	0.106 (18.64%)	100.123 (0.12%)
Frictionless economy	$\eta = 0; B = 0; s = 0$	2.110% (52.97%)	0.172 (11.69%)	1.874 (33080.52%)	0.400 -(1.08%)	0.685 (2406.05%)	0.582 (553.90%)	106.428 (6.43%)

Note: (1) In this table, g_{BGP} is the productivity growth rate in BGP; $i*$ is the average optimal R&D intensity; $\bar{\lambda}$ is the average optimal search effort; $\frac{Patnum_{Hq}}{Patnum}$ is the endogenous proportion of high-quality patents in the patent market; $\frac{Pat\_traded}{Pat\_inv}$ is the fraction of traded patents; g_{market} is the proportion of productivity growth brought by the patent market. (2) η is the search cost; B is the fixed cost; s is the information asymmetry parameter.

The fixed cost's impact on the economy is more complicated. It affects the patent market in two channels. In the first place, the reduction of fixed cost lets more patents to go to the market, and, in general, it will increase the fraction of traded patents and increase the BGP growth rate and welfare. Additionally, it will change the patent-quality structure in patent market. More low-quality patent will enter to the market with the decreasing of fixed cost, and more low-quality patent traded will decrease the patent market's contribution. So we can see in Table 8, if fixed cost increases in a small region, the welfare will even increase a little bit. But if I decrease the fixed cost to zero, the BGP growth rate will increase by 13.3% (i.e., 0.18 percentage) and welfare will increase by 1.7%.

Lastly, I set the information asymmetry s equals to 0, which means all patent quality information is transparent in this market, then high-quality patent can get high price in every patent-buyer meeting. The market will not hurt the high-quality patent. The BGP productivity growth rate increases by only 1% (i.e., 0.01 percentage) and welfare increases by 0.12%.

If I remove all frictions in this market, in a frictionless economy, the BGP growth

[53] If I decrease η by 93.8%, the fraction of traded patents in China can reach to the U.S. level, which is 14.6%

rate can increase by 53% at largest (i.e., 0.7 percentage) and welfare can increase by 6.43%.

Among these three types of frictions, conditional on the under-developed patent market, drastically diminishing the search cost can enlarge the patent market to the maximum extent. Lowering fixed cost and information asymmetry can let more patents to be sold conditional on the patent-buyer's meeting, but the most important thing is that we should let more firm to spend effort to search in this market.

5.2 The Frictions Gap between China and U.S.

The Section 2 gives some motivations for the frictions gap between China and U.S.. Here, using U.S. listed firms 2001-2013 panel data and holding the parameters related with firm unchanged, I re-estimate the parameters related with patent market to target the patent market moments in U.S..

Specifically, conditional on the first six parameters in Table 5 are constant, I adjust last four parameters, cost of search η, search cost elasticity μ, fixed cost B and information frictions parameter s to target moments correlated patent market in U.S., which are shown in Panel B in Table 9. To rule out the influence of firm distribution difference [54], I re-sample the U.S. firm according to Chinese NBS firm size distribution to calculate the moments in the table below.

By the estimation results, in Panel C, I find that compared with Chinese level, in U.S., the search cost is 90% lower, the fixed cost is 6% higher and information asymmetry on patent quality is 87% lower. Holding other frictions parameters constant, move search cost parameter, fixed cost parameter and information asymmetry parameter from Chinese level to U.S. level can move the fraction of traded patents from 4.4% to 11.6%, 4.4% and 5.1% respectively [55].

[54] In Figure D23 in Appendix D, I compare the Chinese NBS firm samples with U.S. listed firm samples in term the firm size distribution. The distribution in two samples are quite different. In U.S. the right tail and left tail are fatter than in China, and the variation of firm size is larger in U.S..

[55] As these four patent market parameters have interaction effect, to analyze their contributions to the gap of fraction of traded patents between U.S. and China, first, I set them all in Chinese level, and gradually change them to U.S. level. The detailed calculation process is in the Table D13 in Appendix D. The results show that the search cost can explain 78% of the gap; the search cost elasticity level can explain 24%; the fixed cost can explain -4%; the information asymmetry can explain 2%.

Table 9: Matching the Moments in U.S. Patent Market

Panel A. Parameter estimations			
Parameter	Description	Value	Standard error
η	Cost of search	5.0305	0.0604
μ	Search cost elasticity	2.8601	0.0097
B	Fixed cost	0.1164	0.0010
s	Information friction	0.9233	0.0158
Panel B. Patent Market Moments match			
Moments	Description	Data	Model
$\frac{Pat\_traded}{Pat\_inv}$	fraction of traded patents	0.146	0.158
$\frac{Numofbuyer}{Numoffirm}$	The share of firms to be buyer	0.115	0.096
$Std(I_b)$	Standard deviation of (buyer=1)	0.319	0.295
$\frac{\%ofbuyer_{large}}{\%ofbuyer_{small}}$	Share of buyer in large firm over small firm	2.075	1.963
$\frac{\%ofbuyer_{up75pcfirm})}{\%ofbuyer_{50-75pcfirm})}$	Share of buyer in upper 75 percentile firm over 50-75 percentile firm	1.544	1.445
$\frac{\frac{Pat\_sold_h}{Pat\_inv_h}}{\frac{Pat\_sold_l}{Pat\_inv_l}}$	Fraction of traded patents ratio (high-quality patent over low-quality patent)	1.380	1.334
Panel C. Frictions comparison			
Parameters	CN $\rightarrow US, (US-CN)/CN(\%)$	$\frac{Pat\_traded}{Pat\_inv}$ CN=4.4%	Welfare$_{US}$ $Baseline_{CN} = 100$
η	50.00 $\rightarrow$ 5.03, -90%	13.6%	101.46
μ	2.70 $\rightarrow$ 2.86, 6%	6.5%	98.95%
B	0.114 $\rightarrow$ 0.116, 2%	4.4%	100.03%
s	0.60 $\rightarrow$ 0.08, -87%	5.1%	100.13%

5.3 Patent Quality Increment and Directed Search

Lots of criticisms have been received on low quality of Chinese patents. In Table 10, I test the patent quality increment's impact on the patent market and the whole economy. In model, step size γ captures patent quality, and I increase this parameter by 10%, 50% and 100%. If I increase γ by 50%, the BGP growth rate can increase by 81% (i.e. 1.4 percentage), and welfare can increase by 9.57%.

Table 10: Counterfactual Exercises: Patent Quality Increment

Quality increment	g_{BGP}	i^*	$\bar{\lambda}$	$\frac{Patnum_{Hq}}{Patnum}$	$\frac{Pat\_traded}{Pat\_inv}$	g_{market}	Welfare
$\gamma_{baseline} = 0.504$	1.379%	0.154	0.006	0.404	0.044	0.089	100.000
$\uparrow$ 10%	1.586%	0.158	0.007	0.435	0.055	0.113	101.945
$\gamma = 0.556$	(15.01%)	(2.92%)	(18.87%)	(7.53%)	(24.92%)	(26.62%)	(1.94%)
$\uparrow$ 50%	2.501%	0.175	0.010	0.396	0.099	0.174	109.566
$\gamma = 0.757$	(81.34%)	(13.74%)	(79.09%)	-(2.05%)	(122.09%)	(95.80%)	(9.57%)
$\uparrow$ 100%	3.706%	0.190	0.012	0.379	0.136	0.199	117.882
$\gamma = 1.009$	(168.72%)	(23.63%)	(118.48%)	-(6.40%)	(205.98%)	(124.03%)	(17.88%)

Note: (1) In this table, g_{BGP} is the productivity growth rate in BGP; $i*$ is the average optimal R&D intensity; $\bar{\lambda}$ is the average optimal search effort; $\frac{Pat\_traded}{Pat\_inv}$ is the fraction of traded patents; g_{market} is the proportion of productivity growth brought by the patent market. (2) η is the search cost; B is the fixed cost; s is the information asymmetry parameter.

Our model is a random search model, where patent and potential buyer meet randomly. However, what if potential buyer can always meet with the patent it needs most, that is, the patent-buyer similarity always equals to 1. In Table 11, I compare the following situations with the baseline model (random search with high search cost): directed search only; low search cost only and directed search with low search cost. When only search cost is reduced by half, the welfare gain is lower than changing the random search to directed search. If these two adjustments happen simultaneously, the welfare can increase by 5.01% and the BGP growth rate increase by 46.47%.

Table 11: Counterfactual Exercises: Search Mode and Search Cost

Search mode	g_{BGP}	i^*	$\bar{\lambda}$	$\frac{Patnum_{Hq}}{Patnum}$	$\frac{Pat\_traded}{Pat\_inv}$	g_{market}	Welfare
Random search	1.379%	0.154	0.006	0.404	0.044	0.089	100.000
Directed search	1.737%	0.157	0.010	0.398	0.214	0.359	103.069
High search cost	(25.92%)	(1.86%)	(79.47%)	-(1.69%)	(681.51%)	(303.06%)	(3.07%)
Random search	1.543%	0.155	0.018	0.389	0.136	0.213	101.464
Low search cost	(11.91%)	(0.91%)	(223.04%)	-(3.75%)	(323.08%)	(139.29%)	(1.46%)
Directed search	2.020%	0.160	0.016	0.389	0.517	0.320	105.009
Low search cost	(46.47%)	(4.14%)	(187.19%)	-(3.76%)	(1791.24%)	(259.84%)	(5.01%)

Note: (1) In this table, g_{BGP} is the productivity growth rate in BGP; $i*$ is the average optimal R&D intensity; $\bar{\lambda}$ is the average optimal search effort; $\frac{Patnum_{Hq}}{Patnum}$ is the endogenous proportion of high-quality patents in the patent market; $\frac{Pat\_traded}{Pat\_inv}$ is the fraction of traded patents; g_{market} is the proportion of productivity growth brought by the patent market. (2) η is the search cost; B is the fixed cost; s is the information asymmetry parameter. (3) High search cost: $\eta_h = 50.00$ (CN level); Low search cost: $\eta_l = \frac{\eta_h}{2} = 5.03$ (US level).

6 Policy Experiment and Efficiency

6.1 Subsidy and Tax Policy Analysis

Here, I try two policy instruments to see the policy implications of this model based on estimated parameters [56]. Firstly, I try the size-independent R&D subsidy combined with lump sum tax [57]. The trade-off of giving R&D subsidy is between the higher growth rate because of more innovation and the higher innovation cost to pay lead-

[56] As search cost is the most important factors we should consider, here, I only do experiment based on the baseline model without fixed cost and information frictions

[57] I have also compared the influence of R&D subsidy in the economy with and without patent market. Figure D24 in Appendix D indicates that in less innovative economy, the R&D subsidy does much more to the welfare increment induced by patent market.

ing to lower consumption in every period. As we can see in Figure 7, by lump sum tax and 58% R&D subsidy, the BGP growth rate increases 0.46 percentage and the welfare increase by 1.7% at largest compared with no subsidy.

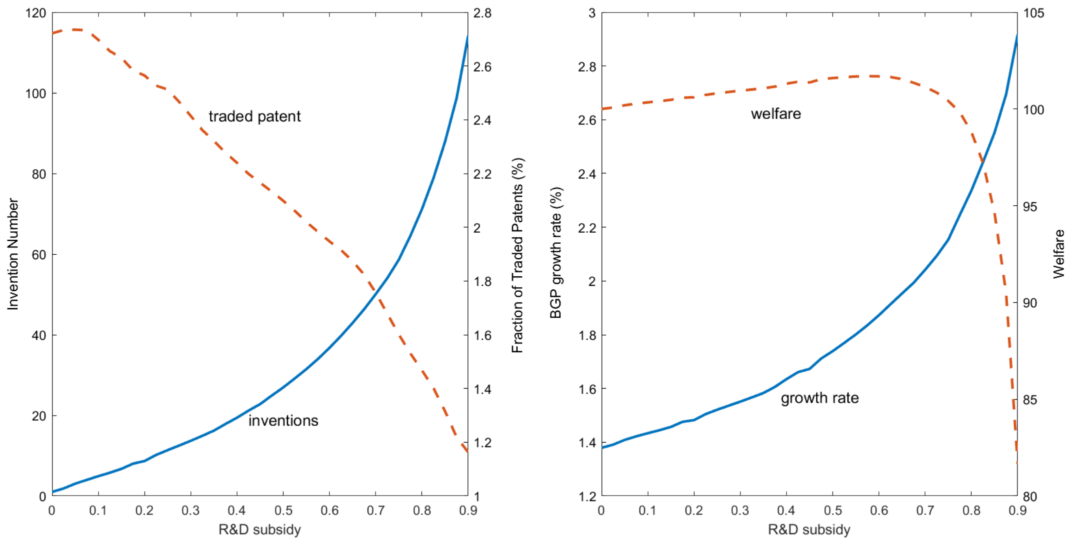


Figure 7: R&D SUBSIDY

Another instrument is to give subsidy to the firms which search in the patent market [58]. On one way, the search subsidy will decrease the cost of search and increase firms' search intensity in the patent market; on the other way, as possibility of selling the patent increases in the patent market, the in-house innovations are excited as well, because even if the patent means little to the inventor, it still can be sold with higher possibility. So more patents will be invented as well. As we can see in Figure 8, the optimal search cost subsidy is 0.84 which means the government takes lump-sum tax from firms and covers 84% search cost of firms. This will lead to about 1.11% welfare increase and 0.15 percentage BGP growth rate increase compared with no subsidy.

[58] I have also tried the policy with both of the R&D subsidy and search cost subsidy, and the result is in Figure D25 in Appendix D.

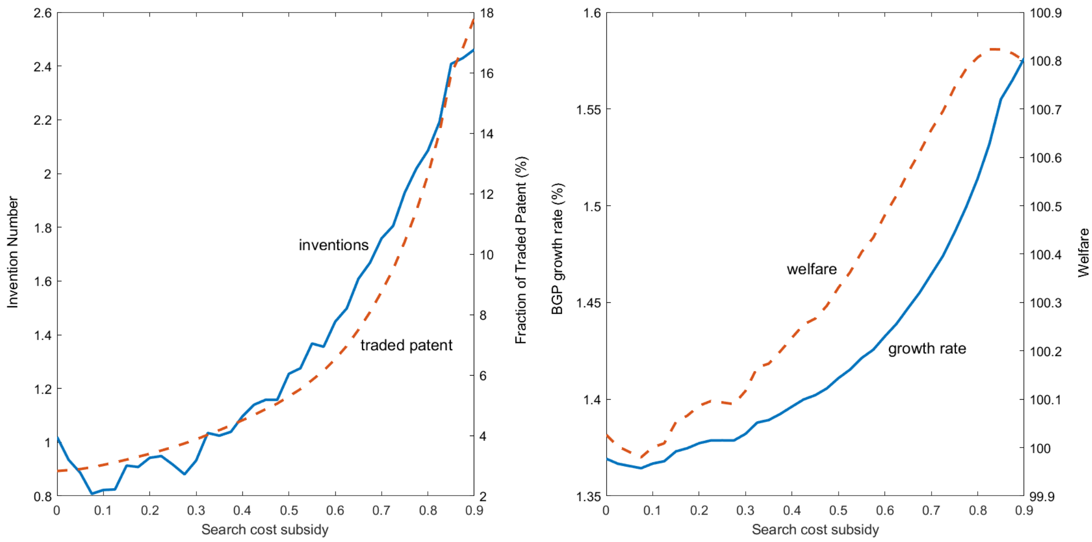


Figure 8: SEARCH COST SUBSIDY

7 Conclusion

Employing large-scale dataset with all China's patent transactions, and merging it with firm-level financial data, I document novel evidence on China's patent market and develop an endogenous growth model which is consistent with the stylized effect. As a result, large firms plays the main role in Chinese innovation activities, not only the in-house R&D but the transaction of patent as well. Up till now, albeit low patents' quality partially can explain the low prosperity level of patent market in China, the high market friction is the main reason for it. The high market friction makes firms cannot meet actively. It reflects that the low IPR protection in China, which is a hurdler for knowledge transfer and makes the innovated cannot be fully used.

There are several promising directions for future research. In theory, which is the large firm's advantage in innovation activity and how large firm is different from small firm in innovation are discussed quite frequently. In this paper, I do not focus on the reason why the large firm has advantage in patent utilization. Deeper research on it may lead to more meaningful policy implications. Besides, how could I decompose the market friction in empirical works. In which dimensions it can be decomposed. Investigating on more concrete patents transactions cases may generate new insights into this problem.

References

Abrams, D. S., Akcigit, U. and Grennan, J. (2013), Patent value and citations: Creative destruction or strategic disruption?, Technical report, National Bureau of Economic Research.

Acemoglu, D., Aghion, P. and Zilibotti, F. (2006), 'Distance to frontier, selection, and economic growth', *Journal of the European Economic association* **4**(1), 37–74.

Aghion, P. and Howitt, P. (1992), 'A model of growth through creative destruction', *Econometrica* **60**(2).

Akcigit, U., Caicedo, S., Miguelez, E., Stantcheva, S. and Sterzi, V. (2018), Dancing with the stars: innovation through interactions, Technical report, National Bureau of Economic Research.

Akcigit, U., Celik, M. A. and Greenwood, J. (2016), 'Buy, keep, or sell: Economic growth and the market for ideas', *Econometrica* **84**(3), 943–984.

Akerlof, G. A. (1978), The market for "lemons": Quality uncertainty and the market mechanism, *in* 'Uncertainty in economics', Elsevier, pp. 235–251.

Antras, P., Fort, T. C. and Tintelnot, F. (2017), 'The margins of global sourcing: Theory and evidence from us firms', *American Economic Review* **107**(9), 2514–64.

Arkolakis, C. (2010), 'Market penetration costs and the new consumers margin in international trade', *Journal of political economy* **118**(6), 1151–1199.

Autor, D., Dorn, D., Katz, L. F., Patterson, C. and Van Reenen, J. (2020), 'The fall of the labor share and the rise of superstar firms', *The Quarterly Journal of Economics* **135**(2), 645–709.

David, J. (2017), 'The aggregate implications of mergers and acquisitions', *Available at SSRN 2033555* .

Donovan, K., Lu, J., Schoellman, T. et al. (2018), Labor market flows and development.

Guo, H. et al. (2007), 'Ip management at chinese universities: A handbook of best practices, chapter 17.9'.

Jovanovic, B. and MacDonald, G. M. (1994), 'The life cycle of a competitive industry', *Journal of Political Economy* **102**(2), 322–347.

Kaplan, G. and Violante, G. L. (2014), 'A model of the consumption response to fiscal stimulus payments', *Econometrica* **82**(4), 1199–1239.

Klette, T. J. and Kortum, S. (2004), 'Innovating firms and aggregate innovation', *Journal of political economy* **112**(5), 986–1018.

König, M. D., Lorenz, J. and Zilibotti, F. (2016), 'Innovation vs. imitation and the evolution of productivity distributions', *Theoretical Economics* **11**(3), 1053–1102.

König, M., Song, Z. M., Storesletten, K. and Zilibotti, F. (2020), From imitation to innovation: Where is all that chinese r&d going?, Technical report, National Bureau of Economic Research.

Lentz, R. and Mortensen, D. T. (2008), 'An empirical model of growth through product innovation', *Econometrica* **76**(6), 1317–1373.

Lim, K. et al. (2017), Firm-to-firm trade in sticky production networks, *in* '2017 Meeting Papers', number 280, Society for Economic Dynamics.

Lucas, R. E. and Moll, B. (2014), 'Knowledge growth and the allocation of time', *Journal of Political Economy* **122**(1), 1–51.

Luttmer, E. G. et al. (2014), *An Assignment Model of Knowledge Diffusion and Income Inequality*, Federal Reserve Bank of Minneapolis, Research Department.

Marco, A. C., Myers, A., Graham, S. J., D'Agostino, P. and Apple, K. (2015), 'The uspto patent assignment dataset: Descriptions and analysis'.

Menzio, G. and Shi, S. (2011), 'Efficient search on the job and the business cycle', *Journal of Political Economy* **119**(3), 468–510.

Perla, J. and Tonetti, C. (2014), 'Equilibrium imitation and growth', *Journal of Political Economy* **122**(1), 52–76.

Pissarides, C. A. (2000), *Equilibrium unemployment theory*.

Romer, P. M. (1986), 'Increasing returns and long-run growth', *Journal of political economy* **94**(5), 1002–1037.

Stokey, N. L. (1988), 'Learning by doing and the introduction of new goods', *journal of Political Economy* **96**(4), 701–717.

Tintelnot, F., Kikkawa, A. K., Mogstad, M. and Dhyne, E. (2018), Trade and domestic production networks, Technical report, National Bureau of Economic Research.

A Data Details

A.1 Chinese Patent and Patent Transaction Data

The Structure of Original Transaction Data In CNIPA database, every filed patent has reassignment information archived like the panel A in Table A1 below. I translate the original data into a patent-assignor-assignee-year form. The line 1 in panel A shows the best condition, where there is a one-to-one correspondence between assignor, assignee and reassignment year. The records like this account for 85.17% in original data. If the record is like the line 2 in panel A, I delete the largest year, and transfer the original record to line 2-3 in panel B. On the contrary, if the records of year's number is more than records of assignee's number, as line 3 in panel A, I use the largest year as the complement of the last assignee's transaction year, and the transformed observations for line 3 in panel A are presented line 4-6 in panel B.

Table A1: Data Structure

Panel A. Original Data			
Application number	Assignor	Assignee	Reassignment year
CNXYYYYYYY	A	D	Y1
CNXXXYYYYY	B	E; F	Y1;Y2;Y3
CNXXXXXYYY	C	G;H;J	Y1;Y2
Panel B. Cleaned Data			
Application number	Assignor	Assignee	Reassignment year
CNXYYYYYYY	A	D	Y1
CNXXXYYYYY	B	E	Y1
CNXXXYYYYY	B	F	Y2
CNXXXXXYYY	C	G	Y1
CNXXXXXYYY	C	H	Y2
CNXXXXXYYY	C	J	Y2

Patent Assignor's and Assignee's Type As I only focus on the patent transactions within Chinese firms, I need to identify assignor or assignee's nationality and type. In the original data, there is no type information of patent market participants. The followings are what I do to identify Chinese firms to the largest extent:

- In CNIPA database, the variable named nationality records the patent's applicant's nationality and the variable named type records the type of patent's applicants [59], whereby, I get a list of applicants who had ever got a granted patent from 1985 to 2013 in China and their corresponding nationality and type. I merge the patent transactions assignor's and assignee's name with this list, and luckily, large numbers of patent market participants had applied patents in China.

- For the rest unrecognizable assignor and assignee, by the book of family name in China, I define the assignor(assignee) with 2-3 characters beginning with common Chinese family name as individuals.

- Japanese firm's Chinese name has distinguishing feature. "株式会"(zhushihui) in Japanese means corporate. By this feature, I can identify Japanese firm easily. What's more, if the name of unrecognized-type's assignor(assignee) possesses the name of nation or the city or province in China, I designate them as foreign firm or the Chinese firm.

- Lastly, some assignor's(assignee's) type are still unrecognized. I merge their name with the firm's name in SAIC database. If their name can match with the firm in SAIC, I define the type of assignor(assignee) as Chinese firms.

The Table A2 shows the assignor-assignee's type after operating the above steps.

Table A2: Assignor-Assignee's Type in Patent Market

		Assignee's type											
		Missing	C	FC	P	FP	R	FR	U	FU	G	N	Total
Assignor's type	Missing	1659	699	7262	112	130	1	19	11	15	8	7	9923
	C	578	83244	755	5827	15	2480	0	1370	0	278	9	94556
	FC	8802	5371	92260	872	273	22	123	34	176	57	104	108094
	P	422	45300	739	7	0	20	0	8	0	12	4	46512
	FP	786	269	1547	2	0	0	0	0	0	0	0	2604
	R	33	7450	11	0	0	111	0	4	0	8	0	7617
	FR	70	16	319	0	0	0	0	0	0	0	0	405
	U	119	13315	45	0	0	40	0	27	0	2	0	13548
	FU	85	11	279	0	0	0	0	0	0	0	0	375
	G	17	752	61	3	0	0	0	4	0	0	0	837
	N	25	25	118	0	0	0	0	0	0	0	0	168
	Total	12596	156452	103396	6823	418	2674	142	1458	191	365	124	284639

- Note: C represents Chinese firms; FC represents foreign firms; P represents Chinese individuals;FP represents foreign individuals;R represents Chinese research institutions; FC represents foreign research institutions;U represents Chinese universities; FC represents foreign universities; G represents government; N represents other types.

[59] the applicants' are divided into 6 types, which are firms(C), individuals(P), government(G), research institutions(R), university(U) and others(N)

Shareholding Relationships For a large group corporate, different subsidiaries may take different role. Some focus on research and development, the others play the role of production. Different subsidiaries may produce distinct goods, whilst the technologies used to produce those goods are complementary. In the above situations, the technology may be transferred or allocated within a group of corporate. However, this behavior is outside the range of this paper. I employ two ways to exclude the transactions like this. Firstly, the SAIC database archive the Chinese registered firm's [60] shareholder information in 2016, and I can easily tell the shareholding relationships between the assignor and assignee in every transaction record. As aforementioned definition, if firm A is the shareholder of firm B, or firm B is the shareholder of firm A, or both A and B are subsidiaries of firm C, the patent transaction between firm A and B is not counted into My sample.

Secondly, the method above may not unearth some relationships between two firms because of firms' name change, name mismatch, or shareholding change after registration [61]. I use the name similarity to delete the transactions of which the assignor's and assignee's name are similar with each other. Two similarity measurements in text analysis are employed here, one is Levenshtein distance, the other is Jaro–Winkler distance [62]. I calculate the average of these two distances and delete the transactions of which the assignor-assignee name similarity is larger than 0.5755. [63]

The Exclusion of Some Transactions As part 2.2 mentioned, I only keep the samples of patent transactions correlated with Chinese firms and eliminate the transactions within affiliated firms. The criterion and process of eliminations of transactions based on original data are in Table A3.

A.2 U.S. Patent Transaction Data

The structure of Original Data The most important difference between U.S. and China reassignment database lies in the structure of original data. As aforementioned struc-

[60]The firm which had existed before 2016

[61]For example,易能乾元（北京）电力科技有限公司(Yinengqianyuan(beijing)) and 易能（中国）电力科技有限公司(Yineng(zhongguo)), in SAIC 2016, there is no relationship between these two firms, but the later was the investor of the former in 2012.

[62]For accuracy, I delete the city and province name in assignor's or assignee's name

[63]The median of the distance here is 0.1055; 0.5755 is the 75 percentile value.

Table A3: The Process of Transactions Exclusion (China)

Criterions	Transaction Number
Initial assignor-assignee patent transactions	284639
No shareholding relationship	270032
Name similarity restriction	186821
No patent agent	182985
Correlated with Chinese firms	121827

ture of Chinese data, the record is based on patent level, yet U.S. reassignment database is independent of USPTO registered patent data, which is based on the every transaction event. The original U.S. reassignment data records 17,930,924 patent transactions before 2018. Marco et al. (2015) have give an exhaustive introduction for the U.S. patent reassignment database. Here, as the requirement of my study, according to the conveyance type [64], I directly delete all the other transactions except for the ones whose types are assignment. What's more, merged with USPTO, I only keep the transactions, where the transacted patents are applied and granted between 1998 and 2013 and the transaction year belongs to this period as well.

Patent Assignor's and Assignee's Type To be consistent with the calculation in CNIPA, I have to identify the assignee and assignor's type in the U.S. reassignment database as well. The good news is that in this database, there exists the assignee's location information, which indicates which country the assignee comes from. However, I cannot get any type or location information about the assignor. The following steps are taken to identify the transactions participants' type:

- Step 1, referring to NBER patent applicant's type identification method [65], I standardize assignor's and assignee's name, and divide them into 4 types —— firm, university, institutions and government. And as I have the location information of the assignee, I define the assignee as the U.S. firms, which is identified as firm and is located in U.S..

[64] The conveyance are divided into ten types: assignment; employer assignment, change of name, security agreement, government interest agreement, merger, release and correction. The concrete definitions of these types can be found in Marco et al. (2015), and only the type of assignment is correlated with firm-to-firm patent transfer and is not intra-firm transfer.

[65] The code can be found in this link, https://sites.google.com/site/patentdataproject/Home/posts/namestandardizationroutinesuploaded

- Step 2, similar with the applicants' list I get by CNIPA database, I get a list of all applicants who has applied patents before 2019 and its' type [66] information by Patentview. I merge this applicants' type list with the reassignment database by the assignee's or assignor's name. After step 1 and step 2, above 88% assignee's type can be identified and above 87% assignor's type can be identified.

The Exclusion of Some Transactions Analogous to the data work in CNIPA, I merely keep the samples of patent transactions correlated with U.S. firms and eliminate the transactions within affiliated firms, but I lack the shareholding relationship data. Therefore, I only drop some transactions observations according to the assignor and assignee name's similarity. The construction of similarity measurement is same as what I do in CNIPA reassignment data, and I take the same criterion value to drop the observations. The transactions of which the assignee or assignor's name contains "license", "licensing", "Intellectual property", or staff like these are deleted.

One more thing to be done here is that as the identification of firm's type is not as good as the identification in CNIPA database, there are still some of the assignor's and assignee's type in transactions unassigned. To test how these type-unidentified observations' effect, I choose the assignors whose transacted patent number are larger than 100, and identify their type via searching on the Internet by hand. Within the 36 type-unidentified assignor, two of them are oversea firms, and two of them are individuals. I delete their transactions in data and the number of left transactions in data shows in the last row of Table A4.

Table A4: The Process of Transactions Exclusion (U.S.)

Criterions	Transaction Number
Initial assignor-assignee patent transactions	970,320
Correlated with U.S. firms	273238
No patent agent	264,380
Name similarity restriction	200,864
Special identification by hand	199,692

Admittedly, the identification here is not perfect enough. Judging a firm whether to be a domestic firm mainly relies on the applicant's type in Patentview database and

[66] US Company or Corporation, Foreign Company or Corporation, US Government,Foreign Government,US Individual,Foreign Individual.

the location information of the assignee in U.S. reassignment database. This identification is not as accurate as the identification by registered capital type of the firm and headquarter location of the firm.

A.3 Name Matching between Different Databases

In this paper, for Chinese data, I merge the CNIPA with NBS database. The name matching method I use is to standardize the similar expression in Chinese and cope with some special symbols [67]:

- Step 1, I standardize firm's name. I use "you xian gong si" to take place of "gu fen you xian gong zi" and "you xian ze ren gong si" in firm's name; I use "chang" to take place of "chang you xian gong si" and "chang qi ye" in firm's name; I delete "dai qing li", "ge zhuan qi", "si ying zhuan he huo" and etc. in firm's name.
- Step 2, I translate all upper cases into lower cases, full-width into half-width.
- Step 3, I delete varieties of special symbols, such as, "*",">"," 《》 ", etc.

For U.S. data, I merge the Patentview registered patent data with USPTO patent reassignment data. The name matching method I use is similar. First, making name standardization in both of these two databases; and then merging them together. The name standardization method is provided by NBER patent database [68].

A.4 Technology Class

In this paper, I mainly use two types of technology class classification: IPC and OST.

IPC classification:

Up till now, IPC classification has eight versions of revisions. The IPC code in CNIPA is original, which is published in patent publication document with a mix of different IPC versions. But in this paper, I do not make any concordance when I use IPC

[67] I would like to thanks Doctor Xin Wang from CUHK. He shares his name matching code with me and the most of the name adjustments or standardization made here are learnt from him.

[68] https://sites.google.com/site/patentdataproject/Home/posts/namestandardizationroutinesuploaded.

classification. Because in the class level (3-digit IPC code), there exists no large changes from version 1 to 8. The following shows the changed classes from version 1 to 8 [69]:

- IPC1→IPC2: A01,A21-A24(d) [70]; B44 (r); C25 (+); E21(+).
- IPC2→IPC3: B09(+); B26(r); C02(r); C12(r); C30(+); E21(r); F16(r); G09(+).
- IPC3→IPC4: B25(r); B29(r); C23(r); G03(r).
- IPC4→IPC5: B67(r); B03(r); F25(r).
- IPC5→IPC6: B09(r).
- IPC6→IPC7: B81(+).
- IPC7→IPC8(2006.1): A21(r); A99(+); B99(+); C40(+); C99(+); D99(+); E99(+); F03(r); F99(+); G99(+); H99(+).
- IPC8(2006.1)→IPC8(2008.4): no changes.
- IPC8(2008.4)→IPC8(2009.1): A61-A63,A99(r).
- IPC8(2009.1)→IPC8(2010.1): A47(r).
- IPC8(20010.1)→IPC8(2014): no changes.
- IPC8(2014)→IPC8(2015): B31(r); B31(+).
- IPC8(2015)→IPC8(2016): no changes.

OST classification

IPC classification provides a comprehensive division for patent's technology. However, even in the class level, there are more than one hundred classes, which is not friendly for research. OST classification is built by the French "Observatoire des Sciences et des Techniques" to simplify IPC classification, which translate IPC classification into 5 sectors [71] and 35 fields meaningful technology classes. There are five requirements for

[69] I would like to thank Mphil student Wei Gu in CUHK for his work to compare different IPC versions detailedly.

[70] (d) means this class is re-divided and new definition is given; (r) means the definition of this class changes, including adding some frontier concepts in this class; (+) means this class is newly added; (-) means this class is deleted in new version.

[71] They are electrical engineering, instruments, chemistry, mechanical engineering and other fields.

the establishment of OST classification: covering all technology classes; balanced size of every fields; based exclusively on codes of the IPC; appropriate level of differentiation; distinct content of the fields [72].

B Patent Market Patterns

B.1 Background: Chinese Technology Market

B.1.1 Basic Statistics

Despite of the statistics in Figure B4, all the statistics in this part's figures come from Chinese annual report of technology market from 2003 to 2019, and they give the most basic descriptions of Chinese technology market.

The following figures document Chinese technology market in four aspects: (1) The total turnover of technology contract and the share of 4 types of contract: technology service, technology development, technology consulting and technology transfer; (2) Within technology transfer, the share of 4 types of technology transfer turnover, and the number of patent right transfer and license; (3) The participants in Chinese technology market and their shares; (4) The technology exchanges' contribution for the technology market.

The main information expressed by these figures are: (1) The technology transactions gradually surge in China. Among all types of technology transactions, technology services are the most important one in terms of its' total contract turnover; (2) Among technology transfer, secret transfer accounts for the largest proportion. In perspective of total contract turnover, patent right transfers' turnover is less than patent licenses' turnover. However, in perspective of the number of cases, the former is more; (3) Firms are the main force in patent market both in sellers side and buyer side. The share of technology transfer with the help of exchange decreases over time.

[72] The IPC-OST concordance guidance is in https://www.wipo.int/export/sites/www/ipstats/en/statistics/patents/pdf/wipo_ipc_technology.pdf

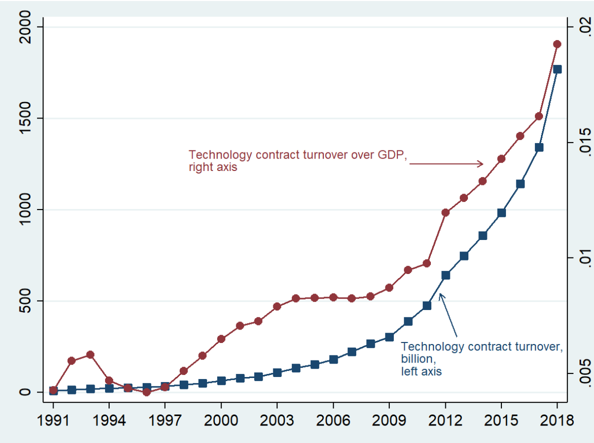


Figure B1: How Large the Technology Market in China is?

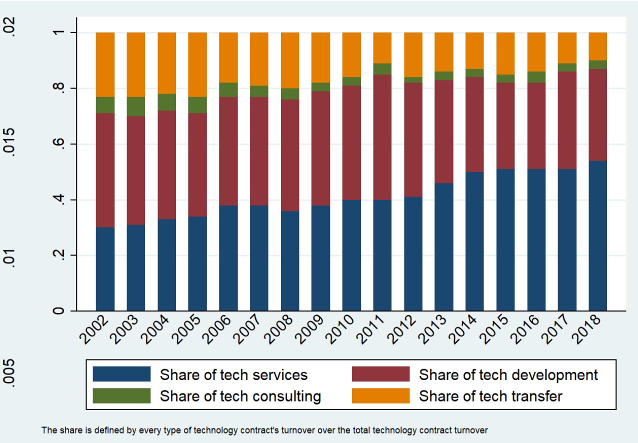


Figure B2: The Share of 4 Types of Technology Contract Turnover

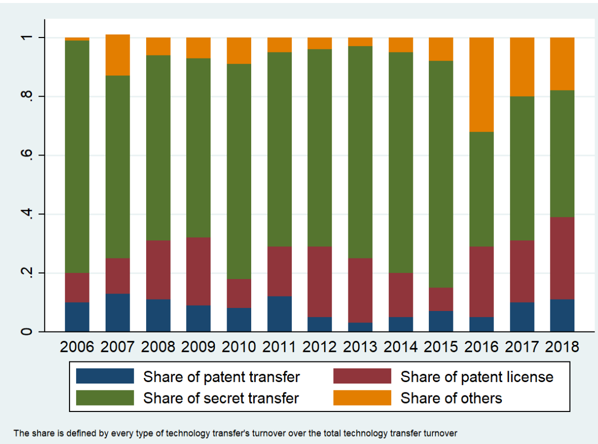


Figure B3: The Share of 4 Types of Technology Transfer

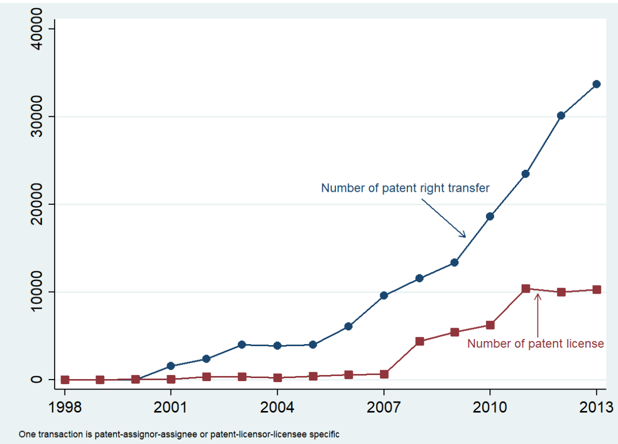


Figure B4: The Number of Patent Right Transfer and License

Note: (1) For Figure B3: Others in this figure contains computer software copyright transfer, exclusive rights to the layout designs of integrated circuits transfer, rights to new plant varieties transfer, new bio-medicine varieties, design copyright transfer and other technologies transfer; (2) For Figure B4: the number of patent right transfer and patent license are calculated by CNIPA database's raw data. Here I do not delete the transactions between shareholders or transactions with oversea firms, and all observations are included.

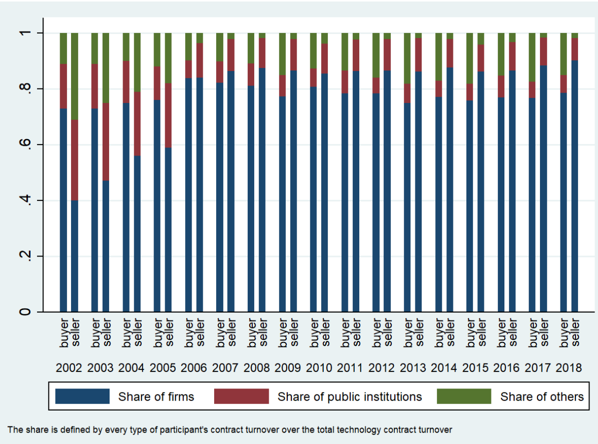


Figure B5: The Share of 4 Types of Technology Market Participants

Figure B6: The Share of Technology Contracts Completed in Technology Exchanges

Note: (1) For Figure B5: Others in this figure contains officials, legal person and other organizations; (2) For Figure B6 only includes the contract completed in main technology exchanges in China as reported by technology market annual report.

B.1.2 Patent Market Case in China: Online Transaction Platform

- Technology E website: www.ctex.cn (hosted by China Technology Exchange built by Ministry of Science and Technology of People's Republic of China, Chinese Intellectual Property Office and local government of Beijing)

Figure B7: Technology E website

- Qixianqin Intellectual Property Operation Platform (Zhuhai): https://ex.7ipr.com/ (permitted bo be built by Ministry of Finance, Chinese Intellectual Property Office and local government of Guangdong)

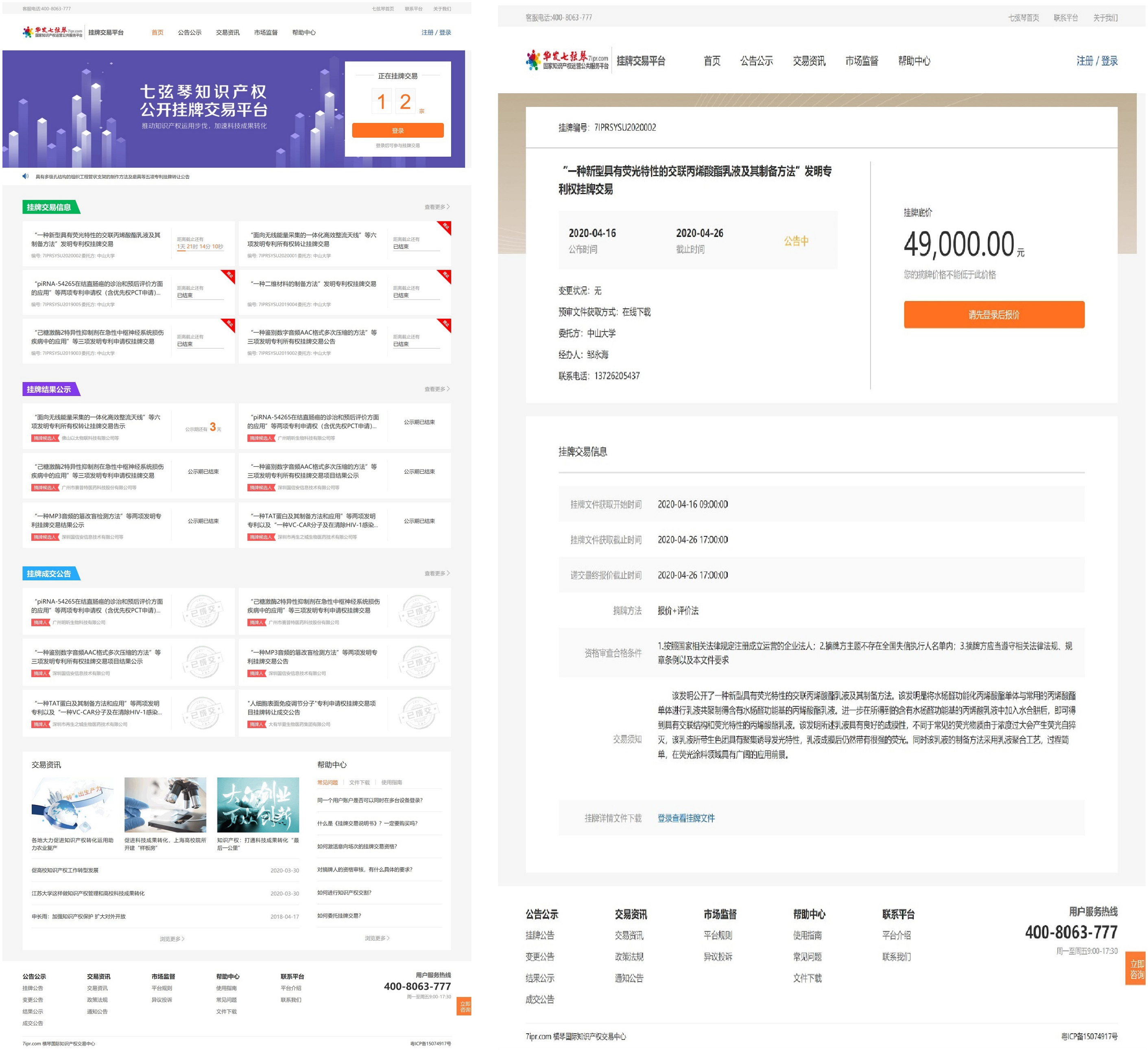


Figure B8: 7 Ipr website

B.1.3 Case Study: Patent Transaction Cost

Officially, patent transaction can be roughly divided into three part: official fees, attorney charges, and translation costs. In the table below, I compare some items in official fees correlated patent filing, granting, reassignment record and others.

Table B1: Official Fee Comparison between U.S. and China

	U.S.	China
Apllication fee	\$300	\$131
Examination fee	\$760	\$366
Annual fee (20 years total)	\$12200	\$9695
Reassignment record	\$50 (electronically)	\$29
	\$0 (non-electronically)	

Note: (1) The exchange rate in this table is 1 RMB=0.15 Dollars; (2) For annual fee, in U.S., during the term of patent, the annual fees are paid three times: in 3.5 year, 7.5 year and 11.5 year. In China, the annual fees are paid every year. I just sum up all annual fee in 20 years in this table.

For the attorney charges and other fees like advertisement fee, these fees are quite law office specific, and I cannot find common standards in both countries. Here I just provide some cases.

Table B2: Fees in Patent transaction (Case Study)

Case 1. Tech Expo				Case 2. Tech Exchange Intermediate					Case 3. Patent Agency	
China Beijing International High-tech Expo (2016, 19th)				China Technology Exchange					Patent agency service cost standard (Shandong, 2018)	
	A	B	C	Turnover	<1million	1-10millions	10-100millions	>1000millions		
Exhibition stand fee	24900/per stand	16600/per stand	8300/per stand	Transaction service fee	3%	1%	0.50%	0.30%	Patent reassignment registration	1000
Exhibition raw space fee	2490/m^2	1660/m^2	850/m^2	Price service fee	>=5000	>=5000	>=5000	>=5000	Patent application reassignment registration	1000
Others	-	-	-	Publication service fee	3000	3000	3000	3000		
				Others	-	-	-	-		

Note: (1) The unit in this table is 1 RMB; (2) The case 1 comes from http://www.cipic.net/showart.asp?cat_id=21&art_id=244; The case 2 comes from https://us.ctex.cn/article/aboutus/introduction/; The case 3 comes from http://www.gxpatent.net/html/ggtz/2725.html

B.2 Patent-firm Similarity

The following figures are the patent-firm similarity distribution before any adjustments and patent-firm similarity distribution after the first adjustment on the IPC distance matrix $D(X,Y)$, where I merely use $D_{us}(X,Y)$ in two countries' calculation. The difference between these two figures are not large, which means that using different distance matrix does not affect the results a lot. However, the differences in firm's knowledge scope distributions in different countries do matters and will affect similarity distribution a lot.

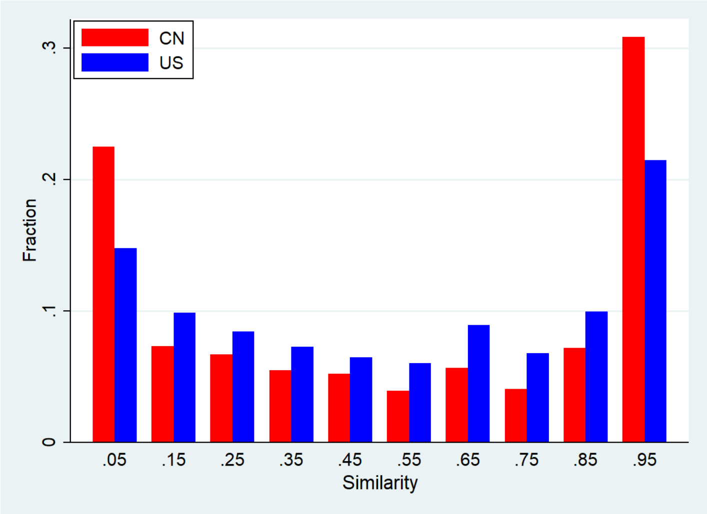


Figure B9: Similarity Distribution between New-born Patent and Knowledge Stock (No Adjustment)

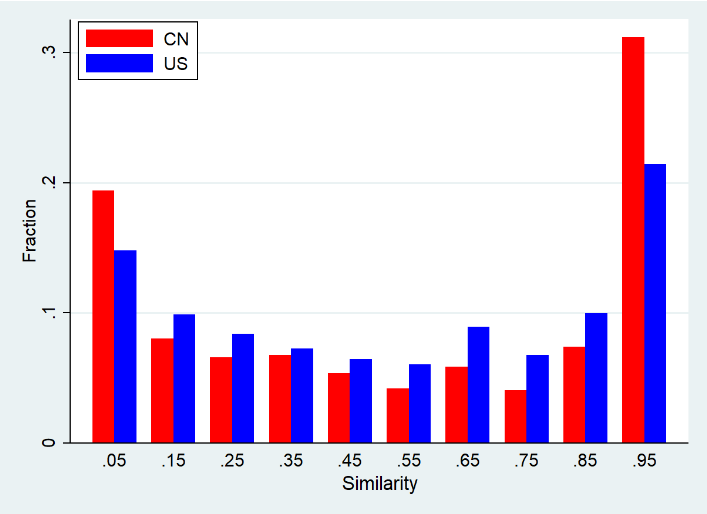


Figure B10: Similarity Distribution between New-born Patent and Knowledge Stock (Adjusted by U.S. IPC Distance Matrix)

In the theoretical model, new-born patent-inventing firm similarity is exogenous, and in estimation, I use the empirical distribution in figure above to calibrate it. However, for patent traded in patent market, it has two types of patent-firm similarity: patent-seller similarity and patent-buyer similarity. They are endogenously determined by firm's profit maximization correlated with how easy it is to sell the patent in market. The intuition is that in a low search friction market, the potential seller is more willing to wait for a better potential buyer, whose similarity with the patent is higher, because even the patent cannot be sold in this period, it is easy to be sold in next period, and it is worth to wait for the next period to meet a better buyer. As a result, for the patent sold in this market, compared with patent-seller similarity distribution, the patent-buyer similarity distribution should shift rightward, and in a lower search friction market, this shift is larger. The following figures shows the patent-firm similarity change before and after patent being sold in China and U.S. patent market. In China, the mean of patent-seller similarity is 0.610 and patent-buyer similarity is 0.624 (0.01 $\uparrow$); In U.S. the mean of patent-seller similarity is 0.509 and patent-buyer similarity is 0.568 (0.06 $\uparrow$). This indicates that the patent market friction in U.S. is much lower in U.S..

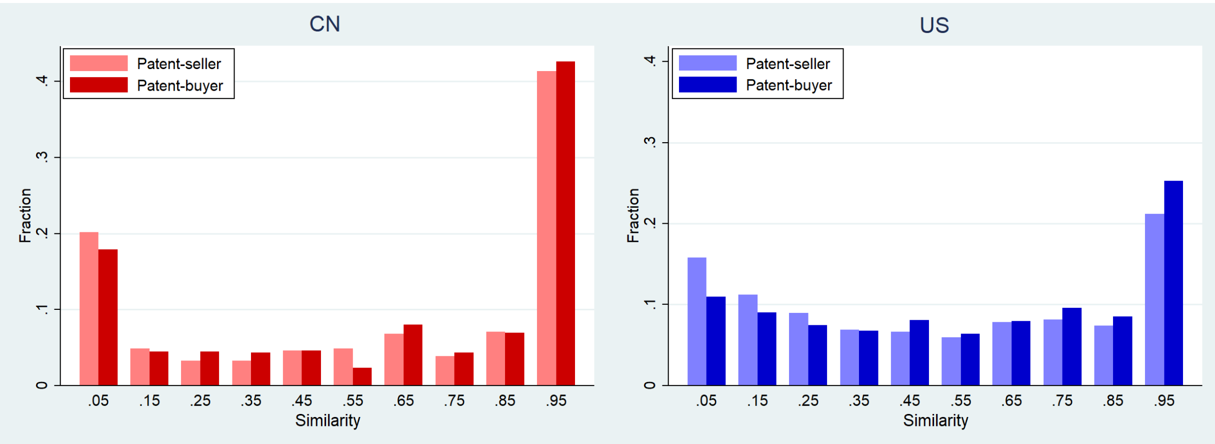


Figure B11: Similarity Distribution between Bought Patent and Knowledge Stock Adjusted by Knowledge Scope

Note: (1) The samples of patents are patents applied, granted and sold from 1998 to 2013. (2) Because every firm's first patent's similarity with the firm is absolutely zero, I drop the observations of patents which are the firm's first owned patents. (3) The lighter color indicates the patent-seller similarity distribution and the darker color indicates the patent-buyer similarity distribution. (4) To control for the firm's knowledge scope fixed effect, analogous to aforementioned, I weighted patent-buyer similarity distribution by the seller's knowledge scope distribution.

C Model

C.1 Firm Productivity Distribution Dynamics

The following equation demonstrates the firm's relative productivity $\hat{z} = \frac{z}{\bar{z}}$ distribution dynamics, where invention means that the firm has in-house invention in t period; sell means that the firm sells the new invention in t period to the patent agent; meet means that the firm meets with a patent agent randomly; patent purchase means that the firm buys the patent from patent agent successfully.

$$
\begin{aligned}
P_{\theta,t+1}(\hat{z}_{t+1} = \hat{z}) = & \underbrace{\hat{g}_{\theta,t} \cdot (\hat{z} = g\hat{z}) \cdot (1 - \theta i^*_\theta) \cdot (1 - m_b)}_{\text{no invention,no meet}} \\
& + \underbrace{\int_x \hat{g}_{\theta,t} \cdot (\hat{z} = g\hat{z})(1 - \theta i^*_\theta) \cdot m_b \cdot (1 - I^b_\theta(\hat{z}, x))\, dX(x)}_{\text{no invention, meet, no purchase}} \\
& + \underbrace{\int_x \hat{g}_{\theta,t}(\hat{z} = g\hat{z}) \cdot \theta i^*_\theta \cdot (1 - I^k_\theta)\, dX(x)}_{\text{invention, sell}} \\
& + \underbrace{\int_{\hat{z},x} \hat{g}_{\theta,t}(\hat{z} : \hat{z} + \gamma x \hat{z}^\beta = g\hat{z}) \cdot (1 - \theta i^*_\theta) \cdot m_b \cdot I^b_\theta\, dX(x) d\hat{z}}_{\text{no invention, meet, purchase}} \\
& + \underbrace{\int_{\hat{z},x} \hat{g}_{\theta,t}(\hat{z} : \hat{z} + \gamma x \hat{z}^\beta = g\hat{z}) \cdot \theta i^*_\theta \cdot I^k_\theta\, dX(x) d\hat{z}}_{\text{invention,keep}}
\end{aligned}
\tag{34}
$$

C.2 Extended Model: Fixed Cost and Information Friction

In this part, I do some simulation exercises based on the extended model to analyse how change of fixed cost and information friction affects the economy and patent market in different conditions. Table C3 shows the parameter settings I have tried.

First, without information friction, I check how fixed cost affects the economy. As shown in column (3) in Table below, fixed cost B varies from 0 to 0.1 with all the other parameters take the value of optimal estimation in Table 6. The variations of variables in economy are presented in Figure C12.

Second, I check how information friction affects the economy in three circumstances: the small market without fixed cost, the small market with high fixed cost and the large market without fixed cost. The parameters settings are from column (4) to (6) in Table C3, and the economy variables variation with the change of information friction are shown in Figure C13-C15. Generally, in all of these three situations, the information friction's welfare implication is not very large compare with the search cost's and fixed cost's welfare implications, while its' welfare implications are more significant in the patent market with high fixed cost or low search cost in these three circumstances relatively.

Table C3: How Fixed Cost and Information Friction Affect the Economy: Parameter Settings

		Change of fixed cost B	Change of information friction s		
(1)Parameter	(2)Description	(3)Figure C12	(4)Figure C13 No fixed cost, small market	(5)Figure C14 High fixed cost, small market	(6)Figure C15 No fixed cost, Large market
β	Productivity difference	0.0909	0.0909	0.0909	0.0909
γ	Step size	0.5120	0.5120	0.5120	0.5120
η	Cost of search	16.7979	16.7979	16.7979	***8.3989***
μ	Search cost elasticity	2.0545	2.0545	2.0545	2.0545
χ	Cost of R&D	8.8821	8.8821	8.8821	8.8821
I_p	High-type firms proportion	0.0998	0.0998	0.0998	0.0998
θ_h	High-type R&D capacity	1.4998	1.4998	1.4998	1.4998
θ_{gap}	R&D capacity gap	0.1204	0.1204	0.1204	0.1204
B	Fixed cost of buying patent	$\mathbf{0 \sim 0.1}$	***0.0000***	***0.0315***	***0.0000***
s	Probability of knowing patent's true type	1.0000	$\mathbf{0 \sim 1}$	$\mathbf{0 \sim 1}$	$\mathbf{0 \sim 1}$

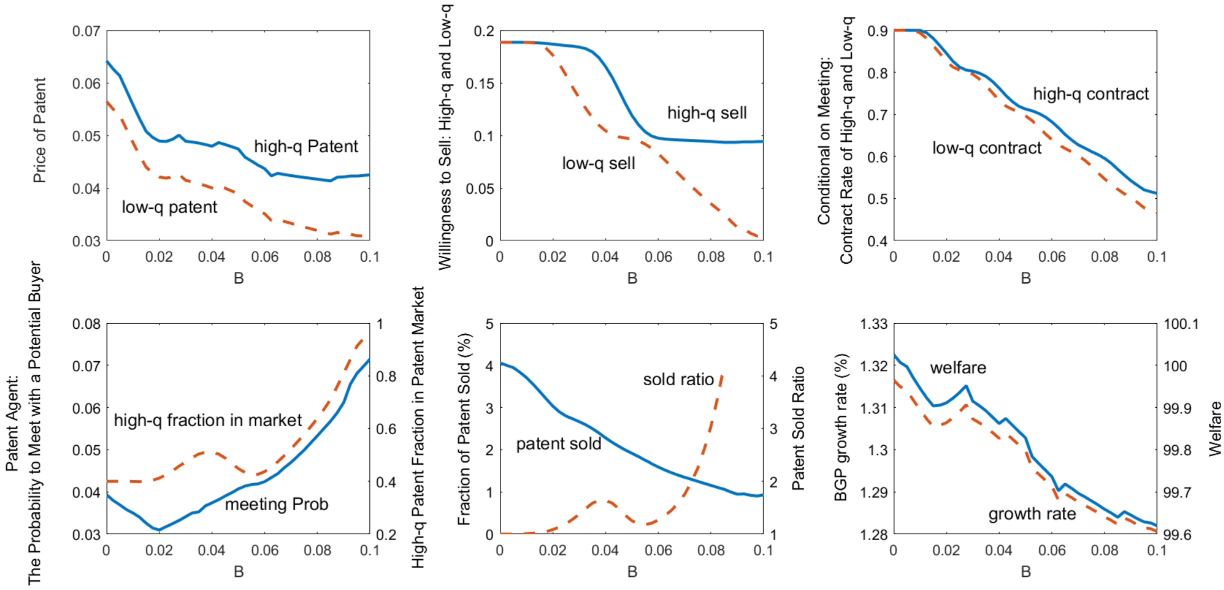


Figure C12: Implication of the Change of Fixed Cost

Note: (1) Except for the variation in fixed cost of buying a patent, all the other parameters are fixed and take the value of column (3) in Panel A in Table **??**. (2) The fixed cost varies from 0 to 0.1.

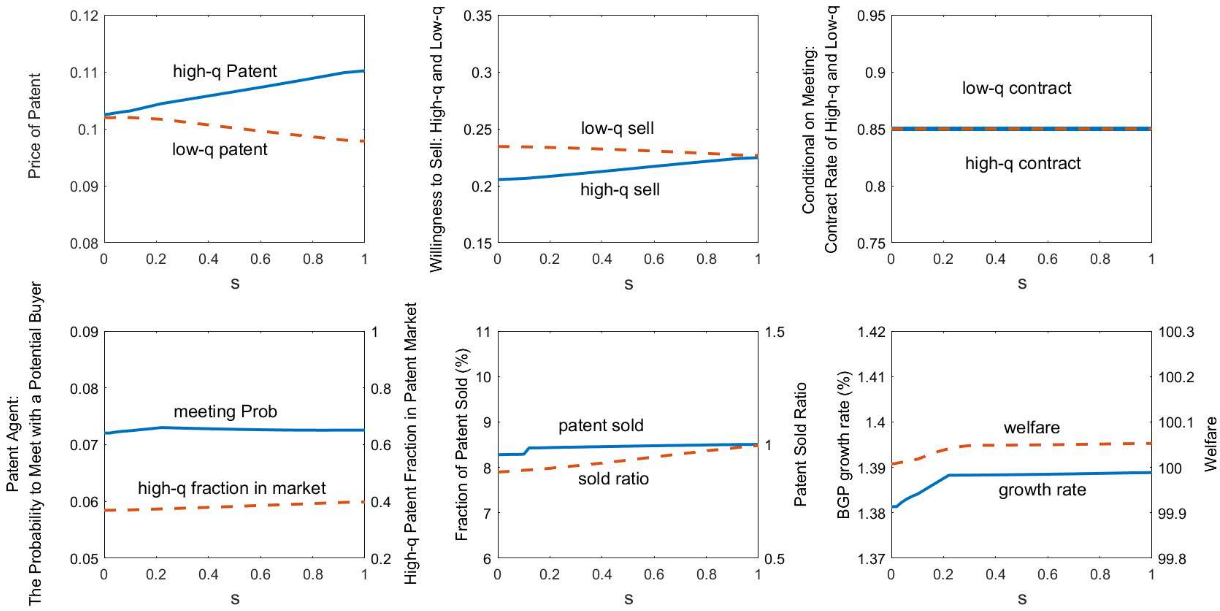


Figure C13: Change of Information Friction in Small Patent Market, No Fixed Cost

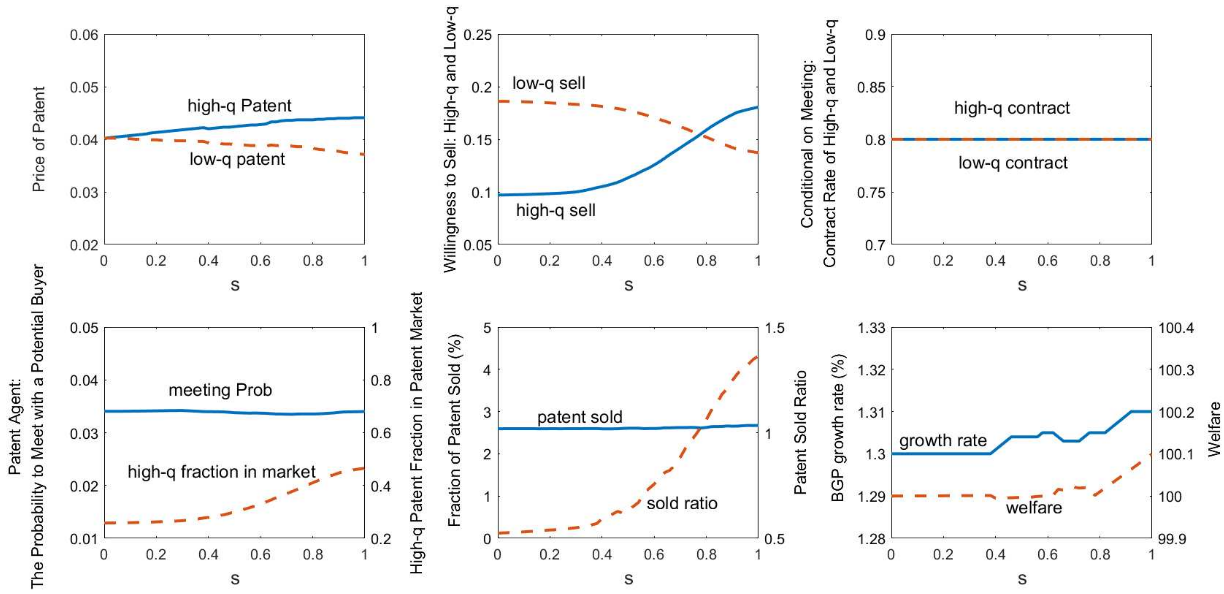


Figure C14: CHANGE OF INFORMATION FRICTION IN SMALL PATENT MARKET, HIGH FIXED COST

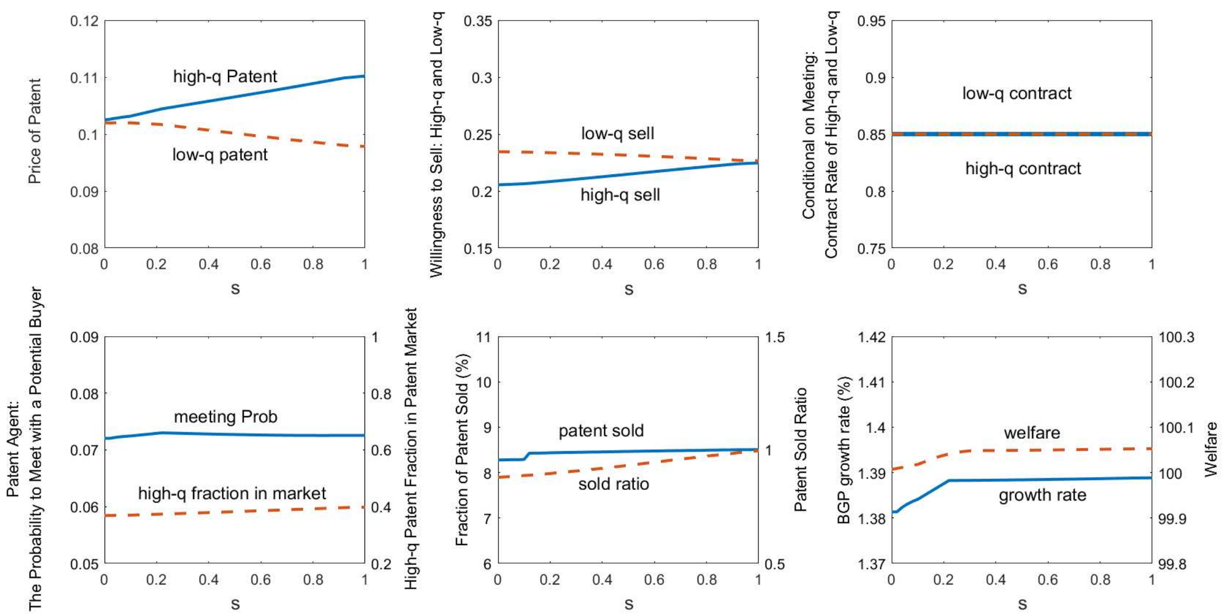


Figure C15: Change of Information Friction in Large Patent Market, High Fixed Cost

D Figure and Table Appendix

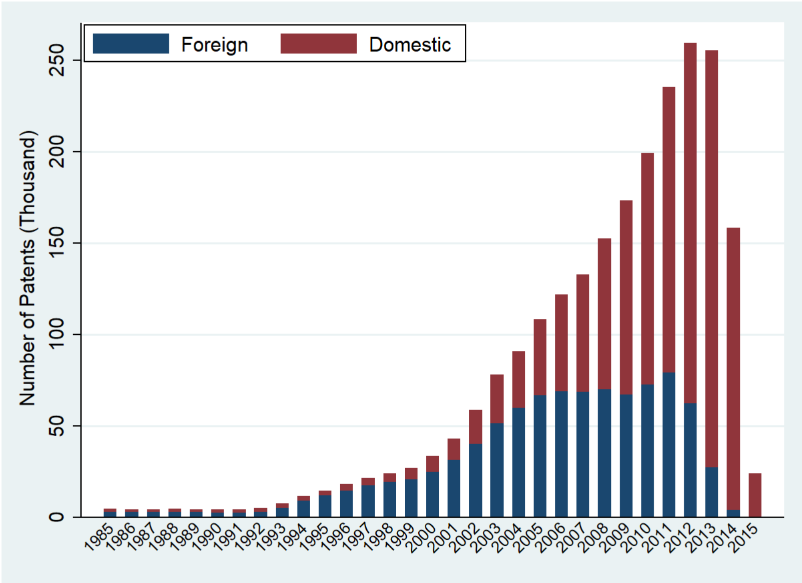


Figure D16: CNIPA: Patent Applications 1985-2015

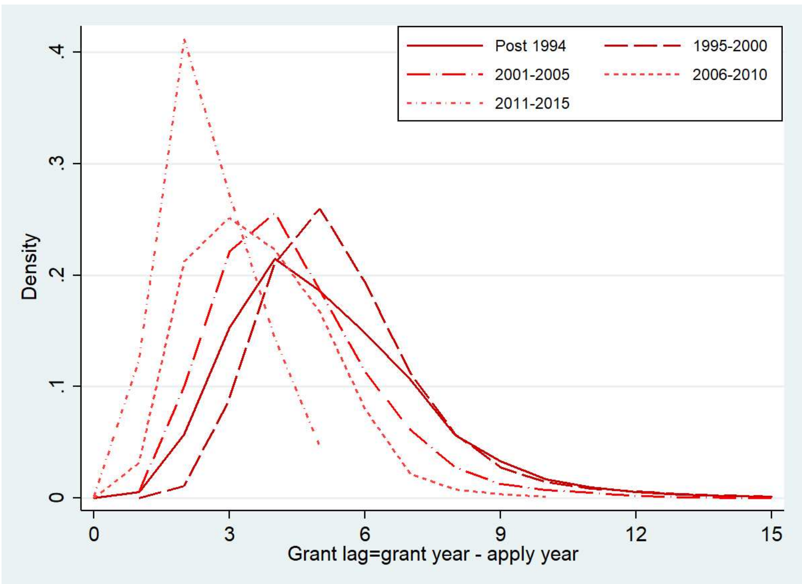


Figure D17: CNIPA: Patent Grant Lag Across Different Cohorts

Table D4: The Low-quality and High-quality Patents Shares and Forward Citation Number Gap in China and U.S.

		CN	US
OST1	Low-quality patent share	60.83%	52.65%
	High-quality patent share	39.17%	47.35%
OST2	Low-quality patent share	61.69%	53.53%
	High-quality patent share	38.31%	46.47%
OST1	Forward citation number ratio (High-quality patent over low-quality patent)	9.4873	9.2528
OST2	Forward citation number ratio (High-quality patent over low-quality patent)	9.0096	8.9672

Note:

(1) To make the forward citation number across year comparable, here, the forward citation number is the the citation the patent received with 4 years after being granted

(2) Low-quality patents' forward citation number are lower than the median value within the technology class and granted year, and the high-quality patents are with forward citation number higher than median value within the technology class and granted year.

(3) Here, I use the OST technology class to guarantee the consistency of technology class in different countries and make the technology classes more concise for analysis. The linkage between OST and IPC classification are shown in Appendix A.4.

(3) For low-quality and high-quality share, first, I divide all patents samples into groups based on their OST class (section in row 1 and field in row 2) and granted year; then, within each group, I calculate the share of low-quality and high-quality patents respectively; third, I calculate the mean of share value across groups weighted by the number of patents in each group.

(4) Similarly, within each OST-granted year group, I define citation gap as the forward citation number of low-quality patent by the forward citation number of high-quality patent. The value in row 3 and 4 are also the mean of gap across OST-granted year groups weighted by the number of patents in each group.

Table D5: Firms' Sales and Accumulated Patents' Forward Citation Numbers

	US listed firms 1998-2013		CN NBS firms 2001-2013		CN listed firms 1998-2013	
	Unbalanced	Balanced	Unbalanced	Balanced	Unbalanced	Balanced
	Lnsales	Lnsales	Lnsales	Lnsales	Lnsales	Lnsales
Ln(acm_fwct)	0.0569***	0.0816***	0.0868***	0.0579***	0.0036	-0.0146
	(0.0179)	(0.0209)	(0.0057)	(0.0092)	(0.0095)	(0.0225)
Ln(labor)	0.5292***	0.4603***	0.1576***	0.1446***	0.3207***	0.2844***
	(0.0405)	(0.0484)	(0.0041)	(0.0078)	(0.0131)	(0.0293)
Ln(capital)	0.0570*	0.0914**	0.0924***	0.1559***	0.2452***	0.4081***
	(0.0350)	(0.0435)	(0.0023)	(0.0059)	(0.0111)	(0.0273)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	10452	6332	60862	15160	5022	1120
R square	0.9022	0.9084	0.9601	0.9693	0.9782	0.9655

Note:

(1) The U.S. listed firm data comes from Compustate database; China listed firm data comes from CSMAR database;

(2) Sales is the operating revenue;

(3) acm_fwct is the firm's accumulated patent number adjusted by patent's forward citation number within 4 years after being granted;

(4) Labor is measured by firm's employment number; Capital is measured by firm's fixed asset;

(5) Firm fixed effect and industry-year fixed effect are controlled in all regressions, and industry in U.S. listed firm is divided by SIC 2-digit code; in China NBS firm is divided by Industrial Classification for National Economic Activities; and in China listed firm is divided by Guidelines for the Industry Classification of Listed Companies (2012).

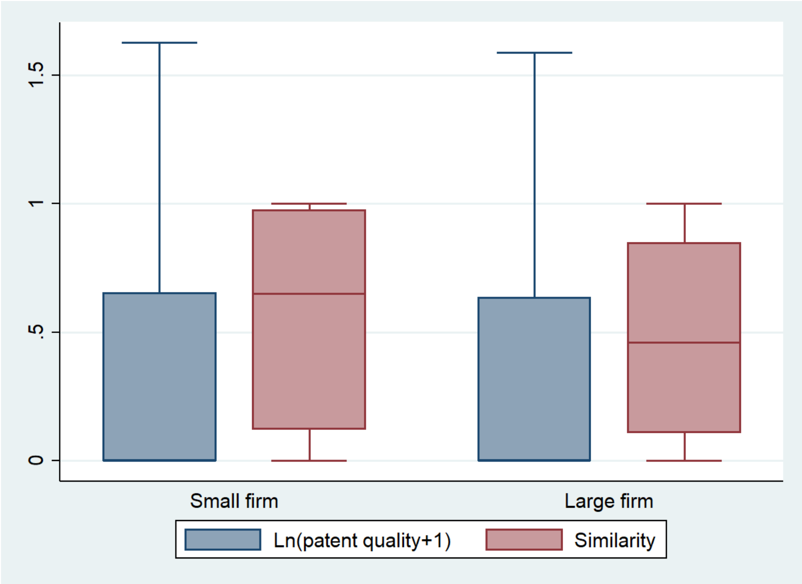


Figure D18: Patent Quality and Similarity (NBS Firm Inventions, Balanced, 2001-2013)

Note: (1) Patent quality equals to the forward citation number divided by the mean of forward citation number within the technology class (IPC) and granted year. (2) Large firm: within the t year innovating firm in the same industry (Industrial classification for national economic activities), whether the firm's sales is larger than the industrial and year's median value. (3) The inventions in this figure include the patents invented by firms belonging to NBS 2001-2013 balanced data. (4) Outside values are excluded in this box graph.

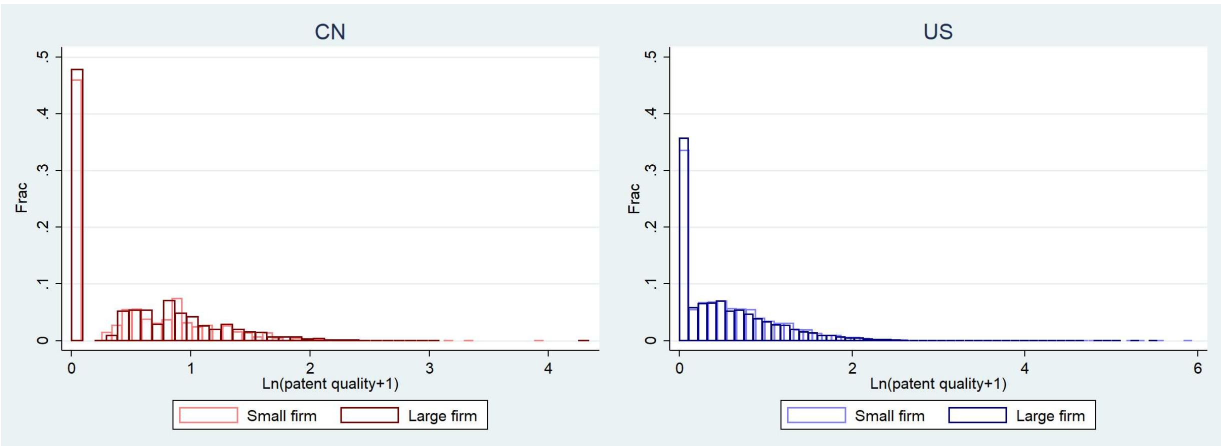


Figure D19: Patent Quality Distribution in China and U.S.

Note:(1) Patent quality equals to the forward citation number divided by the mean of forward citation number within the technology class (IPC) and granted year. (2) Large firm: within the t year innovating firm in the same industry (Industrial classification for national economic activities), whether the firm's sales is larger than the industrial and year's median value. (3) The inventions on the left hand side of this figure include the patents invented by firms belonging to NBS 2001-2013 unbalanced data; The inventions on the right hand side of this figure include the patents invented by firms belonging to U.S. listed firm 2001-2013 unbalanced data.

Table D6: Extensive Margin: Who is the Buyer (All Firms)

	(1) Unbalanced Buyer=1	(2) Unbalanced Buyer=1	(3) Unbalanced Buyer=1	(4) Balanced Buyer=1	(5) 01-13 Buy0113=1
Large	0.0764***	0.0752***	0.0509***	0.1481***	1.3888***
	(0.0047)	(0.0048)	(0.0083)	(0.0309)	(0.2292)
Selfinvdy	2.2767***	2.2767***	1.3720***	1.5533***	
	(0.0166)	(0.0166)	(0.0219)	(0.0551)	
Lnage		0.0103***			
		(0.0031)			
Ownership FE	Yes	Yes			Yes
Ind FE	Yes	Yes			Yes
Prov FE	Yes	Yes			Yes
Year FE	Yes	Yes			
Firm FE			Yes	Yes	
Ind-year FE			Yes	Yes	
N	2686283	2683425	2549126	310493	31049
r2	0.0120	0.0120	0.2624	0.1590	0.0639

Note: (1) In this table, I define whether the firm i is a buyer in patent market in t year ($Buyer = 1$) or not ($Buyer = 0$) as the dependent variable to explore the question that is larger firm more likely to be the buyer or not. The dependent variable is multiplied by 100 for clarity. (2) The main independent variable is $Large$, representing that in t year, within the industry, whether the firm's sales is larger than the median ($Large = 1$) or not ($Large = 0$). I control the dummy variable $Selfinvdy$ indicating that whether the firm has in-house invention in t year as well. (3) Firm age equals the year minus the establish year. (4) Ownership of the firms are divided into 5 groups, SOE, collective firms, private firms, foreign-invested firms and others. (5) Ind is the industry fixed effect; $ProvFE$ is the province fixed effect. (6) The regressions in column (1)-(3) include all NBS firms from 2001 to 2013, while the column (4) restricts the samples on the firms from NBS 2001-2013 balanced data. The last column is the cross section regression, where $Buy0113$ means whether the firm had been a buyer in patent market from 2001 to 2013, and $Large$ is the whether the firm belongs to large firm group in 2001. (7) Standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; *** denotes significance at the 10% level.

Table D7: Extensive Margin: Who is the Buyer (Innovative Firms)

	(1) Unbalanced Buyer=1	(2) Unbalanced Buyer=1	(3) Unbalanced Buyer=1	(4) Balanced Buyer=1	(5) 01-13 Buy0113=1
large	0.1865***	0.2109***	0.2473***	0.3157***	1.5509***
	(0.0239)	(0.0240)	(0.0366)	(0.0734)	(0.5223)
selfinvdy	1.2532***	1.2306***	1.0716***	1.2733***	
	(0.0393)	(0.0394)	(0.0463)	(0.0829)	
lnage		-0.1720***			
		(0.0149)			
Ownership FE	Yes	Yes			Yes
Ind FE	Yes	Yes			Yes
Prov FE	Yes	Yes			Yes
Year FE	Yes	Yes			
Firm FE			Yes	Yes	
Ind-year FE			Yes	Yes	
N	566890	566409	558404	144516	14326
r2	0.0159	0.0161	0.2800	0.1745	0.0708

Note: (1) All variables in this table are same with Table D6; The only difference lies in the sample in this table, which doesn't include all firms, but only include innovative firm. The innovative firm is the firm which has patent during 2001 to 2013, or has R&D investment during that period. (2) Standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; *** denotes significance at the 10% level.

Table D8: Extensive Margin: Who is the Buyer (Patented Firms)

	(1) Unbalanced Buyer=1	(2) Unbalanced Buyer=1	(3) Unbalanced Buyer=1	(4) Balanced Buyer=1	(5) 01-13 Buy0113=1
large	0.3974***	0.4466***	0.5328***	0.6016***	0.6030
	(0.0672)	(0.0678)	(0.1075)	(0.2003)	(1.2749)
selfinvdy	0.0769	0.0740	0.6120***	0.7213***	
	(0.0695)	(0.0695)	(0.0791)	(0.1354)	
lnage		-0.2201***			
		(0.0400)			
Ownership FE	Yes	Yes			Yes
Ind FE	Yes	Yes			Yes
Prov FE	Yes	Yes			Yes
Year FE	Yes	Yes			
Firm FE			Yes	Yes	
Ind-year FE			Yes	Yes	
N	215756	215616	210810	62043	5836
r2	0.0165	0.0167	0.2935	0.2088	0.0967

Note: (1) All variables in this table are same with Table D6; The only difference lies in the sample in this table, which doesn't include all firms, but only include patented firm. The patented firm is The firm which has patent during 2001-2013, no matter how it obtain the patent, by self-invention or purchase. (5) Standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; *** denotes significance at the 10% level.

Table D9: Intensive Margin: Buy-own Ratio and Firm Size

	(1) Buy-own ratio	(2) Buy-own ratio	(3) Buy-own ratio	(4) Buy-own ratio	(5) Buy-own ratio	(6) Buy-own ratio
lnsales2001	-0.0699***	-0.0606***	-0.0610***			
	(0.0079)	(0.0084)	(0.0086)			
large2001				-0.1138***	-0.0888***	-0.0851***
				(0.0236)	(0.0239)	(0.0242)
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE		Yes	Yes		Yes	Yes
Prov FE			Yes			Yes
N	930	930	929	936	936	935
r2	0.1719	0.1897	0.2097	0.1236	0.1564	0.1768

Note: (1) Buy-own ratio equals to the number of patents bought by firm from 2001 to 2013 over the number of patents owned by firm from 2001 to 2013. (2)$lnsales2001$ is the logarithm of firm's sales in 2001 with the 1% outlines deleted; $large2001$ is a dummy, and it equals to 1 means the firm's sales is larger than the median within the industry. (3) This is a cross section regression, while the firm must belong to the 2001-2013 NBS balanced data. (4) Standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; *** denotes significance at the 10% level.

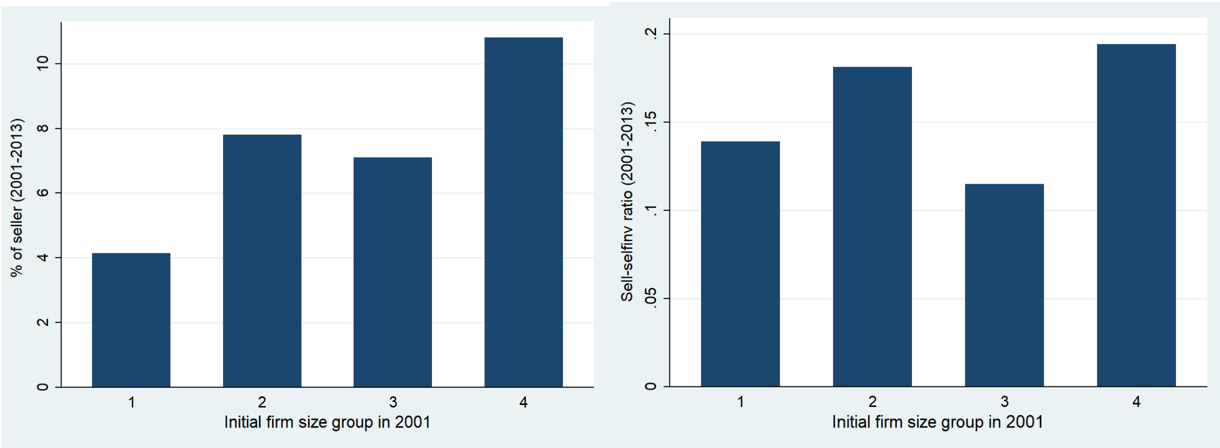


Figure D20: U.S. Listed Firm's Sell Decision: Extensive Margin and Intensive Margin

Note: (1) The listed firms in this graph belong to the panel firm data from 2001 to 2013. In China, there are 1178 firms; In U.S., there are 3399 firms. (2) I divide the firms into five groups (the larger the group number is, the larger the sales is.) based on their sales within industry in initial year, which is 2001. (3) In every group, I define the seller as the firm which had sold no less than one patent between 2001 and 2013. (4) The y-axis shows the percent of firms to be the seller in every group.

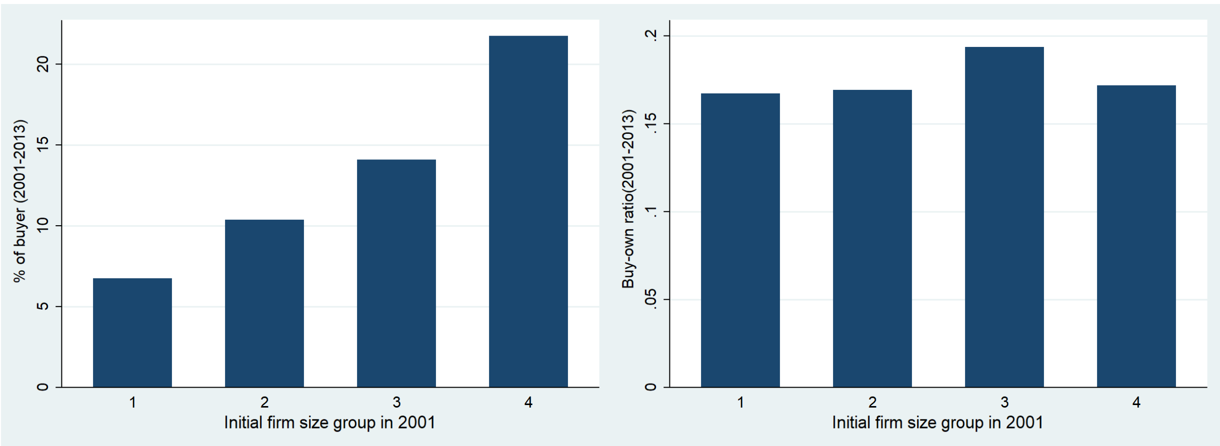


Figure D21: U.S. Listed Firm's Purchase Decision: Extensive Margin and Intensive Margin

Note: (1) The listed firms in this graph belong to the panel firm data from 2001 to 2013. In China, there are 1178 firms; In U.S., there are 3399 firms. (2) I divide the firms into five groups (the larger the group number is, the larger the sales is.) based on their sales within industry in initial year, which is 2001. (3) In every group, I define the seller as the firm which had sold no less than one patent between 2001 and 2013. (4) The y-axis shows the percent of firms to be the seller in every group.

Table D10: Robustness Check: Firm's Revenue, Growth and Patent Stock

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Lnsales	Lnsales	Lnva	Lnsales	Lnsales	Lnsales	Lnsales	Lnsales	Lnsales
Lnpat_sim_adj			0.0391***	0.0160***	0.0540***	0.0404***	0.0270***	0.0695***	0.1006***
			(0.0129)	(0.0057)	(0.0038)	(0.0041)	(0.0036)	(0.0046)	(0.0065)
Lnpat_quality_adj			0.0204*	0.0020	0.0302***	0.0219***	0.0160***	0.0264***	0.0191***
			(0.0104)	(0.0045)	(0.0030)	(0.0032)	(0.0029)	(0.0036)	(0.0048)
Lnpat_sim_quality_adj	0.0148***								
	(0.0034)								
Lnpat	0.0436***								
	(0.0029)								
Lnselfinv_sim_adj		0.0379***							
		(0.0038)							
Lnselfinv_quality_adj		0.0404***							
		(0.0134)							
Lnbuy_sim_adj		0.0208***							
		(0.0030)							
Lnbuy_quality_adj		0.0203**							
		(0.0100)							
lnlabor	0.3228***	0.3227***	0.4743***	0.4452***	0.2803***	0.2634***		0.3359***	0.2106***
	(0.0008)	(0.0008)	(0.0016)	(0.0016)	(0.0008)	(0.0009)		(0.0015)	(0.0029)
lnfixasset	0.1247***	0.1247***	0.1091***	0.1295***	0.1371***	0.2893***		0.1807***	0.1123***
	(0.0004)	(0.0004)	(0.0009)	(0.0011)	(0.0007)	(0.0009)		(0.0010)	(0.0017)
lag_lnsales							0.4156***		
							(0.0007)		
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind_year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2466114	1552700	309231	1782114	1622524	1823349	513408	124632	2466114
r2	0.9019	0.8498	0.9123	0.9191	0.9253	0.9260	0.9156	0.9478	0.9019

Note: (1) In column (1) and (2), $Pat\_sim\_quality\_adj = \sum_{p \in P_f} Quality_p * \cdot Similarity_{pf}$. Pat is the patent number without any adjustment; $selfinv\_sim\_adj$ is the accumulated number of patent invented by the firm itself adjusted by similarity; $selfinv\_quality\_adj$ is the accumulated number of patent invented by the firm itself adjusted by quality; buy_sim_adj is the accumulated number of patent purchased by the firm adjusted by similarity; $buy\_quality\_adj$ is the accumulated number of patent purchased by the firm itself adjusted by quality; (2) In column (3) va is the value added of firms in NBS dataset, however, the dataset only contains firms' value of it before 2007, so the regression in this column include the data from 2001 to 2007; (3) In column (4), to control the labor's skill, I employ wage (salary+welfare) to measure the labor quantity of firms; (4) In column (5) and (6), the capital of firm in t year are measured by fixed asset in $t-1$ year and the mean of fixed asset in t year and $t-1$ year; (5) In column (7), I use sales in $t-1$ year as the proxy for firm's labor and capital at the beginning of t year; (6) In column (8) and (9), the samples are restricted with only innovative or patented firm included; (7) These are 2001-2013 unbalanced panel regressions; (8) For large numbers of zero-value in variables related with patent stock, I add one to them first and then take logarithm; (9) The Firm FE is firm fixed effect, and Ind_year FE is 4-digits industry and year fixed effect; (10) Standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; *** denotes significance at the 10% level.

Table D11: Sales, Patent Stock and Firm Size

Panel A. Revenue				
	(1)	(2)	(3)	(4)
	lnsales	lnsales	lnsales	lnva
Lnacmpat	0.0445***	0.0303***	0.0553***	0.0489***
	(0.0040)	(0.0081)	(0.0058)	(0.0175)
Large_dy	0.3678***	0.5055***	0.4918***	0.2071***
	(0.0013)	(0.0032)	(0.0048)	(0.0023)
Lnacmpat*Large_dy	0.0145***	0.0344***	0.0195***	0.0318**
	(0.0038)	(0.0080)	(0.0056)	(0.0158)
Firm FE	Yes	Yes	Yes	Yes
Ind_year FE	Yes	Yes	Yes	Yes
N	1764073	275513	120492	1067736
r2	0.9209	0.9074	0.9272	0.8692

Panel B. Growth rate				
	(1)	(2)	(3)	(4)
	Gr_tfplp	Gr_tfpop	Gr_va	Gr_sales
Lnpat	-0.0568***	-0.0409***	-0.0622**	0.0130***
	(0.0188)	(0.0095)	(0.0257)	(0.0041)
LnTFP2001	-0.0770***	-0.0831***		
	(0.0007)	(0.0007)		
Lnvalue_added2001			-0.0639***	
			(0.0007)	
Lnsales2001				-0.0484***
				(0.0005)
Lnpat*lnTFP2001	0.0111***	0.0124***		
	(0.0025)	(0.0025)		
Lnpat*lnvalue_added2001			0.0094***	
			(0.0022)	
Lnpat*lnsales2001				0.0021***
				(0.0003)
Ind FE	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes
Prov FE	Yes	Yes	Yes	Yes
N	61186	61181	36926	70011
r2	0.2030	0.2582	0.3407	0.1697

Note: **In panel A: (1)** I measure the firm i's revenue in t year with $sales_{it}$ from column (1) to (3) and $value\_added_{it}$ in column (4). $Ln(acmpat_{i,2001-t})$ is the accumulated patent number invented by firm i from 2001 to t year. $Large\_dy_{it}$ is the dummy variable. I control the average value (constructed combining patent quality and similarity), which equals of patent belonging to firm i. I control the labor, capital, firm fixed effect and industry-year fixed effect as well. The coefficient of the interaction term indicates that given the same patent value to the owner firms, one more accumulated patent in a large firm increases the revenue more largely than in a small firm. **(2)** Column (1) is the unbalanced data from 2001-2013 regression, while Column (2) is the balanced data regression. Furtherly, Column (3) restricts the sample to the innovative firms. **In panel B: (1)** Similar with the last four Column in Table 3, I calculate the annualized TFP and revenue growth rate for Panel B's regressions here. $Lnpat$ is the patents number increment during the regression period. All the other control variable are same with panel A. **(2)** Regressions in panel B are the cross-section regressions. **For two panels: (1)** Same with Table 3, the TFP, value added related regressions merely include 2001-2007, and the sales related regressions include 2001-2013. **(2)** Standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; *** denotes significance at the 10% level.

Table D12: Parameters-targeted Moments Elasticity Matrix at the Optimal Estimated Parameter Points

$\frac{\Delta(moment)/moment}{\Delta(parameter)/parameter}$	β	γ	χ	I_p	θ_h	θ_{gap}	η	μ	B	s
$Std(g\_sales)$	-0.08	1.22	-0.24	0.14	0.56	0.46	-0.02	0.38	-0.06	0.00
$Corr(firmsize, g\_sales)$	-0.60	1.01	-0.61	0.25	0.33	1.73	0.01	1.27	-0.47	0.00
$\frac{TotalR\&D}{TotalSales}$	0.03	1.08	-0.50	0.21	1.13	1.11	0.00	0.02	0.10	0.00
$Std(R\&D - SalesRatio)$	-0.09	1.02	-0.75	0.34	0.87	1.35	0.01	0.42	0.04	0.00
$Avg(LargefirmR\&D - SalesRatio)$	0.14	0.91	-0.56	0.43	1.06	1.06	0.01	0.11	0.07	0.01
$90pc(R\&D - SalesRatio)$	-0.12	1.15	-0.41	-0.08	1.21	1.26	-0.02	0.03	0.04	0.00
$\frac{\%ofinventor_{large}}{\%ofinventor_{small}}$	0.07	0.01	0.01	0.42	0.01	-0.75	0.00	-0.02	0.01	0.00
$\frac{Pat\_traded}{Pat\_inv}$	-0.04	2.03	0.35	-0.74	-2.10	-0.88	-0.75	4.44	-3.14	-0.03
$\frac{Num(buyer)}{Num(firm)}$	0.01	2.32	-0.07	-0.26	-0.10	0.28	-0.59	4.31	-3.50	-0.01
$Std(I\_b)$	0.00	1.31	-0.03	-0.13	-0.05	0.14	-0.29	2.94	-1.53	-0.01
$\frac{(Num(buyer)/Num(firm))_{large}}{(Num(buyer)/Num(firm))_{small}}$	0.50	-1.11	-0.05	0.18	-0.07	-0.09	-0.02	-0.22	0.95	0.00
$\frac{(Num(buyer)/Num(firm))_{up75pc}}{(Num(buyer)/Num(firm))_{50-70pc}}$	0.28	-0.35	-0.08	0.33	-0.04	-0.07	-0.02	-0.14	0.31	-0.04
$\frac{Frac\_of\_patsold_{Hq}}{Frac\_of\_patsold_{Lq}}$	-0.04	-1.51	-0.14	0.09	-0.14	0.24	0.15	-2.22	1.12	-0.27

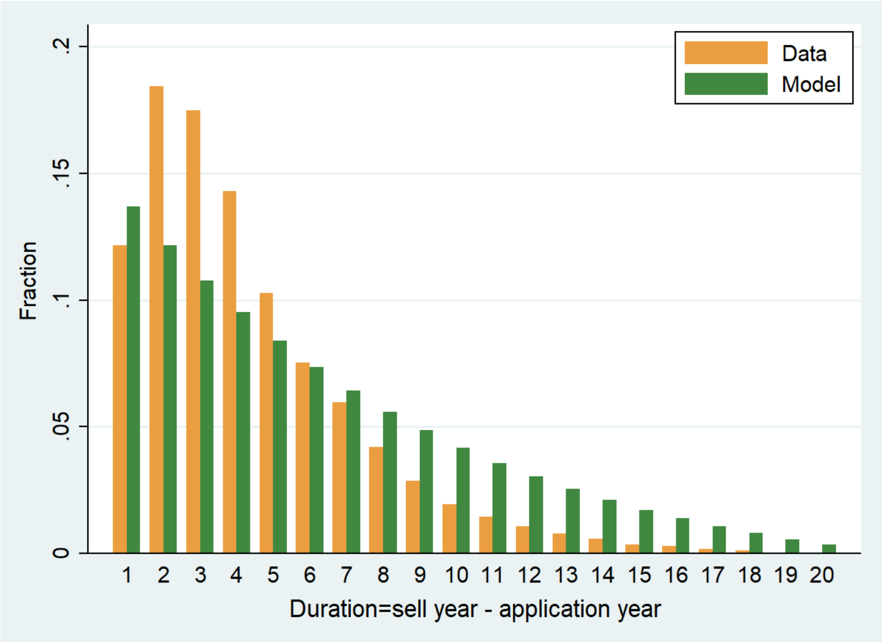


Figure D22: Duration Distribution: Data and Simulation

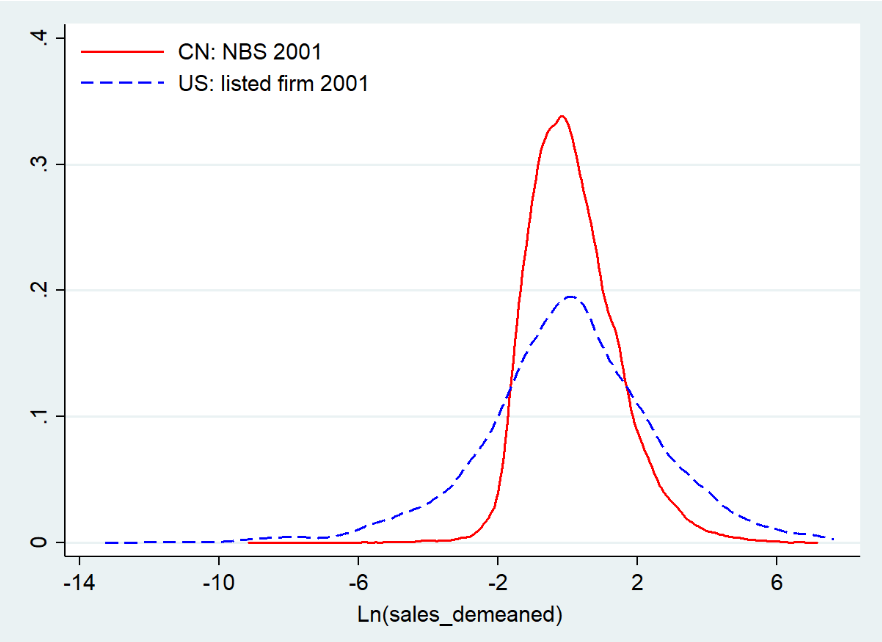


Figure D23: Demeaned Firm Size Distribution

Note: (1) The sample of Chinese NBS firm is the firm which belongs to NBS 2001-2013 panel data and the firm size here is the firm's sales in 2001. (2) The sample of U.S. listed firm is the firm which belongs to 2001-2013 panel data and the firm size here is the firm's sales in 2001. (3) All of sales are demeaned by the median value within every 4-digit industry in 2001.

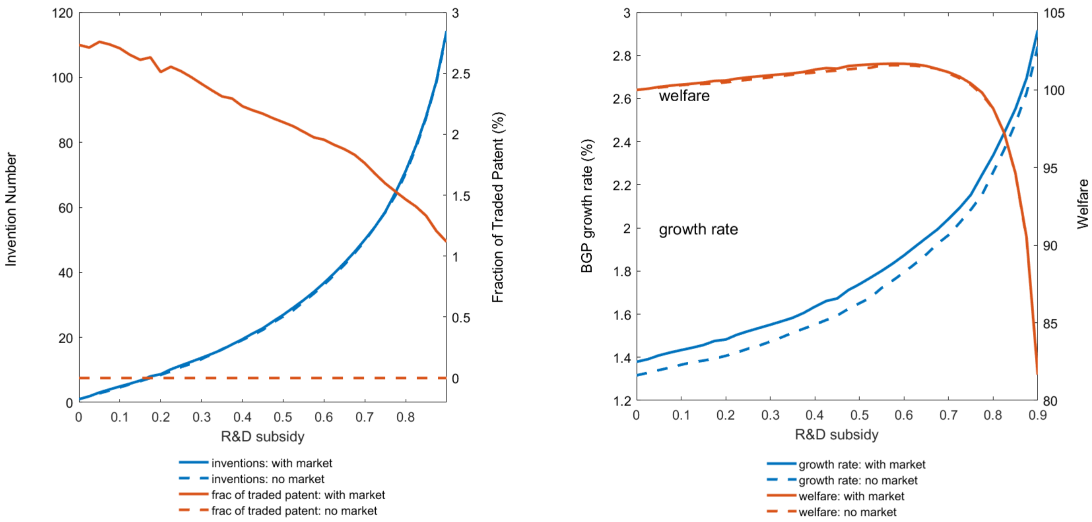


Figure D24: Policy: R&D Subsidy in the Economy with Patent Market and Without Patent Market

Note: The solid lines indicate the results in the economy with patent market and the dot lines indicate the results in the economy without patent market.

Table D13: The Contribution of Each Parameters to the Gap of fraction of traded patents between China and U.S.

		eta	mu	B	s	Frac of traded patent
η	-	50.00	2.70	0.11	0.60	0.03
		5.03	2.70	0.11	0.60	0.12
	μ	50.00	2.86	0.11	0.60	0.04
		5.03	2.86	0.11	0.60	0.15
	B	50.00	2.70	0.12	0.60	0.03
		5.03	2.70	0.12	0.60	0.11
	s	50.00	2.70	0.11	0.08	0.03
		5.03	2.70	0.11	0.08	0.11
	μ, B	50.00	2.86	0.12	0.60	0.04
		5.03	2.86	0.12	0.60	0.15
	μ, s	50.00	2.86	0.11	0.08	0.05
		5.03	2.86	0.11	0.08	0.16
	B, s	50.00	2.70	0.12	0.08	0.03
		5.03	2.70	0.12	0.08	0.11
	μ, b, s	50.00	2.86	0.12	0.08	0.05
		5.03	2.86	0.12	0.08	0.15

η: Mean of frac of traded patent increase =0.094 contribution=$\frac{0.094}{0.12}$=78%

		eta	mu	B	s	Frac of traded patent
μ	-	50.00	2.70	0.11	0.60	0.03
		50.00	2.86	0.11	0.60	0.04
	η	5.03	2.70	0.11	0.60	0.12
		5.03	2.86	0.11	0.60	0.15
	B	50.00	2.70	0.12	0.60	0.03
		50.00	2.86	0.12	0.60	0.04
	s	50.00	2.70	0.11	0.08	0.03
		50.00	2.86	0.11	0.08	0.05
	η, B	5.03	2.70	0.12	0.60	0.11
		5.03	2.86	0.12	0.60	0.15
	η, s	50.00	2.70	0.12	0.08	0.03
		50.00	2.86	0.12	0.08	0.05
	B, s	5.03	2.70	0.11	0.08	0.11
		5.03	2.86	0.11	0.08	0.16
	η, B, s	5.03	2.70	0.12	0.08	0.11
		5.03	2.86	0.12	0.08	0.15

μ: Mean of frac of traded patent increase =0.029 contribution=$\frac{0.029}{0.12}$=24%

		eta	mu	B	s	Frac of traded patent
B	-	50.00	2.70	0.11	0.60	0.03
		50.00	2.70	0.12	0.60	0.03
	η	5.03	2.70	0.11	0.60	0.12
		5.03	2.70	0.12	0.60	0.11
	μ	50.00	2.86	0.11	0.60	0.04
		50.00	2.86	0.12	0.60	0.04
	s	50.00	2.70	0.11	0.08	0.03
		50.00	2.70	0.12	0.08	0.03
	η, μ	5.03	2.86	0.11	0.60	0.15
		5.03	2.86	0.12	0.60	0.15
	η, s	5.03	2.70	0.11	0.08	0.11
		5.03	2.70	0.12	0.08	0.11
	μ, s	50.00	2.86	0.11	0.08	0.05
		50.00	2.86	0.12	0.08	0.05
	η, μ, s	5.03	2.86	0.11	0.08	0.16
		5.03	2.86	0.12	0.08	0.15

B: Mean of frac of traded patent increase =-0.005 contribution=$\frac{-0.005}{0.12}$=-4%

		eta	mu	B	s	Frac of traded patent
s	-	50.00	2.70	0.11	0.60	0.03
		50.00	2.70	0.11	0.08	0.03
	η	5.03	2.70	0.11	0.60	0.12
		5.03	2.70	0.11	0.08	0.11
	μ	50.00	2.86	0.11	0.60	0.04
		50.00	2.86	0.11	0.08	0.05
	B	50.00	2.70	0.12	0.60	0.03
		50.00	2.70	0.12	0.08	0.03
	η, μ	5.03	2.86	0.11	0.60	0.15
		5.03	2.86	0.11	0.08	0.16
	η, B	5.03	2.70	0.12	0.60	0.11
		5.03	2.70	0.12	0.08	0.11
	μ, B	50.00	2.86	0.12	0.60	0.04
		50.00	2.86	0.12	0.08	0.05
	η, μ, B	5.03	2.86	0.12	0.60	0.15
		5.03	2.86	0.12	0.08	0.15

s: Mean of frac of traded patent increase =0.03 contribution=$\frac{0.003}{0.12}$=2%

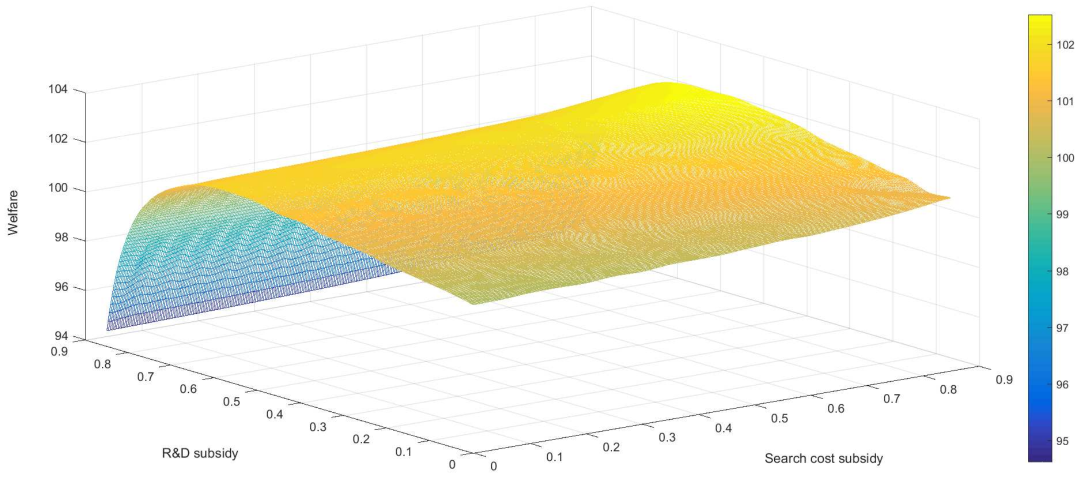


Figure D25: R&D SUBSIDY AND SEARCH COST SUBSIDY