Quantitative Assessment on Frictions in Technology Market

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Technology Market Frictions and Economic Development: Evidence from China

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Abstract

This paper studies how frictions in the patent market inhibit economic growth. I document that the patent market is considerably less developed in China than in the US. To understand this fact, I build a growth model incorporating three frictions in the patent market—search costs, fixed transaction costs, and information asymmetry on patent quality. The calibrated model matches the key features of China's patent market well. Quantitatively, eliminating all the frictions in the patent market would increase China's productivity growth by 44%. I also find that reducing search costs plays the most effective role in promoting the Chinese patent market.

Keywords: China's growth; patent market; frictions
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1 Introduction

A well-functioning technology market plays a crucial role in a country's economic development by facilitating the transfer of technology to the firms that can make the best use of it. For example, Akcigit et al. (2016) show that patent transactions between firms improve allocative efficiency of technologies, leading to higher economic growth for the US. However, the technology market is not immune to frictions that prevail in the goods and factor markets, and these frictions can be more severe in developing economies. Whereas there is a large literature studying the frictions in the goods and factor markets (e.g., Hsieh and Klenow, 2009; Restuccia and Rogerson, 2017; Hsieh et al., 2019), there are fewer studies exploring the frictions that prevail in a technology market.

This paper fills this gap in the literature by studying the frictions prevailing in the Chinese patent market. First, using the micro-level Chinese patent transaction data, I document a set of stylized facts that suggest the persistent underdevelopment of the Chinese patent market, and I also contrast these facts with those of a developed market (the US patent market). Second, I build on Akcigit et al. (2016) to develop an endogenous growth model featuring firms' decisions on patent production and transactions. In this model, I highlight three types of frictions that prevail in the patent market—search costs, fixed transaction costs, and information asymmetry on patent quality. Finally, I estimate the model to shed light on the role of each friction in affecting the efficiency of the Chinese patent market and its implications on aggregate productivity growth.

The Chinese patent market serves as a good laboratory to study frictions within a technology market, due to two reasons. First, I have compiled a comprehensive dataset by merging micro-level patent registration and transaction data with firm annual operation information, allowing for a comprehensive understanding of China's patent transactions and the characteristics of participants in the patent market. Second, due to the fast-growing R&D expenses, the number of China's granted patents has almost caught up with that in the US during the last two decades (see Appendix Figure G1). However, there is still no evidence on the functioning of the Chinese patent market, whereas it is already well-known that China's factor markets are highly distorted (e.g., Song et al., 2011; David et al., 2016; Wu, 2018; Tombe and Zhu, 2019; König et al., 2022).

Using the rich patent data, I document two facts. First, the narrowing gap in the number of granted patents between China and the US did not narrow the gap in the

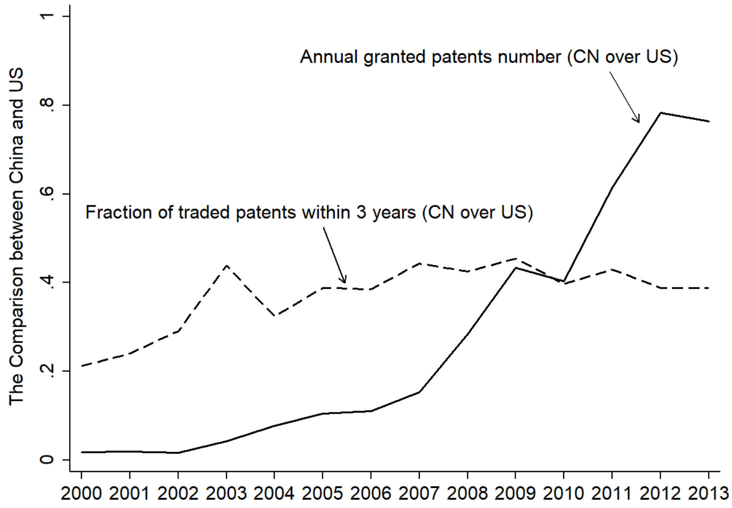

Figure 1: Number of Granted Patent and Fraction of Traded Patents, by Year

Notes: (1) "US" indicates the US, and "CN" indicates China. (2) The US granted patents include all the patents that were invented by the US firms, and filed and granted between 2000 and 2013. The Chinese granted patents include all the patents that were invented by Chinese firms, and filed and granted between 2000 and 2013. I define the nationality of a patent according to its applicant's nationality in the database. (3) The yearly number of granted patents is the number of patents granted in each year, and in the graph, the ratio equals this value in China over that in the US in the corresponding year. (4) The fraction of granted patents sold within 3 years $= \frac{\text{The number of granted patents in year t sold between t and t+3 year}}{\text{The number of granted patents in year t}}$,[2] and the ratio in this graph indicates the gap of the fraction of traded patents between China and the US.

fraction of traded patents between these two countries, as shown in Figure 1.[1] In the Chinese patent market, only 4.5% of domestic patents filed and granted between 1998 and 2013 were traded during this period, and this share was only a quarter of the share of traded patents in the US in the same period (14.6%). I also find this pattern robust to controlling for patents' technology fields, firm size, and time periods considered. Second, I document that high-quality patents were traded more than low-quality patents, and the gap in the fraction of traded patents between the US and China was much larger among high-quality patents than among low-quality patents.

To understand these facts and perform a quantitative analysis, I develop an endogenous growth model featuring firms' patent production and transactions. In the model, firms are heterogeneous in their productivity levels and R&D capacities, and they improve their productivity by either doing the in-house R&D (which generates patents)

[1] Appendix Figures G1 and G2 present the number of granted patents and the fraction of traded patents separately for China and the US, also suggesting that compared with the narrowing gap in the number of granted patents between China and the US, the gap in the fraction of traded patents between these two countries has remained wide persistently.

[2] As it may take a long time for the patent to be sold, counting the number of patents sold within 3 years after getting granted makes the fractions of patents sold in different years comparable.

or purchasing a patent from the patent market. Akcigit et al. (2016) first characterize the patent market in a general setting, in which the patent market plays the role of correcting the mismatch between patents and their initial inventors by reallocating patents to the firms that can make a better use of them. I follow their framework to model the patent market, however, given the purpose of this study to explain the underdevelopment of the Chinese patent market, I newly introduce three frictions into their general framework of the patent market.[3] First, I introduce search costs into the patent market, as firms typically face difficulties in participating in the patent market.[4] Guided by the second fact, I also introduce patent quality and two related frictions: fixed transaction costs, which discourage the trading of low-quality patents relative to high-quality patents; and information asymmetry on patent quality, which can explain why the gap in trading probabilities between the US and China varies by patent quality.

I structurally estimate the model using the simulated method of moments, matching the key data moments from the Chinese patent market. I find that the model is capable of replicating the two facts documented earlier and can also match many non-targeted features of the Chinese patent market.

Using the calibrated model, I conduct several counterfactual exercises. Firstly, I assess the contribution of the patent market to China's long-run productivity growth. The findings indicate that if the patent market were to be shut down, China's productivity growth would decrease by 5%. This highlights the current contribution of this underdeveloped patent market to China's growth, as well as its potential for a larger contribution. Secondly, I examine the effect of eliminating all three frictions in the Chinese patent market. I find that doing so would increase the fraction of traded patents to 67% and improve China's productivity growth by 44%, and the elimination of search costs alone contributes to 78% of this increase in patent market size. However, it is impractical to completely remove all the frictions in an underdeveloped market. Instead, aligning the level of frictions with that of a developed market, such as the US patent market, is a more feasible target. By reducing all the frictions to the US levels, the fraction of traded

[3] Akcigit et al. (2016) show that within a firm, the patent that is technologically distant from the firm's technology specialty is more likely to be sold. In Appendix B.3, I perform similar regressions for Chinese firms' patents, and the results in Table B3 are consistent with the evidence from the US in Akcigit et al. (2016). These pieces of evidence support the basic role of the patent market, which is to provide a platform for initial inventors to sell the patents that are less useful for them.

[4] The difficulty in finding a partner or a patent is reported as one of the main obstacles for European firms as well as Japanese firms that find it hard to enter the technology market (Zuniga and Guellec, 2009; Radauer and Dudenbostel, 2013).

patents in China would increase from 4.5% to 18.4%, resulting in an improvement of 14% in China's productivity growth.

To corroborate the quantitative findings, I perform several robustness checks. In particular, I evaluate two additional factors that potentially affect the size of the patent market: patent quality and patent infringement. These considerations are inspired by the observation that China is frequently criticized for having low patent quality and inadequate intellectual property protection. By incorporating China's lower patent quality and higher patent infringement rate into the model, I recalibrate the model and obtain the following findings. Firstly, eliminating the production of low-quality patents and eradicating patent infringement, in addition to removing the three frictions, can further increase the fraction of traded patents to 77% and 80%, respectively, also resulting in a 4-percentage-point and 1-percentage-point improvement in aggregate productivity growth. It is worth noting that while the enhancement of patent quality and the decrease in patent infringement would separately contribute to 3% and 20% of the overall improvements in patent market size, the decline in search costs still accounts for more than 70% of the observed increase in patent market size.

Finally, I explore policies that may improve the efficiency of the Chinese patent market. Specifically, I evaluate the effectiveness of subsidies to R&D and search costs, respectively. R&D subsidy has a slightly negative impact on the fraction of traded patents, as it leads to an increase in the supply of patents in the patent market. However, subsidies to search costs can effectively enlarge the patent market. Under the optimal subsidies to search costs, the fraction of traded patents would increase from 4.5% to 20%, and aggregate productivity growth would increase by 0.17 percentage points, indicating potential productivity gains from incentivizing firms' search in the patent market.

Related Literature First, this paper is closely related to the literature studying the misallocation of R&D. König et al. (2022) introduce firm-specific labor and capital market distortions into an endogenous growth model, and they show that these distortions also change firms' R&D choices. The R&D misallocation can also arise from the government's ill-targeted policies. For instance, the Chinese patent subsidy program encourages low-quality patent applications (Dang and Motohashi, 2015; Wei et al., 2023), and the InnoCom program leads to firms' relabelling of non-R&D expenditures as R&D expenses to obtain tax exemptions (Chen et al., 2021). All these papers emphasize the misallocation of R&D investments. However, if the technology market functions well, the inefficiency of cross-firm R&D allocations can be partially remedied through technology transactions between firms. Complementing these papers, this paper shows that the frictions in the Chinese technology market lead to too few technology transactions, intensifying the detrimental impact of R&D misallocation on China's growth.

More broadly, a vast literature has delved into the inefficient use of production factors, as reviewed by Restuccia and Rogerson (2017). In the labor market, the inefficient allocation can arise from search costs, discrimination, barriers to forming human capital, and differences in social norms (e.g., Pissarides, 2000; Hsieh et al., 2019; Foster and Rosenzweig, 2022). In the capital market, misallocation can arise from capital adjustment costs, information frictions, and other firm-specific factors (e.g., Akerlof, 1970; David et al., 2016; David and Venkateswaran, 2019). I contribute to this literature by studying the misallocation prevailing in the technology market. Moreover, I show that the underdevelopment of the Chinese patent market can be explained by technology market frictions including search costs, fixed transaction costs, and information frictions. These frictions also similarly exist in labor and capital markets as aforementioned, though the specific forms of these frictions can vary across markets.

Finally, this paper connects with the literature on patent markets. This paper is closely related to Akcigit et al. (2016) who use an endogenous growth model to quantitatively study how efficiency in the patent market affects growth in the US. This paper differs from theirs in two main aspects. First, I incorporate three frictions to speak to the underdevelopment of the Chinese patent market. Second, I empirically and quantitatively compare the performance of the patent markets between the US and China. This comparison can help us understand the impeding factors of the technology market in developing countries. Aside from quantitative research, many studies document that difficulties in finding a partner, fixed transaction costs like broker fees, and information frictions can cause inactive patent transactions (Teece, 1977; Zuniga and Guellec, 2009; Hagiu and Yoffie, 2013; Khan, 2013; Radauer and Dudenbostel, 2013; Serrano, 2018; Han et al., 2022). These studies are mostly empirical, and thus the aggregate implications are unclear. In contrast, I build an endogenous growth model to quantify the aggregate role of these distortions in shaping the patent market and the aggregate growth.

The paper is organized as follows. Section 2 describes the key empirical facts in the Chinese patent market and contrasts them with those in the US patent market. Section 3 develops the model, and Section 4 estimates the model using the Chinese data. Sections 5 uses the calibrated model to perform several counterfactual experiments. Finally, I conclude in Section 6. The details of the data construction and some additional robustness checks are provided in the appendix.

2 Descriptive Facts of the Chinese Patent Market

In this section, I document the descriptive facts of the Chinese patent market and compare them with those of the benchmark US patent market. Sections 2.1 and 2.2 describe the background and the data, respectively, and Section 2.3 documents the facts regarding the underdevelopment of the Chinese patent market.

2.1 Institutional Background

The establishment of China's intellectual property (IP) system occurred in the 1980s, as the country aimed to encourage foreign direct investment and the importation of technologies. To accomplish this, China became a member of the World Intellectual Property Organization in 1980 and enacted its first version of the patent law in 1984. Over time, this patent law has undergone several revisions to enhance patent protection. Notably, there has been a significant increase in patent applications from firms, particularly from domestic firms: as of 2005, over half of all patent applications were submitted by firms (Xie and Zhang, 2015). To regulate patent sales conducted by firms, the Chinese Contract Law, effective since 1999, and the Administration of the Recognition and Registration of Technology Contracts Procedures, effective since 2000, establish the necessary legal framework. The government has also implemented many policies to boost the patent market.[5] Given the continuous development of laws and policies aimed at regulating and standardizing technology transactions, this presents a valuable opportunity to investigate and quantify potential challenges in the patent market within this evolving and maturing context.

Firms are the primary participants in patent transactions, as demonstrated by Appendix Figure B2, which indicates that they account for 80% of technology market par-

[5]For example, the Chinese government provides subsidies to incentivize patent transactions: when a patent transaction is certified and recorded by the local registration institution, both the assignor and assignee can enjoy a reduction in corporate income tax for the trading year.

ticipants in China. In contrast, other participants such as public institutions are less active in such transactions. Given that firms are the main generators of innovations and technology transactions, this paper centers on firm patent transactions occurring within the country.

2.2 Data

I mainly use Chinese patent transaction data from the China National Intellectual Property Administration (hereafter CNIPA). The transaction data record patents' transaction date, transacted patents' application number, assignee name, and assignor name. The data include all transacted patents that were filed and granted between 1985 and 2016 in China. The structure of the original data is described in Appendix A.

I complement the transaction data with the CNIPA patent database to obtain other information about invention patents' characteristics, including their application date, grant date, publication date, inventors, and forward and backward citations.[6] It usually takes three years for a Chinese patent to get granted after application, as shown in Figure G4, and thus the patents filed from 2013 to 2016 may not get granted before 2016. Moreover, in my data, the first patent transaction happened in 1998.[7] Therefore, my empirical analysis focuses on the patents filed and granted between 1998 and 2013.

In the paper, I take the US patent market as a benchmark to study why the Chinese patent market is underdeveloped. As Akcigit et al. (2016) focus on the characteristics of the US patent market from 1976 to 2006, to be consistent with the Chinese data, I update the US patent transaction and registration data to 2013. The US patent registration data come from the Patentview database, and the patent transaction data come from the United States Patent and Trademark Office (hereafter USPTO) publication. The details are described in Appendix A.

[6]The Chinese patents office grants three types of patents: inventions, utility models, and design patents. Among these, only the grant of inventions requires a substantive examination for utility, novelty, and non-obviousness, making it equivalent to US utility patents. In contrast, the criteria for obtaining utility model and design patents are significantly lower. Consequently, the applications for these two types of patents in China may be influenced by non-innovation-related patenting activity driven by strategic considerations and government policy incentives (Hu et al., 2017). Therefore, this paper primarily focuses on invention patents and their transactions. Similarly, in the US, I also concentrate on utility patents, which is in line with the research conducted by Akcigit et al. (2016). It is important to note that throughout this paper, the term "patent" refers specifically to the invention patent in China.

[7]The first transacted patent is CN98107411.1, and this transaction happened between Webasto Kicktbustuen AG and IFE Ind Einrichtungen.

I merge the patent data with firm-level financial data to understand the characteristics of firms participating in the patent market. I obtain the Chinese manufacturing firm data (hereafter NBS) in 2001–2013, the Chinese listed firm data (1998–2013), and the US listed firm data (1998–2013).[8] The firm-level data provide information on firms' operating behavior, such as industry, address, sales, fixed assets, and employment. I merge these firm-level data with the CNIPA database using firm name (see Appendix A.3 for detailed procedure) to obtain a firm-patent panel between 1998 and 2013.

2.3 Descriptive Facts on the Patent Market

I now use the assembled data to document several facts regarding the underdevelopment of the Chinese patent market.

2.3.1 Patent Market Size in China and the US

The Fraction of Traded Patents. To understand the magnitude of the Chinese patent market, I compare the fraction of traded patents in China with that in the US. I define the fraction of traded patents in a period as the share of patents filed and granted in that period that are also transacted in the same period.

In order to conduct a consistent comparison of patent markets between China and the US, I impose three constraints on the patent transaction data. First, to avoid the influence of dual-listed patent registrations, I only include the transactions that happen among domestic entities. For example, the majority of patent transactions between Google and Motorola in the US were also recorded in the Chinese patent office. However, these transactions did not occur in China and were consequently unaffected by any obstacles present in the Chinese patent market.[9] Second, I focus on transactions among firms, as they are the primary drivers of patent invention and play a leading role in the patent market as mentioned in Section 2.1. Finally, I exclude transactions occurring within a corporate group since they are frequently influenced by non-market factors,

[8] The NBS data are conducted by the National Bureau of Statistics (NBS). The survey includes all industrial firms that are either state-owned or non-state firms with sales above 5 million RMB ("above-scale" firms) (Brandt et al., 2012). This paper uses the NBS data in 2001–2007 and 2011–2013.

[9] Out of all the transactions that occurred between 1998 and 2013, approximately 50% consisted of overseas entities' patents in both China and the US. Within these transactions involving overseas entities' patents, around 70% to 80% of the patents were traded to other overseas entities. Appendix A.1 and A.2 provide a detailed explanation of how I differentiate between domestic and overseas entities in the CNIPA and USPTO datasets.

Table 1: Patent Market Statistics in 1998–2013

		Number of Patents	Fraction of Patents Sold
China	All Domestic Firms 1998–2013	322,632	4.5%
	Listed Firms 1998–2013	46,657	1.6%
The US	All Domestic Firms 1998–2013	975,284	14.6%
	Listed Firms 1998–2013	42,125	10.8%
	All Firms 1976-2006 (Akcigit et al., 2016)	3,210,361	16.0%

such as technology transfers from the parent firm to its subsidiaries or from the corporate R&D center to its production firm. Appendix A.1 and A.2 describe the procedure of excluding the transactions within the corporate group.

Table 1 compares the fraction of traded patents between China and the US. In China, Chinese firms had 322,632 patents filed and granted from 1998 to 2013. Among these patents, 4.5% were sold to other Chinese firms. During the same period, the fraction of traded patents in the US was 10.1 percentage points higher than that in China. Thus, compared with the US patent market, the size of the Chinese patent market was relatively very small.

I next present a set of robustness checks to rule out several factors unrelated to market frictions that could potentially explain the small patent market size in China.

Accounting for Firm Size. The first concern is that the pattern in Table 1 reflects variations in firm size compositions across different countries. The literature (Serrano, 2010; Figueroa and Serrano, 2019) finds that smaller inventors tend to have larger rates of patent transfers because of the inability to capture the patent value, and thus the economy with more small firms may have a higher share of patent transactions. If anything, this concern may bias the fraction of traded patents in China upwards, as poorer countries tend to have more small firms (Poschke, 2018). As a robustness check, to rule out the impact of small firms, I compare the fraction of traded patents for listed firms' patents between these two countries.[10] As shown in Table 1, among listed firms, the gap in the fraction of traded patents between China and the US is still 9.2 percentage points. Therefore, firm size cannot explain the relatively smaller patent market size in China compared with the US.

[10] I define the number of patents traded for the listed firm as the number of patents invented by the listed firm and sold to any other domestic firm.

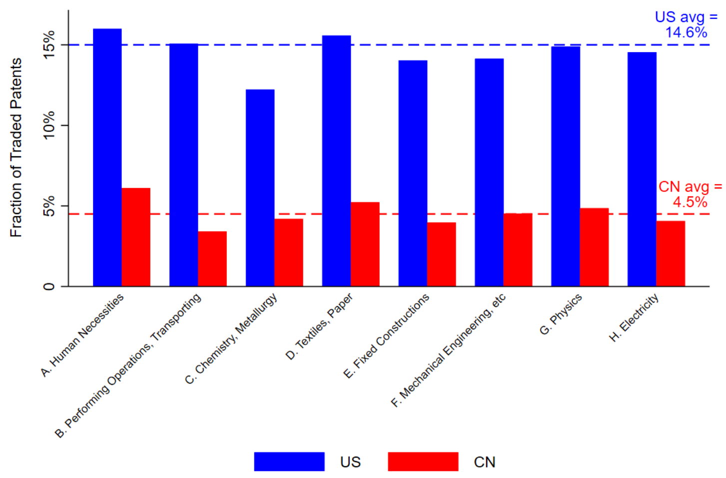

Figure 2: The Fraction of Trade Patents by Technology Field, 1998–2013

Accounting for Technology Fields. The second concern is with regard to the structure of patents' technology fields. As costs and opportunities of technology adoption differ across technology fields (Serrano, 2010), patent transfer rates may also vary across technology fields. This hints that the technology heterogeneity may trigger different patent market sizes among countries with different structures of patents' technology fields. Figure 2 exhibits the fractions of traded patents in each technology field (based on 1-digit IPC code) of China and the US.[11] I find that the scale of patent transactions consistently remains small in every technology field when compared to the benchmark of patent transactions in the US.

Accounting for the Patent-Inventing Firm Similarity. The third concern is that the difference in the distribution of patent-inventing firm similarities could influence the likelihood of a firm selling the patents it invents. Akcigit et al. (2016) constructs the patent-firm similarity measure, which captures how distant the patent's technology field is from the firm's technology field. They find that the patent which is closer to the firm in terms of technological distance contributes more to the firm's value and has a lower possibility of being sold by its inventor.[12] As a robustness check, I construct the distribution of similarity between new-born patents and their inventing firms in both

[11]The structure of patents' technology fields in China is quite different from that in the US, as shown by Appendix Figures G5 and G6. Detailed information about IPC classification is described in Appendix A.4. The IPC 1-digit codes contain eight sections.

[12]In Appendix B.3, I also check this pattern using Chinese data, and the results in Table B3 are in accordance with Akcigit et al. (2016).

countries following Akcigit et al. (2016) and also adjust for knowledge scopes to ease cross-country comparison (see Appendix B.2).[13] As shown in Figure 3, the distributions of patent-firm similarities in these two countries are relatively analogous and thus could not explain why the patent market size in China is much smaller than in the US.

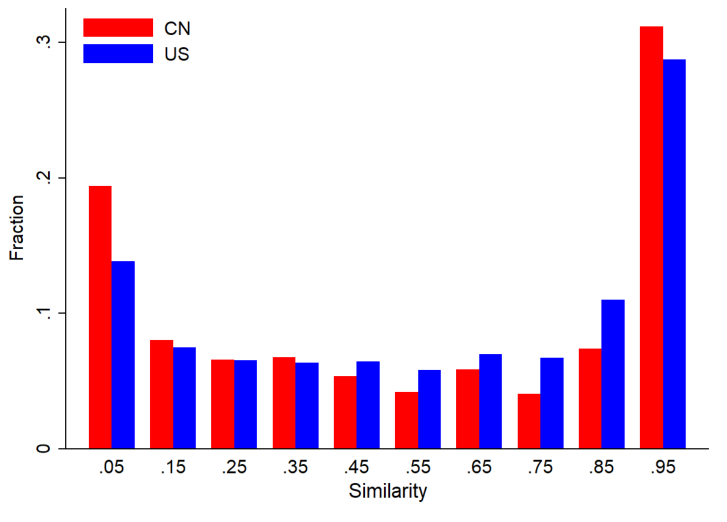

Figure 3: Distribution of Similarity between New-born Patent and Knowledge Stock

Note: (1) The sample used here includes patents filed and granted from 1998 to 2013. (2) Given that every firm's first patent's similarity with the firm is absolutely zero, I drop observations of patents which are firms' first patent applications.

Accounting for Patent License and Litigation. In this robustness check, I take two other patent activities—patent license and litigation—into consideration. Patent license is an alternative way to transfer a technology across firms. In contrast with the patent right transfer (this paper's focus), patent license transfers the right to use a patent, not the ownership of that patent. Consequently, if Chinese firms prefer the patent license to the patent right transfer, the fraction of traded patents could overestimate the actual gap of the patent market size between China and the US. To check this, I merge the Chinese patent license data with the patent registration data and compare the number of traded patents with the number of licensed patents. Within Chinese firms' patents filed and granted between 1998 and 2013, there were 0.86% of patents licensed during this period, versus 4.5% of patents traded during the same period. In the US, around

[13]In practice, the patent-firm similarity measure also depends on knowledge scopes: if Chinese firms produce patents mostly within narrow scopes, then one would expect fewer transactions of patents. Thus, when constructing the similarity distribution, I also adjust for differences in the distribution of firms' knowledge scopes between the two countries. Please see the detailed discussions in Appendix B.2.

5% of patents were licensed and 16% of patents were traded (Arora and Ceccagnoli, 2006; Akcigit et al., 2016). Thus, there exists no large difference in the ratio of the license intensity over the patent right transfer intensity between China and the US. Moreover, according to the survey (Zuniga and Guellec, 2009), patent license is used more as a tool to establish a technological monopoly rather than a technology exchange.

Besides the patent license, the other concern comes from the threat of patent litigation risk. Abrams et al. (2019) argue that patent trolls, such as stick-up artists and middlemen, may purchase the patent from its inventing firm and compel other firms to buy it by the threat of the litigation. Therefore, highly developed IP protection and litigation system, and mature patent agent institutions could be a main reason for the sizeable patent market in the US, not the low market frictions. To rule out this potential channel, this paper merges the Chinese patent litigation data with the patent registration and transaction data. Among all Chinese firms' patents filed and granted between 1998 and 2013 in CNIPA, 0.1% of patents were involved in litigation during this period, and among traded patents, 0.2% of patents were ever litigated. Akcigit et al. (2016) report that about 1% of US patents were involved in litigation, and among traded patents, 2% of patents were ever litigated. Given these small shares in both countries, the difference in litigation risk seems unlikely to drive the large gap in the fraction of traded patents between China and the US.

Other Confounding Factors. One concern for the lack of patent transactions in China is the low quality of Chinese patents. I will show in the next subsection that even among high-quality patents, there still exists a large gap in the fraction of traded patents between China and the US. Additionally, in the quantitative analysis of Section 5.2.1, I will further measure the gap in patent quality between China and the US and explore how the patent market in China would change if its patent quality aligns with the US's.

Another natural concern for few patent transactions in China is the lack of intellectual property right (IPR hereafter) protection. There is much evidence on the fast improvement of the IPR protection in China in the 2000s,[14] however, the gap in the fraction of traded patents between China and the US was still persistently wide as shown in Figure 1. Figures G9 and G10 also show that in the provinces that experienced rein-

[14] Godinho and Ferreira (2012) and Hong et al. (2022) describe the significant changes in design and enforcement of IPR laws, especially after 2000. Awokuse and Yin (2010) and Ang et al. (2014) show that this reinforcement of IPR protection encouraged the surge in FDI and R&D investments in China.

forcement of the IPR protection, there was no significantly faster increase in the fraction of traded patents within these provinces.[15] These pieces of evidence indicate that the IPR protection may not be a main driver for the lack of patent transactions in China. Nevertheless, in the quantitative analysis, I will also consider a model extension that takes into account the high infringement rate of patents in China and study how this factor contributes to the underdevelopment of China's patent market.

2.3.2 The Fraction of Traded Patents by Patent Quality

I now study how patent transactions vary by patent quality. I measure patent quality based on the widely-used forward citation number (e.g., Hall et al., 2001). I divide patents into different quality groups based on the ranking of their forward citation numbers among all the patents within the same technology field and granted year.

Figure 4 presents the fraction of traded patents by patent quality in China and the US, respectively. I highlight two findings. First, higher-quality patents were traded more often, especially in the US.[16] Considering that higher-quality patents usually command higher prices, one would expect the fraction of traded patents for high-quality patents to be similar to that for low-quality patents. The observed difference in trading probabilities between low- and high-quality patents suggests the presence of overhead costs that impede the trading of low-value patents. Second, the disparity in the proportion of traded patents between the US and China was more significant for high-quality patents compared to low-quality patents. Particularly in China, the trading frequency of higher-quality patents was not substantially higher, indicating that buyers may struggle to accurately assess the true quality of patents. Guided by these two observations, I will introduce fixed transaction costs and information asymmetry concerning patent quality into the model. By incorporating these frictions, I will show that the model can match these two observations well, and I will also demonstrate the role of these two frictions in driving the underdevelopment of China's patent market.

[15] I measure the province-year-level IPR protection levels by marketization index or the development of intermediaries & legal environment, which is constructed by Fan et al. (2019). There is large variation in IPR protection levels across provinces and cities, and the literature shows that firms' innovation and R&D investments increased in the regions with better environments of IPR protection (Lin et al., 2010; Ang et al., 2014; Fang et al., 2017).

[16] In China, the fraction of traded patents for patents with above-median quality was 8% than that for patents with below-median quality.

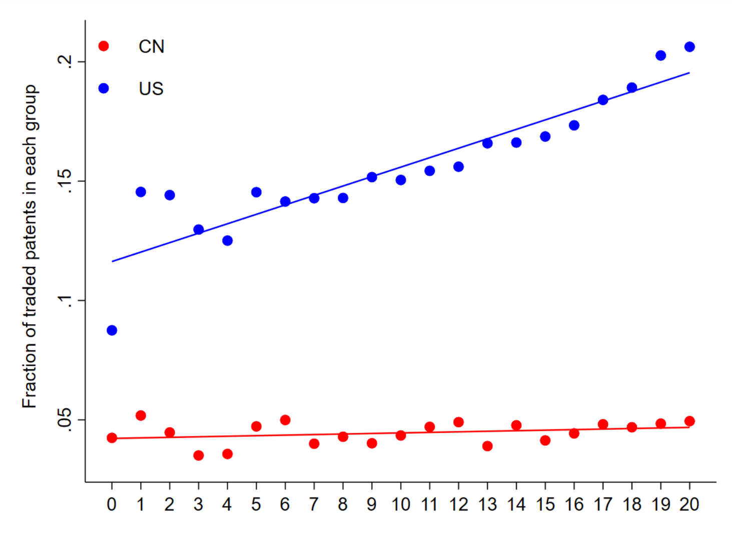

Figure 4: Fraction of Traded Patents by Patent Quality

Note: (1) The x-axis represents the grouping of patents based on their quality, which is measured by the ranking of the number of forward citations among all the patents within each grant year and 3-digit IPC technology class. Group 0 comprises patents with the lowest quality, while Group 20 consists of patents with the highest quality. (2) The y-axis, on the other hand, represents the fraction of traded patents within each group.

3 Model

To quantitatively assess the underdevelopment of the Chinese patent market, I build on the framework of Akcigit et al. (2016) to develop an endogenous growth model featuring firms' decisions on patent production and transactions. To reflect the key features of the Chinese patent market, I embed two main changes into the framework. First, to match the stylized fact regarding how the fractions of traded patents vary by patent quality, I consider patent quality differences and two related frictions: (1) fixed transaction costs, which discourage the trading of low-quality patents relative to high-quality patents; and (2) information asymmetry on patent quality, which can explain why the gap in patent trading probabilities between the US and China varies by patent quality. Second, to account for firms' varying patenting activities observed in the data, I introduce firms' heterogeneity in R&D capacities. Using the model, I will highlight three types of frictions within the patent market—*search costs*, *fixed transaction costs*, and *information asymmetry on patent quality*—and then study their contributions to the underdevelopment of the Chinese patent market in the next section.

3.1 Model Setup

At the start of each period $t = 1, 2, ...$, a measure N_t of incumbent firms exists, each of which occupies a particular technology field j on a circle with a radius of $1/\pi$. The circle represents all different technology fields, where a shorter distance indicates a higher degree of similarity between technologies. The firms are evenly distributed on the circle, and thus the density of firms on the circle is $N_t/2$.

Each patent is positioned at a specific point on the circle. Due to uncertainty about innovation outcomes, the patent's technology field may be different from its inventor's. As shown in Figure 5, a shorter distance between the patent's and the inventor's technology fields implies a higher similarity level x between their technologies. I assume that x is drawn randomly according to a distribution $X(x)$ with support $[0, 1]$. The introduction of uncertainty captures that every firm has its specialization and adept field, but many inventions are generated in other fields accidentally, which may cause a mismatch between the inventing firm and the patent. For example, the initial invention of the microwave oven occurred during a radar test conducted by Raytheon Company, a defense contractor in the United States. However, it was Tappan, an appliance manufacturer, who introduced microwave ovens extensively for household use, a decade after the original invention. This discrepancy between patents and the firms inventing them highlights the necessity of a patent market to bridge this gap and facilitate alignment.

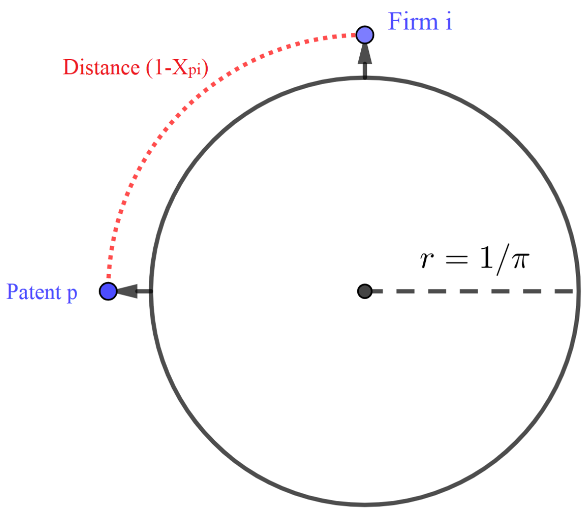

Figure 5: Technology Field Circle: Potential Mismatch between Patent and Firm

3.1.1 Timing

To streamline the exposition of firms' problems, it is useful to first describe the timing of this model.

Step 1: 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.[17]

Step 2: Innovation Activity (In-house R&D or Search in a Patent Market). In order to enhance productivity, a firm can initially engage in in-house R&D. Each firm will independently determine their optimal level of R&D intensity, which in turn influences the rate at which new patents are generated. Upon successfully innovating a new patent, the firm is faced with the decision of whether to retain or sell it. In cases where a new patent fails to be invented, the firm has the option to seek out and acquire a patent from the patent market. After determining the optimal search effort within this market, the firm will randomly encounter a potential patent seller and make a choice between purchasing or refraining from purchasing.

Step 3: Production. Upon acquiring a new patent, whether through in-house innovation or by purchasing, the firm's productivity will increase. In the absence of a new patent, the firm will proceed with production without experiencing any productivity enhancements. Following production, the firm will sell the goods and generate profits.

I will now describe firms' production and innovation activity in more detail.

3.1.2 Production and Evolution of Firms' Productivity

Initial Productivity Distribution in Each Period. Define firms' productivity distribution at the beginning of every period t as $P_t(z)$. Then, the average productivity of incumbents at the beginning of every period is:

$$\tilde{z}_t = \int z dP_t(z). \tag{1}$$

[17] I assume exogenous entry and exits to prevent the explosion of a firm's size and obtain a stationary distribution of firms' productivity. As the new entrant's productivity and type are drawn from the distribution of incumbents' productivity and type, assuming exogenous entry and exit does not change the firm distribution.

When it causes no confusion, I will omit time subscript t for ease of description.

Productivity Improvement. The successful invention or purchase of a patent, as elaborated in the next subsection, will result in an increase in productivity for the firm:

$$z' = L(z, \gamma, x; \tilde{z}) = z + \gamma x z^{\beta} \tilde{z}^{1-\beta}, \qquad \gamma \in \{\gamma_h, \gamma_l\}, \quad x \in [0,1], \quad \beta \in (0,1], \tag{2}$$

where z' is the firm's productivity at the end of the period. Parameter γ captures patent quality, with subscripts h and l indicating the high-quality patent and the low-quality patent respectively. High-quality patents lead to a larger productivity increment, with $\gamma_h > \gamma_l$. Patent quality is determined upon the birth of the patent, and I assume that the share of patents born with high quality is h.[18] x represents the patent-firm similarity, as discussed earlier. If the patent's technology field has a better match with the firm's technology (which implies higher x), the productivity improvement from this patent is also larger. z^{β} captures that the productivity increment may rely on firm initial productivity z.[19] This setting is supported by Appendix Table B2 that the revenue gain of the patent varies by firm size. This is also motivated by the existing literature that has shown that larger firms may have larger markets, abundant advertising experience, and a wide scope of knowledge, thus increasing the surplus of new-born patents (Arkolakis, 2010; Serrano, 2010; Figueroa and Serrano, 2019). Finally, $\tilde{z}$ is the economy-wide average level of productivity. By modeling the dependence of the productivity improvement on $\tilde{z}^{1-\beta}$, I consider productivity improvement to be governed by the economy's average productivity, which indicates knowledge externality and also ensures the existence of a stationary productivity distribution on the balanced growth path.

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

$$Y = (z')^{\alpha} l^{1-\alpha}. \tag{3}$$

[18] I assume that there is no correlation between patent quality and firm size. This is supported by the observation that the quality distributions of patents originating from both large and small firms exhibit minimal differences (see Figure G8 in Appendix G).

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

The firm hires labor l with wage rate w. I assume that there is totally one unit of labor available in the economy (normalization). The firm chooses the amount of labor to maximize its profits:

$$\Pi(z';\tilde{z}) = \max_{l}\,(z')^{\alpha}l^{1-\alpha} - wl. \tag{4}$$

The first-order condition implies the optimal labor $l^* = (\frac{1-\alpha}{w})^{\frac{1}{\alpha}}z'$. The profits are thus:

$$\Pi(z';\tilde{z}) = \alpha \cdot \left(\frac{1-\alpha}{w}\right)^{\frac{1-\alpha}{\alpha}} z'. \tag{5}$$

Obviously, the firm's profits increase with productivity z', and thus the acquisition of a patent will increase profits.

3.1.3 Cost of Innovation Activity

At the beginning of each period, the firm has two options to boost productivity in production. It can either engage in in-house invention or purchase a new patent from the patent market if its internal innovation attempts are unsuccessful. Therefore, the innovation activities in this model encompass in-house R&D and searching for patents in the patent market. In this section, I will provide a detailed explanation of the costs associated with these two types of innovation activities.

Costs of In-house Innovation. Firms differ in in-house R&D capacity $\theta \in \{\theta_H, \theta_L\}$. Upon entry, the firm instantly learns its type θ, which is drawn randomly with probabilities $\mathrm{P}(\theta = \theta_H) = I_p$ and $\mathrm{P}(\theta = \theta_L) = 1 - I_p$, where $I_p \in [0, 1]$ and $\theta_H > \theta_L > 0$. The firm's in-house invention cost is given by:

$$C(i;\tilde{z}) = \chi \frac{i^{1+\rho}}{1+\rho}\tilde{z}^{\alpha}, \tag{6}$$

where i is the R&D intensity chosen by the firm, and $\theta \times i$ governs the arrival rate of a new patent. In line with Klette and Kortum (2004) and Lentz and Mortensen (2008), the R&D cost function is convex in research intensity i. I assume that the invention uses the final good as the input, and the price of the final good is normalized to 1.

Searching for a Patent in the Patent Market. In the event that the firm is unable to generate an in-house invention, it can still acquire a patent from the patent market.

There are three participants in the patent market: the potential seller, the patent agent, and the potential buyer.[20] Once the in-house innovation process is complete, the inventors who were successful must make a decision on whether to sell their newly created patents to the patent agent. These inventors then become potential suppliers in the patent market. Subsequently, the patent agent holds the patents on behalf of the inventing firm, leaving the firm without any new patents after internal innovation. These firms, lacking new-born patents, become potential buyers in the patent market, where they must decide whether to purchase the patents that they encounter.

I make three assumptions regarding the transaction process, following Akcigit et al. (2016). First, whenever a new patent is created and the inventor chooses to sell it, a patent agent will always be available to purchase it from the inventing firm at a given price. Second, each patent agent is only capable of holding one patent at a time and can meet a maximum of one buyer within a single period. The latter restriction is due to search and matching frictions that exist between patent agents and patent buyers. Third, the patent agent has the option to wait until the subsequent period to sell the patent to alternative buyers.

Suppose there are n_a patent agents and n_b potential buyers in the patent market. The potential buyers make efforts, denoted as $\lambda_\theta(z;\tilde{z})$, to search for the appropriate patent that can enhance their productivity. On the other hand, the patent agents simply

[20]The introduction of the patent agent in this model follows Akcigit et al. (2016), which simplifies the model in two aspects. First, the introduction of the patent agent reduces the complexity of the solution, transferring a firm-to-firm-level matching problem to a firm-level buying and selling problem. Second, I do not need to track the stock of unused patents for each firm. When a new patent is created, the inventing firm decides whether to sell it or not. Any unsold patents are held by the patent agent. Additionally, technology exchanges, as one type of technology agent serve as essential platforms for patent transactions in China. The Shanghai Technology Exchange, established in 1993, holds the distinction of being the country's first technology exchange. By 2018, China had a total of 453 national technology exchanges spanning across all provinces, with the exception of Tibet. Additionally, there were 24 permanent technology (property rights) exchanges operating in the country. According to the Annual Reports on Statistics of China Technology Market from 2002 to 2018, the permanent technology (property rights) exchanges facilitated an average of 32,874 technology exchanges per year. Moreover, they organized an average of 1,590 technology promotion and trading activities annually, while providing technology transfer training to approximately 62,804 individuals each year. In line with these observations, Han et al. (2022) found that the increased patent trading facilitated by these exchanges in China is associated with a significant 7.5% rise in firm patenting output. These findings collectively provide suggestive evidence that patent agents play a crucial role in facilitating technology transactions within the Chinese market.

wait to be searched.[21] I assume that search efforts incur costs (David, 2021):

$$B(\lambda; \tilde{z}) = \eta \cdot \frac{\lambda^{\mu}}{\mu} \cdot \tilde{z}^{\alpha}, \quad B'(\lambda) > 0, B''(\lambda) > 0. \tag{7}$$

Here, I introduce the parameter η to capture the degree of the search friction within the patent market. As η approaches infinity, the search friction within the patent market becomes excessively high, leading to a reduction in the size of the patent market. Modeling the search friction is also consistent with the extensive evidence showing that the difficulty in finding a patent is reported as one of the main obstacles to entering the technology market (e.g., Zuniga and Guellec, 2009; Radauer and Dudenbostel, 2013).

Define $Q(\theta, z)$ as the joint distribution of firms' R&D capacity type and productivity when firms enter the patent market. I define the tightness of the buyer side and the seller side in a period as T_b and T_a, respectively, which can be written as:

$$T_b = \min\left(\frac{n_a}{n_b \cdot \int \lambda_\theta(z; \tilde{z})\, dQ(\theta, z)}, 1\right) \qquad T_a = \min\left(\frac{1}{T_b}, 1\right). \tag{8}$$

Therefore, the rate for a patent agent meeting with a potential buyer (θ, z) is:

$$m_a = T_a \cdot \frac{\lambda_\theta(z; \tilde{z}) dQ(\theta, z)}{\int \lambda_\theta(z; \tilde{z})\, dQ(\theta, z)} = T_a \cdot \Gamma_\theta(z; \tilde{z}). \tag{9}$$

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

$$m_b = \lambda_\theta(z; \tilde{z}) T_b. \tag{10}$$

I note that m_a and m_b are firm-specific and depend on firm type θ, firm productivity z, and aggregate productivity levels $\tilde{z}$. For ease of description, I omit these state variables in the expression of m_a and m_b when it causes no confusion.

3.1.4 Three Types of Frictions Involved in the Patent Market

In addition to the search friction, there are two other types of frictions present in the patent market. Since these three frictions are the primary focus of this paper, I will describe them in the subsequent paragraphs, following the operational sequence of the

[21] As I abstract from heterogeneity across patent agents, search efforts are thus homogeneous among patent agents.

patent market. This will facilitate better understanding the role of these frictions.

1. The patent market begins with the creation of a new patent with quality γ and similarity x by a firm. These successful innovators face a decision on whether to keep the patent for their own use or sell it to a patent agent who will handle its sale. This is where the first friction in the patent market, known as *information asymmetry on patent quality*, arises. Due to the challenge of accurately assessing a patent's true quality before it is put into production, the patent's quality remains privately known only to its initial inventor (Chatterjee and Rossi-Hansberg, 2012). Thus, I assume that there is a possibility s that the patent's true quality might not be observable in the patent market. Conversely, with a probability of $1 - s$, the true quality can be observed in the patent market (Menzio and Shi, 2011; Donovan et al., 2018). When the patent's true quality can be observed, the inventor can receive a return of q_γ from the patent agent, which is positively correlated with the patent's quality. However, in cases of information asymmetry, the inventor can only obtain a return of $\mathbb{E}q_\gamma$ from the patent agent, which represents the expected value of the patent based on the endogenous distribution of patent quality in the patent market, irrespective of the true quality of the patent.[22] Thereof, there are two distinct types of patent agents in the market: those holding patents with observable quality, and those representing patents whose quality cannot be verified, but which may be of either high or low quality.

   The parameter s quantifies the extent of information asymmetry on patent quality within the patent market. In the extreme case where $s = 0$, the patent's quality can be entirely verified, enabling all patents entering the market to be traded as *inspection goods*. On the other hand, when $s = 1$, the patent's quality cannot be verified at all. In this scenario, all patents entering the market can only be traded as *experience goods*, with their quality privately observed by the inventors and learned by potential buyers through production processes.

2. Once the patent agents holding patents bought from successful innovators enter the patent market, they become suppliers. Then, when it comes to the buyers' side, Figure 7 below illustrates the sequence of events involving potential buyers' decision-

[22]To guarantee the neutrality of the patent agent, they function as an intermediary in this model. On one hand, the agent is unable to select which patents to take, meaning they cannot choose to handle high-quality or low-quality patents. On the other hand, they are also unable to choose the circumstances under which they take a patent. This means that even in cases of information asymmetry, if an innovator decides to sell a patent, the agent must take that patent regardless.

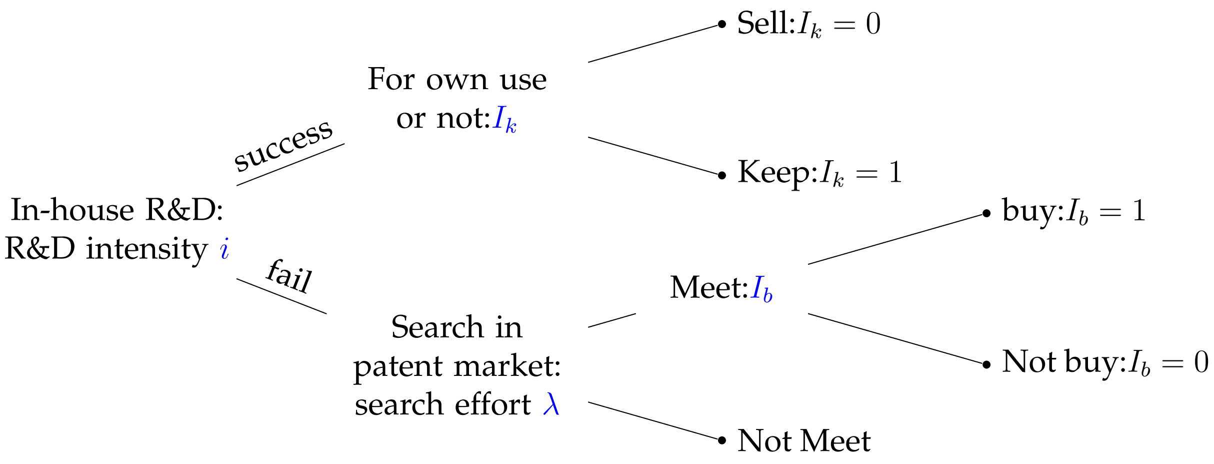

Figure 6: The Sequence of Innovation Activities

making within the patent market. To meet with a patent agent, a potential buyer needs to pay *search costs* as specified in equation (7). Thus, the potential buyer chooses the optimal search efforts λ trading off its expected benefit of entering the patent market and the search costs. The buyer's search efforts determine the meeting rate m_b for the potential buyer to meet with a patent agent in equation (10).

3. Finally, when both the firm and the patent agent agree with the patent transaction, the buyer needs to pay *fixed transaction costs*, which are equal to $F \cdot \tilde{z}^{\alpha}$.

3.2 Solving Firm Decisions on Patent Production and Transaction

I now characterize firm decisions in each period, which are ordered in the sequence as depicted by Figure 6. First, the firm determines the intensity of its R&D efforts. Next, if the firm is successful in obtaining a patent through internal R&D, it must decide whether to retain or sell the newly acquired patent. However, if the firm's in-house invention attempts are unsuccessful, it will then determine the level of search effort it will exert in the patent market. Subsequently, upon encountering a patent in the market, the firm needs to evaluate whether or not to purchase that patent. I will solve the model through backward induction.

Conditional on Successful Invention: Keep or Sell the New-born Patent. For the successful inventing firm, it will choose whether to sell the new-born patent or not. The trade-off in this choice is how much the firm can get from selling that patent or keeping that patent. Let $V_\theta(z;\tilde{z}')$ denote the expected present value of the θ-type firm with productivity z at the beginning of the next period. Let $VK_\theta(z+\gamma x z^\beta \tilde{z}^{1-\beta};\tilde{z})$ denote the expected value of the firm that invents a new patent in this period and keeps it. Keeping the patent leads to an increase in the firm's productivity, leading to higher profits. $VK_\theta(z+\gamma x z^\beta \tilde{z}^{1-\beta};\tilde{z})$ can be written as:

$$VK_\theta(z+\gamma x z^\beta \tilde{z}^{1-\beta};\tilde{z}) = \Pi(L(z,\gamma,x;\tilde{z});\tilde{z}) + r\cdot(1-\delta)\cdot V_\theta(L(z,\gamma,x;\tilde{z});\tilde{z}'), \tag{11}$$

where r is the discount factor and $(1-\delta)$ is the firm's probability of surviving in the next period.

If a firm decides to sell its patent as mentioned before, there is a likelihood (s) that the patent will only be perceived as an experience good in the patent market. In such cases, the expected value of the firm that invents a new patent in the current period and sells it as an experience good, denoted as $VS_\theta^{exp}(z;\tilde{z})$, can be expressed as follows:

$$VS_\theta^{exp}(z;\tilde{z}) = \Pi(L(z,0,0;\tilde{z});\tilde{z}) + \sigma\mathbb{E}q_\gamma + r\cdot(1-\delta)\cdot V_\theta(z;\tilde{z}'). \tag{12}$$

Here, $\mathbb{E}q_\gamma$ represents the revenue earned by selling the patent. As an experience good, the revenue earned from selling high-quality and low-quality patents is the same. This revenue is determined by the expected value of the patent as perceived by the patent market and is based on the expected distribution of patent quality among potential buyers. σ is the patent surviving rate and corresponds to the patent's term of validity, as no patents could be alive forever (in China, the patent can be valid for 20 years).

In a different scenario, when the patent is considered an inspection good, the expected value of a successful innovating firm, $VS_\theta^{ins}(z;\tilde{z})$, can be expressed as follows.

$$VS_\theta^{ins}(z;\tilde{z}) = \Pi(L(z,0,0;\tilde{z});\tilde{z}) + \sigma q_\gamma + r\cdot(1-\delta)\cdot V_\theta(z;\tilde{z}'). \tag{13}$$

q_γ represents the revenue earned from selling a patent with quality γ. It is important to note that high-quality and low-quality patents generate different levels of revenue. All other parameters have the same definitions as Equation (12).

Now, define $I_\theta^{k,c}(z,\gamma,x;\tilde{z})$ as the dummy variable indicating the decision of keeping or selling the new patent when the patent could be traded as an experience good ($c=$

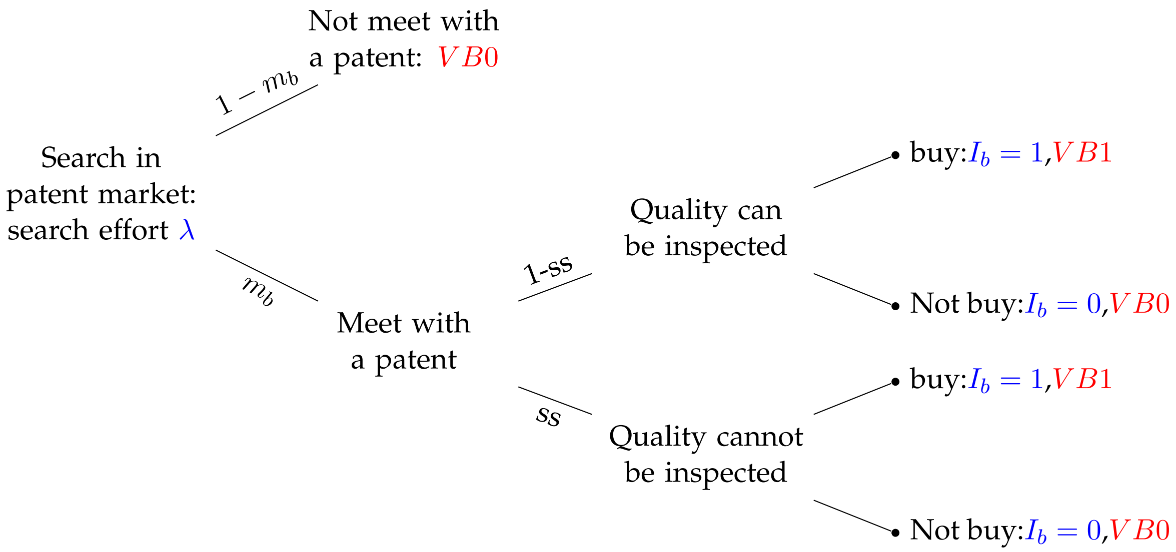

Figure 7: The Sequence of Potential Buyers' Choices in the Patent Market

exp) or inspection good ($c = ins$) in the patent market:

$$I_\theta^{k,c}(z, \gamma, x; \tilde{z}) = \begin{cases} 1(\text{keep}) & \text{if} \quad VK_\theta(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}) > VS_\theta^c(z; \tilde{z}) \\ 0(\text{sell}) & \text{otherwise} \end{cases} \tag{14}$$

Thus, the expected value for a firm that innovates successfully is given by $V_\theta^{inn}(z; \tilde{z})$ (the expectation is taken regarding patent quality and similarity, which are uncertain before the invention is made):

$$\begin{aligned} V_\theta^{inn}(z; \tilde{z}) = & \, s\mathbb{E}_{\gamma,x} \max\{VK_\theta(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}), VS_\theta^{exp}(z; \tilde{z})\} \\ & + (1 - s)\mathbb{E}_{\gamma,x} \max\{VK_\theta(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}), VS_\theta^{ins}(z; \tilde{z})\}. \end{aligned} \tag{15}$$

Conditional on Unsuccessful Invention: Search (and Purchase) a Patent. If a firm fails to create a new patent in a given period, it has the opportunity to explore the patent market by randomly interacting with a patent agent during that period. In this scenario, the unsuccessful innovators become potential buyers in the patent market and are confronted with two decisions. Firstly, they need to decide the level of effort to search for a suitable patent agent. Secondly, upon meeting a patent agent, they must decide whether or not to acquire the patent being presented.

Figure 7 illustrates the decision-making process of potential buyers. The red items in the figure represent the expected discounted present value associated with various outcomes when the firm exits the patent market. To determine the optimal search effort for potential buyers and establish the criteria (marked in blue in Figure 7) for a successful transaction, I will again use backward induction.

When exiting the patent market, potential buyers can either successfully become buyers or leave without acquiring any patents. The expected discounted present value of the buyer, $VB1$, is:

$$VB1_\theta(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}) = \Pi(L(z, \gamma, x; \tilde{z}); \tilde{z}) + r \cdot (1 - \delta) \cdot V_\theta(L(z, \gamma, x; \tilde{z}); \tilde{z}'). \tag{16}$$

The firm leaving without any patent will have the expected value $VB0$ given by

$$VB0_\theta(z; \tilde{z}) = \Pi(L(z, 0, 0; \tilde{z}); \tilde{z}) + r \cdot (1 - \delta) \cdot V_\theta(z; \tilde{z}'). \tag{17}$$

However, the patent agent that the potential buyer encounters may possess a patent that is either an inspection good with a probability of $1 - ss$, or an experienced good with a probability of ss. ss is potentially different from s, as the sale speed of inspection goods' patents may vary from that of experience goods' patents. When the patent is an inspection good with features (γ, x) and it meets a firm with features (θ, z), the price is determined based on the true quality of the patent, as indicated by

$$P^{ins}_\theta(z, \gamma, x; \tilde{z}) = \omega \cdot \left[VB1_\theta(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}) - VB0_\theta(z; \tilde{z}) - F\tilde{z}^\alpha\right] + (1 - \omega) \cdot r\sigma A(\gamma, \tilde{z}'), \tag{18}$$

where $A(\gamma, \tilde{z}')$ is the value for the patent agent holding the patent with quality γ, which is derived in Appendix C.1. The term $F\tilde{z}^\alpha$ represents fixed transaction costs that can reduce the surplus gain of the buyer. For simplicity, I assume that the price is determined by the Nash bargaining,[23] and $\omega \in \{0, 1\}$ is the bargaining power of the patent agent. In the case that the quality of the patent may not be inspected, the price is similarly determined by the expected surplus of the potential buyer and the patent agent's value as follows:

$$P^{exp}_\theta(z, x; \tilde{z}) = \omega \cdot \mathbb{E}_\gamma[VB1_\theta(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}) - VB0_\theta(z; \tilde{z}) - F\tilde{z}^\alpha] + (1 - \omega) \cdot r\sigma A(\tilde{z}'), \tag{19}$$

[23] In the Nash bargaining, the buyer and the patent agent solve $\max_P (VB1_\theta(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}) - VB0_\theta(z; \tilde{z}) - F\tilde{z}^\alpha - P)^{1-\omega}(P - r\sigma A(\gamma, \tilde{z}'))^\omega$, where $VB0_\theta(z; \tilde{z})$ and $r\sigma A(\gamma, \tilde{z}')$ are the outside values of the patent buyer and the patent agent if they do not participate in the transaction. Solving this leads to the price in Equation (19).

where $A(\tilde{z}')$ denotes the value of the patent with an unobserved quality for the patent agent, as derived in Appendix C.1.

Given the values of the patent agent and the potential buyer, the successful transaction of a patent requires the patent price P to be equal or less than the value of the patent for the patent buyer and equal or more than the outside value for the patent agent. Specifically, in the case where the quality of the patent can be fully inspected, the condition for a successful transaction is:

$$VB1_\theta(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}) - VB0_\theta(z; \tilde{z}) - F\tilde{z}^\alpha \geq r\sigma A(\gamma, \tilde{z}'). \tag{20}$$

When the patent's quality (γ_h or γ_l) could not be truly verified before putting it into the production, the condition of the successful transaction is

$$\mathbb{E}_\gamma \left[VB1_\theta(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}) - VB0_\theta(z; \tilde{z}) - F\tilde{z}^\alpha\right] \geq r\sigma A(\tilde{z}'). \tag{21}$$

Now, I can solve the indicator function that specifies whether the patent transaction happens successfully when the patent belongs to inspection goods and when the patent belongs to experience goods, respectively:

$$I_\theta^{b,ins}(z, \gamma, x; \tilde{z}) = \begin{cases} 1, & \text{if } VB1_\theta(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}) - VB0_\theta(z; \tilde{z}) - F\tilde{z}^\alpha \geq r\sigma A(\gamma, \tilde{z}') \\ 0, & \text{otherwise} \end{cases} \tag{22}$$

$$I_\theta^{b,exp}(z, , x; \tilde{z}) = \begin{cases} 1, & \text{if } \mathbb{E}_\gamma \left[VB1_\theta(z + \gamma x z^\beta \tilde{z}^{1-\beta}; \tilde{z}) - VB0_\theta(z; \tilde{z}) - F\tilde{z}^\alpha\right] \geq r\sigma A(\gamma, \tilde{z}') \\ 0, & \text{otherwise} \end{cases} \tag{23}$$

Therefore, the value function for the firm that enters the patent market is

$$
\begin{aligned}
V_\theta^{buy}(z;\tilde{z}) = \max_{\lambda}\ m_b \cdot \int_{\gamma,x} & \left\{ \begin{array}{l} \overbrace{(1-ss)\cdot \left\{ \begin{array}{l} I_\theta^{b,ins}(z,\gamma,x;\tilde{z}) \cdot \left[\begin{array}{l} VB1_\theta(z+\gamma x z^\beta \tilde{z}^{1-\beta};\tilde{z}) \\ -P_\theta^{ins}(z,\gamma,x;\tilde{z}) - F\cdot \tilde{z}^\alpha \end{array} \right] \\ +(1-I_\theta^{b,ins}(z,\gamma,x;\tilde{z}))\cdot VB0_\theta(z;\tilde{z}) \end{array} \right\}}^{\text{Inspection good}} \\ \underbrace{+ss\cdot \left\{ \begin{array}{l} I_\theta^{b,exp}(z,x;\tilde{z}) \cdot \left[\begin{array}{l} VB1_\theta(z+\gamma x z^\beta \tilde{z}^{1-\beta};\tilde{z}) \\ -P_\theta^{exp}(z,x;\tilde{z}) - F\cdot \tilde{z}^\alpha \end{array} \right] \\ +(1-I_\theta^{b,exp}(z,x;\tilde{z}))\cdot VB0_\theta(z;\tilde{z}) \end{array} \right\}}_{\text{Experience good}} \end{array} \right\} dH(\gamma,x) \\
& +(1-m_b)\cdot VB0_\theta(z;\tilde{z}) \\
& -B(\lambda;\tilde{z})
\end{aligned} \tag{24}
$$

where $H(\gamma, x)$ denotes the joint distribution of patent quality and similarity in the market. In this equation, the value of the potential buyer is composed of three elements. The first element is the value when the potential buyer meets with a patent in the market, and that patent is the inspection good, which is captured by the first item in the brace in equation (24). The second element is the value when the potential buyer meets with a patent in the market, and that patent is the experience good, which is captured by the second item in the brace in equation (24). The last element is the value when the potential buyer does not meet with a patent in the market. Given this value function, I can solve for the first-order condition regarding the optimal search efforts of the potential buyer:

$$
\frac{\partial V_\theta^{buy}(z;\tilde{z})}{\partial \lambda} = 0. \tag{25}
$$

Solving for Optimal R&D. By utilizing the provided value functions for successful and unsuccessful inventions, I can determine the firm's in-house R&D intensity. The firm has a probability of $\theta \times i$ to successfully create an invention, and a probability of $(1-\theta\times i)$ to fail in inventing a new patent within the period and subsequently explore the patent market to search for a patent. The R&D cost, denoted as $C(i;\tilde{z})$, is the cost defined in equation (6). Thus, the expected value of the firm is

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

The first-order condition for the optimal R&D intensity of the firm is

$$
\frac{\partial V_\theta(z;\tilde{z})}{\partial i} = 0. \tag{27}
$$

3.3 Closing the Model

3.3.1 General Equilibrium

To close the model, I assume that the representative consumer's utility function follows a CRRA form,

$$U = \sum_t r^{t-1} \frac{C(t)^{1-\zeta}}{1-\zeta}. \tag{28}$$

Thus, I can solve the worker's consumption $C(t)$ from utility maximization. With consumption $C(t)$, I can express the good market clearing condition in period t as:

$$Y(t) = C(t) + C_{rd,t} + B_{search,t} + F_{search,t}, \tag{29}$$

where $C_{rd,t}$ represents the total costs of R&D for firms doing in-house R&D, $B_{search,t}$ represents total search costs of potential buyers, and $F_{search,t}$ represents total fixed transaction costs in patents' transactions.

Given the population normalized to 1, in each time t, the labor market clearing requires:

$$N \int l_i^* \, di = N \int \left(\frac{1-\alpha}{w_t}\right)^{\frac{1}{\alpha}} z dP_t(z) = 1. \tag{30}$$

The wage rate in period t can be solved as:

$$w_t = (1-\alpha)(N \cdot \tilde{z}_t)^{\alpha}. \tag{31}$$

Here, N is the number of firms that are actively operating and is a constant number on the balanced growth path (BGP). And $\tilde{z}_t$ is the average productivity of firms at time t, which grows at some constant rate as defined below.

3.3.2 Balanced Growth Path

Stationary Distribution of Firm Productivity. Define $\hat{P}_{\theta,t}$ as the distribution of firms' productivity (relative to average productivity $\tilde{z}$) contingent on its R&D capacity type θ at the beginning of period t. The dynamics of firms' relative productivity distribution are presented in Appendix C.2. In the steady state, firms' relative productivity distribution will converge to a stationary distribution.

Constant Growth Rate. The growth rate on the BGP is defined as

$$g \equiv \frac{\int z \, dP_{t+1}(z)}{\int z \, dP_t(z)}. \tag{32}$$

Definition of Stationary Equilibrium. A stationary equilibrium of this economy is a tuple $\left\{l_i, V_\theta, i_\theta, \hat{P}_\theta(\hat{z}), w, g\right\}$, which satisfies:
(1) The labor demand of firm i, l_i, maximizes profits as in equation (4);
(2) V_θ is given by the value function in equation (26);
(3) i_θ is the optimal R&D policy, which is solved according to equation (26);
(4) $\hat{P}_\theta(\hat{z})$ evolves as in equation (40) of Appendix C.2 and remains unchanged over time;
(5) w is consistent with the labor market clearing condition in equation (31); and
(6) g is determined by R&D decisions and patent market decisions.

4 Structural Estimation

In this section, I take the model to the data. I first present the computation algorithm. I then estimate the model using the simulated method of moments and finally validate the model fit for a set of nontargeted moments.

4.1 Computation of the Balanced Growth Path

To solve the model, I iterate on the following four aggregate variables such that they converge to a fixed point:

$$\left\{T_{a|b}, A(\gamma; \tilde{z}), g_{BGP}, V_\theta(z; \tilde{z})\right\}. \tag{33}$$

The first two variables are the patent market tightness and the patent agent value, respectively. The third one is the growth of the aggregate TFP on the BGP, and the last variable is the value of the firm with R&D capacity θ and productivity z.

I first post a conjecture for the variables in vector (33). I initiate the firm's productivity to follow a Pareto distribution with the shape parameter 1.1, according to China's NBS data. Then, I iterate on the variables in vector (33) according to the following steps:

(i) Based on equations (14), (20), (21), (24), and (26), I compute the individual firm's keep-or-not decisions on patents I^k, optimal patent market search efforts λ, buy-or-not decisions on patents I^b, and optimal R&D intensity i.

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

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

(iv) The distribution of firms' productivity evolves according to equation (40), and the productivity growth g_{BGP} on the BGP is solved according to equation (32).

(v) I iterate based on the above steps until the four aggregate variables in vector (33) converge.

4.2 Model Estimation

To calibrate the model, I first choose a set of parameters directly from the data and the literature. Then, I calibrate the remaining parameters using the simulated method of moments (SMM hereafter).

Externally Calibrated Parameters. Table 2 presents the set of parameters that are externally calibrated according to the data and the literature. For example, I estimate parameter ρ, which governs the elasticity of R&D costs to R&D intensity, by regressing the logarithm of quality-adjusted patents on the R&D intensity using the Chinese manufacturing firm data. I calibrate the patent surviving rate $\sigma = 1 - 1/20$, according to the term of patents in China (20 years). I choose the exogenous exit rate δ according to the average exit rate of top 1% firms in the NBS database from 2001 to 2013.

I calibrate the share of high-quality patents (h) based on the share of high-quality patents observed in the data, which is approximately 40% in both China and the US.[24] The gap in forward citation numbers between high-quality and low-quality patents is approximately 8.4 times in both countries. To calibrate the elasticity between forward citation numbers and firm revenue, I regress the logarithm of the firm's sales

[24] As mentioned in the empirical section, high-quality patents are defined as those with a forward citation number higher than the median within their respective technology field and granted year. For detailed proportions of high-quality and low-quality patents in both countries, please refer to Table G1 in Appendix G.

Table 2: Externally Calibrated Parameters

Notation	Definition	Value	Source
α	Labor share	0.50	Hsieh and Klenow (2009)
ω	Bargaining power	0.50	Akcigit et al. (2016)
ρ	R&D cost elasticity	3.00	data
r	Discount factor	0.96	literature
σ	Patent surviving rate	0.95	data
δ	Exogenous exit rate	0.075	data
h	High-quality patents share	0.40	data
γ_{gap}	Gap in step size btw high-quality and low-quality patents	1.16	data
$X(x)$	Distribution of patent-inventing firm similarities	Figure 3	data

on the accumulated patent adjusted by forward citation number. This yields an estimated elasticity of 0.069, which can be found in Table G2.[25] Thus, I set $\gamma_{gap} = \gamma_h/\gamma_l = \exp(0.069 \times \ln(8.4)) \approx 1.16$ in the estimation.

Simulated Method of Moment. I estimate the remaining 10 parameters using the SMM. These parameters include: the elasticity of productivity gains to firm size β; step size of productivity increment γ_l; constant in R&D costs χ; the share of firms with high R&D capacity I_p; high-type R&D capacity θ_h; the gap in R&D capacity between high-type and low-type firms θ_{gap}; constant in search costs η; curvature in search costs μ, which governs the strength of increasing marginal costs; fixed transaction costs F; and the share of patents of which the quality could not be verified in the patent market s.

I iterate on the parameter values to minimize the objective function,

$$\hat{\Omega} = \operatorname*{argmin}_{\Omega} G(\Omega)'\hat{W}G(\Omega), \tag{34}$$

where Ω refers to parameters, and $G(\Omega)$ is the vector containing moments. I index each moment by i with $G_i(\Omega) = \frac{|model(i)-data(i)|}{\frac{1}{2}|model(i)|+\frac{1}{2}|data(i)|}$. SMM searches repeatedly across sets of parameter values in the model until the model's moments are as close as possible to the data moments. In each time, I draw samples of equal size to samples from the 2001 to 2013 NBS balanced data, which contain 14,803 innovative firms.[26] The standard errors of the parameter estimates are from the diagonal elements in $\hat{V} = \hat{D}'\hat{W}\hat{D}$, where $\hat{D}'$ is a gradient matrix equal to $\frac{\partial G(\Omega)}{\partial \Omega}|_{\Omega=\hat{\Omega}}$, and $\hat{W}$ is the weighting matrix.

[25] The regression coefficients for the US range from 0.0559 to 0.0816, while those for China range from 0.0579 to 0.0869. I take the average of those values.

[26] I define the innovative firm as the firm which had at least one patent from 2001 to 2013, or had R&D investment during that period.

Table 3: Parameter Estimated Using SMM

Notation	Description	Value	Standard error
β	Elasticity of productivity gains to firm size	0.16	0.00
γ_l	Step size of productivity increment	0.64	0.01
χ	Constant in R&D costs	14.81	2.01
I_p	Share of firms with high R&D capacity	0.06	0.02
θ_h	High-type R&D capacity	1.01	0.52
θ_{gap}	Gap in R&D capacity between high-type and low-type firms	0.12	0.00
η	Constant in search costs	22.62	0.02
μ	Curvature in search costs regarding search efforts	2.25	0.00
F	Fixed transaction costs	0.12	0.00
s	Share of patents that buyers meet without knowing true type	0.42	0.01

Table 4 presents 11 targeted moments in the SMM. I choose these moments to reflect firms' aggregate and heterogeneous innovation patterns. These moments include: the ratio of R&D over sales; standard deviation of firms' R&D-to-sales ratios; large firms' R&D-to-sales ratio; average number of patents of large firms over that of small firms; share of firms as the buyer; standard deviation of buyer status; average number of purchased patents of large firms over that of small firms; fraction of traded patents; and the fraction of traded patents among high-quality patents relative to that among low-quality patents. The details for these moments are shown in Appendix D.

The targeted moments are informative of disciplining the three frictions introduced into the model. To illustrate this, I report the impact of friction-related parameters on the moments associated with the patent market in Appendix Figure G13. Panel (a) of Figure G13 shows that in the absence of fixed transaction costs and information asymmetry, an increase in search costs (η) results in a decline in the proportion of traded patents. However, this effect remains consistent across patents of varying quality levels, resulting in no change in the relative fraction of traded patents across different quality levels. In Panel (b), I incorporate fixed transaction costs into the patent market. As these fixed transaction costs rise, there is a notable decrease in the proportion of traded patents. Additionally, the proportion of traded patents among high-quality patents (relative to low-quality patents) increases, with low-quality patents experiencing more pronounced negative effects. In Panel (c), I incorporate information asymmetry on patent quality into the patent market. As information asymmetry increases, the overall proportion of traded patents remains relatively stable. However, higher information asymmetry on patent quality negatively impacts high-quality patents as it becomes more challenging to differentiate them from low-quality patents. The increased number of transactions in-

Table 4: Targeted Moments in Data and Model

Description	Data	Model
1. Ratio of R&D expenditure over sales	0.01	0.01
2. Standard deviation of firms' R&D-to-sales ratio	0.01	0.01
3. Large firm's R&D-to-sales ratio	0.01	0.01
4. 75% percentile of R&D-to-sales ratio	0.01	0.02
5. Avg number of patents of large firms over that of small firms	2.12	2.13
6. Fraction of traded patents	0.05	0.05
7. Share of firms as the buyer	0.03	0.02
8. Standard deviation of (buyer=1)	0.16	0.14
9. Avg num of patents purchased by large firms (rel. to small firms)	2.26	2.26
10. Avg num of patents purchased by upper 75% percentile firms (rel. to 50-75% percentile)	1.69	1.68
11. Fraction of traded patents among high-quality patents (rel. to low-quality patents)	1.08	1.07

volving low-quality patents compensates for the decreased transactions of high-quality patents, resulting in a decrease in the fraction of traded patents among high-quality patents relative to low-quality patents.

Panels (a)–(c) demonstrate the heterogeneous effects of the three types of frictions on the fraction of traded patents and the relative trading probability between high-quality and low-quality patents. Nevertheless, relying solely on these two moments is insufficient to differentiate between the three frictions (which involve three parameters), particularly fixed transaction costs and information frictions. To address this limitation, Panel (d) includes an additional moment: the average number of patents purchased by large firms compared to that of small firms. This moment is more sensitive to variations in fixed transaction costs (B) as opposed to information asymmetry (s).[27]

4.3 Estimation Results

Parameter Values. Table 3 presents the values of the parameters estimated using the SMM. The parameter values are estimated with small standard errors, indicating good precision. In the calibrated equilibrium, I find that search costs on average account for 10% of the patent value (evaluated by the sellers), whereas fixed transaction costs are 74% of the patent price, indicating that these two frictions are nontrivial in affecting the functioning of the Chinese patent market. My estimation also suggests that in China,

[27]In Table G3, I report the elasticity of the moments discussed in this paragraph to the parameters of the three types of frictions. This further verifies that search costs, fixed transaction costs, and information frictions have heterogeneous effects on the fraction of traded patents, the relative trading probability between high-quality and low-quality patents, and the average number of patents purchased by large firms compared to that of small firms.

Table 5: Nontargeted Moments

Description	Data	Model
1. Aggregate TFP growth	0.03	0.01
2. Sales growth rate for firms with patents (small over large firms)	2.20	2.83
3. Share of firms with R&D-to-sales ratio larger than 0.03	0.02	0.03
4. Share of firms as the seller (large over small firms)	2.12	1.30
5. Sell-invention ratio (large over small firms)	0.77	0.86
6. Share of purchased patents in total owned patents (large over small firms)	0.76	0.66
7. Average duration of a newly-filed patent to be sold	4.44	4.70
8. Standard deviation of duration	2.82	4.28

for 42% of patents faced by potential patent agents, their true quality cannot be verified, indicating considerable information barriers in China's technology markets.

Targeted Moments. Table 4 presents the comparison of the targeted moments between the model and the data. Overall, with the estimated parameter values, the model-generated moments match the data moments reasonably well.[28]

Nontargeted Moments. Table 5 reports that my calibrated model successfully captures various aspects of Chinese firms' sales growth and R&D patterns, which were not targeted in the SMM procedure. For example, the average time it takes for a patent to be sold in China is 4.44 years, whereas my model predicts a similar duration of 4.70 years. Additionally, in line with the data, my model predicts that larger firms are more likely to engage in in-house R&D rather than purchasing patents from the market, as indicated by the proportion of purchased patents among the total owned patents of large firms compared to small firms. These findings suggest that my model can effectively replicate the key characteristics of China's patent market.[29]

[28]The data shows that the ratio of R&D expenditure to sales is 0.012, with its 75th percentile being 0.013. For large firms, this ratio is 0.010. The model-generated values for these three moments are 0.012, 0.018, and 0.009 correspondingly. Therefore, the model-generated moments closely match the data-generated moments, even remaining accurate up to three decimal places.

[29]My calibrated model predicts a long-run productivity growth rate of 1.2%. As I focus on patents and abstract from other factors that affect productivity growth (e.g., SOE reform, reductions in migration barriers, trade liberalization), the model-predicted long-run productivity growth rate is thus lower than evidence on aggregate TFP growth in China, which is estimated to be 2.8% in Brandt et al. (2012) and 3.2% in Zhu (2012). In principle, my model can match the observed aggregate TFP growth by adding exogenous productivity growth that reflects other factors. As exogenous productivity growth does not affect my model predictions on the patent market, I thus abstract from this.

5 Quantitative Analysis

In this section, I perform four sets of counterfactual exercises. Firstly, to assess the impact of different frictions on the underdevelopment of the Chinese patent market, I analyze the effects of eliminating each of the three frictions from the market. However, it is possible that there are other frictions that may influence the patent market. Thus, in the second exercise, I expand the baseline model by incorporating additional factors and analyzing the robustness of my baseline results. These additional factors include patent quality, the issue of junk patents, lack of IPR protection, and the choice of labor share. Third, I study the impact of shifting the search mode from random search (baseline) to directed search, assessing how this transition could influence the patent market and analyzing its wider economic implications. Finally, I perform two policy experiments to understand how the government can improve the efficiency of the patent market.

5.1 Role of Each Type of Friction

To assess the impact of frictions on China's patent market and productivity growth, I will begin by eliminating three frictions. However, it is impractical to completely remove all the frictions in an underdeveloped market. Instead, aligning the level of frictions with that of a developed market, such as the US patent market, is a more feasible target. Thus, I estimate the level of frictions observed in the US and apply these frictions to the Chinese patent market. This analysis will help understand the factors for the underdevelopment of the Chinese patent market in comparison to a developed market.

5.1.1 Eliminations of Frictions in the Patent Market

In Table 6, I present the analysis of how frictions affect the Chinese patent market when they are removed. The table includes the results in the baseline equilibrium as well as several counterfactual scenarios. These scenarios involve the economy without each of the three highlighted frictions and the economy operating with no frictions in the patent market. However, before highlighting the significance of each type of friction, it is essential to establish the patent market's importance to the economy. Accordingly, I obtain the patent market's economic impact by comparing the economy with the patent market to the one without.

When the patent market is shut down in the model, the long-run productivity growth rate decreases to 1.09%,[30] indicating that the patent market accounts for 5% of the Chinese productivity growth attributed to patents.[31] The patent market improves productivity growth due to two reasons. Firstly, it serves as a platform to optimize the utilization of dormant patents. By facilitating the transfer of patent ownership from the inventor to a more suitable buyer, it enhances the allocative efficiency of patents. Secondly, the patent market may incentivize firms to engage in greater innovation. This is because it offers a platform for firms to sell their patents when the patent holds little value and thus raises the returns to R&D activities. As Table 6 shows, the magnitude of the second channel is quantitatively small. The average R&D intensity in the economy without the patent market merely decreases by 0.28% compared with that in the baseline economy, as similarly found in Akcigit et al. (2016). The slight decline is due to the offsetting effects of the patent market on innovation: the patent market encourages firms' innovation by increasing the patent's value as aforementioned; however, the patent market also offers firms a substitute for self-innovation through purchasing a patent from the market, which mitigates firms' R&D efforts.

Table 6: Counterfactual Exercises: Elimination of Frictions

	Aggregate TFP growth	Average R&D intensity	Average meeting rate for buyers	Share of high-quality patents in market	Share of traded patents	Welfare
(1) Baseline	1.15%	0.11	0.30%	45.59%	4.53%	100.00
(2) No patent market	1.09% (-4.98%)	0.11 (-0.28%)	0.00% (-100.00%)	-- (--)	0.00% (-100%)	99.43 (-0.57%)
(3) No search costs	1.65% (43.50%)	0.12 (5.05%)	3.19% (957.05%)	0.39 (-13.79%)	51.20% (1031%)	104.18 (4.18%)
(4) No fixed transaction costs	1.25% (8.98%)	0.12 (2.56%)	0.64% (113.19%)	0.39 (-15.19%)	15.62% (245.03%)	100.98 (0.98%)
(5) No information asymmetry	1.15% (0.13%)	0.11 (-0.11%)	0.31% (2.89%)	0.58 (26.61%)	4.55% (0.52%)	100.02 (0.02%)
(6) Frictionless patent market	1.65% (43.57%)	0.13 (10.86%)	3.16% (947.15%)	0.40 (-12.26%)	67.17% (1383.88%)	104.64 (4.64%)

Note: The bracket represents the percent change relative to the baseline scenario.

[30]See footnote 29 for the discussion on the level of productivity growth rates in the model.
[31]In Section 5.1.2, I estimate all these three friction parameters to target the moments in the US patent market. I find that the US patent market can explain 13% of its productivity growth.

I then separately remove each type of friction one at a time. By eliminating the search friction in the model, captured by setting the constant in search costs η to 0, the fraction of traded patents in China can reach 51.2%. This removal of search friction leads to a significant increase in the productivity growth rate by 43.5% and an overall welfare increase by 4.18%.

The impact of fixed transaction costs is more nuanced, as it operates through two contrasting forces. Firstly, the reduction in fixed transaction costs stimulates an increase in the number of patents available in the market and consequently raises the fraction of traded patents. However, on the other hand, this reduction in fixed transaction costs alters the quality composition of patents within the market. The influx of low-quality patents aggravates information barriers and diminishes the overall contribution of the patent market to the economy. In the aggregate, without fixed transaction costs in the patent market ($F = 0$), the fraction of traded patents increases to 16%, the productivity growth rate increases by 9%, and the welfare increases by 0.98%.

Finally, I remove information asymmetry on patent quality ($s = 0$), so the true quality of all patents becomes common knowledge. Thus, every high-quality patent can obtain a high price it deserves in every transaction. However, Table 6 shows that the effect of removing this friction is almost negligible. The productivity growth rate even decreases by 0.13%, and there is almost no welfare change. This is because while promoting the sale of high-quality patents, the reduction in information asymmetry simultaneously discourages the sale of low-quality patents due to their inability to be pooled with high-quality patents in the market.[32] Nonetheless, trading both low-quality and high-quality patents between firms can mitigate the mismatch between the patent and its inventor. Therefore, the opposite effects on high-quality and low-quality patents offset each other, leading to a negligible aggregate effect.

In the last row of Table 6, I remove all frictions in this market. In the economy with a frictionless patent market, the aggregate productivity growth rate increases by 44% (0.5 percentage points), and welfare increases by 4.6%. This result suggests a large potential for the patent market in promoting China's economic growth.[33]

[32] It is worth noting that the trading of patents must overcome fixed transaction costs, which disproportionately affect low-quality patents compared to high-quality ones. Consequently, when low-quality patents are sold individually in the market rather than being pooled with high-quality patents, their likelihood of being traded is lower.

[33] Given the large impact of search costs on the patent market size, Appendix E discusses the heterogeneous impact of varying search costs on two types of firms, namely high- and low-capacity firms.

5.1.2 Aligning Frictions with the Level of a Developed Country

The previous findings indicate that both search costs and fixed transaction costs play significant roles in hindering the development of the Chinese patent market. However, it may be overly optimistic to propose eliminating all frictions within the market, as certain frictions may serve a necessary purpose. Instead, a more practical approach would be to align the frictions in the Chinese patent market with those observed in a developed country, such as the US patent market. With this in mind, I first estimate the level of frictions present in the US patent market. Subsequently, I consider adjusting all frictions within the Chinese patent market to match the observed level in the US.

To estimate the magnitude of each friction in the US patent market, I first assemble a dataset using the US patent transaction data merged with the 2001–2013 panel data of listed firms. Then, holding all other parameters in Table 3 unchanged, I adjust the parameters related to patent market—costs of search η, fixed transaction costs F, and information friction on patent quality s—to target the data moments on the patent market from the US using the SMM.

According to the estimation results in Table 7, search costs and fixed transaction costs in the US are respectively 87% and 6% lower than their counterparts in China. The probability of a buyer not knowing the true patent type is 42 percentage points lower in the US than in China. By separately adjusting China's search costs, fixed transaction costs, and information asymmetry to the US levels, the fraction of traded patents in China can increase from 4.5% to 17%, 4.7%, and 4.55%, respectively. Hence, while the elimination of search costs and fixed transaction costs both have the potential to stimulate the growth of the Chinese patent market, search costs play a more prominent role in explaining the substantial disparity in the proportion of traded patents between China and the US, compared to other frictions. As demonstrated in Table 7, reducing search costs to the US levels can also lead to greater welfare improvements compared to changing fixed transaction costs and information asymmetry to the US levels.

5.2 Additional Factors Influencing the Impact of Existing Frictions

In this subsection, I expand the baseline model by incorporating additional factors that may affect the patent market and analyzing the robustness of my baseline results in these model extensions.

Table 7: Matching the Moments in the US Patent Market

Panel A: Parameter Values			
Notation	Description	Value	Standard error
η	Costs of search	2.84	0.01
F	Fixed transaction cost	0.11	0.00
s	Information asymmetry on patent quality	0.01	0.01

Panel B: Targeted Moments Regarding the Patent Market		
Description	Data	Model
Fraction of traded patents	0.15	0.17
Average number of patents purchased by large firms (rel. to small firms)	3.50	3.66
Fraction of traded patents among high-quality patents (rel. to low-quality patents)	1.37	1.23

Panel C: Changing China's Frictions to the US Level		
Scenario	Share of traded patents	Welfare
(1) Baseline	4.5%	100
(2) Changing China's search costs to the US level	17.0%	101.37
(3) Changing China's fixed transaction costs to the US level	4.7%	100.09
(4) Changing China's share of patents not revealing true type to the US level	4.5%	100.02
(5) Changing all frictions to the US level	18.4%	101.46

5.2.1 Patent Quality

One alternative explanation for the underdevelopment of the Chinese patent market is the low quality of Chinese patents (Liang, 2012; Prud'homme and Zhang, 2017). In recent years, China has made great progress in technological levels, and Chinese researchers have become preeminent contributors to the scientific enterprise. Although the importance of Chinese research is still discounted (Xie and Freeman, 2020; Qiu et al., 2021), the citations of publications from Chinese researchers have been growing rapidly. These pieces of evidence suggest the increase in China's patent quality in recent years. However, Figure 1 shows that the gap in the patent market size between China and the US has remained persistently large over time, indicating that patent quality cannot fully explain the underdevelopment of the Chinese patent market. Nevertheless, I will now use my model to quantitatively understand the impact of lower patent quality.

In light of different possible reasons for low patent quality in China, I perform two robustness checks. First, I consider that the average level of patent quality is worse in China than in the US, thus lowering the gains from trading the patents in China. Second, I consider that a large portion of China's patents may be junk patents and useless in both production and patent transactions.

The Average Level of Patent Quality. To measure patent quality and evaluate the extent of China's low-quality patents, it is necessary to establish a benchmark. Therefore, I utilize US patents as the benchmark for comparison. To estimate the patent quality gap between China and the US, I employ three estimation methods: comparing the forward citation number of dual-listed patents, utilizing disparities in stock market returns of patents, and assuming a significant gap between the two countries.

The conventional method of measuring patent quality relies on the patent's forward citation number (Hall et al., 2001). However, comparing patent quality between the US and China directly based on citations is challenging because institutional factors may generate country-specific citation patterns that do not directly reflect quality. To address this, I leverage dual-listed patents, which are registered with both the Chinese and US patent offices, as a means to control for country-specific factors. To be specific, by using Chinese dual-listed patents as a bridge, I first compare the citation counts of Chinese patents registered in the US with those of patents registered in the US. Secondly, I compare the citation counts of Chinese patents registered in the US with those of Chinese patents registered in China. Lastly, I use the results from the previous two steps to adjust the citation counts received by Chinese patents registered in China, enabling me to obtain a relative quality index compared to US patents registered in the US. The same rationale applies when utilizing US dual-listed patents as a bridge. The results show that the quality of US patents is 10.2% higher than that of Chinese patents. For a more detailed explanation of the estimation process, please refer to the Appendix F.

In addition to the citation-based measurement of the patent quality gap, a market value-based measure is proposed by Kogan et al. (2017) by analyzing stock market reactions to patent-related news. This method is utilized by Yang and Wu (2020) to estimate the market value-based quality of Chinese patents using data from Chinese listed firms from 1992 to 2020. The average estimated value of US patents, measured by the anticipated stock market return relative to the firm's market capitalization, is 0.32 (Kogan et al., 2017). On the other hand, the average estimated value for Chinese patents is 0.27 (Yang and Wu, 2020). Thus, the market value-based quality of US patents is found to be 18.5% higher than that of Chinese patents.

Based on these two estimates of the patent quality gap between China and the US, I increase the value of Chinese patent quality parameters (both γ_h and γ_l) in the model by 10.2% and 18.5% respectively, as shown in Rows (2) and (3) of Table 8. I also consider a scenario where the quality of US patents is assumed to be 50% higher than that of Chinese patents, as indicated in Row (4) of Table 8. When comparing to the baseline counterfactual (Row (1)), which only removes the three types of frictions in the Chinese patent market, the share of traded patents only experiences a slight increase to 67.5%, even when both the frictions are eliminated and the quality of Chinese patents is enhanced by 50%. Among the factors contributing to the expansion of the patent market, search costs still have the largest contribution at approximately 78%. In comparison, the contribution of increased patent quality is limited, accounting for less than 3%. This is because the increment in patent quality, on the one hand, stimulates the incentives of retaining patents for the inventor's own use, and on the other hand, enhances the gains of acquiring patents in the patent market. These two effects largely offset each other.

Table 8: Counterfactual Exercises: Patent Quality

	Share of traded patents	Contribution of search costs	Contribution of fixed transaction costs	Contribution of information asymmetry	Contribution of quality increment	Aggregate TFP growth	Welfare
Panel A. Baseline counterfactual							
(1) Baseline (remove all three types frictions)	67.17%	78.19%	21.81%	0.00%	–	1.65%	104.64
Panel B. Patent quality increment							
(2) Quality gap estimated by dual-listed patents (quality increase by 10.2%)	67.02%	78.61%	21.06%	-0.07%	0.40%	1.88%	106.65
(3) Quality gap estimated by stock return (quality increase by 18.5%)	67.05%	78.72%	20.36%	-0.08%	1.00%	2.08%	108.30
(4) A assumed large quality gap (quality increase by 50%)	67.50%	78.25%	18.93%	0.06%	2.76%	2.86%	114.22
Panel C. Problem of junk patent							
(5) Junk patent share=10% (junk patent share decrease to 0%)	68.03%	81.37%	15.58%	-0.32%	3.36%	3.83%	117.07
(6) Junk patent share=13% (junk patent share decrease to 0%)	77.34%	78.68%	18.96%	-0.01%	2.37%	5.70%	126.17

Note: The "contribution" columns in the table show the specific factor's contribution to the overall increment of the share of traded patents in each respective counterfactual exercise.

Problem of Junk Patents. Another issue about China's patent quality is the presence of junk patents that hold zero value in the patent market. To study this quantitatively, I introduce junk patents into the benchmark model (a portion of invented patents are junk patents), and junk patents have a quality level (γ) of 0. In contrast to the US, firms in China are incentivized to produce junk patents due to the rewards associated with patent grants. As a result, I assume that there are no junk patents in the US.

I calibrate the proportion of Chinese patents that are junk patents in two ways. Firstly, I use the relative proportion of patents that receive no citations within five years of being filed in China, compared to the US, to indicate the share of patents lacking any value in China. For patents filed and granted by domestic firms between 1998 and 2013, 31% of patents filed in the US received zero citations, whereas 41% received zero citations in China. This indicates that 10% of patents in China hold no value to be learned by others and are defined as junk patents. In the second approach, I use the renewal rate as another measure of patent quality. In the US, 100% of patents granted to inventing firms were renewed within three years from the grant date. In contrast, only 87% of patents granted to inventing firms in China were renewed within the same timeframe, a rate 13% lower than that in the US.

In Panel C of Table 8, I first introduce junk patents with patent quality $\gamma = 0$, where the share of junk patents is either 10% in Row (5) or 13% in Row (6). I then re-estimate all the parameters in the baseline model to match the moments displayed in Table 4. Secondly, I perform a counterfactual analysis on the Chinese patent market in which I remove all three types of frictions while simultaneously reducing the share of junk patents from 10% or 13% to zero. Rows (5) and (6) in the table reveal that the share of traded patents can increase at most to 77%, which is 10 percentage points higher than that in the baseline counterfactual scenario where there are no junk patents and I eliminate all three types of frictions in the Chinese patent market. The primary factor driving the expansion of the patent market remains the contribution of search costs.

5.2.2 Patent Infringement

Apart from the patent quality problem, a high rate of infringement could be another factor contributing to the small patent market in China. The China Patent Survey conducted by the Chinese patent office indicates that the infringement rate for Chinese firms was 36% in 2010 and decreased to 19% in 2013.[34] The study by Zhang (2022) focuses on the analysis of 377 litigated patents and estimates that the patent infringement hazard in China is 40%. This finding aligns with the research by Molnar and Xu (2019), which states that larger firms (with more than 1000 employees) are more likely to face infringement issues, with an infringement rate of around 40% in both modern and traditional manufacturing sectors, compared to 19% for small firms.

Owing to the high infringement rate reported in previous surveys and literature in

[34]The data is from China Patent Survey Report 2015, which can be accessed in https://www.cnipa.gov.cn/art/2016/7/1/art_88_40230.html.

China, I incorporate a patent infringement probability into the baseline model. Specifically, whenever potential buyers and patent agents meet, there is a probability ψ that potential buyers can successfully and surreptitiously steal the patent without purchasing it. I calibrate ψ based on the infringement rates estimated by the prior research, testing values of 19%, 36%, and 40%. Under each value, I then re-estimate all parameters listed in Table 3 to correspond with the data moments presented in Table 4. Lastly, I perform counterfactual analyses in which I eliminate all three types of frictions in the Chinese patent market while simultaneously reducing the infringement probability ψ from 19%, 36%, and 40% to zero, respectively.

Table 9: Counterfactual Exercises: Patent Infringement

	Share of traded patents	Contribution of search costs	Contribution of fixed transaction costs	Contribution of information asymmetry	Contribution of zero infringement	Aggregate TFP growth	Welfare
(1) Baseline counterfactual	67.17%	78.19%	21.81%	0.00%	–	1.65%	104.64
(2) Infringement rate = 19%	80.77%	79.19%	8.33%	0.02%	12.45%	3.05%	112.24
(3) Infringement rate = 36%	80.07%	73.65%	8.19%	-0.03%	18.19%	2.53%	110.51
(4) Infringement rate = 40%	79.71%	73.91%	6.92%	-0.02%	19.18%	2.71%	111.53

Note: Row (1) presents the counterfactual exercise where, in the baseline model without patent infringement, all three types of frictions are removed. The columns remain the same as those in Table 8. Rows (2) to (4) extend the baseline model by introducing patent infringement rates of 19%, 36%, and 40% respectively. I then re-estimate all parameters listed in Table 3 to align with the data moments provided in Table 4. Row (2) illustrates the counterfactual scenario where, in an economy with a 19% patent infringement rate, I eliminate all three types of frictions as well as the patent infringement itself. Similarly, Rows (3) and (4) depict the conditions under patent infringement rates of 36% and 40% respectively.

Table 9 reports the results. It shows that in a patent market where patent infringement is a possibility, eliminating all three types of frictions along with patent infringement can increase the share of traded patents from 4.5% to approximately 80%. This is a 13-percentage-point improvement compared to the counterfactual exercises where only the three types of frictions were eliminated based on the baseline model. Proper intellectual property protection that guarantees zero patent infringement can play a significant role in expanding the size of the patent market, as shown in Table 9 where the contribution of zero infringement ranges from 12.45% to 19.18%. However, the impact of patent infringement on the share of traded patents occurs through complex channels. On one hand, a higher infringement rate reduces the expected benefits for innovators in the patent market, leading to a higher inclination for innovators to retain their patents rather than trading them. This decreases the share of traded patents. On the other hand, a higher probability of acquiring technology without cost during a meeting can increase the expected value of search for potential buyers in the patent market, resulting in an overall increase in the meeting rate. However, as indicated by the results in Table 9, the former channel outweighs the latter. Nevertheless, search costs still make the largest contribution, accounting for 74% to 79% of the increase in the patent market size.

5.2.3 Additional Robustness Checks

Apart from considering low patent quality and patent infringement, I conduct two additional robustness checks in this subsection.

Firstly, in the baseline model, I calibrate $1 - \alpha = 0.5$ according to labor share. As my model does not consider capital, this value implies that the share of payments for intangible assets in total production costs is 0.5, higher than the value used in the literature (e.g., Holmes et al., 2015). As a robustness check, I calibrate $1 - \alpha$ to labor share plus capital share (equivalent to treating labor as equipped labor), which implies that $1 - \alpha = 0.85$ (Akcigit et al., 2016). I then re-estimate the baseline model. Table 10 indicates that when calibrating α to 0.15, eliminating three types of frictions would increase the share of traded patents from 4.5% to 67.5%, which closely aligns with the baseline results. Additionally, the relative contributions of the three types of frictions to the larger market size remain almost unchanged.

Secondly, in the previous subsection, I have already introduced the patent infringement rate as a means to address concerns about the small market size in China being linked to poor IPR protection. However, the patent infringement rate, as a proxy for IPR protection, may not fully capture the level of IPR protection. Therefore, to further investigate this issue, I also examine the fraction of traded patents among dual-listed patents. Theoretically, these dual-listed patents are protected in both China and the US. Among the dual-listed patents applied for and granted between 1998 and 2013, I find that 3.5% of Chinese-invented dual-listed patents were sold to other domestic firms in the Chinese patent market during this period. In comparison, 13.9% of US-invented dual-listed patents were sold to other domestic firms in the US patent market during the same period. This 10.4-percentage-point gap aligns with the 10.1-percentage-point gap in patent market size between China and the US, as observed in the descriptive facts. This additional piece of evidence also suggests that poor IPR protection cannot fully explain the gap in the patent market size between China and the US.

Table 10: Counterfactual Exercise: the Change of Labor Share

	Share of traded patents	Contribution of search costs	Contribution of fixed transaction costs	Contribution of information asymmetry	Aggregate TFP growth	Welfare
(1) Baseline counterfactual	67.17%	78.19%	21.81%	0.00%	1.65%	104.64
(2) $\alpha = 0.15$	67.53%	78.09%	22.25%	-0.35%	3.40%	103.18

5.3 Directed Search

The baseline model is a random search model, where the patent and the potential buyer meet randomly. I now consider an alternative scenario where the potential buyer can always meet with the patent it needs most, indicating the patent-buyer similarity always equals 1. In Table 11, I compare the following situations with the baseline model: directed search with China's search costs, random search with US-level search costs, and directed search with US-level search costs. I find that changing random search to directed search largely increases productivity growth, as patent buyers can now obtain the most suitable patents. If these two adjustments of search costs (from China's level to the US level) and the search mode (from random to directed search) happen simultaneously, the welfare can increase by 4.7%, and the productivity growth rate will increase by 49% (0.56 percentage points).

Table 11: Counterfactual Exercises: Search Mode and Search Costs

	Aggregate TFP growth	Average R&D intensity	Average meeting rate for buyers	Share of high-quality patents in market	Share of traded patents	Welfare
Baseline model	1.15%	0.113	0.30%	45.59%	4.53%	100.00
Directed search China-level search costs	1.40% (21.64%)	0.116 (2.11%)	0.56% (85.86%)	39.59% (-13.16%)	19.78% (336.88%)	102.25 (2.25%)
Random search US-level search costs	1.31% (13.93%)	0.11 (1.27%)	1.11% (267.04%)	40.72% (-10.69%)	18.40% (306.56%)	101.46 (1.46%)
Directed search US-level search costs	1.71% (48.8%)	0.12 (6.25%)	1.00% (230.75%)	41.72% (-8.5%)	49.81% (1000.36%)	104.72 (4.72%)

Note: The bracket represents the percent change relative to the baseline scenario.

5.4 Policy Experiment

I perform two policy experiments to understand how the government can improve the efficiency of the patent market. First, I consider the size-independent R&D subsidy financed by a lump-sum tax paid by firms. A higher R&D subsidy would lead to a higher growth rate because of more innovation, but may also trigger lower consumption in every period because of more innovation costs. As shown in the left-hand panel of Figure 8, compared with the baseline model, with a 60% R&D subsidy, the productivity growth rate will increase by 0.4 percentage points, and the welfare will increase by 1.5%. However, R&D subsidy has a slightly negative impact on the fraction of traded patents, as it leads to an increase in the supply of patents in the patent market.

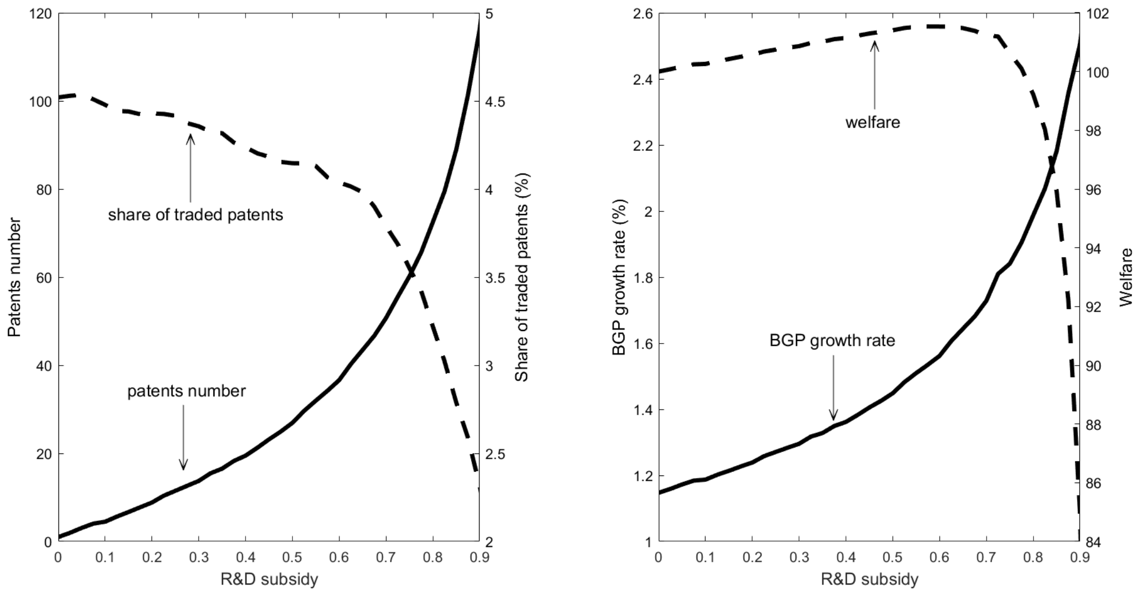

Figure 8: R&D Subsidy

Another policy instrument is subsidizing the firms that search in the patent market. The search subsidy will decrease search costs and increase firms' search intensity in the patent market. As the possibility of successfully selling the patent increases in the patent market, this will also incentivate in-house innovation. Therefore, firms will devote more resources to innovation. As shown in Figure 9, the optimal subsidy rate of search costs is 0.9, which means the government covers 90% of the search costs of firms. This leads to a 0.9% increase in welfare and a 0.17-percentage-point increase in the productivity growth rate, compared with the baseline results. Under the optimal subsidies to search costs, the fraction of traded patents will increase from 4.5% to 20%.

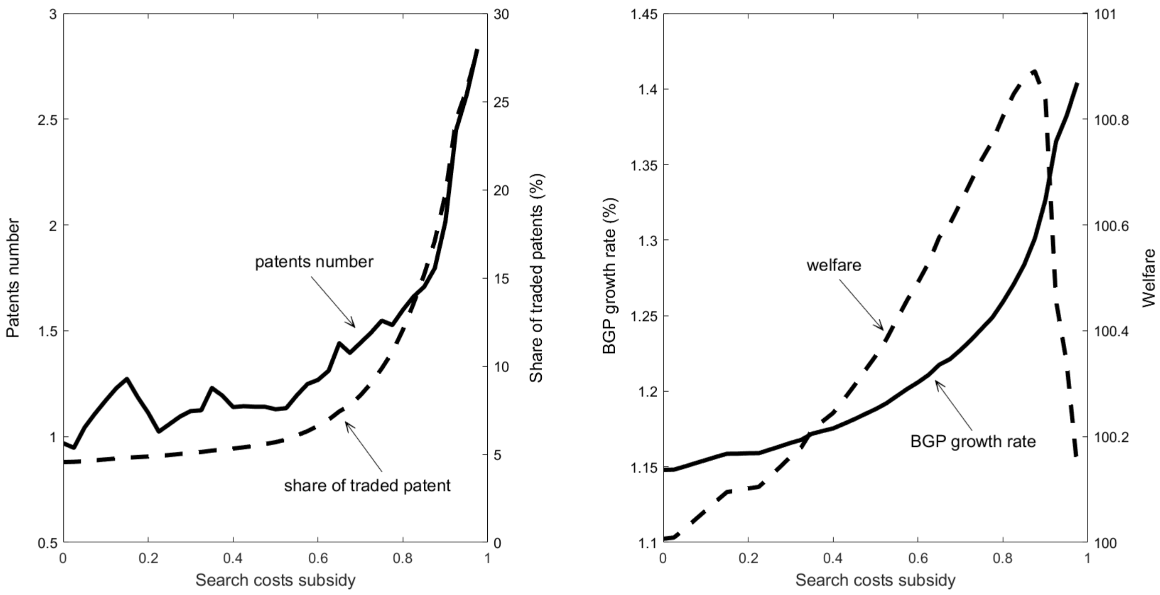

Figure 9: Subsidies to Search Costs

6 Conclusion

This paper studies the frictions prevailing in the Chinese patent market. Using information on all Chinese patent transactions, I document that in China, only 4.5% of domestic patents were traded, whereas in the US, this share was 14.6%. I also document that the gap in the fraction of traded patents between the US and China was much larger among high-quality patents than among low-quality patents. To understand these facts and perform a quantitative analysis, I develop an endogenous growth model featuring firms' patent production and transactions. I model three types of frictions in the patent market—search costs, fixed transaction costs, and information asymmetry on patent quality. By targeting relevant data moments using the SMM, I estimate the magnitude of these three frictions in the Chinese patent market as well as in the US patent market. My findings indicate that both reductions in search costs and fixed transaction costs can contribute to the expansion of the patent market in China. However, the primary factor causing the significant disparity in the size of the patent market between China and the US is the high search costs within the Chinese patent market.

There are many promising avenues for future research. For instance, this paper manifests that the search friction is the primary factor that impedes patent transactions in China. By obtaining additional data on meetings between patent buyers and sellers, we can gain insights into the underlying factors causing search frictions, ultimately enhancing our understanding of policy tools that can effectively reduce search frictions.

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A Data Details

A.1 Chinese Patent Transaction Data

Structure of Patent Transaction Data Within the CNIPA database, each filed patent contains detailed information on reassignments, including the date of patent right transfer and the names of buyers (assignors) and sellers (assignees). To facilitate research, I have constructed a patent-assignor-assignee-transaction date panel using the original data. This panel contains 284,639 observations, where each observation in this panel represents a specific patent transaction between a particular assignor and assignee.

Patent Assignor's and Assignee's Type The original CNIPA patent transaction database lacks crucial information on the types of buyers (assignees) and sellers (assignors) in patent trading. To identify this information, I utilized extra data, including the CNIPA patent basic information database, which records the type of all patent applicants, namely firms (C), individuals (P), government (G), research institutions (R), university (U), and others (N). By merging this data with the buyers and sellers in the patent transaction dataset, I was able to identify the types of buyers and sellers who had previously been patent applicants. Additionally, I used the Chinese Firm Registration Database (SAIC), which contains information on all firms registered in China before 2016, to identify all Chinese firms. For the rest of unidentifiable assignors and assignees, I used linguistic information. Based on the book of family names in China, I define assignors (assignees) with two to three characters beginning with a common Chinese family name as individuals. Furthermore, the Chinese name of a Japanese firm contains the phrase "株式会" (Zhūshìhuì), meaning "corporate" in Japanese. Using this feature, I could easily identify Japanese firms. Figure A1 below displays the type structure on both the assignor and assignee side.

Shareholding Relationships In the case of a large corporate group, different subsidiaries may have different functions; some may focus on research and development while others may primarily engage in production. Subsidiaries may produce distinctive goods, but complementary technologies are used in their production. In such scenarios, technology may be transferred or allocated within the corporate group. However, this behavior is not covered in this paper. I utilize two steps to exclude such transactions.

Table A1: Types of Assignor and Assignee in Patent Transactions

	Assignor		Assignee	
	Num	Share	Num	Share
Firm	214,115	75.22%	274,034	96.27%
Individual	53,876	18.93%	7,858	2.76%
University & research institute	14,168	4.98%	1,668	0.59%
Government	687	0.24%	290	0.10%
Others	1,793	0.63%	789	0.28%
Total	284,639	100%	284,639	100%

Note: The column labeled "num" in the dataset indicates the count of assignor-assignee-patent transactions in which the assignor or assignee belongs to a specific type1. This column provides valuable information about the frequency of transactions involving specific types of assignors or assignees.

Firstly, the SAIC database contains the shareholder information of Chinese registered firms in 2016.[35] This allows me to easily identify the shareholding relationships between the assignor and assignee in each transaction record. According to the definition mentioned earlier, if firm A is a shareholder of firm B, or if firm B is a shareholder of firm A, or if both A and B are subsidiaries of firm C, then the patent transaction between firm A and B is not included in my sample.

Secondly, the first step may not uncover certain relationships between two firms due to factors such as name changes, name mismatches, or changes in shareholding after registration.[36] To address this limitation, I standardize firms' name and employ text analysis techniques to assess the similarity between the names of the assignor and assignee.[37] I exclude transactions where the assignee and assignor's names are highly similar, as these are likely to be transactions between related firms.

A.2 The US Patent Transaction Data

Structure of Patent Transaction Data The primary difference between the US and Chinese patent transaction databases lies in the structure of the original data. As previously mentioned, in the Chinese dataset, the record is based on the patent level, whereas the

[35]SAIC includes all firms that existed and were registered in China before 2016.

[36]For example, in SAIC database, there is no relationship between 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)) when they established, but the latter began to be an investor in the former in 2012.

[37]The standardization of firms' names involves removing province/city names and normalizing the names of limited liability companies, firms, factories, etc. To assess the similarity between firms' names, I utilize the Levenshtein distance and the Jaro–Winkler distance.

US reassignment database is independent of the USPTO registered patent data and is based on every transaction event. The original US reassignment dataset contains records of 17,930,924 patent transactions that occurred prior to 2018. Marco et al. (2015) provides a comprehensive introduction to the US patent reassignment database, which includes various conveyance types such as assignment, employer assignment, change of name, security agreement, and more.[38] To meet the requirements of this paper, I only consider transactions where the conveyance type is assignment. Moreover, similar to the Chinese data, I only include transactions where the transacted patents were applied for and granted between 1998 and 2013, and the transaction year falls within this period.

Patent Assignor's and Assignee's Type Similar to the Chinese patent transaction dataset, the US reassignment database also lacks information on the assignee's and assignor's type. To determine their type, I first utilize the NBER patent applicant's type identification method.[39] Additionally, I merge the US reassignment database with the Patentview database, which contains the applicant's type for all patents registered in the USPTO.[40] Furthermore, the location information of the assignee can be used to identify their nationality.

A.3 Rule for Name Matching

In this paper, I combine the CNIPA patent basic information and transaction dataset with the NBS database to analyze the Chinese data. To ensure accurate name matching, I implement a name matching method that involves standardizing firms' names. The specific steps for standardization are as follows:[41]

- Step 1: I standardize the firm's name by making the following adjustments: (1)

[38]The conveyances are classified into 7 types: assignment, employer assignment, change of name, security agreement, government interest agreement, merger, release, and correction. The specific definitions of these types can be found in Marco et al. (2015). Only the assignment type of conveyance is associated with firm-to-firm patent transfer and not correlated with M&A, which is essential for the purpose of this paper.

[39]The code for this method can be found at this link: `https://sites.google.com/site/patentdataproject/Home/posts/namestandardizationroutinesuploaded`.

[40]In the Patentview database, applicants are categorized into six types: US Company or Corporation, Foreign Company or Corporation, US Government, Foreign Government, US Individual, and Foreign Individual.

[41]I would like to express my gratitude to Doctor Xin Wang from CUHK for generously sharing his name matching code with me. I have adopted and learned most of the name adjustment and standardization methods from him.

I replace "gu fen you xian gong zi" and "you xian ze ren gong si" with "you xian gong si" in the firm's name; (2) I replace "chang you xian gong si" and "chang qi ye" with "chang" in the firm's name; (3) I remove terms such as "dai qing li," "ge zhuan qi," "si ying zhuan he huo," and so on from the firm's name.

- Step 2: I convert all uppercase letters to lowercase and transform full-width characters into half-width characters.

- Step 3: I remove various special symbols from the data, such as, "*",">","《》", etc.

For the US data, I merge the Patentview database, which contains basic information on US patents, with the USPTO patent reassignment data. The name matching method used is similar to the one described above, following the name standardization rule provided by the NBER patent database.[42]

A.4 Technology Field

In this paper, I mainly use IPC technology field classification, which was established by the Strasbourg Agreement in 1971, and offers a hierarchical system of language-independent symbols for patent and utility model classification based on their respective areas of technology. Up to now, the IPC classification has undergone eight versions of revisions. This paper primarily utilizes 3-digit level IPC codes, and significant changes have not occurred at this level from version 1 to 8.

The IPC code in the CNIPA is original, which is published in a patent publication document. Thus, for the patents in the CNIPA database, their IPC codes may come from different IPC versions. However, in this paper, I do not make any concordance when I use IPC classification because in the 3-digit level IPC code, there exists no large changes from version 1 to 8. The following shows the changed classes from version 1 to 8:[43]

- IPC1→IPC2: A01,A21-A24(d); B44 (r); C25 (+); E21(+).

- IPC2→IPC3: B09(+); B26(r); C02(r); C12(r); C30(+); E21(r); F16(r); G09(+).

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

[43] In items below,(d) means this class is re-divided and a 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 the new version.

- 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.

B Patent Market Patterns

B.1 Background: Basic Statistics of Chinese Technology Market

Detailed official data on Chinese patent transactions is scarce. One of the few sources that provides aggregate-level descriptions and statistics for the Chinese technology market is the Annual Reports on Statistics of China Technology Market from 2003 to 2019. These reports can assist us in acquiring a more comprehensive understanding of technology trading in China at the aggregate level. However, it is important to note that the technology market encompasses a broader definition that includes technology services, development, consulting, and transfer. Patent transactions, specifically, represent a subset of technology transfer activities.

The Following figures provide data on the share of four types of technology contract amounts and the participation of four types of technology market players in China. The data used in these figures is just sourced from Annual Reports on Statistics of China technology market spanning from 2003 to 2019. As previously mentioned, the technology market encompasses technology services, development, consulting, and transfer contracts. Figure B1 demonstrates that technology service contracts constitute the largest share, while technology transfer contracts accounted for 10%-20% of the Chinese technology market from 2002 to 2018. Figure B2 displays the participant structures from the perspective of buyers and sellers. It reveals that firms are the dominant players in the patent market, representing approximately 80% of both buyers and sellers in most years.

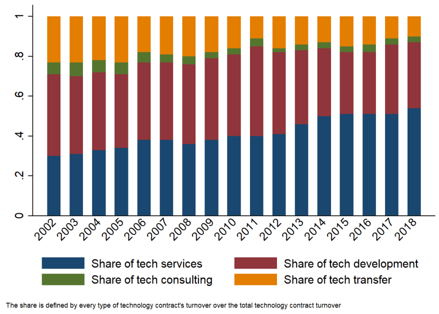


Figure B1: Shares of the Four Types of Technology Contract Amount

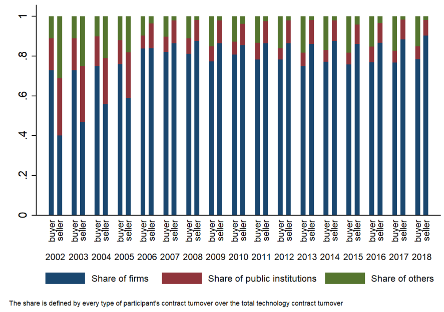


Figure B2: Shares of the Three Types of Technology Market Participants

B.2 Patent-firm Similarity

B.2.1 Constructing Distribution of Patent-firm Similarity

In line with Akcigit et al. (2016), I construct the measurement of the patent-firm similarity in two steps. First, I define the distance between technology fields as below:

$$D(X, Y) = 1 - \frac{Num(X \cap Y)}{Num(X \cup Y)} \tag{35}$$

where $D(X, Y)$ is the distance between technology fields X and Y;[44] $Num(X \cap Y)$ is the number of patents that cite the patent in technology fields X and Y simultaneously; and $Num(X \cup Y)$ is the number of patents that cite the patent in technology field X and/or Y.[45] Second, based on the distance between technology fields, I then calculate the $d(p, f)$, the patent-firm-specific distance between patent p and firm f. In equation

[44]Here, I use the 3-digit IPC code to define the technology field that the patent belongs to.

[45]In an extreme case where all the patents that cite the patent in technology field X will cite the patent in technology field Y as well, and vice versa, the distance between technology fields X and Y is zero.

(36), $\mathcal{P}_f$ represents the patent package of firm f, and $D(X_p, Y_{p'})$ indicates the distance between patent p's field and patent p''s field.[46] Both of patent p and patent p' are in $\mathcal{P}_f$. On the basis of the distance, $1 - d(p, f)$ indicates the similarity between patent p and firm f.

$$d(p, f) = \left[\frac{1}{||\mathcal{P}_f||} \sum_{p' \in \mathcal{P}_f} D(X_p, Y_{p'})^{\iota} \right]^{\frac{1}{\iota}}, \quad \iota = \frac{2}{3} \tag{36}$$

Obviously, this definition will cause the new-born patent, whose inventing firm locates on diversified technology fields, to have a lower patent-firm similarity. And diversified firms are found to be prevalent in emerging market economies like China, for reasons such as government expropriation (Du et al., 2015). To deal with this concern, to begin with, I count the technology field concentration of Chinese and US firms through the lens of the number of technology fields that the firm's patents locate on. It is the firm's knowledge scope. In the US, the average firms' knowledge scope is 1.75, which is close to 1.66 in China.[47] Then, I calculate the distribution of the patent-firm similarity for each knowledge scope in the US and obtain a weighted-average distribution across knowledge scopes based on the distribution of Chinese firms' knowledge scopes. The comparison of unweighted distributions is illustrated in panel Figure B3 (a). As the US firms' average knowledge scope is slightly larger, the difference in the weighted distribution of the patent–firm similarity between these two countries is much smaller.

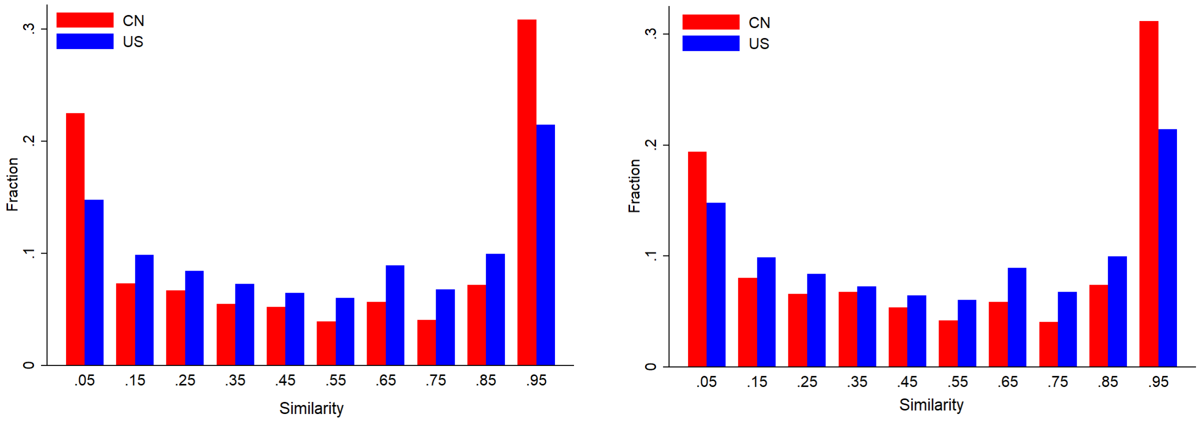
B.2.2 Additional Results

The purpose of the patent market is to reconcile the mismatch between the patent and its initial inventor. Figure B3 (a) depicts the distribution of similarity between patents and their initial inventors, as calculated by the raw data from China and the US. However, differences in the similarity distribution between China and the US could be influenced by the disparity in the IPC distance matrix $D(X, Y)$ between the two countries, as per the definition of patent-firm similarity presented in Equation (36). To

[46] Citation practices vary depending on the country, for example, citation is voluntary in China, but it is mandatory in the US. Thus, apart from the knowledge scope difference, the technology field distance matrix $D(X, Y)$ will also differ in the US and China. The Pearson correlation coefficient of $D(X, Y)$ between the US and China is 0.68. To ensure comparability of the similarity distribution, I use $D_{US}(X, Y)$ in both countries to calculate the patent-firm distance and similarity. I also use the Chinese distance matrix to calculate the patent-firm distance in both countries, with a result that is nearly similar to that shown in Figure B3 (b) in Appendix B.2.2.

[47] Here I consider the firms that had invented patents from 1998 to 2013. The 99% percentile of knowledge scope is 11 in the US, which is 9 in China, respectively.

address this, Figure (b) below compares the patent-inventor similarity distribution between China and the US, where the Chinese IPC distance matrix $D(X, Y)$ is replaced with that of the US during the calculation of Chinese patent-inventor similarity. Notably, there is minimal disparity observed between sub-figure (a) and (b) in Figure B3, indicating that using a different distance matrix has a negligible impact on the results.



(a) No Adjustment (b) Adjusted by the US Matrix

Figure B3: Empirical Patent-inventor Similarity Distribution

Note: (1) Samples of patents are patents filed and granted from 1998 to 2013. (2) Given that every firm's first patent's similarity with the firm is absolutely zero, I drop observations of patents which are the firms' first patent applications.

B.3 Benefits from Patents, Characteristics of Traded Patents, and Purchasers

The study by Akcigit et al. (2016) uncovers a mismatch between patents and the firms that invent them in the US. In response, the patent market aims to allocate these mismatched patents to more suitable firms, ultimately increasing the market value for patent buyers. This raises three key questions when considering the Chinese patent market. Firstly, it examines how firms can benefit from patents that exhibit higher similarities, thereby incentivizing their participation in the patent market. Secondly, it explores which patents are more likely to be sold by their inventors. Lastly, it delves into the characteristics of patent buyers in the Chinese patent market.

Benefits from Patents To address the first question, a regression analysis similar to the approach used by Akcigit et al. (2016) is conducted. This analysis examines the relationship between a firm's revenue and its patent stock, considering both quality and similarity. Firm and industry-year fixed effects are included in the analysis. The basic results of this analysis are presented in Table B1. In this analysis, the firm's revenue is measured using the logarithm of sales or value-added. The firm's patent stock is evaluated by adjusting the logarithm of the accumulated number of patents based on similarity and quality.[48] Columns (1) to (3) gradually introduce controls for the firm's labor, capital, and age.[49] These controls are based on NBS firm-level data from 2001 to 2013. In column (2), capital is included to account for the complementarity between a firm's capital and the technology it utilizes. This inclusion reduces the coefficient of the accumulated patents adjusted for similarity and quality. To provide a robustness check, column (4) utilizes value-added as a proxy for firms' revenue.[50] To address the issue of firm entry and exit, column (5) restricts the samples to a balanced NBS firm-level panel from 2001 to 2013. In columns (7) and (8), the samples are further restricted to innovative firms that had invented patents or R&D investment from 2001 to 2013 (Inn=1), and to patenting firms that must have invented patents during the sample period (Pat=1). The results indicate that an increase in patent stock, particularly patents with higher quality and similarity, is associated with higher firm revenue. Additionally, the impact of similarity, which measures the level of matching between patents and firms, is more or less equal in importance to patent quality in influencing firm revenue.

Is there a difference in the utilization efficiency of patents between small and large firms? It is possible that larger firms, with their larger market share and greater advertising experience or expenditures, are better positioned to leverage new patents to

[48]Firstly, the accumulated number of patents adjusted by similarity (Lnpat_sim_adj), denoted as $\sum_{p \in P_f} Similarity_{pf}$, represents the sum of similarities between firm f and each patent p in the firm's patent portfolio P_f. Similarly, the accumulated number of patents adjusted by quality (Lnpat_quality_adj), denoted as $\sum_{p \in P_f} Quality_p$, represents the sum of individual patent qualities $Quality_p$ in the firm's patent portfolio. Here, p refers to a specific patent belonging to firm f, and P_f represents the collection of patents owned by firm f. Secondly, since the patent data is merged with NBS firm-level data, the calculation of the accumulated patent numbers begins from the year 2001. In other words, the accumulated patent number for a given year t is the total count of patents invented by the firm from 2001 up to year t.

[49]The variable "Lnlabor" indicates the logarithm of the total employment of the firm. The variable "Lncapital" represents the logarithm of the net value of the firm's fixed assets. The variable "Lnage" denotes the age of the firm.

[50]Since the reporting of value-added is not mandatory after 2007 in the NBS database, the regression analysis in column (4) is restricted to samples prior to 2007.

Table B1: Firm's Revenue, Growth, and Patent Stock

	(1) Unbalanced Lnsales	(2) Unbalanced Lnsales	(3) Unbalanced Lnsales	(4) Unbalanced Lnva	(6) Balanced Lnsales	(7) Inn=1 Lnsales	(8) Pat=1 Lnsales
Lnpat_sim_adj	0.0382***	0.0222***	0.0343***	0.0322**	0.0528***	0.0547***	0.1000***
	(0.0045)	(0.0044)	(0.0043)	(0.0145)	(0.0072)	(0.0054)	(0.0072)
Lnpat_quality_adj	0.0449***	0.0354***	0.0403***	0.0196*	0.0428***	0.0382***	0.0191***
	(0.0035)	(0.0034)	(0.0033)	(0.0111)	(0.0057)	(0.0041)	(0.0058)
Lnlabor	0.3537***	0.3227***	0.3051***	0.4744***	0.2893***	0.3365***	0.2223***
	(0.0008)	(0.0008)	(0.0008)	(0.0016)	(0.0018)	(0.0015)	(0.0029)
Lncapital		0.1247***	0.1174***	0.1091***	0.1887***	0.1818***	0.1212***
		(0.0004)	(0.0004)	(0.0009)	(0.0012)	(0.0010)	(0.0017)
Lnage			0.0978***				
			(0.0010)				
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	2486713	2466114	2391081	1552700	309480	512497	124130
R square	0.8966	0.9019	0.9092	0.8498	0.8971	0.9156	0.9464

Note: (1) "Firm FE" denotes the firm fixed effect, while "Ind-year FE" indicates the industry-year fixed effect. (2) Standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

promote new products, resulting in a higher surplus of patents in these firms (Arkolakis, 2010). To explore this further, I examine the heterogeneous impact of patents on firms' revenue and growth rate, which are known to be correlated with firm size. The results, shown in B2, demonstrate that after controlling for firm and industry-year fixed effects and considering firms with the same patent value, an additional accumulated patent in a large firm has a larger positive effect on revenue than in a small firm.

Table B2: Sales, Patent Stock, and Firm Size

	(1) Lnsales	(2) Lnsales	(3) Lnsales	(4) Lnva
Lnacmpat	0.0392***	0.0292***	0.0550***	0.0347**
	(0.0041)	(0.0082)	(0.0060)	(0.0169)
Large_dy	0.3675***	0.5056***	0.4907***	0.2067***
	(0.0013)	(0.0032)	(0.0048)	(0.0023)
Lnacmpat*Large_dy	0.0199***	0.0345***	0.0177***	0.0439***
	(0.0038)	(0.0080)	(0.0057)	(0.0144)
Firm FE	Yes	Yes	Yes	Yes
Ind-year FE	Yes	Yes	Yes	Yes
Obs	1764073	275513	120749	1067736
R square	0.9209	0.9073	0.9272	0.8692

Note: (1) To measure the revenue of firm i in year t, I utilize $sales_{it}$ from columns (1) to (3), as well as $value\_added_{it}$ from column (4). (2) The variable $Ln(acmpat_{i,2001,t})$ represents the accumulated number of patents acquired by firm i from 2001 to year t. (3) In order to define a firm i as large firm in year t, I compare its sales to the average sales within the industry in the previous year (year $t-1$). The dummy variable $Large\_dy_{it}$ equals one if the firm meets the criteria for being a large firm based on its sales in year $t-1$. (4) All regressions in the table control for the average value of patents up to year t, which are constructed by combining patent quality and similarity. Additionally, I account for labor, capital, firm fixed effects, and industry-year fixed effects. (5) The coefficient of the interaction term indicates that, given the same patent value for owner firms, the revenue increases to a greater extent when one more accumulated patent is held by a large firm compared to a small firm. (6) Standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

Characteristics of Traded Patents The correlation between revenue increment and similarity provides a rationale for the establishment of a patent market. Inventor firms may choose to sell patents with low patent-firm, while potential buyers may search for patents with high patent-firm similarity. Consequently, the second question is to investigate on the seller side, whether patents with lower patent-firm similarity are more likely to be sold within a firm. To address this question, I use the dependent variable $sell\_dy$, which equals one if the patent is to be sold and zero otherwise, and estimate a regression model as shown in Equation (37) to identify the factors that determine a firm's decision to sell a patent.

$$Sell\_dy_{pist} = \beta_0 + \beta_1 Similarity_{pi} + \beta_2 Quality_p + \delta_{scope,t} + \delta_s + \delta_t + \delta_i \tag{37}$$

In the equation above, the variable $sell\_dy_{pist}$ indicates whether the patent p belonging to technology field s and invented by firm i in period t is sold (=1) or not (=0). The variable $Similarity_{pi}$ represents the patent-firm specific similarity, which is calculated by comparing patent p to all the patents owned by firm i prior to year t (including patents invented by firm i and patents purchased by firm i). The variable $Quality_p$ represents the quality of patent p. To control for the effect of the inventing firm's knowledge scope in year t, which is associated with the patent-firm similarity, I include a fixed effect for the number of patents owned by the inventing firm in year t, denoted as $\delta_{scope,t}$. Additionally, the regression controls for the 3-digit IPC technology class (δ_s) fixed effect, patent application year(δ_t) fixed effect, and patent's inventing firm(δ_i) fixed effect. The empirical results are presented in Table B3.

Table B3: Firm's Selling Decision: Whether Sell or Not

	(1)	(2)	(3)	(5)	(6)	(7)
	All Samples			NBS Samples		
	Sell_dy	Sell_dy	Sell_dy	Sell_dy	Sell_dy	Sell_dy
Similarity	-0.6496***	-0.5638***	-0.6451***	-0.9409***	-0.7941***	-0.7029***
	(0.1293)	(0.1291)	(0.1130)	(0.1474)	(0.1470)	(0.1404)
Quality	0.0104	0.0732***	0.0305***	0.0623***	0.1067***	0.0254*
	(0.0157)	(0.0157)	(0.0115)	(0.0183)	(0.0183)	(0.0148)
Scope FE	Yes	Yes	Yes	Yes	Yes	Yes
IPC FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes		Yes	Yes
Firm FE			Yes			Yes
Obs	323090	323090	314948	185176	185176	181133
R square	0.0171	0.0249	0.6190	0.0166	0.0239	0.5155

Note: (1) The dependent variable is a dummy variable, denoted by "Sell_dy", which indicates whether a patent was traded (Sell_dy=1) or not (Sell_dy=0). For clarity, "Sell_dy" is multiplied by 100 for clarity. (2) Scope FE, IPC FE, Year FE, and Firm FE correspond to $\delta_{scope,t}$,δ_s,δ_t, and δ_i in Equation (37). (3) 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 B3, I conduct regressions separately for patents invented by Chinese firms and patents invented by NBS firms. Columns (1) to (3) progressively include several fixed effects as controls. The coefficient of patent-firm similarity indicates that, while controlling for patent quality, firms tend to sell patents that are mismatched with them.

Characteristics of Patents Buyers Lastly, I examine the characteristics of buyers on the buyer side. Specifically, I investigate which types of firms are more inclined to purchase patents from other innovators. Are they large or small firms? Are they innovative firms or non-innovative firms? To address these questions, I conduct regression analyses, the results of which are presented in Table B4. I define a firm as a patent buyer (Buyer_dy=1) if it has purchased at least one patent between 2001 and 2013. Using whether a firm is a patent buyer or not as the dependent variable, I examine its correlation with several firm characteristics in Table B4, such as whether the firm is a large firm (Large_dy=1), an innovative firm (Inn_dy=1), or a patenting firm (Pat_dy=1).[51] In columns (1) to (3), I introduce the dummy variables for large firms, innovative firms, and patenting firms separately. In column (4), I include all three variables in the regression. In columns (5) and (6), I further restrict the samples to only innovative firms or patenting firms, respectively, to examine whether large firms are more likely to be patent buyers within these subsets. To account for industry, location, and ownership factors, all regressions in Table B4 control for the industry fixed effect, province fixed effect, and ownership fixed effect. The positive coefficients in Table B4 indicate that large firms, innovative firms, and patenting firms, particularly large firms with patents, are more likely to be buyers in the patent market.

[51] I classify a firm as a large firm (Large_dy=1) if its sales surpass the industry average in the initial year, which is 2001. The definitions of innovative firms and patenting firms are the same as those used in Table B1, where an innovative firm (Inn_dy=1) indicates a firm that invented patents or invested in R&D between 2001 and 2013, and a patenting firm (Pat_dy=1) indicates a firm that must have invented patents during the same period.

Table B4: The Characteristics of Patent Buyers

	(1) All firms Buyer_dy	(2) All firms Buyer_dy	(3) All firms Buyer_dy	(4) All firms Buyer_dy	(5) Inn=1 Buyer_dy	(6) Pat=1 Buyer_dy
Large_dy=1	0.0098***			0.0072***	0.0151***	0.0519**
	(0.0014)			(0.0014)	(0.0027)	(0.0207)
Inn_dy=1		0.0123***		0.0052***		
		(0.0014)		(0.0014)		
Pat_dy=1			0.0850***	0.0817***		
			(0.0033)	(0.0034)		
Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
Prov FE	Yes	Yes	Yes	Yes	Yes	Yes
Ownership FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	30720	30720	30720	30720	13055	1037
R square	0.0537	0.0548	0.0725	0.0738	0.0649	0.2478

Note: (1) "Ind FE" represents the industry fixed effect at the 4-digit level, while "Prov FE" refers to the province fixed effect. Firms in the sample are classified into five different ownership types: state-owned, collective, private, foreign-invested, and other. The variable "Ownership FE" captures the fixed effect associated with ownership. (2) Standard errors are in parentheses. *** denotes significance at the 1% level; ** denotes significance at the 5% level; * denotes significance at the 10% level.

C Additional Theoretical Results

C.1 Value of the Patent Agent

I now turn to the value function of the patent agent. There are two types of patent agents—the patent agent with inspection goods and the patent agent with experienced goods. As aforementioned, a $1 - ss$ share of patent agents in the patent market are possessing patents of which the quality could be observed. They buy the patent from the inventing firm at the competitively determined price q_γ. With probability T_a a patent agent will meet with a potential buyer on the patent market, and with $1 - T_a$ probability it will not. Conditional on the meeting with a potential buyer, the function $I_\theta^{b,ins}(z, \gamma, x; \tilde{z})$ serves as an indicator that determines whether a successful transaction occurs between a firm with R&D capacity θ and productivity z, and a patent agent whose patent has a quality level γ and patent-buyer similarity x, in the case when the patent is an inspection good.[52] $H(x)$ is the patent-firm similarity distribution in the market. The value for a patent agent whose patent quality is equal to γ is thus given by

$$\begin{aligned} A(\gamma,\tilde{z}) =& T_a \cdot \iint_{x;\theta,z} \begin{bmatrix} I_\theta^{b,ins}(z,\gamma,x;\tilde{z}) P_\theta^{ins}(z,\gamma,x;\tilde{z}) + \\ (1 - I_\theta^{b,ins}(z,\gamma,x;\tilde{z})) r\sigma A(\gamma,\tilde{z}') \end{bmatrix} \cdot \Gamma(\theta,z) dH(x) dF(\theta,z) \\ &+ (1-T_a)\cdot r\sigma A(\gamma,\tilde{z}') \end{aligned} \tag{38}$$

A $(1-ss)$ share of patent agents in the patent market are possessing patents of which the quality is unobservable. The value for these specific patent agents $A(\tilde{z}')$ can be calculated in a similar manner as the equation presented above, resulting

$$\begin{aligned} A(\tilde{z}) =& T_a \cdot \iint_{\gamma,x;\theta,z} \begin{bmatrix} I_\theta^{b,exp}(z,\gamma,x;\tilde{z}) P_\theta^{ins}(z,\gamma,x;\tilde{z}) + \\ (1 - I_\theta^{b,exp}(z,\gamma,x;\tilde{z})) r\sigma A(\tilde{z}') \end{bmatrix} \cdot \Gamma(\theta,z) dH(\gamma,x) dF(\theta,z) \\ &+ (1-T_a)\cdot r\sigma A(\tilde{z}') \end{aligned} \tag{39}$$

where $I_\theta^{b,exp}(z,\gamma,x;\tilde{z})$ is the indicator function that specifies whether the patent transaction happens successfully between the firm with R&D capacity θ, productivity z and the patent agent whose patent is of quality γ and patent-buyer similarity x when the patent is an experience good. The joint distribution of patent quality and similarity in the market, denoted as $H(\gamma,x)$, is determined endogenously by the decisions of successful inventors on whether to keep or discard their newly created patents, but these patents cannot be traded as inspection goods.

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

C.2 Firm Productivity Distribution Dynamics

The following equation demonstrates the firm's relative productivity $\hat{z} = \frac{z}{\tilde{z}}$ distribution dynamics, where invention means that the firm has in-house invention in the t period. "sell" means that the firm sells the new invention in the 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 the patent agent successfully.

[52] It equals 1 if the transaction happens at the end, and otherwise, it equals 0.

$$
\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_{\gamma,x}\hat{g}_{\theta,t}\cdot(\hat{z}=g\hat{z})(1-\theta i^*_\theta)\cdot m_b\cdot\begin{bmatrix} ss\cdot\Big(1-I^{b,exp}_\theta(\hat{z},\gamma,x)\Big)+ \\ (1-ss)\cdot\Big((1-I^{b,ins}_\theta(\hat{z},x)\Big)\end{bmatrix}dH(\gamma,x)}_{\text{no invention, meet, no purchase}} \\
&+\underbrace{\int_x\hat{g}_{\theta,t}(\hat{z}=g\hat{z})\cdot\theta i^*_\theta\cdot\begin{bmatrix} h\cdot\Big(s\cdot(1-I^{k,exp}_\theta(\hat{z},\gamma_h,x))+(1-s)\cdot(1-I^{k,ins}_\theta(\hat{z},\gamma_h,x))\Big)+ \\ (1-h)\cdot\Big(s\cdot(1-I^{k,exp}_\theta(\hat{z},\gamma_l,x))+(1-s)\cdot(1-I^{k,ins}_\theta(\hat{z},\gamma_l,x))\Big)\end{bmatrix}dX(x)}_{\text{invention, sell}} \\
&+\underbrace{\iint_{\hat{z},x}\begin{bmatrix} h\cdot\hat{g}_{\theta,t}(\hat{z}:\hat{z}+\gamma_h x\hat{z}^\beta=g\hat{z})\cdot(1-\theta i^*_\theta)\cdot m_b\cdot\int\limits_{\gamma,x}\begin{bmatrix} ss\cdot I^{b,exp}_\theta(\hat{z},\gamma,x)+ \\ (1-ss)\cdot I^{b,ins}_\theta(\hat{z},x)\end{bmatrix}dH(\gamma,x)+ \\ (1-h)\cdot\hat{g}_{\theta,t}(\hat{z}:\hat{z}+\gamma_l x\hat{z}^\beta=g\hat{z})\cdot(1-\theta i^*_\theta)\cdot m_b\cdot\int\limits_{\gamma,x}\begin{bmatrix} ss\cdot I^{b,exp}_\theta(\hat{z},\gamma,x)+ \\ (1-ss)\cdot I^{b,ins}_\theta(\hat{z},x)\end{bmatrix}dH(\gamma,x)\end{bmatrix}dX(x)d\hat{z}}_{\text{no invention, meet, purchase}} \\
&+\underbrace{\iint_{\hat{z},x}\begin{bmatrix} h\cdot\hat{g}_{\theta,t}(\hat{z}:\hat{z}+\gamma_h x\hat{z}^\beta=g\hat{z})\cdot\theta i^*_\theta\cdot(s\cdot I^{k,exp}_\theta(\hat{z},\gamma_h,x)+(1-s)\cdot I^{k,ins}_\theta(\hat{z},\gamma_h,x))+ \\ (1-h)\cdot\hat{g}_{\theta,t}(\hat{z}:\hat{z}+\gamma_h x\hat{z}^\beta=g\hat{z})\cdot\theta i^*_\theta\cdot(s\cdot I^{k,exp}_\theta(\hat{z},\gamma_l,x)+(1-s)\cdot I^{k,ins}_\theta(\hat{z},\gamma_l,x))\end{bmatrix}dX(x)dF(\hat{z})}_{\text{invention,keep}}
\end{aligned}
\tag{40}
$$

D Construction of Data Moments

D.1 Targeted Moments

Large firms' R&D-to-sales ratio, 75 percentile of the R&D-to-sales ratio. The average of large firms' R&D-to-sales ratios is 1.0%, and the 75 percentile of large firms' R&D-to-sales ratios is 1.3%. These ratios are affected by the same parameter χ, same with the third moment, the ratio of R&D expenditure over sales. Moreover, to what extend the high-type firm's R&D capacity θ_h is and the proportion of firms with high R&D capacity I_p are positively correlated with this moment as well.

Average number of patents of large firms over that of small firms. On average, the number of patents of large firms is 2.116 times more than that of small firms in China. The parameters β and θ_{gap} will affect this ratio. The larger the differences in the invention surplus and R&D capacity between large and small firms are, the higher value this ratio will be.

Fraction of traded patents and its ratio (high-quality over low-quality patents). According to Table 1, 4.5% of patents filed and granted by Chinese firms between 1998 to 2013 were sold to other Chinese firms. This fraction of traded patents serves as an indicator of the level of frictions in the patent market. More specifically, the matching function is governed by η, which determines the ease of finding a patent in the market. Additionally, the presence of high fixed transaction costs (F) can impede potential buyers and sellers from reaching a deal if the expected transaction surplus is not substantial. Thus, high fixed transaction costs tend to have a greater impact on the trading of low-quality patents compared to high-quality patents. Therefore, alongside the fraction of traded patents, this paper considers its ratio (high-quality over low-quality patents) in the analysis. The 11th moment presented in Table 4 is consistent with Figure 4, which demonstrates that high-quality patents are traded more frequently than low-quality patents. This observation is crucial in providing motivation for the existence of fixed transaction costs.

The final friction incorporated into the model is information asymmetry on patent quality (s), which leads patent owners to only receive a price based on the expected value of the patent if information asymmetry on patent quality happens. This information friction discourages owners of high-quality patents from trading, while encouraging the patents trading of owners of low-quality patents. Consequently, the total impact of this information friction on the fraction of traded patents is ambiguous. However, it will decrease the ratio of traded patents (high-quality over low-quality), which operates in the opposite direction of fixed transaction costs with regards to this ratio. As these two moments are insufficient in isolating the three types of frictions introduced in the model, Table 4 incorporates additional moments associated with the purchase behavior of firms.

Share of firms as the buyer and standard deviation of buyers. From 2001 to 2013, there were approximately 2.5% manufacturing firms that had been buyers in the patent market during this period. In addition, if I define an indication function $I_b(buyer = 1)$ as an indicator for whether the firm was a buyer or not, then the standard deviation will be 0.155. Similar to the fraction of traded patents, the parameters governing the matching function, η and μ, are important to this moment. The parameters connected with the firms' heterogeneity, β, θ_{gap} and I_p are also significant to the variance of I_b.

Average number of purchased patents of large firms over that of small firms, upper 75 percentile firms over 50-75 percentile firms. These two ratios reflect the curvature of the distribution of firms' search efforts. I compare the number of purchased patents in the large firm group with the small firm group, as well as firms of which the size is upper 75 percentile and 50-75 percentile. These moments provide extra information for identifying key frictions in the patent market, especially facilitating the identification of fixed transaction costs B and .

D.2 Nontargeted Moments

Firms' growth rate. Table 5 presents abundant information on aggregate TFP growth rate as well as a comparison of sales growth rates between firms with patents (small firms) and larger firms. The model predicts an average sales growth rate of 1.2%. However, it should be noted that the model only captures growth induced by innovation, while other crucial factors such as imitation and knowledge spillovers, which have been proven to significantly contribute to growth (Bloom et al., 2013; Perla and Tonetti, 2014), are not considered. Consequently, there exists a considerable disparity between the model-generated growth rate and the actual data moments. Moreover, small firms demonstrate a higher average sales growth rate compared to larger firms, albeit slightly higher than what is observed in the data. Aside from the limitation of ignoring imitation as a potential avenue for growth, another plausible explanation is the model's restriction on obtaining multiple patents within a single period. If these constraints were relaxed, allowing larger firms to engage in more imitations or secure a greater number of patents compared to smaller firms, the model would produce a higher sales growth ratio than what is observed in the data.

R&D-to-sales ratio. The share of firms of which the R&D-to-sales ratio is larger than 3% is 0.02 in the data; this moment predicted by my model fits well with the data.

Firm's participation in the patent market on the seller side. To reduce the computation load, this paper transforms the firm-to-firm patent transaction into the firm-to-patent agent-to-firm patent transaction. Correspondingly, I mainly match the moments on the buyer side, especially the extensive margin of the buyer side. However, in rows 5 and 6 in Table 5, I check the fit of this model regarding the firm's participation patterns on the seller side. In the extensive margin, the share of firms as sellers in the large firm group is higher than that in the small firm group. In the intensive margin, for the firm as the seller, our model predicts that as large firms can generate more surplus, conditional on the patent's quality and similarity, the proportion of inventions to be sold in large firms is lower than that in small firms. It means that the sell-invention ratio is larger in small firms,[53] which is consistent with the data.

Intensive margin on the buyer side. In Table 5, I also check the buyer side pattern in the intensive margin (row 6): the buy-own ratio, which is equal to the number of patents purchased by the firm over the number of patents owned by the firm. On average, this is lower for larger firms in the data. My model predicts the same result because large firms account for for a much higher proportion of inventors than do small firms, even if the number of their purchases is higher than that of small firms; however, the market is small in China. As a result, the buy-own ratio (large firms over small firms) is smaller than 1.

Sales Duration. The sales duration of patent is equal to the year when the 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 model prediction is 4.71.

E Heterogeneous Impact of Search Costs Decline on Two Types of Firms

In this section, I examine the heterogeneous impact of varying search costs on these two types of firms. Figure E4 illustrates that as search costs decrease, both high-capacity and low-capacity firms invest more effort into searching for patents in the market. Consequently, the share of firms as the buyer increases in both groups. However, high-capacity firms, being more likely to be large firms, benefit more from purchasing patents and thus experience a greater increase in their participation in the patent market compared to low-capacity firms.

[53] It is equal to the number of the patents sold by the firm over the number of the patents invented by the firm.

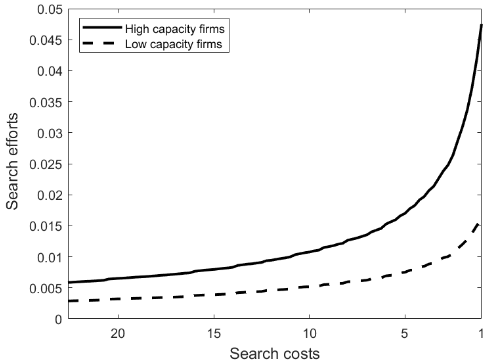
Regarding in-house innovation, the decline in search costs has both positive and negative effects. On one hand, lower search costs lead to higher meeting rates and an expected surplus for potential buyers in the patent market. As a result, firms allocate fewer resources to in-house R&D and instead opt to purchase patents from the market. On the other hand, lower search costs also make it easier to trade patents, increasing the value of each in-house invented patent. These two effects counterbalance each other, resulting in minimal changes in the in-house innovation numbers of both types of firms, as depicted in subfigure (c) of Figure E4.

Lastly, with more firms participating in the patent market, the TFP growth rates of both high-capacity and low-capacity firms experience substantial increases. However, the TFP growth rate of low-capacity firms tends to increase more due to their initially lower TFP levels.

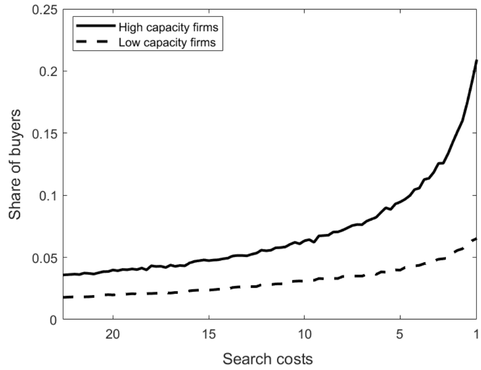
F Patent Quality Gap between the US and China

For the protection of patents globally, large quantities of patents will be not only registered in their home country but also in foreign countries. Those patents represent the same underlying intellectual property across different countries, which could be used to control for country-specific factors and then estimate quality from citations.

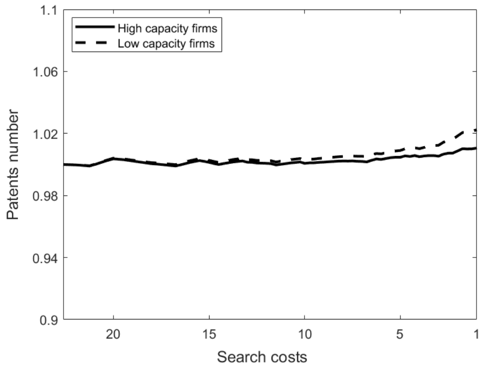
In this paper, I analyze two types of dual-listed patents: those invented by the US and dual-listed in both the US and China, and those invented by Chinese firms and dual-listed in both China and the US. To identify these patents, I utilize patent family data. Patent families consist of patents or applications filed in multiple countries that are related through common priority filings. This indicates that patents within a family contain similar techniques and are filed by the same assignee (Zuniga et al., 2009). By leveraging the patent family information obtained from the USPTO and CNIPA databases, I can accurately determine the number of dual-listed patents invented in the US as well as those invented in China, and their registration in both CNIPA and USPTO. According to the CNIPA report, between 1985 and 2013, a total of 123,852 US-invented patents were granted in CNIPA, and my methodology successfully identifies 111,380 of them. Similarly, the USPTO report states that from 1985 to 2013, 23,181 Chinese-invented patents were granted in the USPTO, and my approach identifies 17,772 of them. The annual number of granted US-invented and Chinese-invented dual-listed patents, as reported



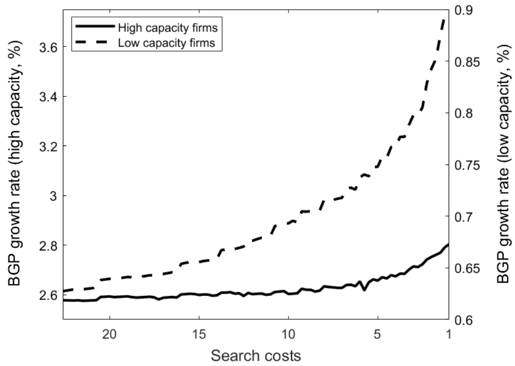
(a) Search efforts



(b) Share of firms as the buyer



(c) Patents number



(d) Aggregate TFP growth

Figure E4: Impact of Decline in Search Costs on High-capacity and Low-capacity Firms

Note: (1) These four figures illustrate the heterogeneous impact of varying search costs (ranging from 22.6 to 1) on the search efforts, the share of firms acting as buyers, the number of patented inventions, and the overall growth rate of aggregate TFP of high-capacity firms and low-capacity firms. (2) In subfigure (c), I normalize the number of patents for both types of firms to one when search costs are equal to 22.6.

by official sources and identified by this paper, is depicted in Figure F5. Please note that the figure displays the official report's data alongside the data identified through the methodology outlined in this paper.

To maintain consistency with the limitations on patent trading data, I only consider dual-listed patents that were filed and granted between 1998 and 2013 by firms.

To quantify the quality gap between patents in China and the US, I follow these steps. Firstly, for US- and Chinese-invented dual-listed patents, I calculate the forward citation numbers compared to all the other domestic patents within each home country's patent office. I also normalize the forward citation number of these dual-listed

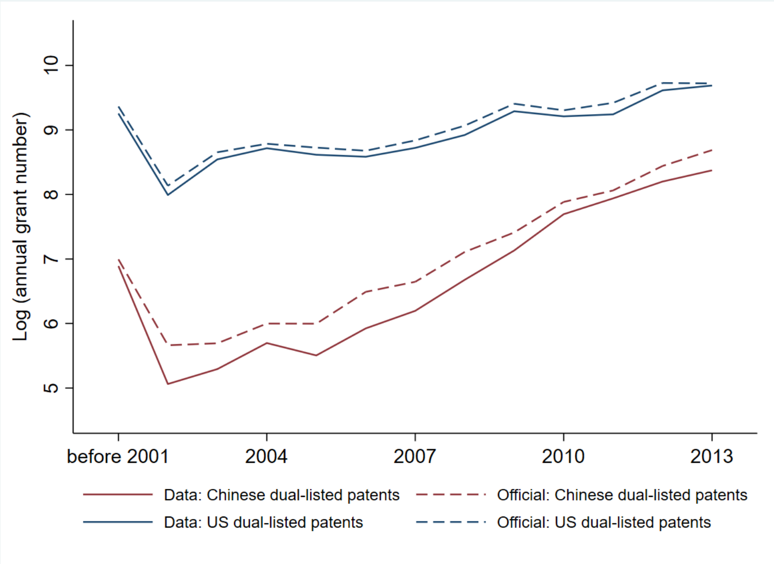


Figure F5: Annual Numbers of Granted US-invented and Chinese-invented Dual-Listed Patents

Notes: The solid lines in the figure represent the annual numbers of granted dual-listed patents identified using the data employed in this paper, while the dashed line represents the numbers provided by the official report. Specifically, the red solid line depicts the statistics of Chinese-invented patents, while the blue solid line represents the statistics of US-invented patents.

patents to one.[54] Secondly, I calculate the forward citation numbers of those dual-listed patents compared to foreign patents within the foreign country's patent office and normalized the forward citation number to one as well. Panel A of Table F5 showcases the US-invented dual-listed patents, where the average forward citation number of US domestic patents is 38% lower than that of the US-invented dual-listed patents within the USPTO. Also, within the CNIPA, the average forward citation number of Chinese domestic patents is 43% higher than that of the US-invented dual-listed patents. Panel B presents the results of Chinese-invented dual-listed patents.

As shown in Table F5, the forward citation numbers of US domestic patents versus that of Chinese domestic patents are different when US- and Chinese-invented dual-listed patents are used as the bridge, respectively. This difference could be influenced by the home bias problem in patent citation when dual-listed patent citations are compared with the forward citation numbers of foreign patents within a foreign country. To address this problem, I assume that there exists a home bias that could discount the citations of dual-listed patents in a foreign country and exaggerate the forward citation

[54]To control for the technology class and application year fixed effect, I performed all comparisons within the same 3-digit level IPC class and application year.

Table F5: Estimation of Patent Quality Gap Utilizing Dual-listed Patents

Panel A. US-invented dual-listed patents as the bridge			
Forward citation comparison in home country USPTO		Forward citation comparison in foreign country CNIPA	
(1) Forward citation number of US domestic patents	(2) Forward citation numbers of Dual-listed patents	(3) Forward citation number of CN domestic patents	(4) Forward citation number of Dual-listed patents
0.72	1.00	1.43	1.00
Panel B. Chinese-invented dual listed patents as the bridge			
Forward citation comparison in home country CNIPA		Forward citation comparison in foreign country USPTO	
(1) Forward citation number of CN domestic patents	(2) Forward citation number of Dual-listed patents	(3) Forward citation number of US domestic patents	(4) Forward citation number of Dual-listed patents
0.95	1.00	2.29	1.00

numbers of foreign country's domestic patents by a factor of $\xi \in [1, +\infty]$. For instance, when I use US-invented dual-listed patents as a bridge and compare their forward citation numbers with those of Chinese domestic patents, the forward citation number of Chinese domestic patents should be enlarged due to the home bias problem. Using the ratios $\frac{q_{US}}{q_{CN}}|_{bridge=US}$ and $\frac{q_{US}}{q_{CN}}|_{bridge=CN}$ to represent the observed patent quality gap between the US and China, with US-invented and Chinese-invented dual-listed patents as bridges, respectively, as presented in Table F5. Here, $\tilde{q}_{US}$ and $\tilde{q}_{CN}$ represent the true quality of US and Chinese domestic patents, respectively. Based on these considerations, the following equation can be derived:

$$\frac{q_{US}}{q_{CN}}|_{bridge=US} = \frac{0.72}{1.43} = \frac{\tilde{q}_{US}}{\tilde{q}_{CN} \cdot \xi} \qquad \frac{q_{US}}{q_{CN}}|_{bridge=CN} = \frac{2.29}{0.95} = \frac{\tilde{q}_{US} \cdot \xi}{\tilde{q}_{CN}} \tag{41}$$

Hence, I can estimate the actual patent quality gap between the United States and China as $\frac{\tilde{q}US}{\tilde{q}CN} \approx 1.102$.

G Appendix Figures and Tables

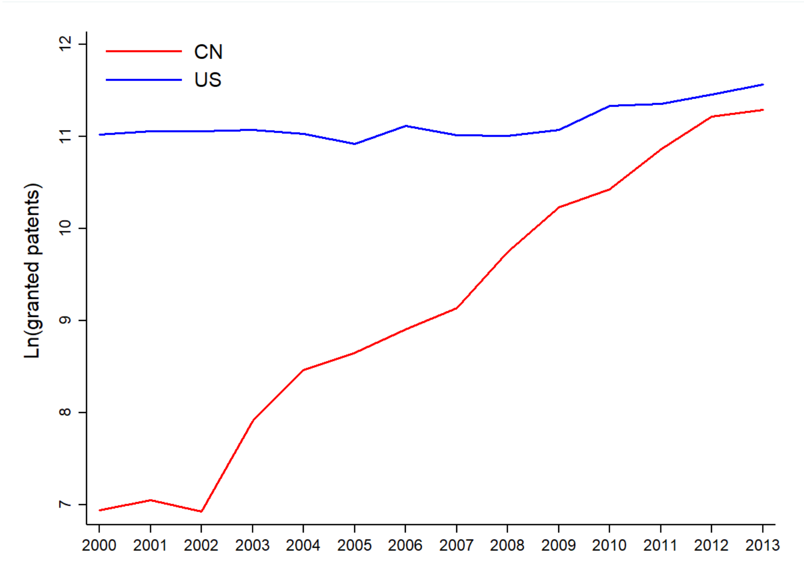


Figure G1: Logarithm of annual granted patents number in China and the US

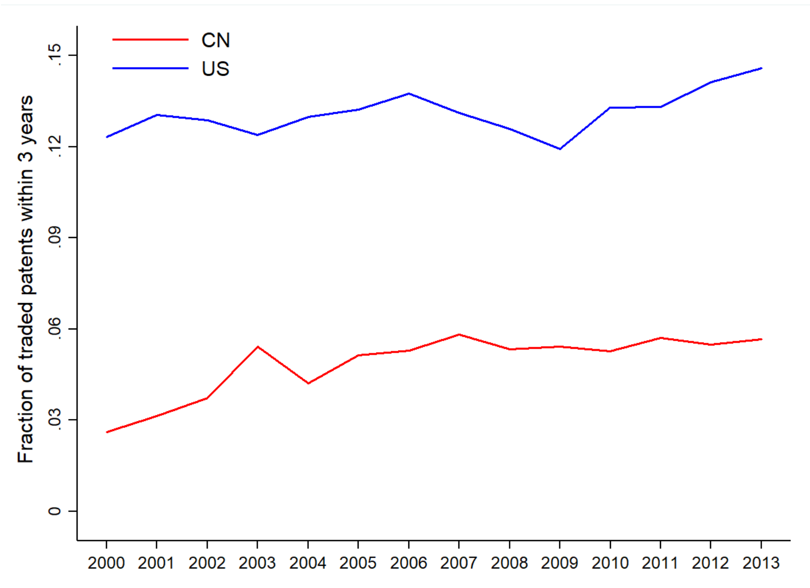


Figure G2: Annual fraction of traded patents in China and the US

Notes: All definitions for these two figures are same with the definitions below the Figure 1.

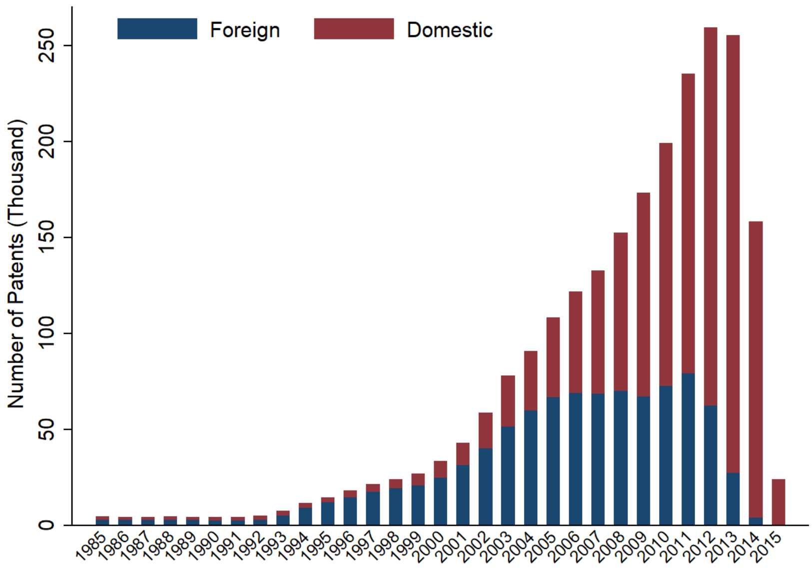


Figure G3: CNIPA: Patent Applications 1985-2015

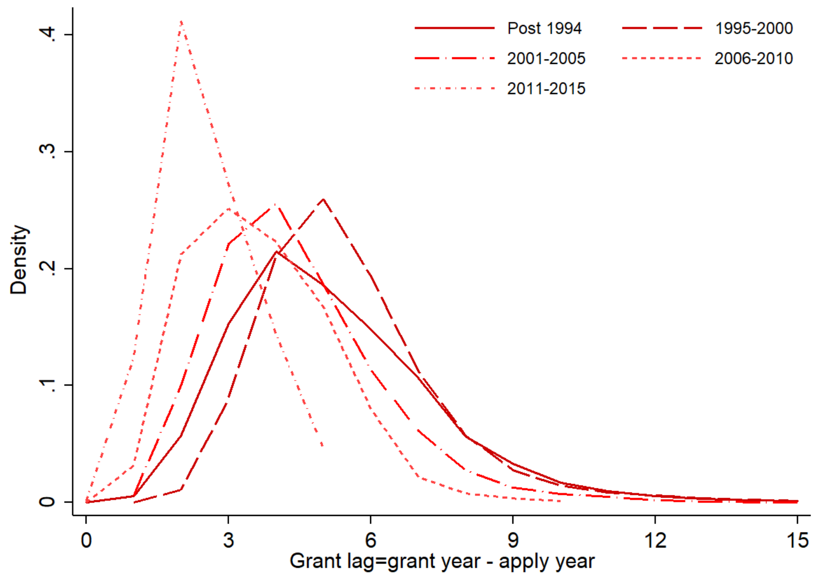


Figure G4: CNIPA: Patent Grant Lag across Different Cohorts

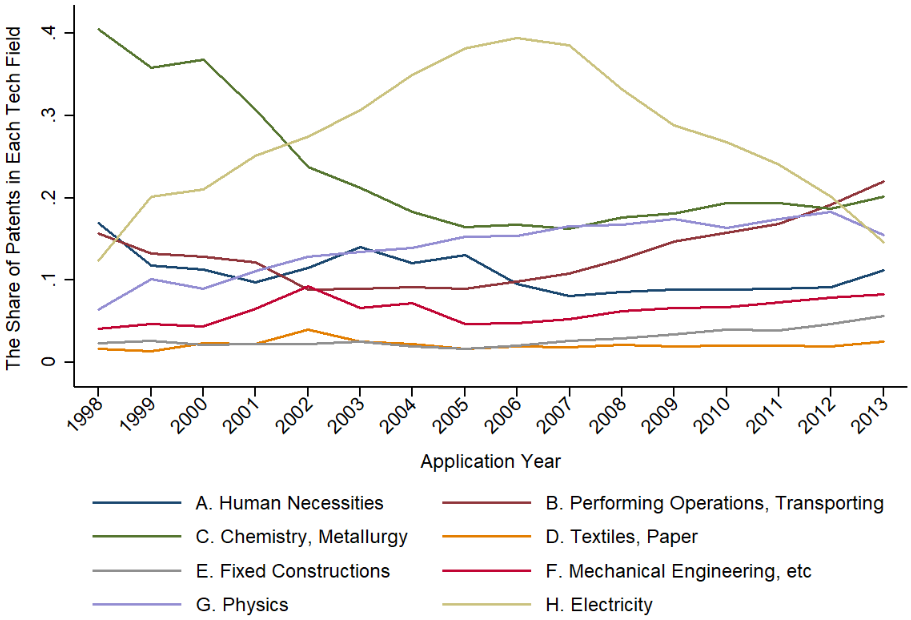


Figure G5: CNIPA: Patent Application Share of Each Technology Field, 1998–2013

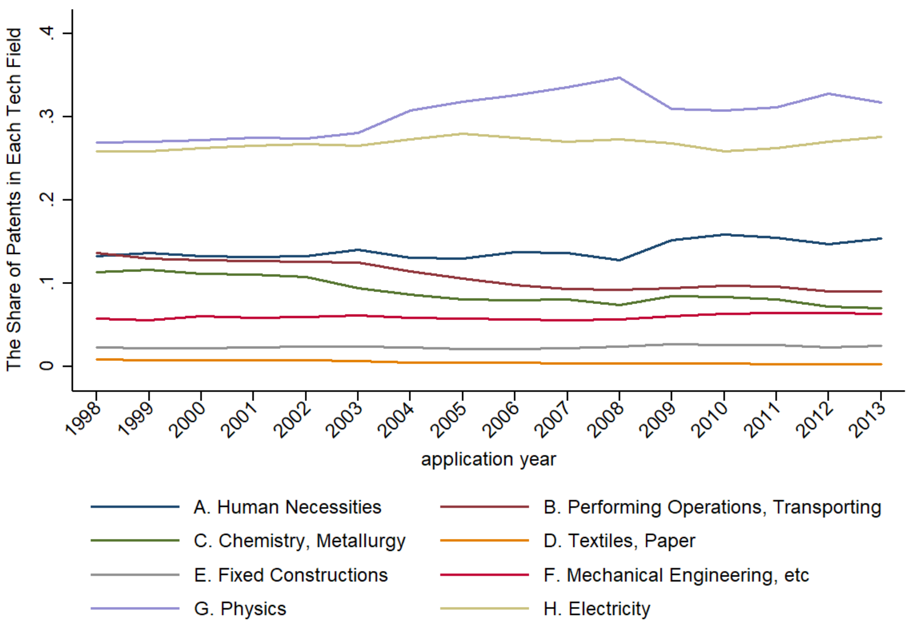


Figure G6: USPTO, Patent Application Share of Each Technology Field, 1998–2013

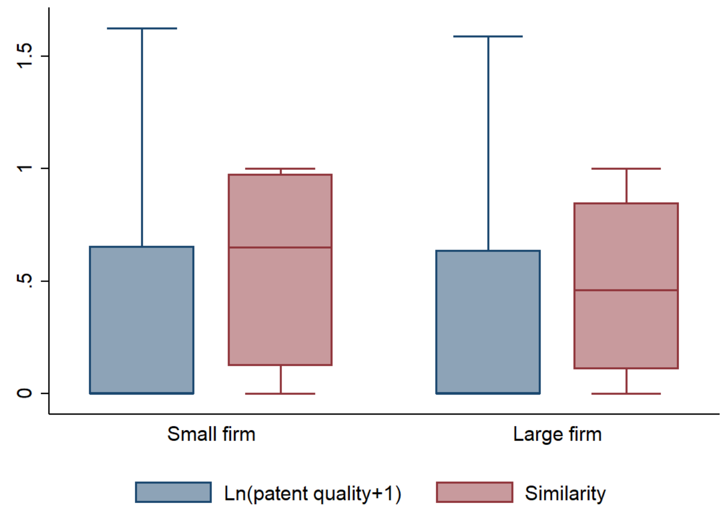


Figure G7: Patent Quality and Similarity (NBS Firm Inventions, Balanced, 2001–2013)

Note: (1) Patent quality equals the forward citation number divided by the mean of forward citation number within the technology field (IPC 3-digit code) 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 the NBS 2001–2013 balanced data. (4) Outside values are excluded in this box graph.

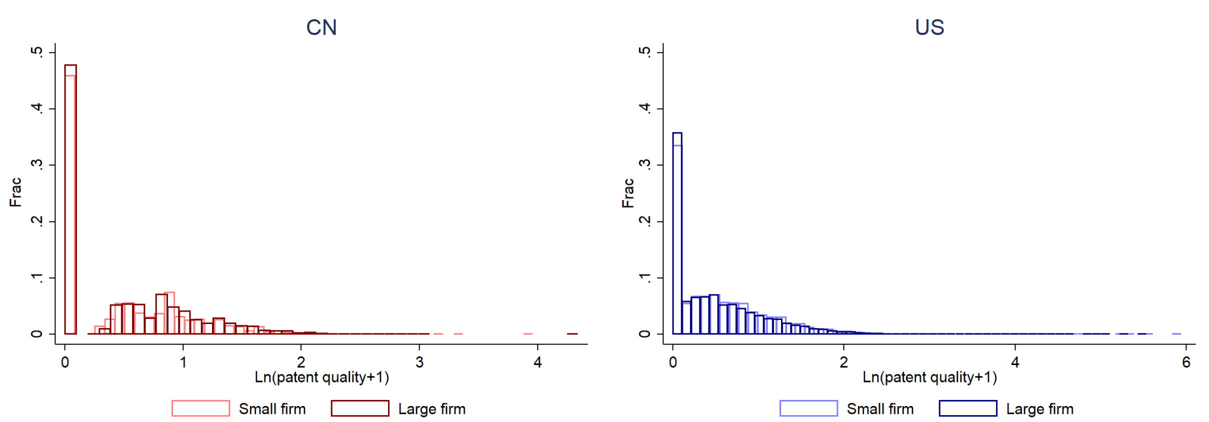


Figure G8: Patent Quality Distribution in China and the US

Note:(1) Patent quality equals the forward citation number divided by the mean of forward citation number within the technology field (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 included in the figure on the left-hand side contain the patents invented by firms belonging to the NBS 2001–2013 unbalanced data, and the inventions included the right hand side of this figure included in the figure on the right-hand side contain the patents invented by firms belonging to the US listed firm 2001–2013 unbalanced data.

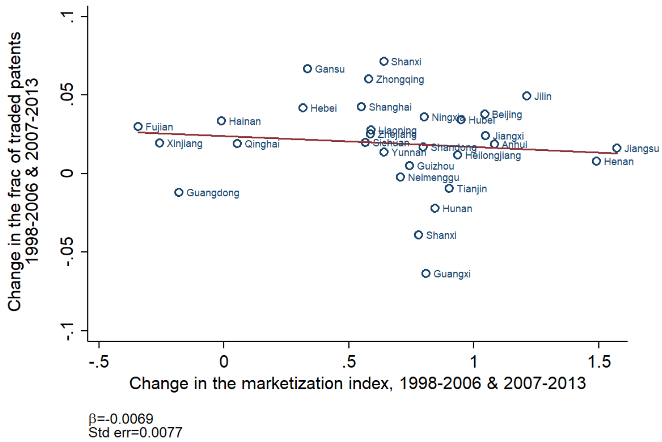


Figure G9: Change in the Provincial Fraction of Traded Patents and Marketization Index (1998–2006 vs. 2007-2013)

Note: (1) Change in one variable in province i equals to the average value of that variable in province i from 2007 to 2013 less the average value of that variable in province i from 1998 to 2006; (2) X variable indicates the change in the marketization index in a province between two periods. The marketization index 1998–2013 comes from marketization index in Fan et al. (2019), which measures the development level of marketization in different provinces in China; and (3) Y variable indicates the change in the fraction of traded patents in a province between two periods.

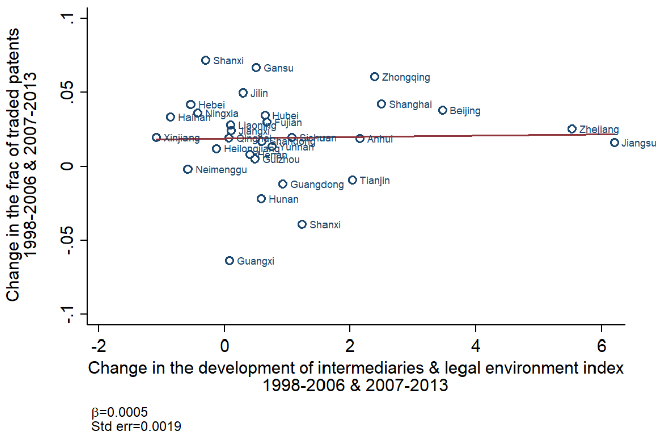


Figure G10: Change in the Provincial Fraction of Traded Patents and the Development of Market Intermediaries & Legal Environment (1998–2006 vs. 2007-2013)

Note: (1) The definition of the change in one variable in province i is same with the definition in Figure G9; (2) X variable indicates the change in the development of market intermediaries & legal environment index in a province between two periods. This index is a sub-index of the marketization index above; and (3) Y variable is same with Figure G9.

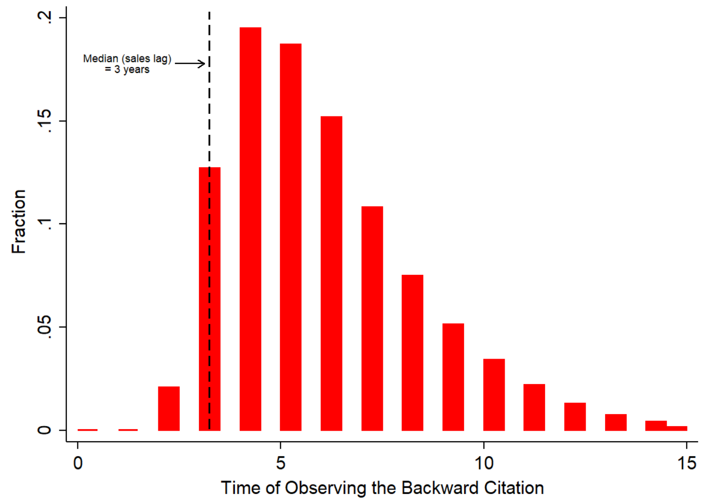


Figure G11: The Lag Time of Forward Citation and Sales in China

Note: (1) The lag time of forward citation equals the citing patent's application year less the cited patent's application year; (2) The lag time of sales equals the year when the patent is traded less the patent's application year; (3) The red pillars document the distribution of the lag time of forward citations in Chinese patent data; (4) The black dash line indicates the median value of the lag time of sales in Chinese patent transaction data.

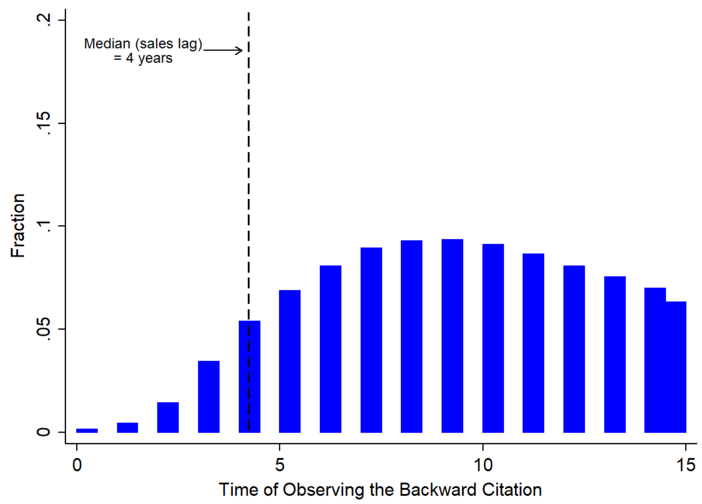
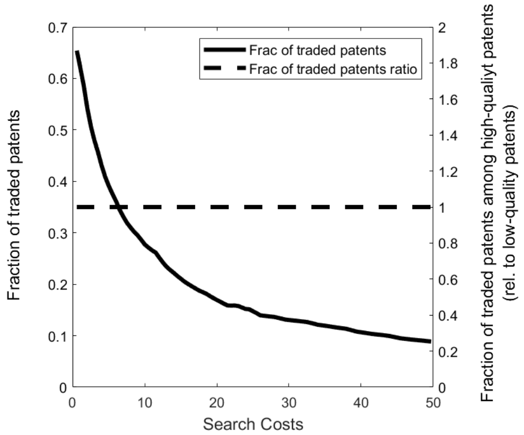
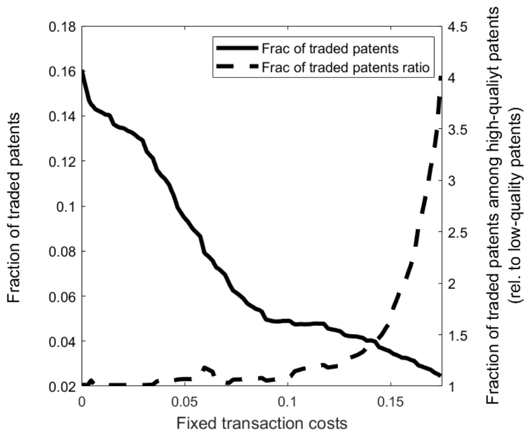


Figure G12: The Lag Time of Forward Citation and Sales in the US

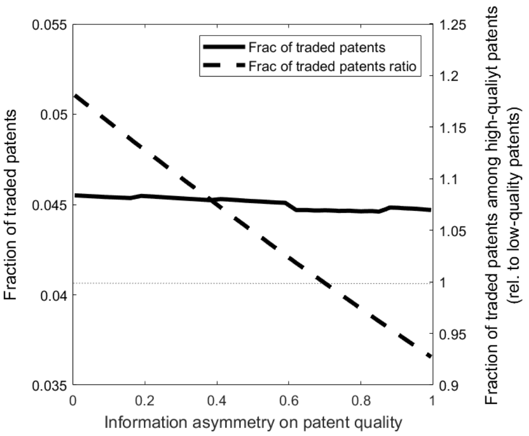
Note: (1) The lag time of forward citation equals the citing patent's application year less the cited patent's application year; (2) The lag time of sales equals the year when the patent is traded less the patent's application year; (3) The blue pillars document the distribution of the lag time of forward citations in the US patent data; (4) The black dash line indicates the median value of the lag time of sales in the US patent transaction data.



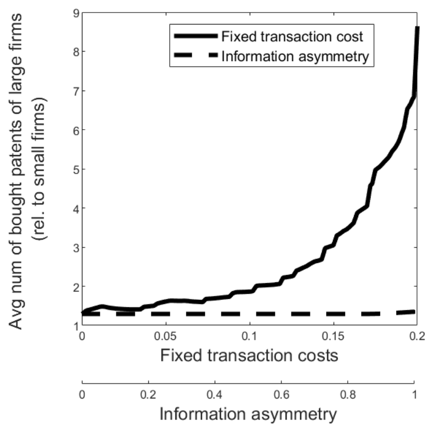
(a) Search costs



(b) Fixed transaction costs



(c) Information asymmetry



(d) Fixed transaction costs & Information asymmetry

Figure G13: The Impacts of Frictions on Moments

(1) Subfigure (a) depicts the relationship between the fraction of traded patents and the ratio of high-quality patents to low-quality patents, as the value of search costs (η) ranges from 0 to 50. This analysis assumes no fixed transaction costs ($B = 0$) and no information asymmetry regarding patent quality ($s = 0$). (2) Building upon subfigure (a), subfigure (b) adds fixed transaction costs and examines how the fraction of traded patents and the ratio of high-quality patents to low-quality patents change as the value of fixed transaction costs (B) varies from 0 to 0.17. Again, this analysis assumes no information asymmetry on patent quality ($s = 0$) and sets the value of search costs (η) to 23. (3) Moving to a patent market with both search costs (η) and fixed transaction costs (B), subfigure (c) demonstrates the impact of varying the value of information asymmetry on patent quality (s) from 0 to 1 on the fraction of traded patents and the ratio of high-quality patents to low-quality patents. (4) Subfigure (d) focuses on the relationship between the average number of purchased patents by large firms and small firms, varying either fixed transaction costs (B) or information asymmetry on patent quality (s) in a patent market with search costs ($\eta = 23$). (5) For the values of other parameters, please refer to Table 3.

Table G1: Shares of Low-quality and High-quality Patents and Forward Citation Number Gap in China and the US

Technology class	Statistics	CN	US
IPC 3-digit class	High-quality patents share	40%	47%
	Forward citation number gap (high-quality patents over low-quality patents)	7.23	8.41
IPC 4-digit class	High-quality patents share	42%	46%
	Forward citation number gap (high-quality patents over low-quality patents)	7.07	8.57

Note: (1) Low-quality patents are identified as those with forward citation numbers lower than the median value within their respective technology field and granted year. High-quality patents, on the other hand, are those with forward citation numbers higher than the median value within their respective technology field and granted year. (2) To ensure comparability of forward citation numbers across years, I define the forward citation number as the number of citations received by a patent within 5 years after being granted. (3) While this paper primarily uses the IPC 3-digit class to categorize patents, I conduct a robustness check by employing a more detailed classification – the IPC 4-digit level class – to ascertain that the shared characteristics of high-quality patents and the forward citation gap between high-quality and low-quality patents are not sensitive to the chosen digit level.

Table G2: Sales of Firms and Forward Citation Numbers of Accumulated Patents

	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) US listed firm data come from the Compustate database, and the Chinese listed firm data come from the 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 5 years after being granted. (4) Labor is measured by the firm's employment number; Capital is measured by the firm's fixed asset; (5) Firm fixed effect and industry-year fixed effect are controlled in all regressions, and industry of the US listed firm is classified by SIC 2-digit code. The industry of Chinese NBS firm is classified by Industrial Classification for National Economic Activities, and the industry of Chinese listed firm is classified by Guidelines for the Industry Classification of Listed Companies (2012).

Table G3: The Elasticity between Frictions-related Parameters and Moments

	η	F	s
Fraction of traded patents	-0.21	-0.14	-0.01
Avg num of bought patents of large firms (rel. to small firms)	-0.05	0.65	0.02
Fraction of traded patents among high-quality patents (rel. to low-quality patents)	0.05	0.09	-0.10

Note: This table presents the elasticity between parameters that represent patent market frictions and corresponding moments that aid in identifying these frictions. The parameters included are search costs (η), fixed transaction costs (F), and information asymmetry related to patent quality (s).