Does Trading Spur Specialization? Evidence From Patenting*

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Abstract

Exploiting staggered establishments of patent exchanges in China, we examine how patent trading affects firm innovation and specialization. We find that patent trading and in-house innovation are complements for patent sellers, whereas they are substitutes for the buyers. Our findings demonstrate that the market for technology induces (i) specialization between patent buyers and sellers, (ii) specialization between patent licensors and licensees, and (iii) specialization based on a firm's R&D efficiency. All these three patterns of specialization indicate that a firm's response to an emerging market for technology hinges on its comparative advantages. Firms with a comparative advantage in creating innovation redirect their resources from advertising to patenting activities, whereas firms with a comparative advantage in commercializing innovation switch their effort from patenting to advertising activities. Moreover, enhanced patent trading contributes to improved firm performance and increasing market concentration. Our findings suggest patent trading promotes comparative-advantage-based specialization and enhances firm performance.

Keywords: Innovation, Market for Technology, Patent Trading, Patent Licensing, Specialization, Division of Labor, R&D, Patent
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1 Introduction

Dating back to the pin factories depicted in *Wealth of Nations* (1776), Adam Smith underscored the pivotal roles of trade and the division of labor, as well as their far-reaching implications on productivity growth. Inspired by Adam Smith, the impact of trade has been an everlasting theme for economic studies. In the specific field of innovation, however, how does the market for technology affect the incentives of innovation and the division of innovative labor? We aim to empirically address these questions in this study. Based on the unique institutional setting of patent trading and patent exchanges in China, we attempt to identify the causal effects of patent trading on firm innovation and specialization.

Does patent trading promote or discourage a firm's in-house innovation? The answer is ambiguous because of two opposite effects of patent trading on a firm's incentives to innovate. To begin with, a patent holder (a firm in our setting) may not be in the best position to commercialize its technology. When patents can be easily traded, a patent holder can sell its patent to another firm that has a higher valuation for this patent. The possibility of selling its patents provides stronger incentives for the firm to conduct in-house innovation. Hence, patent trading can be a complement to a firm's in-house innovation. We define this effect of patent trading on innovation as the *"complementarity effect."* On the other hand, a firm that may not be in the best position to produce patents but are good at commercializing them can readily buy a patent from the market when patents can be easily traded. As a consequence, a firm may rely on external technology acquisition instead of in-house innovation. Thus, patent trading can be a substitute for a firm's in-house innovation. We define this effect of patent trading on innovation as the *"substitution effect."* The overall effect of patent trading on firm innovation hinges on the relative strength of the complementarity effect and the substitution effect. We empirically investigate this issue in this paper to determine whether patent trading promotes or discourages a firms in-house innovation.

In general, trade induces comparative-advantage-based specialization and, thus, contributes to more efficient resource allocation. In terms of technological innovation, how does patent trading affect the division of innovative labor? In the absence of patent trading, a firm has to engage in two types of distinct activities: (i) create an innovation in-house; (ii) commercialize this innovation and market its products. For instance, drug development is characterized by discovering and patenting a compound for a new drug, testing the drug's safety and efficacy in clinical trials, and marketing the drug to wholesalers and pharmacies. During this drug development process, some firms (e.g., an adventurous biotechnology startup founded by university professors) are characterized by a comparative advantage of *creating* innovation, while some firms (e.g., an established pharmaceutical company) feature a comparative advantage of *commercializing* innovation. When patents can be easily traded, a firm with a comparative advantage of creating innovation can specialize in patenting its technological achievement and sell its patents to others. Analogously, a firm with a comparative advantage of commercializing innovation can buy patents from others and specialize in marketing its products. To the extent that patent trading spurs such a pattern of specialization, we expect to observe patent sellers (buyers) redirect more resources toward creating (commercializing) innovation when opportunities of patent trading arise. To test whether patent trading spurs such comparative-advantage-based specialization, we examine how firms adjust their strategies to create and commercialize innovation in response to rising opportunities for patent trading.

To empirically evaluate the effect of patent trading on firm innovation and specialization, we compile a unique dataset on patent exchanges in China and assemble a novel dataset that contains elaborate micro-level information of firms' financial statements, patent filings, patent trading, and patent licensing. China provides an ideal setting for us to explore this research question because of two reasons. First, recent decades have witnessed a boom in innovation and a flourishing market for technology in China. Research and development (R&D) spending in China has grown by more than 20 times in the past 2 decades. Accounting for 22.5% of global R&D spending in 2017, China has become the second-largest R&D spender in the world, only second to the United States.[1] Together with rapid technological advancement, a market for technology has emerged and flourished in China. The value of technology transfer transactions in China has grown from 20 billion RMB (about $2.86 billion) in 2001 to 140 billion RMB (about $20 billion) in 2017. As a comparison to in-house R&D, the value of technology transfer transactions between 2001 and 2017 is 9.7% of aggregate corporate R&D during this period.[2] Among the patents granted in China between 2001 and 2017, 8.6% have been traded at least once during this time period. Corporations in China are actively participating in patent trading. Among the publicly listed firms that file any patents between 2001 and 2017, 50.3% has traded at least one patent in this period. More importantly, micro-level, detailed information on firms' financial statements, patent filings, patent trading, and patent licensing is available for Chinese firms, which allows us to undertake rigorous empirical tests that cannot be done using other countries' data.

Second, identifying the causal effects of patent trading on innovation specialization is usually difficult because patent trading is likely endogenous. Unobservable market and firm heterogeneity correlated with both patent trading and innovation specialization could bias the results (i.e., the omitted variable concern), and firms with different levels of innovation specialization could affect patent trading (i.e., the reverse causality concern). Staggered establishments of patent exchanges in China provide us a unique setting to address the endogeneity problem and establish causality. A patent exchange in China is a facility where patents can be traded or licensed. Patent trading is rife with search and matching frictions, as well as information frictions. As a focal point of patent trading and a major organizer of trade fairs, a patent exchange reduces search friction and enhances the matching efficiency of patent trading. A patent exchange also reduces information frictions

[1] As a comparison, the U.S. share of world R&D in 2017 is 25.0%. Both the R&D expenditures of China and the United States are measured in constant PPP dollars. Source: U.S. National Science Foundation.

[2] These are transactions transferring technology from its owner to another user. In particular, both patent trading and licensing are included in this category of technology transfer contracts. The source of data is the *Statisitcal Yearbook on the Market for Technology In China,* various years.

of patent trading by (i) verifying whether a patent is authentic and valid; (ii) requesting from the patent holders for elaborate information on the technical attributes and potential commercial applications of their patents. Patent exchanges were gradually established across different regions of China over time and hence they affected different firms at exogenously different times, which provides another advantage because it largely avoids a common identification difficulty faced by studies with a single shock, i.e., the existence of potential omitted variables coinciding with the shock that directly affect firms' innovation specialization. Exploiting staggered establishments of patent exchanges in China, we conduct a difference-in-differences (DiD) analysis to assess how patent trading affects firm innovation and specialization.

Our baseline DiD estimation suggests that enhanced patent trading (facilitated by the establishment of patent exchanges) leads to a 7.5% increase in firm patenting. This finding implies that the complementarity effect of patent trading on average dominates its substitution effect. The effect of patent trading on patent buyers, however, is opposite to its effect on patent sellers. While enhanced patent trading contributes to a 21.3% boost in firm patenting for an average patent seller, it leads to a 9.7% decline in firm patenting for an average patent buyer. To evaluate how patent trading affects a firm's effort to commercialize innovation, we examine how a firm changes its advertising expenditures in response to the establishment of patent exchanges. Our DiD estimate indicates that on average a firm increases its advertising expenditures by 21 million RMB (9.6% of sample mean) after the patent exchange is established. In addition, the effect of patent trading on a firm's advertising expenditures is also different between patent buyers and sellers. To be specific, an average patent buyer expands its advertising expenditures by 97 million RMB (44.5% of sample mean) after a patent exchange is established, whereas an average patent seller cuts its advertising expenditures by 40 million RMB (18.3% of sample mean). Hence, our findings demonstrate that enhanced patent trading increases (decreases) in-house innovation of a patent seller (buyer), and decreases (increases) advertising expenditures of a patent seller (buyer). That is to say, patent sellers (buyers) divert more resources toward creating (commercializing) innovation when opportunities of patent trading arise.

A patent can be both traded and licensed in a patent exchange in China. While we focus on patent trading in our baseline analysis, patent licensing constitutes another crucial segment of the market for technology. How does patent licensing affect firm innovation and specialization? To address this question, we extend our analysis of patent trading to the context of licensing transactions. According to our DiD estimations, enhanced patent licensing (facilitated by the establishment of patent exchanges) contributes to a 23.2% boost in patenting for an average licensor, whereas it leads to a 4.8% decline in patenting for the average licensee in our sample. While an average licensor cuts its advertising expenditures by 30 million RMB (13.8% of sample mean) after the patent exchange is established, the average licensee expands its advertising expenditures by 71 million RMB (32.6% of sample mean). Analogous to the effect of patent trading on specialization between patent buyers and sellers, our findings suggest patent licensing also promotes specialization between patent licensors and licensees. While patent licensors redirect their resources from advertising to patenting activities as a response to the establishment of patent exchanges, licensees switch their effort from patenting to advertising activities.

In our study of specialization between patent buyers and sellers, a firm's buyer-seller status is detected by its net number of patents sold. To the extent that a firm with a competitive advantage in creating innovation tends to be a net seller of patents, the net number of patents sold by a firm is informative of its "revealed" competitive advantage. To refine our analysis along this dimension, we apply a firm's R&D efficiency as a more direct proxy of its competitive advantage in creating innovation. Our measure of R&D efficiency gauges the efficiency of transforming a firm's innovative input (R&D expenditures) into innovative output (patents), so it captures a firm's competitive advantage in creating innovation.[3] We find that R&D efficiency is a strong predictor for a firm's demand for and supply of patents in trading. Firms with high R&D efficiency tend to be net sellers of patents and their supply of patents is increasing in their R&D efficiency. In contrast, firms with low R&D efficiency tend to be net buyers of patents and their demand for patents is decreasing in their R&D efficiency. These findings suggest the net number of patents sold by a firm reveals its competitive advantage in creating innovation.

As a complement to our study of specialization between patent buyers and sellers, we replace a firm's net number of patents sold by its R&D efficiency and we reassess the effect of patent trading on innovation specialization. Echoing the patterns of specialization between patent buyers and sellers, we find a firm's response to rising opportunities for patent trading hinges on its R&D efficiency. To illustrate, consider a comparison between an average firm (at the sample mean of R&D efficiency) in our sample and a firm with high R&D efficiency (at the 99th percentile of R&D efficiency). We find that an emerging market for technology (facilitated by the establishment of patent exchanges) contributes to a 37.7% boost in patenting for a firm with high R&D efficiency, whereas it leads to an 11.5% decline in patenting for the average firm in our sample. In addition, a firm with high R&D efficiency cuts its advertising expenditures by 126 million RMB (47.7% of sample mean) after the patent exchange is established, whereas the average firm in our sample expands its advertising expenditures by 15 million RMB (5.7% of sample mean). These observations imply that a firm with high R&D efficiency tends to specialize in creating innovation as a response to an emerging market for technology, whereas a firm with low R&D efficiency tends to specialize in commercializing innovation.

Our findings uncover three patterns of specialization induced by an emerging market for technology: (i) specialization between patent buyers and sellers, (ii) specialization between patent licensors and licensees, and (iii) specialization based on a firm's R&D efficiency. All these three patterns of specialization indicate that a firm's response to an emerging market for technology hinges on its comparative advantages. Firms with a comparative advantage in creating innovation redirect their

[3] Following Hirshleifer et al. (2013), the R&D efficiency of a firm in a year is the number of patent applications it files in that year divided by its R&D capital. More details can be found in Section 3.2.

resources from advertising to patenting activities, whereas firms with a comparative advantage in commercializing innovation switch their effort from patenting to advertising activities. Therefore, the market for technology spurs specialization based on a firm's comparative advantage in creating versus commercializing innovation, and, thus, contributes to a more efficient allocation of the resources for innovation.

Despite the multiple-shock advantage provided by the staggered establishments of patent exchanges, there are still two potential concerns for the findings of our DiD analysis. The first concern is reverse causality, i.e., a patent exchange may be chosen to be established in provinces characterized by vigorous patenting activities. This is because more patent filings in these regions imply a higher demand for patent trading, and a patent exchange may be precisely founded to meet such demand for trading. Admittedly, such a demand-driven argument can explain the positive relation between patenting and the establishment of patent exchanges. To address the concerns for reverse causality, we examine the dynamic treatment effect of the establishments of patent exchanges. To the extent that a patent exchange is established as a response to more patenting activities and higher demand for trading, a significant difference in patenting between the treatment group and the control group should have been observed even *before* the establishment of patent exchanges. According to our dynamic treatment analysis, however, the treatment group and the control group are not characterized by any significant differences in patenting before the establishment of patent exchanges. On the contrary, the treatment effect starts to be significant once the patent exchange has been established and this effect is persistent in the long run. Therefore, the results of the dynamic treatment analysis reject the demand-driven interpretation of our results and rule out the reverse causality argument.

The second concern for our DiD analysis is that the establishment of patent exchanges may be correlated with other factors that drive firm innovation and specialization. To strengthen our identification along this dimension, we take a difference-in-difference-in-differences (DDD) approach based on the following intuition. To the extent that patent exchanges affect firm innovation and specialization, the effect should be more pronounced for patent traders than non-traders. Hence, we refine our treatment and control groups by distinguishing patent traders from non-traders in the DDD setup. To be concrete, our DDD specification is designed to single out the variation of the dependent variable that is (i) specific to the patent traders (relative to non-traders) and (ii) in provinces where a patent exchange is established (relative to provinces where no patent exchanges exist) and (iii) in the years after the exchange is established (relative to the years before its establishment). Moreover, if patent trading does affect firm innovation and specialization, its effect should be more salient for firms facing a liquid market for patent trading than their counterparts confronted with an illiquid market. From this perspective, we differentiate firms facing high trading liquidity from those confronted with low trading liquidity in the DDD specification. As demonstrated by the results of our DDD analysis, the treatment effect is stronger for patent traders than non-traders and more pronounced for firms facing a liquid market for patent trading than their counterparts confronted with an illiquid market. Therefore, the findings of our DDD analysis lends further support to our argument that the treatment effect is indeed attributed to patent trading instead of other factors.

In light of the effect of patent trading on firm specialization, we explore a "bottom line" question: how does patent trading affect firm performance? We investigate this question by assessing four measures of firm performance: the quality of innovation, firm productivity, firm profitability, and market capitalization. We find that enhanced patent trading contributes to higher quality of patents filed by the firms, higher total factor productivity (TFP), higher return on assets (ROA), and higher market value of the firms. According to our DiD estimations, enhanced patent trading (facilitated by the establishment of patent exchanges) leads to an increase in firm TFP by 2.0%, an increase in firm ROA by 0.3 percentage points (8.9% of sample mean), and an increase of firm market value by RMB 377 million (4.4% of sample mean). These findings suggest patent trading enhances firm performance by promoting comparative-advantage-based specialization.

Through its effect on firm specialization, patent trading can in turn affect the industrial organization structure. To the extent that patent trading spurs comparative-advantage-based specialization, we expect to observe that patenting (advertising) activities will be increasingly concentrated among firms with a comparative advantage of creating (commercializing) innovation. As a consequence, our analysis predicts an increase in the concentration of patenting activities and advertising activities after a patent exchange has been established. This prediction of increasing concentration is corroborated by our empirical analysis. Using the HerfindahlHirschman index (HHI) as a proxy of market concentration, we find that the establishment of patent exchanges in a province is associated with an increase of HHI by 0.062 (0.024) for patenting (advertising) activities in that province.[4] Our findings indicate that enhanced patent trading (facilitated by the establishment of patent exchanges) in a province contributes to a higher level of concentration for patenting activities and advertising activities in that province. These results provide complementary evidence to reinforce our finding of how patent trading affects firm specialization.

Furthermore, we conduct three additional tests to assess the robustness and validity of our findings. First, we construct a measure of patent trading liquidity to examine the effect of patent trading along the intensive-margin. That is to say, we replace the treatment dummy by a continuous variable of trading liquidity proxy, and we examine how firms adjust their strategies to create and commercialize innovation when they face a more liquid market for patent trading. Second, one might be concerned that a firm's buyer-seller status may be correlated with the treatment indicator of patent exchanges. To address this concern, we redo our analysis using a firm's buyer-seller status during the period *before* the establishment of patent exchanges. Our findings are robust in both tests. Lastly, we undertake a placebo test by randomly assigning the treatment and control status to observations in our sample. We find that our main results are absent in the sample with artificially

[4] As a comparison, this marginal effect is equivalent to 23.5% (14.4%) of the sample mean of patenting (advertising) HHI.

assigned treatment and control status, which suggests that our main findings are unlikely to be driven by chance.

Our paper contributes to two strands of the literature on the economics of innovation. First, our paper adds to the literature on the impact of the market for technology. Constructing a measure of the technological distance between a patent and a firm, Akcigit, Celik, and Greenwood (2016) show that a patent traded is technologically closer to the buying firm than to the selling firm. Based on the stylized facts of patent trading, Akcigit, Celik, and Greenwood (2016) develop a search-theoretic growth model to quantify the impact of ideas misallocation on economic growth and social welfare. Ma et al. (2018) document that firms sell more redeployable and liquid patents during bankruptcy reorganizations and the effect is driven by firms facing "fire-sale" pressures and lacking access to external financing. Developing a measure of patent market liquidity, Hochberg et al. (2018) find that patent trading facilitates lending to startups, particularly for those with more redeployable (less firm-specific) patent assets. Galasso et al. (2013) argue that patent trading can be attributed to firms' comparative advantage in patent enforcement, and trade driven by this motive reduces the risk of patent litigation. Based on a survey of Belgian firms in the manufacturing industry, Cassiman and Veugelers (2006) document that internal R&D and external technology acquisitions are considered as complements by these firms.

Second, our paper is related to a growing body of literature that studies innovation in China, the second-largest R&D spender in the world and an emerging global powerhouse for innovation. Tian and Xu (2019) find that the establishment of national high-tech zones in China has a positive effect on local innovation output and entrepreneurial activities. In addition, they uncover three channels for this positive effect of high-tech zones: access to financing resources, reductions in administrative burdens, and talent cultivation. Giannetti et al. (2015) show that the performance of Chinese firms increases after hiring directors with foreign experience and delineates how the emigration of talent may lead to a brain gain. Fang et al. (2017) and Tan et al. (2020) find that innovation output increases after Chinas state-owned enterprises (SOEs) are privatized. Tian and He (2018, 2020) provide surveys on how finance and institutions affect corporate innovation, including China.

We contribute to the literature by uncovering the causal effect of patent trading on firm innovation and specialization. We focus on how patent trading affects specialization based on a firm's comparative advantage of creating versus commercializing innovation. This particular source of comparative advantages and motives to trade is remarkably different from other studies (e.g., Galasso et al. (2013)). In addition, we also add to the emerging literature that aims to unveil the ecosystem of innovation in China. We delineate the institutional arrangement of patent trading, compile a unique dataset on patent exchanges in China, and assemble a novel micro-level dataset that combines accounting information with patent trading information for all Chinese listed firms. Our analysis sheds light on the general pattern of how patent trading affects firm innovation and specialization.

The rest of the paper is organized as follows. Section 2 describes the institutional background of patent exchanges and patent trading in China. In Section 3, we delineate the datasets used in our study and provide descriptive statistics of the firms in our sample. We conduct a DiD analysis in Section 4 to study how the market for technology affects firm innovation and specialization. We strengthen our identification strategy by dynamic DiD analysis and DDD analysis in Section 5. We assess the effect of patent trading on firm performance and the industrial organization structure in 6. Three additional robustness checks are undertaken in Section 7. Section 8 concludes our paper.

2 Patent Exchanges In China

How are patents traded in China? The institutional background of patent exchanges and patent trading in China is delineated in this section. As documented in Section 2.1, patent exchanges were gradually established across different regions of China over time. Section 2.2 elaborates on the rules and procedures of patent trading in patent exchanges. Based on this institutional background, we discuss how patent exchange facilitates patent trading in Section 2.3.

2.1 Staggered Establishment of Patent Exchanges In China

A patent exchange in China is a facility where patents can be traded or licensed. Apart from being a focal point for patent trading and licensing, a patent exchange may organize trade fairs where patent holders can showcase their technologies and potential buyers can search for technology suppliers.

Patent exchanges in China enjoy various government support such as favorable policies for financing and land use. To gain such support, however, a patent exchange must maintain satisfactory performance. The performance of a patent exchange is evaluated along two dimensions: (i) the number of patents traded and licensed in the exchange, as well as the value of such transactions; (ii) the number of trade fairs organized by the exchange and the number of participants to such events. As a consequence of persistent poor performance, a patent exchange can be shut down.

Patent exchanges were gradually established across different regions of China over time.[5] To be specific, 15 exchanges were established in 2006, 4 were established in 2007, 16 were established in 2008 and 6 were established in 2009. A complete list of these exchanges, their location, and their founding dates are enumerated in Table 1.

[Insert Table 1 Here.]

[5] Before the establishment of patent exchanges, patent trading had to rely on decentralized transactions. As a consequence, the market for patent trading was remarkably more illiquid. For instance, only 2.7% of patents granted between 2001 and 2003 were traded within three years after being granted. As a comparison, this number has risen to 5.5% for patents granted between 2009 and 2015. As a more formal assessment, we evaluate how patent exchanges affect the market liquidity of patent trading in Table A2. According to our DiD estimations, the establishment of patent exchanges has improved the odds for a patent to be traded by 51.8%.

2.2 Rules and Procedures of Patent Trading

How are patents traded in a patent exchange? To demonstrate how a patent exchange functions in China, Shenzhen Patent Exchange will be used as a running example throughout this section.

Figure 1 is a snapshot of the website of Shenzhen Patent Exchange. As illustrated by the website, a patent holder can provide the information of her patents for sale and a potential buyer can post her demand for patents. Analogously, a potential buyer can search for patents available for sales and a patent holder can look for patent demand information. For instance, Figure 2 will pop up when a potential buyer starts searching for patents available for sale on this website. As shown on top of this figure, a potential buyer can further refine her search by selecting a particular industry, a particular patent type,[6] and a particular patent. To illustrate, two examples of patents posted for sale are provided on the bottom of Figure 2. The patent on the left is titled "An Account Management System Based on Cloud Service." It can be used in the area of information digitalization and its patent holder has posted a suggested trading price of 52 thousand RMB. The patent on the right is titled "A Gear Cutter For 3D Printing Waste." It is classified into the category of instruments and apparatuses and its patent holder has posted a suggested trading price of 48 thousand RMB. When clicking each patent available for sale, the buyer will be directed to another web page with further information on the patent, such as the detailed terms of contract (e.g., trading or licensing) and contact information of the patent holder.

[Insert Figure 1 and Figure 2 Here.]

How do the buyers and sellers participate in trading at the patent exchange? The procedures of patent trading are delineated in Figure 3. To participate in patent trading, both patent holders and potential buyers are required for applying for exchange membership. After such applications are approved by the patent exchange, a patent holder can provide the information of her patents for sale and a potential buyer can post her demand information. Based on such demand and supply information, the exchange matches the buyers with sellers and recommends a potential deal. If both parties are interested in the deal, the exchange can arrange a meeting for them. If the buyer and the seller agree to trade after negotiating the deal, the exchange provides related legal documents to them and certifies this transaction. The exchange charges a fee for the services provided during this process.

[Insert Figure 3 Here.]

[6] There are three types of patents in China: invention patents, utility patents, and design patents. Compared to utility model patents and design patents, invention patents are subject to more rigorous examination and enjoy a longer term of protection.

2.3 How A Patent Exchange Facilitates Patent Trading

As demonstrated by the rules and procedures of patent trading, a patent exchange facilitates patent trading by reducing (i) search and matching frictions and (ii) information frictions of trading. We elaborate on both friction reduction roles of a patent exchange as follows.

Patent trading is rife with search and matching frictions. A seller can have trouble looking for a buyer who is willing to pay for her technology, especially when the knowledge embodied in her patent is hard to articulate. It can be also difficult for a buyer to find the exact technology that fulfills its specific technical requirements and commercial needs. Even if a buyer and a seller meet, bargaining to determine the price can be both time-consuming and financially costly. In spite of gains from patent trading, a potential transaction can be obstructed if the costs of such frictions exceed the benefits of trade. A patent exchange facilitates patent trading by reducing search and matching frictions. Designed as a focal point for patent trading, a patent exchange reduces search frictions and enhances matching efficiency. Patent holders can provide elaborate information of their patents to the website of the exchange and specify preliminary terms of trade as the starting point of negotiation. Buyers can also enunciate their specific technical requirements and commercial needs on the website. Complimenting this online channel of matchmaking, the exchange also organizes offline trade fairs to facilitate the exchange of information and communication between buyers and sellers. In addition, the exchange can recommend a potential deal to the buyer and the seller based on their information provided on the website. If both parties are interested in the deal, the exchange can arrange a meeting for them and provide related legal documents to facilitate their negotiation.

Apart from the search and matching frictions, information frictions also pose a serious challenge to patent trading. Both the technological and commercial potential of a patent can be uncertain. What practical applications can a technology create? How commercially successful these applications can be? Answers to such questions can be uncertain and ambiguous, especially for nascent technologies and in technically sophisticated areas. On top of such uncertainties confronting both parties, asymmetric information between buyers and sellers can also be an acute problem for patent trading. As demonstrated by Akerlof (1970), such information asymmetry may undermine the functioning of the entire market. To address this "lemons problem," the exchange applies three strategies to reduce information frictions of patent trading. First, the exchange verifies the authenticity and validity of the patents posted for sales. Second, the exchange requests for a technical report of the elaborate technological attributes of the patents from its holder. Third, patent holders also need to provide a study on potential commercial applications of their patents, including a forecast for market demand. A patent will be rejected from trading on the exchange if these three conditions are not properly satisfied. These roles of the patent exchange alleviate potential problems caused by the uncertainty of the technology and asymmetric information between buyers and sellers.

3 Data and Descriptive Statistics

Exploiting staggered establishments of patent exchanges in China, we examine the causal effect of patent trading on firm innovation and specialization. To undertake a rigorous empirical analysis, we assemble a novel dataset that contains elaborate micro-level information of firms' financial statements, patent filings, and patent trading. Section 3.1 describes the various databases used in our analysis, Section 3.2 delineates how the variables are constructed, and Section 3.3 provides summary statistics for the firms in our sample.

3.1 Data Description

To study patent trading in China, we obtain a comprehensive dataset of patents[7] granted at the Chinese National Intellectual Property Administration (CNIPA). Similar to the patent data provided by the United States Patent and Trademark Office (USPTO), the CNIPA database contains elaborate information on patent applications, patent assignees, and a record of ownership changes.

Based on the change of patent ownership, we can identify a patent sale in the CNIPA database. In some cases, however, the change in ownership status is attributed to an ownership reassignment from the inventors to their employers. We single out such inventor-employer reassignment in the data and exclude them from our analysis. To be specific, an ownership change is classified as a reassignment from the inventors to their employers if the following four conditions are satisfied: (i) the original assignee is an individual inventor when the patent is granted at CNIPA; (ii) the assignor in a reassignment record is the same as the patent inventor; (iii) the assignee in a reassignment record is a corporation; (iv) the assignor and the assignee share the same address.

To alleviate the concern for invalid patent information in the data, we further clean the data by excluding the following records: (i) the assignor in a reassignment record is the same as the assignee; (ii) the assignee in a reassignment record is the same as the original patent inventor; (iii) a patent expires before the ownership change is recorded; (iv) the ownership change is recorded before the patent application date.

To gather firm accounting information, we focus on publicly traded companies in China's A-share stock market.[8] Our data on Chinese public companies is retrieved from the China Stock Market and Accounting Research (CSMAR) database. CSMAR provides elaborate information on financial statements and stock trading for Chinese listed firms, and it is widely used by research institutions and data service providers around the world (e.g., Wharton Research Data Services). In addition, we collect the information of firm R&D expenditures from WIND, a major financial

[7] Three types of patents can be granted at CNIPA: invention patents, utility patents, and design patents. Compared to utility model patents and design patents, invention patents are subject to more rigorous examination and enjoy a longer term of protection. Among these three types of patents, invention patents in China are the most comparable to the utility patents granted at the United States Patent and Trademark Office (USPTO). We focus on invention patents in this study, and they will be subsequently referred to as "patents" for brevity.

[8] We exclude firms in the financial industry in this study.

data provider serving more than 90% of financial institutions in China.

To combine firm accounting information with patenting information, we merged the CSMAR database with the CNIPA patent database in China. Data merging is accomplished by matching company names in these 2 datasets, and we account for the unique features of the Chinese language during the merging process.[9] Our merged dataset contains elaborate micro-level information of firms' financial statements, patent filings, and patent trading. This sample represents 90.0% of China's publicly traded firms between 2001 and 2016, 83.2% of their sales, and 98.7% of their R&D expenditures.

3.2 Variable Construction

The variables used throughout this paper are defined in Table A1 in the appendix. Our measure of a firm's innovative output in a year is the natural logarithm of one plus the number of patent applications a firm files (and eventually granted) in that year. To account for different qualities of patents, we also examine the relative citation strength of a patent. To be specific, we gauge the relative citation strength of a patent by the number of citations it has received by 2018, divided by the average number of citations received by patents in its cohort (i.e., patents applied in the same year and the same technology class). We apply a firm's advertising expenditures as a proxy of its effort to commercialize its innovation.

Following the method of Hochberg et al. (2018), we construct a measure of patent trading liquidity that each firm faces each year. This measure of patent trading liquidity is a proxy of the likelihood that a firm's patents will be traded in each year.[10] As in Hochberg (2018), we adjust the pool of potentially tradable patents by excluding patent sales that occur a long time after a patent is granted.[11] In our baseline results, we consider patent trading during the first 6 years in a patent's lifetime. Our results are robust when using shorter horizons (e.g., 5 years) and longer horizons (e.g., 7 years) as the cutoff.[12]

To distinguish patent buyers from sellers, we examine the net number of patents a firm sells (i.e., the number of patents sold subtracted by the number of patents bought) in each year. A positive (negative) value of the net number of patents sold implies that a firm is a seller (buyer) in the market of patent trading. This measure is instrumental to evaluate the effect of patent

[9] To clean company names, we convert all full-width numbers into half-width and convert all full-width letters into half-width. We also convert all Chinese numbers into Arabic. To standardize company names, we remove all corporate identifiers before name matching.

[10] To be specific, our measure of patent trading liquidity is obtained by the following two steps. First, we compute the fraction of patents in each cohort (i.e., patents with the same grant year and industry classification) that are traded in each year after being granted. This fraction of patents traded in each cohort in each year is applied as a proxy of the likelihood that every patent in this cohort will be traded in that year. Based on this proxy, we obtain a measure of trading liquidity for each patent in a firm's patent portfolio in each year. Second, we construct the measure of firm-level trading liquidity in a year as the average trading liquidity of all patents in its patent portfolio in that year.

[11] As shown in Serrano (2010), the likelihood for a patent to be traded decreases over the lifetime of a patent.

[12] Due to space limits, the results of such robustness checks are not reported, but they can be sent upon request.

trading on firm specialization between buyers and sellers. To distinguish patent licensors from licensees, we examine the net number of patents a firm licenses out (i.e., the number of patents licensed out subtracted by the number of patents licensed in) each year. A positive (negative) value of the net number of patents licensed out implies that a firm is a licensor (licensee) in patent licensing transactions. This measure facilitates our analysis of the effect of patent licensing on firm specialization between licensors and licensees.

To gauge a firm's productivity of creating innovation, we construct a measure of a firm's R&D efficiency in its patenting activities. Following Hirshleifer et al. (2013), the R&D efficiency of a firm in a year is the number of patent applications it files in that year divided by the weighted average of its R&D expenditures in the past 3 years. To be specific, a firm's R&D efficiency is defined as follows:

$$\text{R\&D Efficiency}_{i,t} = \frac{\text{Patent}_{i,t}}{\text{R\&D}_{i,t} + 0.8 \times \text{R\&D}_{i,t-1} + 0.6 \times \text{R\&D}_{i,t-2}}$$

$\text{Patent}_{i,t}$ refers to the number of successful patent applications filed by firm i in year t. $\text{R\&D}_{i,t}$, $\text{R\&D}_{i,t-1}$, and $\text{R\&D}_{i,t-2}$ are the R&D expenditures of firm i in year t, $t-1$, and $t-2$, respectively. This measure captures the efficiency of transforming a firm's innovative input (R&D expenditures) into innovative output (patents). Hence, a firm's R&D efficiency is informative of its competitive advantage in creating innovation.

To assess how patent trading affects firm performance, we apply total factor productivity (TFP) as a measure of firm productivity and we tap return on assets (ROA) as a measure of firm profitability. Our measure of ROA is calculated as a firm's net profit divided by its book value of assets. Our TFP estimation is based on the method developed in Ackerberg, Caves, and Frazer (2015). Built on Olley and Pakes (1996) and Levinsohn and Petrin (2003), Ackerberg, Caves, and Frazer (2015) propose an estimation method that avoids the functional dependence problem in previous studies.[13] To be specific, we estimate a Cobb–Douglas production function where the variable input is labor, the state variable is capital, and the proxy variable is the intermediate input.[14] In addition to firm productivity and profitability, we also examine how patent trading affects firm market value.[15]

Our control variables used in the regressions include a firm's book value of assets (in natural logarithm), age (in natural logarithm), R&D intensity (R&D expenditures divided by book value of assets), capital expenditures ratio (capital expenditures divided by book value of assets), PPE ratio (net value of property, plant, and equipment divided by the book value of assets), leverage ratio (book value of total debt divided by the book value of total assets), and its growth opportunities

[13] In particular, Ackerberg, Caves, and Frazer (2015) shows that the labor coefficient may not be identified in the estimation methods of Olley and Pakes (1996) and Levinsohn and Petrin (2003).

[14] Following Giannetti et al. (2015), output is measured as a firm's total revenue (in RMB), capital is measured as a firm's total assets (in RMB), labor is measured as a firm's employment (in persons), and the intermediate input is measured as a firm's expenditure on labor and capital goods (in RMB).

[15] The market value of a firm is measured as the product of a firm's total number of shares outstanding and annual closing price.

captured by Tobin's Q (market-to-book ratio).

3.3 Descriptive Statistics

Our empirical analysis is based on publicly listed Chinese companies that have filed at least one patent at CNIPA between 2001 and 2017. To gain a better understanding of these firms, we provide summary statistics for our sample in Table 2. To alleviate the concerns for outliers, every variable in Table 2 is winsorized at the 1^{st} and 99^{th} percentiles of its distribution.

How does the accounting information of an average Chinese public firm look like? As unveiled by Table 2, the average firm in our sample has gone public for 8.1 years, has a market capitalization of 8.6 billion RMB, an asset of 7.5 billion RMB, and a return on asset of 3.4%. On average, R&D expenditures amount to approximately 1% of firm assets or 1.9% of firm sales in our sample. A firm's average capital expenditures and net PPE (property, plant, and equipment) value are 5.8% and 25.3% of firm assets, respectively. The average firm features a leverage ratio (debt-to-asset ratio) of 45.5% and Tobin's Q (market-to-book ratio) of 2.2.

What is a firm's innovating performance and how much does it spend on commercializing its innovation? The average firm in our sample files approximately 7 patent applications each year, though some firms do not have any patent applications in some years and some firms have as many as 162 applications in a year. The R&D efficiency has a sample mean of 0.187.[16] Hence, every 10 million RMB R&D expenditure (3-year weighted average) is associated with 1.87 patent applications. To commercialize its innovation, an average firm spends 218 million RMB each year to advertise its products. This advertising expenditure constitutes 3.8% of firm assets or 6.5% of firm sales in our sample.

How many patents do firms trade? The net number of patents a firm sells in a year has a mean of -0.092 and a standard deviation of 0.62. Note some active traders in our sample may buy (sell) up to 4 (2) patents in particular years. As an alternative perspective to assess the effect of patent trading, consider the cumulated number of patents bought (sold) by the firms. On average, a firm has bought (sold) 6 (5) patents by the end of our sampling period, though some large buyers (sellers) have bought (sold) 88 (55) patents. Patent licensing activity is less frequent than patent trading. The net number of patents a firm licenses out in a year has a mean of -0.017 and a standard deviation of 0.38, and some active participants in patent licensing may license out (in) 3 patents in particular years. In terms of the cumulated number of patents involved in licensing transactions, an average firm has licensed out (in) 3 (2) patents by the end of our sampling period, though some active participants have licensed out (in) 39 (13) patents.

[Insert Table 2 Here.]

[16] A firm's R&D expenditures are measured in millions of RMB. Note that a firm's R&D efficiency can be missing in some years. In such scenarios, we assume it stays at the same level as the latest available value of R&D efficiency in previous years.

4 The Market for Technology and Innovation Specialization

As highlighted in Section 2, patent exchanges were gradually established across different regions of China over time and hence they affected different firms at exogenously different times. The staggered establishments of patent exchanges provide an advantage for our analysis because it largely avoids a common identification difficulty faced by studies with a single shock, i.e., the existence of potential omitted variables coinciding with the shock that directly affect firms' innovation specialization decisions. As demonstrated by Table A2 of the appendix, the establishment of the patent exchanges contributes to a substantial increase in the market liquidity of patent trading and licensing transactions. Therefore, patent exchanges in China provide us a unique and ideal setting to address the endogeneity problem and establish causality. Exploiting staggered establishments of patent exchanges in China, we conduct a DiD analysis to examine the causal effect of the market for technology on three patterns of innovation specialization in this section. Section 4.1 is our baseline analysis of specialization between patent buyers and sellers. We extend our analysis to specialization between patent licensors and licensees in section 4.2, and we delve further into specialization based on a firm's R&D efficiency in section 4.3.

4.1 Specialization Between Patent Buyers and Sellers

How do the establishments of patent exchanges affect firm innovation? To probe into this question, we compare patenting activities of treatment group with the control group in Figure 4. Year 0 on the horizontal axis of Figure 4 marks the year when a patent exchange is established. A firm is included in the treatment group if a patent exchange is established in the province where it is located. The solid (dash) line in Figure 4 is the average number of patents applied by the firms in the treatment (control) group. As unveiled by Figure 4, the difference between the treatment group and the control group is fairly stable before the patent exchange is founded.[17] As a stark contrast, the patenting gap between the treatment group and the control group quickly widens after the patent exchange is established. While firm patenting in the control group barely increases, firm patenting in the treatment group surges over time.

[Insert Figure 4 Here.]

In light of this pattern in Figure 4, we apply the establishment of the patent exchange as a quasi-experiment for DiD analysis in this section. Our DiD analysis is based on all publicly listed Chinese companies that have filed at least one patent at CNIPA between 2001 and 2016. To be

[17] Note the level difference between the treatment group and the control group is entirely compatible with the DiD approach. As a more rigorous test, our dynamic DiD analysis in the subsequent section assesses the parallel trend assumption in a more formal manner.

specific, we estimate the following firm-level panel regressions in this section:

$$y_{i,t+1} = \text{Treatment}_{i,t} \times \beta + \delta' X_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t} \quad (1)$$

In equation (1), $y_{i,t+1}$ is the dependent variable where the subscript i indexes for firm and t indexes for year. The dummy variable $\text{Treatment}_{i,t}$ equals one if a patent exchange has been established in the province where firm i is located by year t.[18] The term $\text{Treatment}_{i,t}$ is introduced to conduct a comparison along 2 dimensions. To be specific, β in equation (1) captures the variation of the dependent variable that is (i) specific to firms in provinces where a patent exchange is established (relative to provinces where patent exchanges do not exist) and (ii) in the years after the exchange is established (relative to the years before its establishment). Hence, β captures the effect of patent exchange on the dependent variable, and, thus, is the key regression coefficient of interest. γ_i (γ_t) in equation (1) stands for firm fixed effect (year fixed effect). Since firm fixed effect is included in the regression, we have controlled for all time-invariant differences between firms in the treatment group and their counterparts in the control group. X is a vector of our control variables. To be specific, X includes a firm's book value of assets (in natural logarithm), age (in natural logarithm), R&D intensity (R&D expenditures divided by book value of assets), return on assets (net profit divided by book value of assets), capital expenditures ratio (capital expenditures divided by book value of assets), PPE ratio (net value of property, plant, and equipment divided by the book value of assets), leverage ratio (book value of total debt divided by the book value of total assets), and its growth opportunities captured by Tobin's Q (market-to-book ratio). ϵ in equation (1) is the error term. We cluster standard errors at the firm level to account for potential serial dependence of the error terms. Table 3 reports the results of our baseline DiD estimations.

[Insert Table 3 Here.]

Does patent trading promote or discourage a firm's in-house innovation? As underlined in Section 1, the answer hinges on the relative strength of the complementarity effect and substitution effect of patent trading on firm innovation. When patents can be easily traded, a patent holder can sell its patent to someone else who can better commercialize this patented technology. The possibility of selling its patent provides stronger incentives for a firm to innovate, so patent trading can be a complement for a firm's in-house innovation. On the other hand, a firm that may not

[18] Since the website of patent exchanges has already provided a considerable amount of information of patents, one may wonder why geographic boundaries matter. In fact, most patent trading transactions rely heavily on in-person meetings and negotiations at patent exchanges. This is because trading patents is substantially more difficult than trading tangible goods. Tacit knowledge embodied in patents is hard to articulate. Commercial applications of patented technologies can be highly uncertain. Bargaining to determine the price can be both time-consuming and financially costly. Transfer of patent ownership entails numerous legal documents that must be signed in person. Because of such difficulties of patent trading, transactions do rely on in-person meetings and geographic boundaries do matter. As a matter of fact, 65.3% of patent trading transactions were attributed to participants located in the same province. In light of this, we define a firm to be treated if a patent exchange is established in the province where its headquarters is located.

be in the best position to produce patents but are good at commercializing them can readily buy a patent from the market when patents can be easily traded. As a consequence, a firm may substitute its in-house innovation by external technology acquisition. Which of the complementarity effect and substitution effect dominates the other? As uncovered by regression (1) of Table 3, the complementarity effect of patent trading is on average stronger than its substitution effect. According to our DiD estimate in regression (1), the establishment of patent exchanges induce a 7.5% increase in firm patenting, so patent trading on average enhances a firm's in-house innovation.

How does patent trading affect the division of innovative labor? When patents can be easily traded, a firm with a comparative advantage of creating innovation can specialize in patenting its technological achievement and sell its patents to others. Analogously, a firm with a comparative advantage of commercializing innovation can buy patents from others and specialize in marketing its products. To the extent that patent trading spurs specialization, we expect to observe patent sellers (buyers) redirect more resources toward creating (commercializing) innovation when opportunities of patent trading arise. To test whether patent trading spurs such comparative-advantage-based specialization, we examine whether patent sellers and buyers react differently to the establishment of patent exchanges. To distinguish patent buyers from sellers, we interact the treatment indicator with the net number of patents a firm sells each year. To be more precise, the net number of patents sold by a firm is the number of patents it sells subtracted by the number of patents it buys each year. A positive (negative) value of the net number of patents sold implies that a firm is a seller (buyer) in the market of patent trading. To the extent that a firm with a competitive advantage in creating innovation tends to be a net seller of patents, the net number of patents sold by a firm is informative of its "revealed" competitive advantage. While we study specialization between patent buyers and sellers based on a firm's net number of patents sold in this section, we apply a more direct proxy of a firm's competitive advantage in Section 4.3.

As suggested by regression (2) of Table 3, the cross term between the treatment indicator and the net number of patents sold is positive. Hence, the effect of patent trading on patent buyers is opposite to its effect on patent sellers. To assess the magnitude of the effect, consider a comparison between an average buyer (at the mean value of the number of patents bought) and an average seller (at the mean value of the number of patents sold).[19] While the establishment of patent exchanges contributes to a 21.3% boost in firm patenting for an average patent seller, it leads to a 9.7% decline in firm patenting for an average patent buyer. These findings indicate that patent trading and in-house innovation are complements for the patent sellers, whereas they are substitutes for the patent buyers.

While the patent sellers (buyers) spend more (less) resources on in-house innovation, how do they change their strategies of commercializing their innovation? We investigate this issue in

[19] A firm is defined to be a patent buyer (seller) if the number of patents it buys is greater (smaller) than the number of patents it buys. The mean value of the number of patents bought (sold) is 1.96 (1.49) for the patent buyers (sellers) in our sample.

regression (3) and (4) of Table 3, where we apply a firm's advertising expenditures as a proxy of its effort to commercialize its innovation. Our DiD estimate in regression (3) indicates that on average a firm increases its advertising expenditures by 21 million RMB (9.6% of sample mean) after a patent exchange is established. Analogous to the heterogeneous effects of patent trading on firm patenting, the effect of patent trading on a firm's advertising expenditures is also different between patent buyers and sellers. According to the estimates of regression (4) of Table 3, an average patent buyer expands its advertising expenditures by 97 million RMB (44.5% of sample mean) after the patent exchange is established, whereas an average patent seller cuts its advertising expenditures by 40 million RMB (18.3% of sample mean).

Our DiD estimations in this section suggest that enhanced patent trading (facilitated by the establishment of patent exchanges) (i) increases (decreases) innovation of a patent seller (buyer); (ii) decreases (increases) advertising expenditures of a patent seller (buyer). These findings indicate that patent sellers (buyers) redirect more resources toward creating (commercializing) innovation. This is suggestive evidence that patent sellers (buyers) tend to specialize in creating (commercializing) innovation when opportunities for patent trading arise.

4.2 Specialization Between Patent Licensors and Licensees

As elaborated in Section 2, a patent can be both traded and licensed in a patent exchange in China. While we focus on patent trading in the previous section, patent licensing constitutes another crucial segment of the market for technology. How does patent licensing affect firm innovation and specialization? To the extent that our economic reasoning for how patent trading affects specialization is valid, we expect to observe that the effect of patent licensing is similar to trading transactions. Hence, we replace the variable "net number of patents *sold*" in Table 3 by "net number of patents *licensed out*" in Table 4 to assess specialization between patent licensors and licensees.

The regression setup in Table 4 is the same as that in Table 3, except that a firm's net number of patents sold is replaced by its net number of patents licensed out. To be more precise, the net number of patents licensed out by a firm is the number of patents it licenses out subtracted by the number of patents it licenses in each year. A positive (negative) value of the net number of patents licensed out implies that a firm is a licensor (licensee) in patent licensing transactions. Echoing the findings in Table 3, the cross term between the treatment indicator and a firm's net number of patents licensed out is positive (negative) when the dependent variable is patent applications (advertising expenditures). Hence, the effect of patent licensing on licensors is opposite to its effect on licensees. To assess the magnitude of the effect, consider a comparison between an average licensor (at the mean value of the number of patents licensed out) and an average licensee (at the mean value of the number of patents licensed in).[20]

[20] A firm is defined to be a licensor (licensee) if the number of patents it licenses out is greater (smaller) than the

As suggested by regression (1) of Table 4, the establishment of patent exchanges contributes to a 23.2% boost in patenting for an average licensor, whereas it leads to a 4.8% decline in patenting for the average licensee in our sample. According to regression (2) of Table 4, an average licensor cuts its advertising expenditures by 30 million RMB (13.8% of sample mean) after a patent exchange is established, whereas the average licensee in our sample expands its advertising expenditures by 71 million RMB (32.6% of sample mean). Analogous to the effect of patent trading on specialization between patent buyers and sellers, our findings suggest patent licensing also promotes specilaization between patent licensors and licensees. While patent licensors redirect their resources from advertising to patenting activities as a response to the establishment of patent exchanges, licensees switch their effort from patenting to advertising activities. This is suggestive evidence that patent licensors (licensees) tend to specialize in creating (commercializing) innovation when a market for technology emerges.

4.3 Specialization Based On R&D Efficiency

In our study of specialization between patent buyers and sellers, a firms trading status in patent transactions is detected by the net number of patents it sells. To the extent that a firm with a competitive advantage in creating innovation tends to be a net seller of patents, the net number of patents sold by a firm is informative of its "revealed" competitive advantage. To refine our analysis along this dimension, we apply a firm's R&D efficiency as a more direct proxy of its "ex-ante" competitive advantage in creating innovation. As a bridge to our analysis of buyer-seller-based specialization in previous sections, we examine the relationship between the net number of patents sold by a firm and its R&D efficiency in Section 4.3.1. As a complement to our buyer-seller-based specialization, we replace a firm's net number of patents sold by its R&D efficiency and we recast our analysis of how patent trading affects innovation specialization in Section 4.3.2.

4.3.1 R&D Efficiency and Buyer-Seller Status In Patent Trading

What types of firms are more likely to be on the supply side of patent trading and what types of firms are more likely on the demand side? Does the net number of patents sold by a firm reveal its competitive advantage in creating innovation? We investigate these questions by firm-level regressions and report the results in Table 5. The regressions in Table 5 are based on all publicly listed Chinese companies that have filed at least one patent at CNIPA between 2001 and 2016. The dependent variable in Table 5 is the net number of patents sold by a firm in year $t+1$ divided by a firm's patent stock by the end of year t. A positive (negative) value of the net number of patents sold implies that a firm is a seller (buyer) in the market of patent trading. The explanatory

number of patents it licenses in. The mean value of the number of patents licensed out (in) is 1.63 (1.41) for the licensors (licensees) in our sample.

variables in Table 5 are various firm characteristics in year t. We add control variables in regression (2), year dummies in regression (3), and both firm dummies and year dummies in regression (4).

[Insert Table 5 Here.]

The regressions in Table 5 unveil how each firm characteristic is related to its status in patent trading. In particular, our key variable of interest is a firm's R&D efficiency. As delineated in Section 3.2, the R&D efficiency of a firm in a year is measured by the number of patent applications it files in that year divided by the weighted average of its R&D expenditures in the past 3 years. This measure gauges the efficiency of transforming a firm's innovative input (R&D expenditures) into innovative output (patents), so it captures a firm's competitive advantage in creating innovation. As demonstrated across all regressions in Table 5, a firm's R&D efficiency is positively correlated with the net number of patents it sells (as a fraction of its patent stock) and the magnitude of the effect of R&D efficiency is fairly large. According to regression (4) of Table 5, a one-standard-deviation increase in a firm's R&D efficiency predicts an increase of the net number of patents it sells (as a fraction of its patent stock) by 0.13 percentage points (17.8% of the sample mean).[21] Therefore, R&D efficiency is a strong predictor for a firm's demand for and supply of patents in trading. Firms with high R&D efficiency tend to be net sellers of patents and their supply of patents is increasing in their R&D efficiency. In contrast, firms with low R&D efficiency tend to be net buyers of patents and their demand for patents is decreasing in their R&D efficiency. These findings suggest that the net number of patents sold by a firm reveals its competitive advantage in creating innovation.

4.3.2 R&D Efficiency and Firm Specialization

As a complement to our study of buyer-seller-based specialization, we apply a firm's R&D efficiency as a more direct proxy of its "ex-ante" competitive advantage in creating innovation. To be specific, we replace a firm's net number of patents sold in Table 3 by its R&D efficiency and we recast our DiD analysis of innovation specialization in Table 6.

The regresson setup in Table 6 is the same as that in Table 3, except that a firm's net number of patents sold is replaced by its R&D efficiency. As demonstrated by the results in Table 6, the cross term between the treatment indicator and a firm's R&D efficiency is positive (negative) when the dependent variable is patent applications (advertising expenditures). Hence, a firm's response to the establishment of patent exchanges hinges on its R&D efficiency. To illustrate, consider a comparison between an average firm (at the sample mean of R&D efficiency) in our sample and a firm with high R&D efficiency (at the 99th percentile of R&D efficiency).[22] According to regression (1) of Table 6, the establishment of patent exchanges contributes to a 37.7% increase in

[21] The standard deviation of R&D efficiency is 0.563 in our sample.

[22] The sample mean of R&D efficiency is 0.187 and the 99th percentile is 4.468.

patenting for a firm with high R&D efficiency, whereas it leads to an 11.5% decrease in patenting for the average firm in our sample. Our DiD estimate in regression (2) of Table 6 indicates that a firm with high R&D efficiency decreases its advertising expenditures by 126 million RMB (47.7% of sample mean) after a patent exchange is established, whereas the average firm in our sample increases its advertising expenditures by 15 million RMB (5.7% of the sample mean). Our findings imply that a firm with high R&D efficiency tend to specialize in creating innovation as a response to the establishment of patent exchanges, whereas a firm with low R&D efficiency tends to specialize in commercializing innovation.

[Insert Table 6 Here.]

Taking stock of our DiD analysis in Section 4, our findings uncover three patterns of specialization induced by an emerging market for technology: (i) specialization between patent buyers and sellers, (ii) specialization between patent licensors and licensees, and (iii) specialization based on a firm's R&D efficiency. All these three patterns of specialization indicate that a firm's response to an emerging market for technology hinges on its comparative advantages. Firms with a comparative advantage in creating innovation redirect their resources from advertising to patenting activities, whereas firms with a comparative advantage in commercializing innovation switch their effort from patenting to advertising activities. Therefore, our DiD analysis in Section 4 suggests that the market for technology spurs specialization based on a firm's comparative advantage in creating versus commercializing innovation.

5 Further Identification Analyses

Despite the multiple-shock advantage provided by the staggered establishments of patent exchanges, there are still two concerns for our DiD analysis. The first concern is reverse causality, i.e., a patent exchange may be chosen to be established in provinces characterized by vigorous patenting activities. The second concern is that the establishment of patent exchanges may be correlated with other factors that drive firm innovation and specialization. To strengthen our identification strategies, we conduct a dynamic DiD analysis to address the first concern in Section 5.1 and we take a difference-in-difference-in-differences (DDD) approach to address the second concern in Section 5.2.

5.1 Dynamic Difference-In-Difference Analysis

A potential concern for our DiD specification is reverse causality, i.e., a patent exchange may be chosen to be established in provinces characterized by vigorous patenting activities. This is because more patent filings in these regions imply a higher demand for patent trading, and a patent exchange may be precisely founded to meet such demand for trading. Admittedly, such a demand-driven argument can explain the positive relationship between patenting and the establishment of patent exchanges observed in Table 3. To address the concerns for reverse causality, we study the dynamic treatment effect of the establishment of patent exchanges. To the extent that a patent exchange is established as a response to more patenting activities and higher demand of trading, a significant difference in patenting between the treatment group and the control group should have been observed even *before* the establishment of patent exchanges. In light of this, we replace the treatment dummy in equation (1) by a set of dummies representing the years around the establishment of patent exchanges. The results of this dynamic treatment setup are presented in Table 7.

[Insert Table 7 Here.]

The empirical specification of Table 7 is analogous to Table 3, except for one crucial difference. In Table 7, $Treatment(-2)$ and $Treatment(-1)$ correspond to 2 years and 1 year before the establishment of patent exchanges, respectively. Analogously, $Treatment(0)$ is defined with respect to the year when a patent exchange is established, and $Treatment(1+)$ is associated with one and more years after the establishment of patent exchanges. If the demand-driven hypothesis is true, the treatment group and the control group would have featured a significant difference in patenting even *before* the establishment of patent exchanges. However, neither $Treatment(-2)$ nor $Treatment(-1)$ in Table 7 is statistically significant and the magnitude of both estimates are tiny. That is to say, we do not observe any significant differences in patenting between the treatment group and the control group before the patent exchange is established. On the contrary, the treatment effect starts to be significant once the patent exchange has been established and this effect is persistent in the long run. In addition, the magnitude of the estimate of the treatment dummies is much larger than their counterparts before the treatment event. In light of the findings in Table 7, we reject the demand-driven interpretation of our results and rule out the reverse causality argument.

5.2 Difference-In-Difference-In-Difference (DDD) Analysis

As highlighted in our DiD analysis, the staggered establishments of patent exchanges provide an advantage for causal analysis, because it largely avoids a common identification difficulty faced by studies with a single shock, i.e., the existence of potential omitted variables coinciding with the shock that directly affect firms' innovation specialization. Despite this multiple-shock advantage, there is still a potential concern for our DiD specification: the establishment of patent exchanges could still be correlated with other factors that drive firm innovation and specialization. To address this concern, we take a difference-in-difference-in-differences (DDD) approach to strengthen our DiD analysis and further establish causality. In Section 5.2.1, we refine our treatment and control groups in the DDD setup by distinguishing patent traders from non-traders. Analogously, we differentiate firms facing a liquid market for patent trading from their counterparts confronted with an illiquid market in Section 5.2.2.

5.2.1 DDD Analysis: Patent Traders vs Non-Traders

If the treatment effect on firm innovation and specialization is attributed to patent trading, the effect must be more pronounced for patent traders than non-traders. In light of this, we refine our treatment and control groups by distinguishing patent traders from non-traders in Figure 5.

[Insert Figure 5 Here.]

Throughout Section 5.2, Year 0 on the horizontal axis of a figure marks the year when a patent exchange is established. A firm is included in the treatment group if a patent exchange is established in the province where it is located. Otherwise, the firm is covered in the control group as a comparison. In Figure 5, we further categorize firms in the treatment group into 3 sub-groups: (i) patent buyers; (ii) patent sellers; (iii) non-traders. To be specific, a patent trader in the treatment group is defined to be a buyer (seller) if the number of patents it bought is greater (less) than the number of patents it sold during our sampling period. A firm in the treatment group is classified as a non-trader if it did not trade any patents during our sampling period. The vertical axis of Figure 5 is the average number of patents applied by firms in each of these 4 sub-groups.

As unveiled by Figure 5, patenting of non-traders in the treatment group is almost the same as their counterparts in the control group. Hence, any observed treatment effects of patent exchanges are attributed to the patent traders in the treatment group. Moreover, among the patent traders in the treatment group, a stark difference between patent buyers and sellers is also manifested in Figure 5. To the extent that patent trading spurs comparative-advantage-based specialization, we hypothesize patent sellers should redirect more resources toward creating innovation than patent buyers. Figure 5 provides favorable evidence for this hypothesis. Patenting of buyers and sellers is largely parallel to each other before the patent exchange is introduced. Upon the establishment of the patent exchange, however, a remarkable difference of patenting between buyers and sellers appears. While patenting of buyers largely follows its pre-event trend, patenting of sellers soars after the patent exchange is established. This salient difference of patenting behaviors between buyers and sellers is suggestive evidence that a patent exchange spurs comparative-advantage-based specialization. As a more rigorous analysis, we estimate the following firm-level panel regressions in a DDD setup:

$$y_{i,t+1} = \text{Treatment}_{i,t} \times \alpha + \text{Treatment}_{i,t} \times \text{Trader}_i \times \beta + \delta' X_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{2}$$

Our DDD analysis is based on all publicly listed Chinese companies that files at least one patent at CNIPA between 2001 and 2016. Most of the notations in equation (2) mirror their counterparts in equation (1). In particular, the treatment dummy $\text{Treatment}_{i,t}$ equals one if a patent exchange has been established in the province where firm i is located by year t. To capture potentially different effects of patent trading on patent traders and non-traders, we interact $\text{Treatment}_{i,t}$ with a dummy variable Trader_i. To be specific, Trader_i equals one if a firm has traded any patents during our sampling period. The rest of the setup is the same as in equation (1) in the previous section.

The interaction term "$\text{Treatment}_{i,t} \times \text{Trader}_i$" in equation (2) is introduced to conduct a comparison along 3 dimensions. Precisely speaking, β captures the variation of the dependent variable that is specific to (i) the patent traders (relative to non-traders) and (ii) in provinces where a patent exchange is established (relative to provinces where no patent exchanges exist) and (iii) in the years after the exchange is established (relative to the years before its establishment). β is the key regression coefficient of interest in equation (2).

The results of our baseline DDD estimations are reported in Table 8. Echoing the results of our DiD estimations, regression (1) suggests that there is an increase in patenting for patent traders (relative to non-traders) in provinces where a patent exchange is established and in the years after its establishment. Therefore, the complementarity effect of patent trading dominates its substitution effect and, thus, patent trading on average enhances a firms in-house innovation. To examine how patent trading affects the division of innovative labor, we interact the term "Treatment $\times$ Trader" with the net number of patents a firm sells in each year. Since this interaction term is positive in regression (2) of Table 8, the establishment of patent exchanges leads to an increase (decrease) of patenting for a patent seller (buyer). This finding suggests patent trading and in-house innovation are complements (substitutes) for patent sellers (buyers). The dependent variable in regression (3) and (4) of Table 8 is a firms advertising expenditures, a proxy of its effort to commercialize its innovation. Consistent with our findings of the DiD estimations, our DDD estimates also suggest that the establishment of patent exchanges induces a decrease (increase) of advertising expenditures of a patent seller (buyer).

[Insert Table 8 Here.]

As demonstrated by the results in Table 8, the treatment effect is stronger for patent traders than non-traders. Hence, our DDD analysis in this section provides favorable evidence that the treatment effect is attributed to patent trading instead of other factors.

5.2.2 DDD Analysis: Liquid Market for Trading vs Illiquid Market

The effect of trade hinges on the liquidity of the market for patent trading. An illiquid market for patent trading can be characterized by severe search and matching frictions, as well as information frictions. Despite the potential benefits of trade, firms in an illiquid market can be discouraged from trading if it is too difficult to find a proper trading partner or too costly to negotiate the deal. To the extent that patent trading affects firm innovation and specialization, its effect should be more salient for firms facing a liquid market for patent trading than their counterparts confronted with an illiquid market. In light of this, we differentiate firms facing high trading liquidity from those confronted with low trading liquidity in this section.

Following the method of Hochberg et al. (2018), we construct a measure of patent trading liquidity that each firm faces each year. As delineated in the section of variable construction, this measure of patent trading liquidity is a proxy of the likelihood that a firm's patents will be traded in each year. Based on this liquidity measure, we further refine our treatment and control groups by distinguishing firms facing different trading liquidities in Figure 6.

[Insert Figure 6 Here.]

As usual, a firm is included in the treatment group if a patent exchange is established in the province where it is located. Otherwise, the firm is covered in the control group as a comparison. Based on our measure of patent trading liquidity, we further divide firms in the treatment group into 2 sub-groups in Figure 6: high liquidity group vs low liquidity group. To be specific, a firm is included in the high (low) liquidity group if the average trading liquidity it faces during the sampling period is above (below) the sample average of all firms. The vertical axis of Figure 6 is the average number of patents applied by firms in each sub-group of firms.

Albeit experiencing the establishment of the patent exchange, patenting of treated firms in the low-liquidity group closely tracks firm patenting in the control group. Hence, any observed treatment effects primarily reflect the changes of firms in the high-liquidity group. Patenting of treated firms in the high-liquidity group grows very slowly before the establishment of the patent exchange. As a contrast, the growth of patenting in the high-liquidity group accelerates once the patent exchange has been founded. To be more rigorous, we estimate the following firm-level panel regressions in a DDD setup:

$$y_{i,t+1} = \text{Treatment}_{i,t} \times \alpha + \text{Treatment}_{i,t} \times \text{High Liquidity}_i \times \beta + \delta' X_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t} \qquad (3)$$

The setup of equation (3) is largely the same as equation (2). In particular, the treatment dummy $\text{Treatment}_{i,t}$ equals one if a patent exchange has been established in the province where firm i is located by year t. As a key difference from equation (2), we replace the trader dummy in equation (2) by a dummy variable "High Liquidity_i" in equation (3). High Liquidity_i is a time-invariant dummy variable for firms facing a high liquidity of patent trading. As defined above in this section, we divide firms into 2 groups by the average patent trading liquidity that they are confronted with. To be specific, a firm is included in the high (low) liquidity group if the average trading liquidity it faces during the sampling period is above (below) the sample average of all firms.

Analogous to equation (2), the interaction term "$\text{Treatment}_{i,t} \times \text{High Liquidity}_i$" in equation (3) is introduced to conduct a comparison along 3 dimensions. To be specific, β captures the variation of the dependent variable that is (i) specific to firms in the high-liquidity group (relative to their counterparts in the low-liquidity group) and (ii) in provinces where a patent exchange is established (relative to provinces where no patent exchanges exist) and (iii) in the years after the exchange is established (relative to the years before its establishment). β is the key regression coefficient of interest in equation (3).

The estimation results of this DDD specifications are reported in Table 9. According to regression (1) of Table 9, there is an increase in patenting for firms in the high-liquidity group (relative to their counterparts in the low-liquidity group) in provinces where a patent exchange is established and in the years after its establishment. Analogous to Table 8, we interact the term "Treatment $\times$ High Liquidity" with the net number of patents a firm sells in regression (2) of Table 9. The positive sign of this interaction term in regression (2) suggests that the establishment of patent exchanges contributes to an increase (decrease) of patenting for a patent seller (buyer). To study how patent trading affects a firm's effort to commercialize innovation, we replace the dependent variables by a firms advertising expenditures in regression (3) and (4). Since the interaction term in regression (4) is negative, patent sellers (buyers) decrease (increase) their advertising expenditures after a patent exchange is established. These findings indicate that patent sellers redirect their resources from advertising to patenting activities as a response to the establishment of patent exchanges, whereas patent buyers switch their effort from patenting to advertising activities.

[Insert Table 9 Here.]

As demonstrated by the results in Table 9, the treatment effect is stronger for firms facing a liquid market for patent trading than their counterparts confronted with an illiquid market. Therefore, our DDD findings in this section lends further support to our argument that the treatment effect is attributed to patent trading instead of other factors.

6 Implications of Innovation Specialization

In light of the effect of patent trading on firm specialization, what are its implications for firm performance and the industrial organization structure? To investigate these questions, we evaluate how patent trading affects firm performance in Section 6.1, and we study its effect on the industrial organization structure in Section 6.2.

6.1 Patent Trading and Firm Performance

In light of the effect of patent trading on firm specialization, we explore a "bottom line" question: how does patent trading affect firm performance? We investigate this issue by assessing four measures of firm performance: the quality of patents, firm productivity, firm profitability, and market capitalization. We report the DiD results in Table 10. To control for the persistence of the dependent variables, we include lagged dependent variables in all regressions in Table 10.

The dependent variable in regression (1) of Table 10 is the relative citation strength of a firm's patents, a measure of the quality of innovation. As delineated in Section 3.2, the relative citation strength is gauged by the number of citations a patent received by 2018, divided by the average number of citations received by patents in its cohort (i.e., patents applied in the same year and the same technology class). As demonstrated by regression (1) of Table 10, the quality of patents filed by the firms improves after the establishment of patent exchanges. Combining the results of Table 10 with Table 3, we conclude that patent trading improves both the quantity and the quality of firm innovation.

Apart from innovating performance, how does patent trading affect firm productivity and profitability? To explore this question, we use firm TFP as a measure of productivity in regression (2) of Table 10, and firm ROA as a proxy of profitability in regression (3). As delineated in Section 3.2, our measure of ROA is calculated as a firm's net profit divided by its book value of assets, and our TFP estimation is based on the method developed in Ackerberg, Caves, and Frazer (2015).[23] As revealed by regression (2) and (3), both firm TFP and ROA are improved after patent exchanges are established. According to our DiD estimations, the establishment of patent exchanges leads to an increase in firm TFP by 2.0% and an increase in firm ROA by 0.3 percentage points (8.9% of sample mean). Improvement in firm TFP and ROA are factored into share prices by the investors. According to regression (4) of Table 10, the establishment of patent exchanges contributes to a higher market value of the firm by RMB 377 million (4.4% of sample mean). Taking stock of the regression results in Table 10, our findings suggest patent trading enhances firm performance by promoting comparative-advantage-based specialization.

6.2 Patent Trading and Industrial Organization Structure

By promoting comparative-advantage-based specialization, patent trading can in turn affect the industrial organization structure. As a response to rising opportunities of patent trading, firms with a comparative advantage in creating innovation redirect their resources from advertising to patenting activities, whereas firms with a comparative advantage in commercializing innovation switch their effort from patenting to advertising activities. To the extent that patent trading spurs such a pattern of comparative-advantage-based specialization, we expect to observe that patenting (advertising) activities will be increasingly concentrated among firms with a comparative advantage of creating (commercializing) innovation. As a consequence, our analysis predicts an increase in the concentration of patenting activities and advertising activities after a patent exchange has been established. Does patent trading affects the industrial organization structure in this way? We

[23] Specifically, we estimate a Cobb–Douglas production function where the variable input is labor, the state variable is capital, and the proxy variable is the intermediate input. See Section 3.2 for more details.

investigate this question by estimating the following province-year-level DiD regressions:

$$y_{i,t+1} = \text{Treatment}_{i,t} \times \beta + \delta' X_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{4}$$

In equation (4), $y_{i,t+1}$ is the dependent variable where the subscript i indexes for province and t indexes for year. The dummy variable $\text{Treatment}_{i,t}$ equals one if a patent exchange has been established in province i by year t and zero otherwise. The effect of patent exchange on the dependent variable is captured by β, the key regression coefficient of interest. γ_i (γ_t) in equation (4) stands for province fixed effect (year fixed effect). Since province fixed effect is included in the regression, we have controlled for all time-invariant differences between provinces in the treatment group and their counterparts in the control group. In addition, we control for GDP per capita and R&D-to-GDP ratio in vector X. We report the results of this DiD estimation in Table 11.

We apply the HerfindahlHirschman index (HHI) as a measure of market concentration. The dependent variable in regression (1) of Table 11 is the province-level HHI for firm patenting activities, and the dependent variable in regression (2) is the HHI for advertising expenditures. According to the estimates of Table 11, the establishment of patent exchanges in a province is associated with an increase of HHI by 0.062 (0.024) for patenting (advertising) activities in that province. As a comparison, this marginal effect is equivalent to 23.5% (14.4%) of the sample mean of patenting (advertising) HHI. Our findings indicate that enhanced patent trading (facilitated by the establishment of patent exchanges) in a province contributes to a higher level of concentration for patenting activities and advertising activities in that province. These results lend further support to our finding of how patent trading affects firm specialization.

[Insert Table 11 Here.]

7 Robustness Checks

In this section, we conduct three additional tests to assess the robustness and validity of our findings. First, we examine the intensive-margin effect of patent trading in Section 7.1. Second, we redo our analysis using a firm's buyer-seller status during the period before the establishment of patent exchanges in Section 7.2. Lastly, we undertake a placebo test by randomly assigning the treatment and control status to observations in our sample in Section 7.3.

7.1 Intensive-Margin Analysis

When relying on the establishment of patent exchanges as our identification strategy, we essentially focus on the effect of patent trading along the extensive-margin. In fact, firms in both the treatment group and the control group face different liquidities of patent trading. Do our results hold along the intensive margin? To probe into this question, we study the intensive-margin effects of patent trading liquidity in Table 12. That is to say, we replace the treatment dummy by a continuous variable of trading liquidity proxy, and we examine how firms adjust their strategies to create and commercialize innovation when they face a more liquid market for patent trading.

[Insert Table 12 Here.]

We study how patent trading liquidity affects firm innovation in regression (1) of Table 12, where the dependent variable is the natural logarithm of one plus a firm's patent applications in the next year. To assess how patent trading liquidity affects a firm's effort to commercialize its innovation, we replace the dependent variable by a firm's advertisement expenditures in regression (2) of Table 12. The key explanatory variable in Table 12 is our measure of patent trading liquidity. As enunciated in the section of variable construction, this measure of patent trading liquidity is a proxy of the likelihood that a firm's patents will be traded in each year. To evaluate how patent trading liquidity affects specialization, we interact patent trading liquidity with the net number of patents a firm sells each year.

When firms are facing a more liquid market for patent trading, how do they change their strategies to create innovation and to commercialize them? As revealed by regression (1) of Table 12, while the estimate of the measure of patent trading liquidity is positive, the interaction term has a negative sign. Therefore, the relationship between firm patenting and the patent trading liquidity it faces is positive for the sellers but negative for the buyers. Echoing our previous findings, patent trading and in-house innovation are complements for patent sellers, whereas they are substitutes for the buyers. To be specific, a one-standard-deviation increase in patent trading liquidity is associated with a 25.0% increase (14.3% decrease) of firm patenting for the sellers (buyers). Analogous to the results in regression (1), regression (2) suggests that a firm's advertisement expenditures are negatively (positively) correlated with the patent trading liquidity for the patent buyers (sellers). To be concrete, a one-standard-deviation increase in patent trading liquidity is associated with an increase of 93 million RMB (42.7% of sample mean) of advertisement expenditures for the buyers, but a decrease of 81 million RMB (37.2% of sample mean) for the sellers. Our findings suggest patent sellers (buyers) redirect more resources toward creating (commercializing) innovation when they are facing a more liquid market for patent trading. Hence, the results of our intensive-margin analysis lend further support to our findings on how patent trading affects firm specialization.

7.2 Patent Buyer-Seller Status Before Patent Exchange Establishments

In our study of specialization between patent buyers and sellers, a firm's patent buyer-seller status in a year is detected by the net number of patents it sells in that year. One might be concerned that a firm's buyer-seller status may be correlated with the treatment indicator of patent exchanges. To address this concern, we redo our analysis using the net number of patents a firm sold during the period *before* the establishment of patent exchanges.[24] The regression setup is the same as that in equation 1 and the results are reported in Table 13.

As demonstrated by the results in Table 13, after the establishments of patent exchanges, patent sellers increase (decrease) their in-house innovation (advertising expenditures), whereas patent buyers decrease (increase) their in-house innovation (advertising expenditures). That is to say, patent sellers (buyers) tend to specialize in creating (commercializing) innovation after the establishment of patent exchanges. Therefore, we find the same pattern of specialization using this time-invariant patent buyer-seller status during the period before the establishment of patent exchanges.

[Insert Table 13 Here.]

7.3 Placebo Tests

As a further robustness check, we conduct a placebo test where the treatment and control status of observations in our sample are randomly assigned. If the results in Table 3 are indeed driven by the establishment of patent exchanges (instead of by chance), such results should not be observed in this artificially treated sample.

The results under such random assignment of treatment are reported in Table 14. The empirical specification of Table 14 is the same as that of Table 3, but the treatment and control status are randomly assigned in Table 14. As demonstrated by this table, no statistically significant treatment effects are observed when the observations are treated by chance. This placebo test lends further support to our findings that the observed effects on firm innovation and specialization are indeed driven by the establishment of patent exchanges.

[Insert Table 14 Here.]

8 Conclusion

How does the market for technology affect the incentives of innovation and the division of innovative labor? To address this question, we compile a unique dataset on patent exchanges in China and we assemble a novel dataset that contains elaborate micro-level information of firms' financial statements, patent filings, patent trading, and patent licensing. A patent exchange facilitates patent trading by reducing search and matching frictions, as well as information frictions of trading. Exploiting staggered establishments of patent exchanges in China, we examine the causal effect of patent trading on firm innovation and specialization. We find that patent trading affects the innovation of patent buyers and sellers in opposite directions: patent trading and in-house innovation are complements for patent sellers, whereas they are substitutes for the buyers.

[24] Since we focus on a firm's buyer-seller status during the period before the establishment of patent exchanges, we exclude firms that do not file any patents during this period in the regressions.

Our findings uncover three patterns of specialization induced by an emerging market for technology: (i) specialization between patent buyers and sellers, (ii) specialization between patent licensors and licensees, and (iii) specialization based on a firm's R&D efficiency. All these three patterns of specialization indicate that a firm's response to an emerging market for technology hinges on its comparative advantages. Firms with a comparative advantage in creating innovation redirect their resources from advertising to patenting activities, whereas firms with a comparative advantage in commercializing innovation switch their effort from patenting to advertising activities. In addition, the effect of patent trading is stronger for patent traders than non-traders and more pronounced for firms facing a liquid market for patent trading than their counterparts confronted with an illiquid market. As demonstrated by these findings, patent trading spurs specialization based on a firm's comparative advantage in creating versus commercializing innovation, and, thus, contributes to a more efficient allocation of the resources for innovation. Moreover, we find that patent trading contributes to higher quality of patents filed by the firms, higher TFP, higher ROA, and higher market value of the firms. Therefore, we conclude that patent trading promotes comparative-advantage-based specialization and enhances firm performance.

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FIGURE 1: **Shenzhen Patent Exchange**

This figure is a snapshot of the website of the Shenzhen Patent Exchange. As illustrated by the website, a patent holder can provide the information of her patents for sale and a potential buyer can post her demand for patents. Analogously, a potential buyer can search for patents available for sales and a patent holder can look for patent demand information.

FIGURE 2: **Patents Available for Sale**

This figure will pop up when a potential buyer starts searching for patents available for sale on this website. As shown on top of this figure, a potential buyer can further refine her search by selecting a particular industry, a particular patent type, and a particular patent. To illustrate, two examples of patents posted for sale are provided at the bottom of this figure. The patent on the left is titled “An Account Management System Based on Cloud Service.” It can be used in the area of information digitalization and its patent holder has posted a suggested trading price of 52 thousand RMB. The patent on the right is titled “A Gear Cutter For 3D Printing Waste.” It is classified into the category of instruments and apparatuses and its patent holder has posted a suggested trading price of 48 thousand RMB. When clicking each patent available for sale, the buyer will be directed to another web page with further information on the patent, such as the detailed terms of contract (e.g., trading or licensing) and contact information of the patent holder.

Figure 3: **Patent Trading Procedures**

The procedures of patent trading are delineated in this figure. To participate in patent trading, both patent holders and potential buyers are required for applying for exchange membership. After such applications are approved by the patent exchange, a patent holder can provide the information of her patents for sale and a potential buyer can post her demand information. Based on such demand and supply information, the exchange recommends a potential deal to the buyer and the seller. If both parties are interested in the deal, the exchange can arrange a meeting for them. If the buyer and the seller agree to trade after negotiating the deal, the exchange provides related legal documents to them and certifies this transaction. The exchange charges a fee for its services provided during this process.

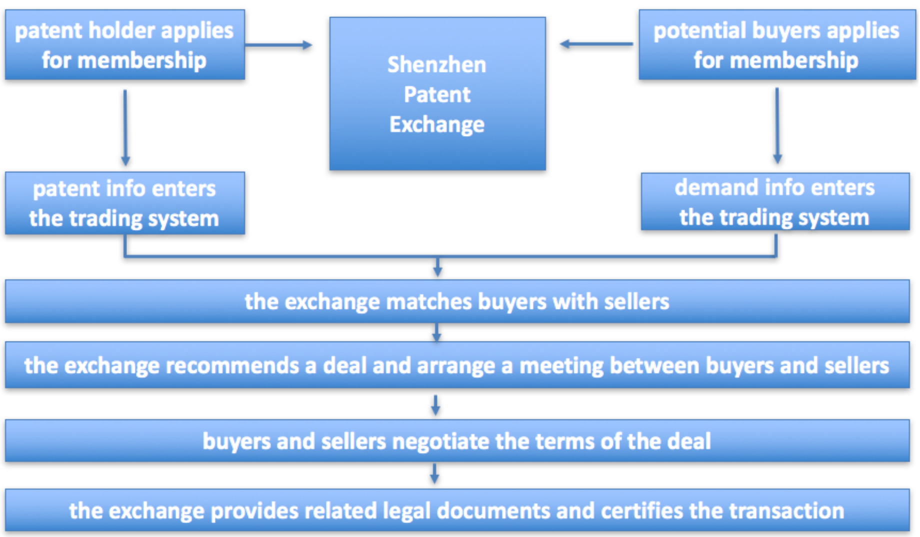

Figure 4: **Parallel Trend Assumption for DiD Analysis**

To assess its validity for DiD analysis, the parallel trend assumption is examined in this figure. Year 0 on the horizontal axis of this figure marks the year when a patent exchange is established. A firm is included in the treatment group if a patent exchange is established in the province where it is located. Otherwise, the firm is covered in the control group as a comparison. The vertical axis of this figure is the average number of patents applied by firms (together with a 95% confidence interval) in the treatment group and the control group, respectively. As unveiled by this figure, the difference between the treatment group and the control group is fairly stable before the patent exchange is founded. As a stark contrast, a salient gap of patenting between the treatment group and the control group emerges and quickly widens after the patent exchange is established. While firm patenting in the control group barely increases, firm patenting in the treatment group surges over time.

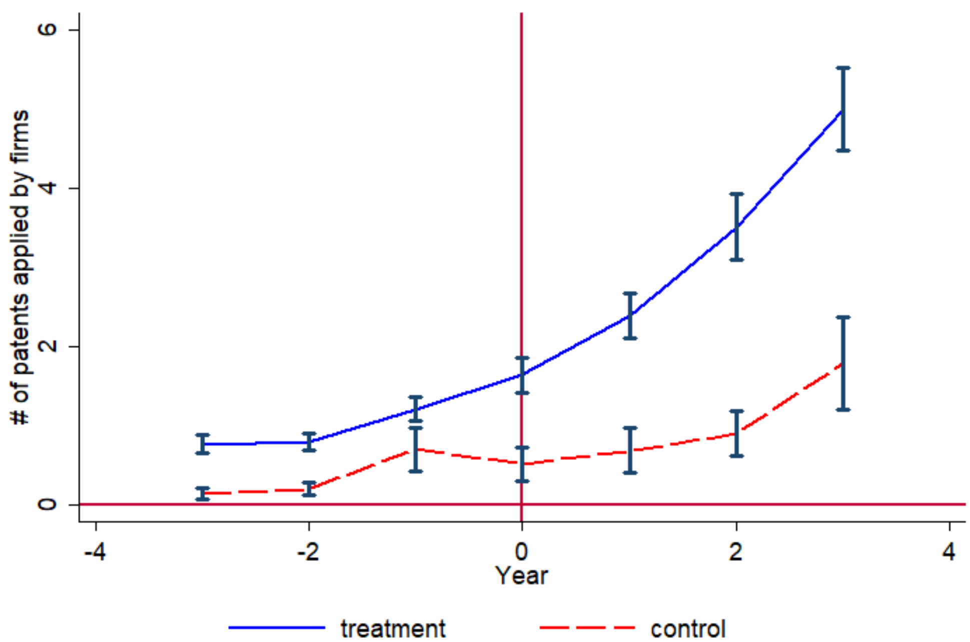

Figure 5: **DDD Analysis, Patent Traders vs Non-Traders**

In this figure, we further refine our treatment and control groups by distinguishing patent traders from non-traders. Year 0 on the horizontal axis of this figure marks the year when a patent exchange is established. A firm is included in the treatment group if a patent exchange is established in the province where it is located. Otherwise, the firm is covered in the control group as a comparison. In this figure, we further categorize firms in the treatment group into 3 sub-groups: (i) patent buyers; (ii) patent sellers; (iii) non-traders. To be specific, a patent trader in the treatment group is defined to be a buyer (seller) if the number of patents it bought is greater (less) than the number of patents it sold during our sampling period. A firm in the treatment group is classified as a non-trader if it did not trade any patents during our sampling period. The vertical axis of this figure is the average number of patents applied by firms (together with a 95% confidence interval) in each of these 4 sub-groups. As unveiled by this figure, the patenting of non-traders in the treatment group is almost the same as their counterparts in the control group. Among the patent traders in the treatment group, a stark difference between patent buyers and sellers is also manifested in this figure. Patenting of buyers and sellers is largely parallel to each other before the patent exchange is introduced. Upon the establishment of the patent exchange, however, a remarkable difference of patenting between buyers and sellers appears. While patenting of buyers largely follows its pre-event trend, patenting of sellers soars after the patent exchange is established. This salient difference of patenting behaviors between buyers and sellers is suggestive evidence that a patent exchange spurs comparative-advantage-based specialization.

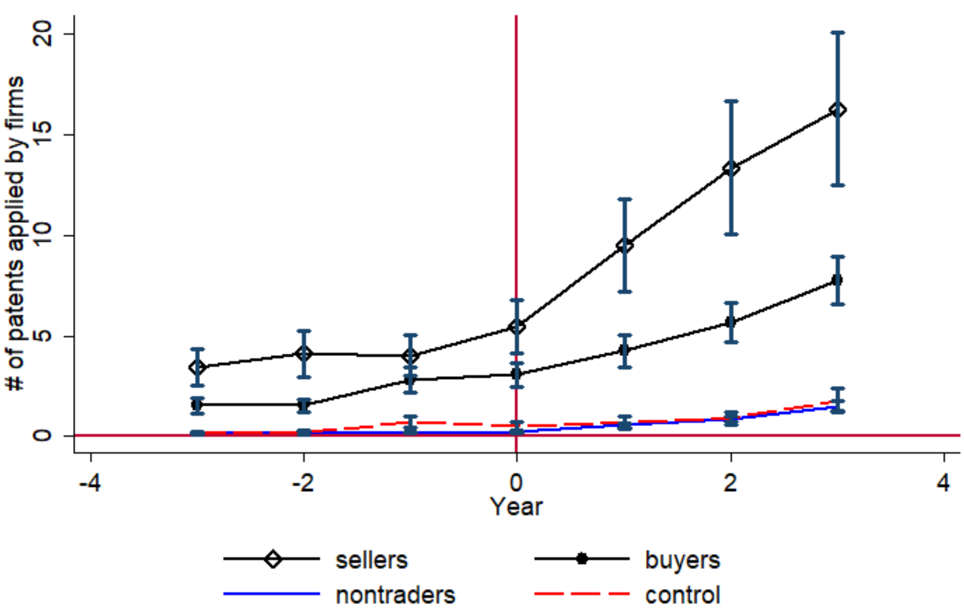

Figure 6: **DDD Analysis, High vs Low Trading Liquidity**

In this figure, we further refine our treatment and control groups by distinguishing firms facing a liquid market for patent trading from their counterparts confronted with an illiquid market. Year 0 on the horizontal axis of this figure marks the year when a patent exchange is established. A firm is included in the treatment group if a patent exchange is established in the province where it is located. Otherwise, the firm is covered in the control group as a comparison. Based on our measure of patent trading liquidity, we further divide firms in the treatment group into 2 sub-groups in this figure: high liquidity group vs low liquidity group. To be specific, a firm is included in the high (low) liquidity group if the average trading liquidity it faces during the sampling period is above (below) the sample average of all firms. The vertical axis of this figure is the average number of patents applied by firms (together with a 95% confidence interval) in each sub-group of firms. Patenting of treated firms in the high-liquidity group grows very slowly before the establishment of the patent exchange. Once the patent exchange is founded, the growth of patenting in the high-liquidity group accelerates in response. Patenting of treated firms in the low-liquidity group, however, has undergone a drastically different path in this figure. Albeit experiencing the establishment of the patent exchange, patenting of treated firms in the low-liquidity group closely tracks firm patenting in the control group.

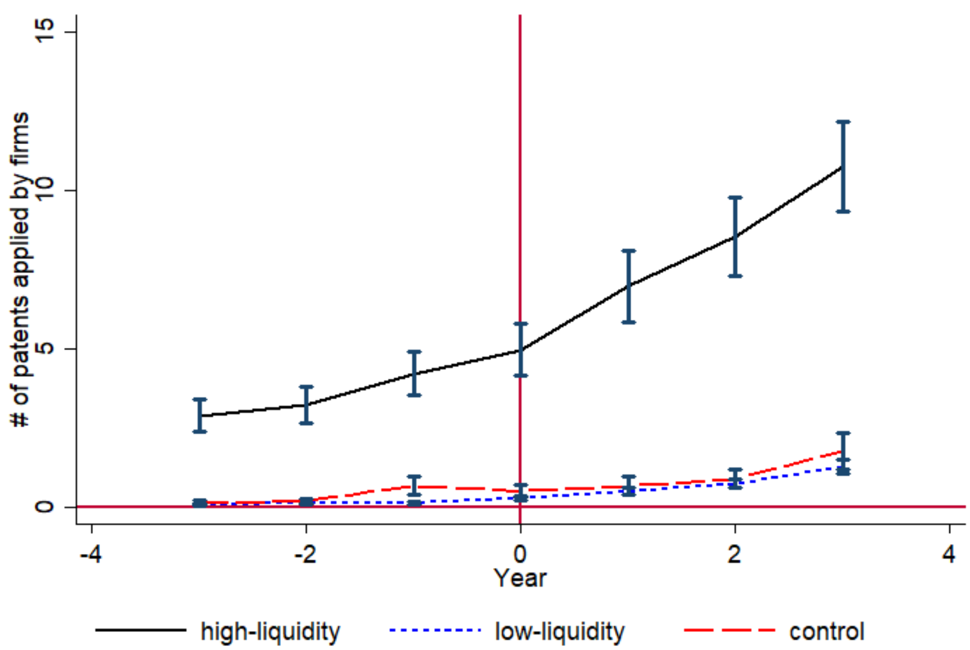

Table 1: **Patent Exchanges In China**

Patent exchanges were gradually established across different regions of China over time. This table is a list of these patent exchanges, their location, and their founding dates.

Patent Exchange	Location	Year Established
Bengbu Patent Exchange	Bengbu	2006
Huaibei Patent Exchange	Huaibei	2006
Beijing Patent Exchange	Beijing	2006
Lanzhou Patent Exchange	Lanzhou	2006
Foshan Patent Exchange	Foshan	2006
Dongguan Patent Exchange	Dongguan	2006
Henan Patent Exchange	Zhengzhou	2006
Wuhan Patent Exchange	Wuhan	2006
Changchun Patent Exchange	Changchun	2006
Jinan Patent Exchange	Jinan	2006
Shaanxi Patent Exchange	Xi'an	2006
Shanghai Patent Exchange	Shanghai	2006
Sichuan Patent Exchange	Chengdu	2006
Tianjin Patent Exchange	Tianjin	2006
Chongqing Patent Exchange	Chongqing	2006
Yichang Patent Exchange	Yichang	2007
Changsha Patent Exchange	Changsha	2007
Jiangxi Patent Exchange	Nanchang	2007
Ningbo Patent Exchange	Ningbo	2007
Hefei Patent Exchange	Hefei	2008
Fuzhou Patent Exchange	Fuzhou	2008

(Continued On the Next Page)

Table 1: Patent Exchanges In China, *Continued*

Patent Exchange	Location	Year Established
Guangzhou Patent Exchange	Guangzhou	2008
Shenzhen Patent Exchange	Shenzhen	2008
Guiyang Patent Exchange	Guiyang	2008
Hainan Patent Exchange	Haikou	2008
Xiangfan Patent Exchange	Xiangfan	2008
Suzhou Patent Exchange	Suzhou	2008
Changzhou Patent Exchange	Changzhou	2008
Wuxi Patent Exchange	Wuxi	2008
Shenyang Patent Exchange	Shenyang	2008
Huhhot Patent Exchange	Huhhot	2008
Qingdao Patent Exchange	Qingdao	2008
Taiyuan Patent Exchange	Taiyuan	2008
Kunming Patent Exchange	Kunming	2008
Jiaxing Patent Exchange	Jiaxing	2008
Xinxiang Patent Exchange	Xinxiang	2009
Nanjing Patent Exchange	Nanjing	2009
Anshan Patent Exchange	Anshan	2009
Ningxia Patent Exchange	Yinchuan	2009
Yantai Patent Exchange	Yantai	2009
Xinjiang Patent Exchange	Urumqi	2009

Table 2: Descriptive Statistics

Our empirical analysis is based on all publicly listed Chinese companies that file at least one patent at CNIPA between 2001 and 2016. To gain a better understanding of these firms, we provide summary statistics for our sample in this table. To alleviate the concerns for outliers, all variables in this table are winsorized at the 1^{st} and 99^{th} percentiles.

	Mean	Standard Deviation	Min	Median	Max	Observations
ln(# of patents + 1)	1.018	1.238	0	0.693	5.081	26,770
relative citation strength	0.248	1.27	0	0	9.959	26,770
advertising expenditures (billion RMB)	0.218	0.526	0	0.0553	3.730	26,770
trading liquidity, %	1.023	0.856	0	1.184	2.982	26,770
net # of patents sold	-0.0916	0.622	-4	0	2	26,770
net # of patents licensed out	-0.0169	0.377	-3	0	3	26,770
R&D efficiency	0.187	0.563	0	0.0389	4.468	15,224
ln(TFP)	2.189	0.62	0.722	2.144	4.022	26,579
ROA	0.0337	0.0624	-0.264	0.0348	0.192	26,770
market value (billion RMB)	8.569	13.17	0.467	4.354	89.5	26,696
ln(asset + 1)	21.71	1.251	19.19	21.55	25.64	26,770
ln(age + 1)	1.926	0.843	0	2.079	3.135	26,770
R&D intensities, %	0.995	1.502	0	0.0679	7.395	26,770
capex ratio	0.0580	0.0553	0.000246	0.0414	0.264	26,770
PPE ratio	0.253	0.173	0.00331	0.220	0.743	26,770
leverage ratio	0.455	0.218	0.0495	0.452	1.100	26,770
Tobin's Q	2.203	2.001	0.224	1.596	11.53	26,770

Table 3: DiD Regressions, Patent Trading and Firm Specialization

This table reports the main regression results of our DiD analysis. The dependent variable in regression (1) and (2) is the natural logarithm of one plus the number of patent applications a firm files (and eventually granted) in that year. The dependent variable in regression (3) and (4) is a firm's advertising expenditures in each year. The dummy variable "Treatment" equals one in a year if a patent exchange has been established in the province where a firm is located by that year. The variable "net # of patents sold" is the number of patents a firm sells subtracted by the number of patents it buys each year. All regressions in this table include year fixed effect and firm fixed effect. Standard errors are clustered at the firm level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	$ln(\text{\# of patents} + 1)_{t+1}$		Advertising $\text{Expenditures}_{t+1}$	
	(1)	(2)	(3)	(4)
Treatment	0.075**	0.079**	0.021*	0.019*
	(0.036)	(0.035)	(0.011)	(0.011)
Treatment × net # of patents sold		0.090***		-0.040**
		(0.035)		(0.019)
net # of patents sold		-0.140***		0.027
		(0.032)		(0.018)
ln(asset + 1)	0.172***	0.169***	0.141***	0.141***
	(0.020)	(0.020)	(0.012)	(0.012)
R&D intensities	0.081***	0.080***	0.030***	0.030***
	(0.010)	(0.010)	(0.005)	(0.005)
Tobin's Q	0.007	0.007	0.009***	0.009***
	(0.005)	(0.005)	(0.002)	(0.002)
ROA	0.129	0.129	0.112**	0.110**
	(0.113)	(0.113)	(0.049)	(0.048)
leverage ratio	-0.015	-0.013	0.087***	0.087***
	(0.061)	(0.060)	(0.031)	(0.031)
ln(age + 1)	0.029	0.028	-0.056***	-0.056***
	(0.024)	(0.024)	(0.013)	(0.013)
PPE ratio	0.227***	0.221***	0.008	0.007
	(0.072)	(0.071)	(0.036)	(0.035)
capex ratio	0.031	0.017	-0.085	-0.086
	(0.129)	(0.129)	(0.056)	(0.056)
Constant	-3.359***	-3.300***	-2.940***	-2.931***
	(0.426)	(0.423)	(0.251)	(0.251)
Observations	26,770	26,770	26,770	26,770
Control Variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.695	0.696	0.803	0.803

Table 4: DiD Regressions, Patent Licensing and Firm Specialization

This table reports the regression results of our DiD analysis of the effect of patent licensing. The dependent variable in regression (1) is the natural logarithm of one plus the number of patent applications a firm files (and eventually granted) in that year. The dependent variable in regression (2) is a firm's advertising expenditures in each year. The dummy variable "Treatment" equals one in a year if a patent exchange has been established in the province where a firm is located by that year. The variable "net # of licensed out" is the number of patents a firm licenses out subtracted by the number of patents it licenses in each year. All regressions in this table include year fixed effect and firm fixed effect. Standard errors are reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	$ln(\#\text{ of patents} + 1)_{t+1}$	Advertising $\text{Expenditures}_{t+1}$
	(1)	(2)
Treatment	0.082***	0.024***
	(0.025)	(0.009)
Treatment × net # of patents licensed out	0.092*	-0.033*
	(0.056)	(0.020)
net # of patents licensed out	-0.104*	0.043**
	(0.055)	(0.019)
R&D intensities	0.081***	0.028***
	(0.005)	(0.002)
Tobin's Q	-0.022***	-0.015***
	(0.004)	(0.001)
ROA	0.414***	0.375***
	(0.092)	(0.032)
leverage ratio	0.111***	0.186***
	(0.039)	(0.014)
ln(age + 1)	0.062***	-0.035***
	(0.015)	(0.005)
Constant	0.266***	-0.004
	(0.031)	(0.011)
Observations	26,770	26,770
Control Variables	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Adjusted R^2	0.691	0.790

Table 5: R&D Efficiency and Net Number of Patents Sold

The regressions in this table examine how each firm characteristic is related to its buyer-seller status in patent trading. The dependent variable is the net number of patents sold by a firm in year $t+1$ divided by a firm's patent stock by the end of year t. As delineated in Section 3.2, the R&D efficiency of a firm in a year is measured by the number of patent applications it files in that year divided by the weighted average of its R&D expenditures in the past 3 years. Standard errors are clustered at the firm level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Net Number of Patents Sold$_{t+1}$/Patent Stock$_t$			
	(1)	(2)	(3)	(4)
R&D Efficiency	0.087**	0.122***	0.141***	0.223**
	(0.044)	(0.046)	(0.048)	(0.088)
ln(asset + 1)		0.095***	0.057	-0.001
		(0.035)	(0.036)	(0.144)
R&D intensities		0.111***	0.110***	0.007
		(0.022)	(0.022)	(0.044)
Tobin's Q		-0.005	-0.037	-0.072*
		(0.021)	(0.024)	(0.043)
ROA		-1.674**	-1.213	-1.195
		(0.783)	(0.781)	(1.168)
leverage ratio		0.105	0.151	-0.016
		(0.240)	(0.242)	(0.521)
ln(age + 1)		0.051	0.040	0.165
		(0.052)	(0.053)	(0.172)
PPE ratio		0.555**	0.531**	0.012
		(0.267)	(0.268)	(0.739)
capex ratio		-2.343***	-1.978**	-2.068
		(0.847)	(0.871)	(1.318)
Constant	-0.749***	-3.076***	-2.001**	-0.523
	(0.038)	(0.744)	(0.791)	(3.011)
Observations	15,224	15,224	15,224	15,224
Year fixed effect	No	No	Yes	Yes
Firm effect	No	No	No	Yes
Adjusted R^2	5.96e-05	0.00355	0.00354	0.0711

Table 6: DiD Regressions, Patent Trading and Firm Specialization Based On R&D Efficiency

This table reports the regression results of our DiD analysis of R&D-efficiency-based specialization. The dependent variable in regression (1) and (2) is the natural logarithm of one plus the number of patent applications a firm files (and eventually granted) in that year. The dependent variable in regression (3) and (4) is a firm's advertising expenditures in each year. The dummy variable "Treatment" equals one in a year if a patent exchange has been established in the province where a firm is located by that year. The R&D efficiency of a firm in a year is measured by the number of patent applications it files in that year divided by the weighted average of its R&D expenditures in the past 3 years. All regressions in this table include year fixed effect and firm fixed effect. Standard errors are clustered at the firm level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	$ln(\text{\# of patents} + 1)_{t+1}$	Advertising Expenditures$_{t+1}$
	(1)	(2)
Treatment × R&D Efficiency	0.115**	-0.033**
	(0.046)	(0.014)
Treatment	-0.137	0.021
	(0.100)	(0.045)
R&D Efficiency	0.030	0.031**
	(0.041)	(0.012)
ln(asset + 1)	0.097***	0.155***
	(0.030)	(0.020)
R&D intensities	0.020*	0.017***
	(0.011)	(0.004)
Tobin's Q	0.004	0.001
	(0.007)	(0.003)
ROA	0.482**	0.257***
	(0.210)	(0.088)
leverage ratio	-0.048	0.132***
	(0.091)	(0.046)
ln(age + 1)	0.054*	-0.086***
	(0.032)	(0.018)
PPE ratio	0.047	0.051
	(0.114)	(0.056)
capex ratio	-0.164	-0.014
	(0.203)	(0.076)
Constant	-1.313**	-3.277***
	(0.630)	(0.439)
Observations	15,224	15,224
Control Variables	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Adjusted R^2	0.725	0.881

Table 7: DiD Regressions, Dynamic Treatment Effects

This table reports the results of our analysis of the dynamic treatment effect. $Treatment(-2)$ and $Treatment(-1)$ correspond to 2 years and 1 year before the establishment of patent exchanges. $Treatment(0)$ is defined with respect to the year when a patent exchange is established, and $Treatment(1+)$ is associated with one and more years after the establishment of patent exchanges. All regressions in this table include year fixed effect and firm fixed effect. Standard errors are reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	$ln(\# \text{ of patents} + 1)_{t+1}$		Advertising $\text{Expenditures}_{t+1}$	
	(1)	(2)	(3)	(4)
$Treatment(-2)$	0.023	0.023	0.006	0.006
	(0.032)	(0.032)	(0.011)	(0.011)
$Treatment(-1)$	0.028	0.028	0.010	0.010
	(0.034)	(0.034)	(0.012)	(0.012)
$Treatment(0)$	0.102***	0.102***	0.021	0.020
	(0.038)	(0.038)	(0.013)	(0.013)
$Treatment(1+)$	0.091**	0.095**	0.034***	0.032**
	(0.037)	(0.037)	(0.013)	(0.013)
$Treatment(1+)$ × net # of patents sold		0.065***		-0.032***
		(0.025)		(0.008)
net # of patents sold		-0.115***		0.018**
		(0.024)		(0.008)
ln(asset + 1)	0.171***	0.169***	0.141***	0.141***
	(0.010)	(0.010)	(0.003)	(0.003)
R&D intensities	0.082***	0.081***	0.030***	0.030***
	(0.005)	(0.005)	(0.002)	(0.002)
Tobin's Q	0.007*	0.007*	0.009***	0.009***
	(0.004)	(0.004)	(0.001)	(0.001)
ROA	0.131	0.129	0.112***	0.110***
	(0.094)	(0.094)	(0.032)	(0.032)
leverage ratio	-0.014	-0.012	0.087***	0.087***
	(0.040)	(0.040)	(0.014)	(0.014)
ln(age + 1)	0.028*	0.027*	-0.056***	-0.056***
	(0.015)	(0.015)	(0.005)	(0.005)
PPE ratio	0.227***	0.220***	0.008	0.007
	(0.048)	(0.048)	(0.016)	(0.016)
capex ratio	0.030	0.018	-0.084**	-0.086**
	(0.101)	(0.100)	(0.034)	(0.034)
Constant	-3.356***	-3.298***	-2.939***	-2.930***
	(0.215)	(0.215)	(0.073)	(0.073)
Observations	26,770	26,770	26,770	26,770
Control Variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.695	0.696	0.803	0.803

Table 8: DDD Regressions, Patent Traders vs Non-Traders

This table reports the results of our DDD analysis. We distinguish patent traders from non-traders in this regression specification. To be specific, the dummy variable “Trader” equals one if a firm has traded any patents during our sampling period. The dummy variable “Treatment” equals one in a year if a patent exchange has been established in the province where a firm is located by that year. The variable “net # of patents sold” is the number of patents a firm sells subtracted by the number of patents it buys each year. All regressions in this table include year fixed effect and firm fixed effect. Standard errors are clustered at the firm level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	ln(# of patents + 1)$_{t+1}$		Advertising Expenditures$_{t+1}$	
	(1)	(2)	(3)	(4)
Treatment × Trader	0.361***	0.357***	0.070***	0.066***
	(0.047)	(0.047)	(0.024)	(0.023)
Treatment × Trader × net # of patents sold		0.084***		-0.030*
		(0.031)		(0.016)
Treatment	-0.097**	-0.091**	-0.012	-0.012
	(0.040)	(0.039)	(0.014)	(0.014)
net # of patents sold		-0.125***		0.018
		(0.029)		(0.015)
ln(asset + 1)	0.161***	0.159***	0.139***	0.139***
	(0.019)	(0.019)	(0.012)	(0.012)
R&D intensities	0.075***	0.074***	0.029***	0.028***
	(0.010)	(0.010)	(0.005)	(0.005)
Tobin’s Q	0.006	0.006	0.009***	0.009***
	(0.005)	(0.005)	(0.002)	(0.002)
ROA	0.154	0.154	0.117**	0.115**
	(0.111)	(0.111)	(0.048)	(0.048)
leverage ratio	0.010	0.011	0.092***	0.091***
	(0.059)	(0.059)	(0.031)	(0.031)
ln(age + 1)	0.027	0.027	-0.056***	-0.056***
	(0.024)	(0.024)	(0.013)	(0.013)
PPE ratio	0.220***	0.214***	0.007	0.006
	(0.069)	(0.069)	(0.035)	(0.035)
capex ratio	0.032	0.019	-0.085	-0.086
	(0.127)	(0.127)	(0.056)	(0.055)
Constant	-3.150***	-3.102***	-2.900***	-2.893***
	(0.415)	(0.412)	(0.248)	(0.248)
Observations	26,770	26,770	26,770	26,770
Control Variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.698	0.699	0.804	0.804

Table 9: DDD Regressions, High vs Low Trading Liquidity

This table reports the results of our DDD analysis. We distinguish firms facing a liquid market for patent trading from their counterparts confronted with an illiquid market. "High Liquidity$_i$" is a time-invariant dummy variable for firms facing high liquidity of patent trading. We divide firms into 2 groups by the average patent trading liquidity that they are confronted with. A firm is included in the high (low) liquidity group if the average trading liquidity it faces during the sampling period is above (below) the sample average of all firms. The dummy variable "Treatment" equals one in a year if a patent exchange has been established in the province where a firm is located by that year. The variable "net # of patents sold" is the number of patents a firm sells subtracted by the number of patents it buys each year. All regressions in this table include year fixed effect and firm fixed effect. Standard errors are clustered at the firm level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	$ln(\#\text{ of patents} + 1)_{t+1}$		Advertising Expenditures$_{t+1}$	
	(1)	(2)	(3)	(4)
Treatment × High Liquidity	0.202***	0.219***	0.113***	0.106***
	(0.050)	(0.049)	(0.026)	(0.025)
Treatment × High Liquidity × net # of patents sold		0.179***		-0.044***
		(0.026)		(0.012)
Treatment	-0.009	-0.008	-0.026*	-0.025*
	(0.040)	(0.040)	(0.013)	(0.013)
net # of patents sold		-0.187***		0.023***
		(0.022)		(0.009)
ln(asset + 1)	0.170***	0.169***	0.140***	0.140***
	(0.020)	(0.020)	(0.012)	(0.012)
R&D intensities	0.076***	0.075***	0.027***	0.026***
	(0.010)	(0.010)	(0.005)	(0.005)
Tobin's Q	0.007	0.007	0.008***	0.008***
	(0.005)	(0.005)	(0.002)	(0.002)
ROA	0.138	0.152	0.117**	0.112**
	(0.113)	(0.112)	(0.048)	(0.048)
leverage ratio	-0.005	0.001	0.092***	0.091***
	(0.060)	(0.060)	(0.031)	(0.031)
ln(age + 1)	0.020	0.021	-0.061***	-0.061***
	(0.024)	(0.024)	(0.013)	(0.013)
PPE ratio	0.214***	0.206***	0.001	0.001
	(0.071)	(0.070)	(0.036)	(0.035)
capex ratio	0.048	0.027	-0.075	-0.075
	(0.129)	(0.128)	(0.056)	(0.056)
Constant	-3.344***	-3.321***	-2.932***	-2.916***
	(0.423)	(0.418)	(0.249)	(0.248)
Observations	26,770	26,770	26,770	26,770
Control Variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.696	0.698	0.805	0.805

Table 10: Patent Trading and Firm Performance

This table evaluates how patent trading affects firm performance. The dependent variable in regression (1) is the relative citation strength of a firm's patents, a measure of the quality of innovation. The dependent variable in regression (2) is firm ROA measured as a firm's net profit divided by its book value of total assets. The dependent variable in regression (3) is the natural logarithm of firm TFP estimated by the method of Ackerberg, Caves, and Frazer (2015). The dependent variable in regression (4) is firm market value measured as the product of a firm's total number of shares outstanding and annual closing price. The dummy variable "Treatment" equals one in a year if a patent exchange has been established in the province where a firm is located by that year. All regressions in this table include year fixed effect and industry fixed effect. Standard errors are reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Relative Citation Strength	$ln(\text{TFP})_{t+1}$	ROA_{t+1}	Market Value_{t+1}
	(1)	(2)	(3)	(4)
Treatment	0.053*	0.020***	0.003*	0.377***
	(0.032)	(0.008)	(0.001)	(0.141)
ln(asset + 1)	0.083***	-0.003	0.003***	0.921***
	(0.008)	(0.002)	(0.000)	(0.046)
R&D intensities	0.024***	0.000	0.003***	0.148***
	(0.007)	(0.002)	(0.000)	(0.030)
leverage ratio	-0.010	0.131***	-0.025***	-0.487**
	(0.043)	(0.011)	(0.002)	(0.198)
ln(age + 1)	-0.001	0.001	-0.004***	-0.083*
	(0.011)	(0.003)	(0.000)	(0.050)
PPE ratio	-0.030	0.018	0.001	0.028
	(0.057)	(0.014)	(0.002)	(0.253)
capex ratio	0.371**	0.215***	0.006	0.745
	(0.155)	(0.039)	(0.007)	(0.692)
Constant	-1.538***	0.367***	-0.040***	-19.484***
	(0.161)	(0.040)	(0.007)	(0.930)
Observations	26,770	26,579	26,730	26,696
Control Variables	Yes	Yes	Yes	Yes
Lagged Dependent Variables	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.0319	0.760	0.292	0.821

Table 11: Concentration of Patenting Activities and Advertising Activities

This table reports how the establishments of patent exchanges in a province affects the concentration of patenting activities and advertising activities in that province. The dependent variable in regression (1) is the province-level HerfindahlHirschman Index (HHI) for firm patenting activities, and the dependent variable in regression (2) is the HHI for advertising expenditures. The dummy variable "Treatment" equals one in a year if a patent exchange has been established in a province by that year. The control variables are GDP per capita and R&D-to-GDP ratio. All regressions in this table include year fixed effect, province fixed effect, and a constant. Standard errors are reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	HHI of Patent Applications	HHI of Advertising Expenditures
	(1)	(2)
Treatment	0.062**	0.024**
	(0.028)	(0.010)
Observations	490	496
Control Variables	Yes	Yes
Province fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Adjusted R^2	0.577	0.810

Table 12: Intensive Margin Analysis of Patent Trading

This table reports the results of our intensive-margin analysis of the effect of patent trading. That is to say, we examine how firms adjust their strategies to create and commercialize innovation when the market for patent trading becomes more liquid. The variable "trading liquidity" is a measure of patent trading liquidity that each firm faces in each year. This measure of patent trading liquidity is a proxy of the likelihood that a firm's patents will be traded in each year. The variable "net # of patents sold" is the number of patents a firm sells subtracted by the number of patents it buys each year. All regressions in this table include year fixed effect and firm fixed effect. Standard errors are clustered at the firm level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	$ln(\# \text{ of patents} + 1)_{t+1}$	Advertising Expenditures$_{t+1}$
	(1)	(2)
trading liquidity × net # of patents sold	0.133***	-0.059***
	(0.027)	(0.015)
trading liquidity	0.094***	-0.007
	(0.011)	(0.005)
net # of patents sold	-0.286***	0.092***
	(0.048)	(0.025)
ln(asset + 1)	0.169***	0.140***
	(0.020)	(0.012)
R&D intensities	0.078***	0.030***
	(0.010)	(0.005)
Tobin's Q	0.007	0.009***
	(0.005)	(0.002)
ROA	0.137	0.108**
	(0.112)	(0.048)
leverage ratio	-0.017	0.087***
	(0.060)	(0.031)
ln(age + 1)	0.016	-0.055***
	(0.024)	(0.013)
PPE ratio	0.209***	0.009
	(0.070)	(0.035)
capex ratio	0.015	-0.086
	(0.128)	(0.056)
Constant	-3.306***	-2.918***
	(0.418)	(0.250)
Observations	26,770	26,770
Control Variables	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Adjusted R^2	0.697	0.804

Table 13: Buyer-Seller Status Before the Establishments of Patent Exchanges

In this table, we use the net number of patents a firm sold during the period *before* the establishment of patent exchanges. The dependent variable in regression (1) is the natural logarithm of one plus the number of patent applications a firm files (and eventually granted) in that year. The dependent variable in regression (2) is a firm's advertising expenditures in each year. The dummy variable "Treatment" equals one in a year if a patent exchange has been established in the province where a firm is located by that year. All regressions in this table include year fixed effect and firm fixed effect. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	$ln(\#\text{ of patents} + 1)_{t+1}$	Advertising $\text{Expenditures}_{t+1}$
	(1)	(2)
Treatment	0.107***	0.003
	(0.031)	(0.012)
Treatment × net # of patents sold	0.083**	-0.130***
	(0.034)	(0.014)
ln(asset + 1)	0.200***	0.168***
	(0.012)	(0.005)
R&D intensities	0.090***	0.031***
	(0.007)	(0.003)
Tobin's Q	0.009*	0.011***
	(0.005)	(0.002)
ROA	0.159	0.164***
	(0.118)	(0.047)
leverage ratio	-0.023	0.141***
	(0.050)	(0.020)
ln(age + 1)	0.020	-0.082***
	(0.019)	(0.008)
PPE ratio	0.212***	-0.021
	(0.063)	(0.025)
capex ratio	0.087	-0.095*
	(0.131)	(0.052)
Constant	-3.859***	-3.468***
	(0.264)	(0.106)
Observations	18,700	18,700
Control Variables	Yes	Yes
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Adjusted R^2	0.710	0.808

Table 14: DiD Regressions, Placebo Test

This table reports the results of our placebo test. The empirical specification of this table is the same as that of our DiD regressions, but the treatment and control status is randomly assigned in this table. All regressions in this table include year fixed effect and firm fixed effect. Standard errors are clustered at the firm level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	ln(# of patents + 1)$_{t+1}$		Advertising Expenditures$_{t+1}$	
	(1)	(2)	(3)	(4)
Treatment	0.007	0.007	-0.004	-0.005
	(0.011)	(0.011)	(0.004)	(0.004)
Treatment × net # of patents sold		0.002		-0.011
		(0.024)		(0.011)
net # of patents sold		-0.057***		-0.004
		(0.019)		(0.009)
ln(asset + 1)	0.172***	0.169***	0.141***	0.141***
	(0.020)	(0.020)	(0.012)	(0.012)
R&D intensities	0.082***	0.081***	0.030***	0.030***
	(0.010)	(0.010)	(0.005)	(0.005)
Tobin's Q	0.007	0.007	0.009***	0.009***
	(0.005)	(0.005)	(0.002)	(0.002)
ROA	0.127	0.123	0.112**	0.111**
	(0.113)	(0.113)	(0.049)	(0.048)
leverage ratio	-0.017	-0.016	0.086***	0.087***
	(0.061)	(0.060)	(0.031)	(0.031)
ln(age + 1)	0.029	0.028	-0.056***	-0.056***
	(0.024)	(0.024)	(0.013)	(0.013)
PPE ratio	0.228***	0.221***	0.009	0.007
	(0.072)	(0.071)	(0.036)	(0.035)
capex ratio	0.032	0.020	-0.085	-0.087
	(0.129)	(0.129)	(0.056)	(0.056)
Constant	-3.369***	-3.313***	-2.939***	-2.927***
	(0.425)	(0.422)	(0.251)	(0.251)
Observations	26,770	26,770	26,770	26,770
Control Variables	Yes	Yes	Yes	Yes
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.695	0.696	0.803	0.803

Appendix A. Variable Definition

Table A1: Variable Definitions

This table is a list of variables used in the regressions. Our measure of a firm's innovative output in a year is the natural logarithm of one plus the number of patent applications a firm files (and eventually granted) in that year. To account for different qualities of patents, we also examine the relative citation strength of a patent. To be specific, we gauge the relative citation strength of a patent by the number of citations it has received by 2018, divided by the average number of citations received by patents in its cohort (i.e., patents applied in the same year and the same technology class). Following the method of Hochberg et al. (2018), we construct a measure of patent trading liquidity that each firm faces each year. This measure of patent trading liquidity is a proxy of the likelihood that a firm's patents will be traded in each year. Following Hirshleifer et al. (2013), the R&D efficiency of a firm in a year is measured by the number of patent applications it files in that year divided by the weighted average of its R&D expenditures in the past 3 years. Our measure of TFP is estimated by the method of Ackerberg, Caves, and Frazer (2015).

Variable	Definition
$ln(\#\text{ of patents} + 1)_{t+1}$	the natural logarithm of one plus the number of patent applications a firm files (and eventually granted) in year $t+1$
relative citation strength$_{t+1}$	the number of citations a patent has received by 2018, divided by the average received by patents in its cohort (i.e., patents applied in the same year and in the same technology class)
advertising expenditures$_{t+1}$	advertising expenditures in year $t+1$
trading liquidity	a measure of patent trading liquidity, constructed as a proxy of the likelihood that a firm's patents will be traded in each year
net # of patents sold	number of a patents a firm sold subtracted by the # of patents bought
net # of patents licensed out	number of a patents a firm licenses out subtracted by the number of patents licensed in
market value$_{t+1}$	product of total number of shares outstanding and annual closing price
R&D efficiency	# ofpatent applications in a year divided by the weighted average of R&D expenditures in the past 3 years
TFP$_{t+1}$	total factor productivity estimated by the method of Ackerberg, Caves, and Frazer (2015)
ROA$_{t+1}$	net profit divided by book value of total assets
ln(asset + 1)	natural logarithm of one plus book value of total assets
ln(age + 1)	natural logarithm of one plus the number of years a firm has been listed
R&D intensities	R&D expenditures divided by book value of total assets
capex ratio	capital expenditures divided by book value of total assets
PPE ratio	net value of property, plant, and equipment divided by book value of total assets
leverage ratio	book value of total debt divided by book value of total assets
Tobin's Q	market-to-book ratio

Appendix B. Patent Exchanges and The Market For Technology

Is the establishment of patent exchanges relevant for patent trading and licensing transactions? Theoretically speaking, a patent exchange facilitates patent trading and licensing by reducing searching and matching frictions, as well as information frictions. In practice, however, the magnitude of the effect of patent exchanges on the market liquidity of patent trading and licensing is important for our study. To address this question, we pinpoint the magnitude of the effect of patent exchanges in Table A2.

The regressions in Table A2 are based on a panel of patents that are valid between 2001 and 2016. The effect of patent exchanges on the market liquidity of patent trading and licensing is assessed in panel A and B, respectively. The dependent variable in panel A (B) equals one in a year if a patent is traded (licensed) in that year and zero otherwise. The key explanatory variable is a time-varying dummy variable "Treatment." This treatment indicator equals one in a year if a patent exchange has been established by the year in the province where the patentee is located and zero otherwise. To control for the time-invariant characteristics of the treatment group, we add a time-invariant dummy variable that equals one if a patent exchange has ever been established in the province where the patent assignee is located and zero otherwise. In addition, we add the relative citation strength of a patent to control for the quality of innovation. As delineated in Section 3.2, the relative citation strength is gauged by the number of citations a patent received by 2018, divided by the average number of citations received by patents in its cohort (i.e., patents applied in the same year and the same technology class). To control for the aggregate shock and cohort effects of patents, we gradually add the following dummy variables to control for a variety of fixed effects: year dummies, dummy variables for the application year of patents, dummy variables for the technology class of patents, and dummy variables for the type of patent assignees.[25] All regressions are based on logit models and the coefficient estimates are expressed in terms of marginal effects calculated at the means of the independent variables.

As demonstrated by the results in both panels of Table A2, the marginal effect of the treatment indicator is positive and significant at the 1% level across all regressions. Hence, controlling for the characteristics of patents, a patent is more likely to be traded and licensed after a patent exchange has been established in the province where the patent assignee is located. According to regression (5) of panel (A) in which all fixed effects are included, the odds for a patent to be traded increase by one percentage point after the establishment of the patent exchanges. As a comparison, the average odds for a patent to be traded is 1.93%, so the establishment of the patent exchanges has improved the odds for a patent to be traded by 51.8%. Analogously, regression (5) of panel (B) implies that the establishment of the patent exchanges has enhanced the odds for a patent to be licensed by 62.5%. Therefore, the establishment of the patent exchanges contributes to a substantial increase

[25] To be specific, patent assignees are classified into six types: individuals, corporations, universities, research institutions, government agencies, and other types.

in the market liquidity of patent trading and licensing transactions.

Table A2: Patent Exchanges and The Market For Technology, Logit Regressions

This table evaluates the effect of patent exchanges on the market liquidity of patent trading and licensing. The dependent variable in panel A (B) equals one in a year if a patent is traded (licensed) in that year and zero otherwise. The dummy variable "Treatment" in both tables equals one in a year if a patent exchange has been established by that year in the province where the patentee is located. All regressions in both tables are based on logit models and the coefficient estimates are expressed in terms of marginal effects calculated at the means of the independent variables. Standard errors are reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Panel A: Patent Exchanges and Patent Trading

	1{Patent Traded }				
	(1)	(2)	(3)	(4)	(5)
Treatment	0.016***	0.006***	0.008***	0.008***	0.010***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Observations	8,518,883	8,518,883	8,518,003	8,517,973	8,517,973
year dummy	No	Yes	Yes	Yes	Yes
application year dummy	No	No	Yes	Yes	Yes
technology class dummy	No	No	No	Yes	Yes
patent assignee type dummy	No	No	No	No	Yes
control variable	Yes	Yes	Yes	Yes	Yes

Panel B: Patent Exchanges and Patent Licensing

	1{Patent Licensed }				
	(1)	(2)	(3)	(4)	(5)
Treatment	0.007***	0.002***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	8,518,883	8,470,550	8,449,172	8,449,129	8,449,129
year dummy	No	Yes	Yes	Yes	Yes
application year dummy	No	No	Yes	Yes	Yes
technology class dummy	No	No	No	Yes	Yes
patent assignee type dummy	No	No	No	No	Yes
control variable	Yes	Yes	Yes	Yes	Yes