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 specialization patterns 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 specialization, 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 specialization? 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 firm's in-house innovation.

In general, trade induces comparative-advantage-based specialization and, thus, contributes to more efficient resource allocation. In the specific field 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 a university professor) 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 for 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 records. 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 two decades. Accounting for 23.3% 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 $3.1 billion) in 2001 to 140 billion RMB (about $22.0 billion) in 2017. As a comparison to in-house R&D, the value of technology transfer transactions is 9.7% of aggregate

[1] As a comparison, the U.S. share of world R&D in 2017 is 25.6%. Both the R&D expenditures of China and the United States are measured in constant 2005 PPP dollars. Source: the United Nations Educational, Scientific and Cultural Organization.

corporate R&D between 2001 and 2017.[2] Among the patents granted in China between 2001 and 2017, 8.6% have been traded at least once during this period. Corporations in China are actively participating in patent trading. Among the patent-filing publicly listed firms, 50.3% has traded at least one patent between 2001 and 2017. More importantly, micro-level, detailed information on firms' financial statements, patent filings, patent trading, and patent licensing transactions 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 frictions and 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 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.

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

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 output. 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 output for an average patent seller, it leads to a 9.7% decline in firm patenting output for an average patent buyer. To evaluate how patent trading affects a firm's effort to commercialize innovation, we examine how a firm adjusts its advertising expenditures in response to the establishment of patent exchanges. Our estimation results suggest that the effect of patent trading on a firm's advertising expenditures is also remarkably 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) the in-house innovation of a patent seller (buyer), and decreases (increases) the advertising expenditures of a patent seller (buyer). That is to say, patent sellers (buyers) divert more resources toward creating (commercializing) innovation when opportunities for 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 output for an average licensor, whereas it leads to a 4.8% decline in patenting output 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 their trading activities. 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 99^{th} 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 output for a firm with high R&D efficiency, whereas it leads to an 11.5% decline in patenting output for the average firm in our sample. In the meanwhile, 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

[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.

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 have uncovered 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, 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 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. 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. In contrast, the treatment effect starts to be significant once the patent exchange has been established and this effect persists in the long run. Therefore, the results of the dynamic treatment analysis reject the demand-driven interpretation of our findings and rule out the reverse causality argument.

The second concern for our DiD analysis is that the establishment of patent exchanges could 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. In light of this, 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 provide a vote of confidence 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 firm performance along four dimensions: innovation quality, firm productivity, profitability, and valuation. We find that enhanced patent trading contributes to higher quality of patents, higher total factor productivity (TFP), higher return on assets (ROA), and higher Tobin's Q. According to our DiD estimations, enhanced patent trading (facilitated by the establishment of patent exchanges) leads to an increase in firm TFP by 1.5%, an increase in firm ROA by 0.4 percentage points (11.9% of sample mean), and an increase of firm Tobin's Q by 0.049 (2.2% 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. In light of this, our analysis predicts increasing concentration of patenting activities and advertising activities after patent exchanges are established. This prediction of increasing concentration is corroborated by our empirical analysis. Using the Herfindahl-Hirschman index (HHI) as a proxy of market concentration, we find 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 findings on the effects of the market for technology.

Furthermore, we conduct five additional tests to assess the validity and robustness of our findings. First, we undertake a placebo test by randomly assigning a false treatment status to observations in our sample while maintaining the true distribution of the event time. We find that our main results are absent in this pseudo-treated sample, which suggests that our main findings are unlikely to be driven by chance or other omitted shocks. Second, one may be concerned that our results could be driven by China's economic stimulus plan during the 2007–2008 global financial crisis. While our DDD analysis and placebo test alleviate this concern to some extent, we conduct further robustness checks to explicitly control for the amount of government subsidy a firm receives. Third, we construct a measure of patent trading liquidity to examine the effect of patent trading along the intensive margin. To be specific, we replace the treatment indicator in our baseline analysis 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. Fourth, 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. Lastly, some patents are of low quality and of little values. In light of the concern for low quality patents, we restrict our sample to patents that have been renewed at least three times. Our findings are robust in all these tests.

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. Serrano (2010) characterizes the stylized facts about patent transfers and renewals. Galasso et al. (2013) show that patent trading can be attributed to a firm's comparative advantage in patent enforcement and trade reduces the risk of patent litigation. Akcigit et al. (2016) create a measure of technological distance and develop a search-theoretic growth model to quantify the impact of ideas misallocation. Cohen et al. (2016) demonstrate that nonpracticing entities amass patent portfolios to sue cash-rich firms for patent infringement and discourage the innovation activity at targeted firms. Hochberg et al. (2018) find that patent trading facilitates lending to startups, particularly for those with more redeployable patent assets. Ma et al. (2019) document that firms sell more redeployable and liquid patents during bankruptcy reorganizations and the effect is driven by firms facing "fire-sale" pressures. Bian et al. (2021) find that bilateral investment treaties between countries promote technology adoption, sourcing, and R&D collaborations.

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 innovation powerhouse. Giannetti et al. (2015) find that the performance of Chinese firms improves after hiring directors with foreign experience and talent emigration can lead to a brain gain. Fang et al. (2017) and Tan et al. (2020) find that innovation output increases after China's state-owned enterprises (SOEs) are privatized. Tian and Xu (2021) find that the establishment of national high-tech zones in China has a positive effect on local innovation output and entrepreneurial activities. Creating a measure for technology decoupling between the U.S. and China, Han et al. (2021) study how industrial policies affect U.S.-China technology decoupling and how technology decoupling affects firm performance. He and Tian (2018) and He and Tian (2020) provide surveys on how finance and institutions affect corporate innovation, including China.

There is a paucity of solid and elaborate empirical evidence on the effects of patent trading on innovation specialization. Hence, we contribute to the patent trading literature by providing causal evidence on how patent trading affects specialization based on a firm's comparative advantages in creating versus commercializing innovation. This particular source of comparative advantages and motive to trade is remarkably different from previous studies (e.g., Galasso et al. (2013)). We also add to the emerging literature that aims to unveil the innovation ecosystem in China. We compile a unique dataset on patent exchanges in China and assemble a novel micro-level dataset that combines firm accounting information with patent trading and licensing information. Exploiting China's unique institutional arrangement of patent exchanges to establish causality, our study is instrumental to illuminate the effects of the market for technology in general. Our findings on patent exchanges also shed light on how public policies can be designed to foster 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. To strengthen our identification strategy, Section 5 reports the results for dynamic DiD analysis, DDD analysis, and five robustness checks. We assess the effect of patent trading on firm performance and the industrial organization structure in Section 6. Section 7 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. Section 2.1 provides an overview of patent exchanges and Section 2.2 elaborates on trading rules and procedures. We highlight how patent exchange facilitates patent trading in Section 2.3.

2.1 An overview of patent exchanges

A patent exchange in China is a facility where patents can be traded or licensed. Apart from being a focal point for the market of technology, a patent exchange also organizes technology trade fairs where patent holders can showcase their technologies and potential buyers can search for technology suppliers.

Patent exchanges were gradually established across different regions of China over time.[4] 15 patent exchanges were established in 2006, 4 were established in 2007, 16 were established in 2008, and 6 were established in 2009. These patent exchanges receive various government support such as favorable policies for financing and land use. To gain such public 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 technology 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.

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.

Appendix Figure A1 is a snapshot of the website of Shenzhen Patent Exchange. As illustrated by this web pate, a patent holder can provide the information of patents for sale and a potential buyer can post the patent demand information. Analogously, a potential buyer can search for patents available for sales and a patent holder can look for patent demand information. For instance, Appendix Figure A2 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 exhibited at the bottom of Appendix Figure A2. 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

[4]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 Appendix Table A4. According to our DiD estimations, the establishment of patent exchanges has improved the odds for a patent to be traded by 51.8%.

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 the contract (e.g., trading or licensing) and contact information of the patent holder.

How do the buyers and sellers participate in trading at the patent exchange? The procedures of patent trading are delineated in Appendix Figure A3. To participate in patent trading, both patent holders and potential buyers are required to apply for exchange membership. After such applications are approved by the patent exchange, a patent holder can provide the information of patents for sale and a potential buyer can post the patent demand information. Based on such demand and supply information, the exchange matches the buyers with sellers and recommends a potential deal. The exchange can arrange a meeting if both parties are interested in the deal. 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.

2.3 How patent exchanges facilitate patent trading

As demonstrated by the rules and procedures of patent trading, a patent exchange facilitates patent trading by reducing search frictions and information frictions of trading. We discuss both friction reduction roles of a patent exchange in this section.

Patent trading is rife with search frictions. It is challenging for the seller to find a buyer who is willing to pay for her technology, especially when the knowledge embodied in the patent is hard to articulate. It is also difficult for a buyer to find the exact technology that fulfills her 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 potential gains from patent trading, a transaction can be obstructed if the costs of such frictions exceed the benefits of trade. As demonstrated by Akcigit et al. (2016), such frictions are of vital importance on how the market for technology functions. Designed as a focal point for patent trading, a patent exchange facilitates patent trading by reducing search frictions and enhancing matching efficiency. Patent holders can provide elaborate information of their patents to the exchange website and specify preliminary terms of trade to initiate the 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 on-site technology trade fairs to facilitate the communication between buyers and sellers. In addition, the exchange can recommend a potential deal to buyers and sellers based on their information provided to the exchange. If both parties are interested in the deal, the exchange can arrange a meeting for them and provide related legal documents to aid their negotiation.

Apart from search frictions, information frictions also pose a serious challenge to patent trading. Trading patents is remarkably more difficult than trading tangible goods. It is hard to articulate the tacit knowledge embodied in patents and 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 patent exchange create 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 from patent holders a technical report of the elaborate technological attributes of the patents. Third, patent holders also need to provide an assessment of potential commercial applications of their patents, including a forecast for market demand. A patent will be rejected from being listed on the exchange if these three conditions are not properly satisfied. Therefore, patent exchanges contribute to deterring potential frauds, weeding out low-quality patents, and facilitating the sellers to gather information about business opportunities to commercialize the patented technologies. These roles of patent exchanges are instrumental to addressing problems caused by the uncertainty of the technology and asymmetric information between buyers and sellers.

In light of these theoretical predictions on how patent exchanges facilitate patent trading, we quantify the liquidity-enhancing effects of patent exchanges in Appendix Table A4. In this table, we exploit the staggered establishments of patent exchanges to conduct a difference-in-differences (DiD) analysis. According to our DiD estimations, the establishment of patent exchanges has improved the odds for a patent to be traded by 51.8% (significant at the 1% level).[5] Therefore, patent exchanges have substantially contributed to enhancing the market liquidity of patent trading.

3 Data and descriptive statistics

To undertake a rigorous empirical analysis of how patent trading affects firm innovation and specialization, 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 granted at the Chinese National Intellectual Property Administration (CNIPA).[6] 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 the record of ownership changes. We identify a patent sale in the CNIPA database based on the change of patent ownership. In some cases, however, the change in ownership status is attributed to an ownership reassignment from the

[5] According to regression (5) of panel (A) where all fixed effects are included, the odds for a patent to be traded increase by one percentage point after the patent exchanges are established. Since the average odds for a patent to be traded in a year is 1.93%, patent exchanges have improved the odds for a patent to be traded by 51.8%. Analogously, regression (5) of panel (B) suggests that patent exchanges have enhanced the odds for a patent to be licensed by 62.5%.

[6] Analogous to the procedures at the USPTO, a patent applicant in China will go through three stages before a patent is granted: patent filing, patent examination, and patent publication. There are three types of patents in China: invention patents, utility model patents, and design patents. Invention patents are subject to more rigorous examination and enjoy a longer term of protection than the other two types. Among the three types of Chinese patents, invention patents are the most comparable to utility patents granted at the USPTO and hence we focus on invention patents (subsequently referred to as "patents") in this study.

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 an inventor-employer reassignment if the following four conditions are satisfied: (i) the original assignee is an individual inventor when the patent is granted; (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.[7]

To gather firm accounting information, we focus on publicly traded companies in China's A-share stock market.[8] 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 two datasets, accounting for the unique features of the Chinese language during the merging process. 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 in our study are defined in Appendix Table A1. To evaluate a firm's innovating performance, we examine the quantity and the quality of its patenting output. *Innovation Output* is the natural logarithm of one plus the number of patent applications a firm files and eventually granted. The quality of patents is gauged by its relative citation strength. To be specific, *Innovation Quality* is the number of citations a patent 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). This measure facilitates quality comparison of patents from different time vintages and technology classes. *Advertising* is a firm's advertising expenditures, a proxy of its effort to commercialize innovation.

[7]To alleviate the concern for invalid patent reassignment information, 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.

[8]Following the common practice in the literature, we exclude firms in the financial industry in this study.

As a measure of the market liquidity of patent trading, *Trading Liquidity* is constructed by the method in Hochberg et al. (2018). *Trading Liquidity* is a proxy of the likelihood that a firm's patents will be traded in each year.[9] As in Hochberg et al. (2018), we adjust the pool of potentially tradable patents by excluding patent sales that occur a long time after a patent is granted.[10]

To detect a firm's buyer-seller status in patent trading, *Net # of Patents Sold* is the number of patents a firm sells subtracted by the number of patents it buys. A positive (negative) value of the net number of patents sold indicates that a firm is a net seller (buyer) in the market of patent trading. This measure is instrumental to evaluate the effect of patent trading on specialization between patent buyers and sellers. To make a distinction between patent licensors and licensees, *Net # of Patents Licensed Out* is the number of patents a firm licenses out subtracted by the number of patents it licenses in. A positive (negative) value of the net number of patents licensed out indicates that a firm is a net licensor (licensee) in patent licensing transactions. This measure aids our analysis of how patent licensing affects specialization between patent licensors and licensees.

We evaluate a firm's productivity of creating innovation by its R&D efficiency. Following Hirshleifer et al. (2013), *R&D Efficiency* of a firm in a year is the number of successful patent applications it files in that year divided by the weighted average of its R&D expenditures in recent years. To be specific, a firm's *R&D Efficiency* is defined as follows:

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

$Patent_{i,t}$ refers to the number of successful patent applications filed by firm i in year t. $R\&D_{i,t}$, $R\&D_{i,t-1}$, and $R\&D_{i,t-2}$ are the R&D expenditures of firm i in year t, $t-1$, and $t-2$, respectively. *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

[9]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 granted in the same year and the same technology class) that are traded in each year after being granted. This fraction of patents traded in each cohort reflects the likelihood for a patent to be traded and constitutes a patent-level measure of trading liquidity. Second, the firm-level measure of trading liquidity is constructed as the average trading liquidity of all patents in a firm's patent portfolio.

[10]Serrano (2010) shows that the likelihood for a patent to be traded decreases over the lifetime of a patent. In our baseline results, we consider patent trading during the first six years in a patent's lifetime. Our results are robust when using shorter horizons (e.g., five years) and longer horizons (e.g., seven years) as the cutoff.

innovation.

As our measure of firm productivity, *TFP* is the natural logarithm of a firm's total factor productivity. To gauge firm TFP, we apply the method developed in Ackerberg et al. (2015) to estimate a Cobb–Douglas production function.[11] The proxy variables in our TFP estimation follow Giannetti et al. (2015).[12] As our measure of firm profitability, *ROA* refers to a firm's return on assets (computed as a firm's net profit divided by its book value of assets). Firm valuation is measured by its *Tobin's Q*, approximated by the ratio of the sum of the market value of equity and book value of debt to the sum of the book value of debt and equity.

We include the following standard control variables in the regressions. *Assets* is the natural logarithm of one plus a firm's book value of assets. *Age* is the natural logarithm of one plus the number of years since a firm has been publicly listed. *R&D Intensity* is the ratio of a firm's R&D expenditures to its book value of assets. *Capex* is the ratio of a firm's capital expenditures to its book value of assets. *PP&E* is the net value of property, plant, and equipment divided by a firm's book value of assets. *Leverage* is a firm's book value of total debt divided by the book value of total assets.

3.3 Descriptive statistics

Our empirical analysis is based on publicly listed Chinese companies that have filed at least one patent between 2001 and 2016. We provide summary statistics for the firms in our sample in Appendix Table A2. All potentially unbounded variables are winsorized at the 1% extremes unless otherwise specified.

As reported in Table A2, the average firm in our sample has gone public for 8.1 years, has an asset of 7.5 billion RMB, and a return on asset of 3.4%. On average, R&D expenditures, capital expenditures, and *PP&E* amount to 1.0%, 5.8%, and 25.3% of firm assets, respectively. The average firm features a leverage ratio of 45.5% and Tobin's Q of 2.2.

[11] Ackerberg et al. (2015) develop an estimation method to address the functional dependence problem in previous studies on TFP estimations.

[12] To be specific, output in our TFP estimation is proxied by a firm's total revenue, labor is approximated by the total number of employees, capital is approximated by total assets, and intermediate inputs are approximated by cash payments for raw materials and service.

In terms of innovating output, the average firm in our sample files approximately seven successful patent applications each year, though some firms do not have any patent applications in some years and some firms have as many as 160 applications in a year. Firm R&D efficiency has a sample mean of 0.187.[13] Hence, every 10 million RMB R&D capital is associated with 1.87 successful patent applications. To commercialize innovation, an average firm spends 218 million RMB on advertising expenditures, amounting to 3.8% of firm assets or 6.5% of firm sales in our sample.

The net number of patents a firm sells in a year has a sample mean of −0.092 and some active traders have bought four patents and sold two patents in a year. We also examine the cumulated number of patents traded by a firm to characterize its patent trading activities. On average, a firm has bought six patents and sold five patents by the end of our sample period, and some large buyers have bought 82 patents and some large sellers have sold 55 patents. Patent licensing transaction is less frequent than patent trading. The net number of patents a firm licenses out in a year has a sample mean of −0.017 and some active participants have licensed in or out three patents in a year. In terms of the cumulated number of patents involved in licensing transactions, an average firm has licensed out three patents and licensed in two patents by the end of our sample period, and some active participants have licensed out 39 patents and licensed in 13 patents.

4 The market for technology and innovation specialization

A patent exchange facilitates patent trading and licensing by reducing search frictions and information frictions. As demonstrated by Appendix Table A4, patent exchanges have substantially improved the market liquidity of patent trading and licensing transactions.[14] Facing enhanced market liquidity induced by patent exchanges, how do firms adjust their innovation and specialization strategies? To investigate this question, we conduct a DiD analysis to examine the causal effect of the market for technology on three patterns of innovation specialization in this section. We discuss how the staggered establishments of patent exchanges can be exploited as a quasi-experiment to

[13] 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.

[14] According to Table A4, patent exchanges have improved the odds for a patent to be traded by 51.8%. In addition, patent exchanges have enhanced the odds for a patent to be licensed by 62.5%.

establish causality in Section 4.1. Section 4.2 is our baseline analysis of specialization between patent buyers and sellers. We extend our analysis to specialization between patent licensors and licensees in Section 4.3, and we delve further into specialization based on a firm's R&D efficiency in Section 4.4.

4.1 Staggered establishments of patent exchanges as a quasi-experiment

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. Hence, patent exchanges in China provide us a unique and ideal setting to address the endogeneity problem and establish causality.

One may be concerned if the presence of a patent exchange in the local market matters because the website of a patent exchange has already provided some information. While the information on the website is instrumental to initiate negotiations, most patent trading transactions still rely heavily on subsequent in-person meetings and negotiations at patent exchanges because trading patents is substantially more difficult than trading tangible goods. In particular, tacit knowledge embodied in patents is hard to articulate; technical and commercial potential of patented technologies can be highly uncertain; bargaining to determine the price can be both time-consuming and financially costly; and transfer of patent ownership entails numerous legal documents that must be signed in person. Because of such difficulties of patent trading, most patent transactions do rely on in-person meetings and geographic boundaries do matter.

One may also wonder if firms can rely on patent exchanges located in other provinces to complete patent transactions. Though this might be a feasible option, the presence of a patent exchange in the local market is still critical for patent trading for two reasons. First, traveling entails significant time and financial costs. Second, a patent exchange in the local market is instrumental in gathering particular soft information about the trading participants. The importance of geographic proximity has been well-documented in a host of studies (e.g., Tian (2011)). In the specific context of patent trading, 65.3% of transactions are attributed to participants located in the same province. In light of this, the establishment of a patent exchange in the local market is a crucial boost for patent trading. As demonstrated by our estimation results in Appendix Table A4, patent exchanges contribute to a substantial improvement in trading liquidity in the local market.

4.2 Specialization between patent buyers and sellers

We track firm patenting activities around the establishment of patent exchanges in Figure 1. Year 0 on the horizontal axis of Figure 1 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 1 is the average number of patents applied by the firms in the treatment (control) group. As unveiled by Figure 1, the difference between the treatment group and the control group is fairly stable before the patent exchange is founded.[15] 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 1 Here.]

Exploiting the staggered establishments of patent exchanges as a quasi-experiment, we estimate the following firm-level panel regressions:

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

Our regression sample covers all publicly listed Chinese companies that have filed at least one patent between 2001 and 2016. The subscript i in equation (1) indexes for firm and t indexes for year. The dependent variable $y_{i,t+1}$ is either *Innovation Output* or *Advertising* as defined in Section 3.2. The dummy variable $\mathit{Treatment}_{i,t}$ equals one if a patent exchange has been established

[15] 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 perform a dynamic DiD analysis to assess the parallel trend assumption in Section 5.1.

in the province where firm i is located by year t and zero otherwise.[16] $X_{i,t}$ is a vector of control variables including standard firm characteristics, as delineated in Section 3.2. γ_t (year fixed effect) is included to absorb the aggregate shocks and γ_i (firm fixed effect) is incorporated to control for all time-invariant firm heterogeneity. 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.[17] β captures the treatment effect of the patent exchanges, and, thus, is the key regression coefficient of interest. Table 1 reports the results of our baseline DiD estimations.

[Insert Table 1 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. In light of the positive estimates for the treatment indicator in Table 1, the complementarity effect of patent trading is on average stronger than its substitution effect, so patent trading enhances in-house innovation for the average firm. According to our DiD estimate in regression (1), the establishment of patent exchanges induce a 7.5% increase in firm patenting output.

How does patent trading affect innovation specialization? 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 for 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 variable *Net # of Patents Sold* (i.e., the number of patents a firm sells subtracted by the number of patents it buys each year) in Table 1. A positive (negative) value of the net number

[16] The treated provinces and treatment time are delineated in Appendix Table A3.

[17] In our baseline estimations, we cluster standard errors at the firm level. Our results are robust when the standard errors are clustered at the province level.

of patents sold indicates that a firm is a net 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 this section focuses on specialization between patent buyers and sellers based on a firm's net number of patents sold, we also apply a more direct proxy of a firm's competitive advantage in Section 4.4.

Regression (2) of Table 1 suggests that the cross term between the treatment indicator and a firm's 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).[18] While the establishment of patent exchanges contributes to a 21.3% boost in firm patenting output for an average patent seller, it leads to a 9.7% decline in firm patenting output 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 adjust their strategies of commercializing innovation? We investigate this question in regression (3) and (4) of Table 1, where we apply a firm's advertising expenditures as a proxy of its effort to commercialize innovation. Analogous to the heterogeneous effects of patent trading on firm innovation, 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 1, 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 findings 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)

[18]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.

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) specialize in creating (commercializing) innovation when opportunities for patent trading arise.

4.3 Specialization between patent licensors and licensees

A patent can be both traded and licensed in a patent exchange in China. While we study 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 # of Patents Sold* in Table 1 by *Net # of Patents Licensed Out* in Table 2 to assess the specialization pattern between patent licensors and licensees. A positive (negative) value of the net number of patents licensed out indicates that a firm is a net licensor (licensee) in patent licensing transactions.

[Insert Table 2 Here.]

Echoing the findings in Table 1, 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 firm patenting output (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).[19] Regression (1) of Table 2 suggests that the establishment of patent exchanges contributes to a 23.2% boost in patenting output for an average licensor, whereas it leads to a 4.8% decline in patenting output for the average licensee. According to regression (2) of Table 2, an average licensor cuts its advertising expenditures by 30

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

million RMB (13.8% of sample mean) after a patent exchange is established, whereas 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 indicate that 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. This is suggestive evidence that patent licensors (licensees) specialize in creating (commercializing) innovation when a market for technology emerges.

4.4 Specialization based on R&D efficiency

In our study of specialization between patent buyers and sellers, a firm's trading status 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 4.4.1. As a complement to the specialization pattern between patent buyers and sellers, we investigate how patent trading affects R&D-efficiency-based specialization in Section 4.4.2.

4.4.1 R&D efficiency and buyer-seller status in patent trading

What types of firms are the suppliers in patent trading and what types of firms are on the demand side? Does the net number of patents sold by a firm reveal its competitive advantage in creating innovation? We explore these questions in Table 3 where the sample construction, the fixed effects, and the recurring variables are the same as those in Table 1. The dependent variable in Table 3 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 indicates that a firm is a net seller (buyer) in the market of patent trading.

[Insert Table 3 Here.]

The regressions in Table 3 unveil how each firm characteristic is related to its patent trading status. 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 its R&D capital. 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. Across all regressions in Table 3, 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 3, 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).[20] Therefore, R&D efficiency is a strong predictor for a firm's demand for and supply of patents in trading transactions. 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 indeed reveals its competitive advantage in creating innovation.

4.4.2 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 # of Patents Sold* in Table 1 by its *R&D Efficiency* and we recast our DiD analysis of innovation specialization in Table 4.

The results in Table 4 indicate that the cross term between the treatment indicator and firm R&D efficiency is positive (negative) when the dependent variable is firm patenting output (advertising expenditures). Thus, a firm's response to the establishment of patent exchanges hinges on

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

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 99^{th} percentile of the R&D efficiency distribution).[21] According to regression (1) of Table 4, the establishment of patent exchanges contributes to a 37.7% increase in patenting output for a firm with high R&D efficiency, whereas it leads to an 11.5% decrease in patenting output for the average firm in our sample. Regression (2) of Table 4 suggests 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 specializes in creating innovation as a response to the establishment of patent exchanges, whereas a firm with low R&D efficiency specializes in commercializing innovation.

[Insert Table 4 Here.]

Taking stock of our DiD analysis in Section 4, our findings have uncovered 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 findings in this section have demonstrated how the market for technology spurs specialization based on a firm's comparative advantage in creating versus commercializing innovation.

5 Further identification analyses and robustness checks

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

[21] The sample mean of R&D efficiency is 0.187 and the 99^{th} percentile of the R&D efficiency distribution is 4.468.

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. In addition, we conduct five additional tests to assess the validity and robustness of our findings in 5.3.

5.1 Dynamic difference-in-differences 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 may lead to a higher demand for patent trading, and a patent exchange may be established to meet rising demand for trading. Admittedly, such a demand-driven argument can potentially explain the positive relationship between patenting and the establishment of patent exchanges. 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 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. In light of this, we replace the treatment indicator in Table 1 with a set of dummies representing the years around the establishment of patent exchanges. The results of this dynamic DiD analysis are presented in Table 5.

[Insert Table 5 Here.]

In Table 5, $Treatment(-2)$ and $Treatment(-1)$ correspond to two years and one 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 5 is statistically significant and the magnitude of both estimates is tiny. Hence, we do not observe any significant differences in patenting between the treatment group and the control group before the patent exchange is established. In contrast, the treatment effect starts to be significant once the patent exchange has been established and this effect persists in the long run. In addition, the magnitude of the estimate for the treatment dummies is remarkably larger than their counterparts before the treatment event. Therefore, the findings in Table 5 reject the demand-driven interpretation of our results and rule out the reverse causality argument.

5.2 Difference-in-difference-in-differences analysis

One may wonder if the establishment of patent exchanges could 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.[22] In light of this, we refine our treatment and control groups by distinguishing patent traders from non-traders in Figure 2.

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. In Figure 2, we further categorize firms in the treatment group into three sub-groups: patent buyers, patent sellers, and 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 (smaller) than the number of patents it sold during our sample period. A firm in the treatment

[22] Based on our definitions for traders and non-traders in this section, our results reflect the effects of patent trading along both the extensive margin (new firms entering the market for technology) and the intensive margin (enhanced trading among existing market participants). We will also examine a firm's trading status *before* the establishment of patent exchanges in a subsequent robustness check.

group is classified as a non-trader if it did not trade any patents during our sample period. The vertical axis of Figure 2 is the average number of patents applied by firms in each of these four sub-groups.

[Insert Figure 2 Here.]

As illustrated in Figure 2, 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 2. To the extent that patent trading spurs comparative-advantage-based specialization, we hypothesize that patent sellers should redirect more resources toward creating innovation than patent buyers. Figure 2 provides supporting evidence for this hypothesis. Patenting activities of buyers and sellers are 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 emerges. 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 activities between buyers and sellers is suggestive evidence that a patent exchange spurs comparative-advantage-based specialization. To conduct a more rigorous analysis, we estimate the following triple-difference regressions at the firm (i)-year (t) level:

$$y_{i,t+1} = Treatment_{i,t} \times \alpha + Treatment_{i,t} \times Trader_i \times \beta + \delta' X_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{2}$$

In this equation, the sample construction, the dependent variable, the fixed effects, and the recurring variables are the same as those in our baseline estimations (i.e., Table 1). To capture potentially different effects of patent trading on patent traders and non-traders, we interact $Treatment_{i,t}$ with a dummy variable $Trader_i$. To be specific, $Trader_i$ equals one if a firm has traded any patents during our sample period and zero otherwise. The cross term "$Treatment_{i,t} \times Trader_i$" in equation (2) is introduced to conduct a comparison along three dimensions and β is the key regression coefficient of interest. To be concrete, β captures the variation of the dependent variable that is specific to (i) 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).

The results of our DDD estimations are reported in Table 6. As demonstrated by the results in this table, the treatment effect is stronger for patent traders than non-traders and we observe the same pattern of specialization as that in our baseline estimations (i.e., Table 1). Hence, our DDD analysis in this section provides further supporting evidence that the treatment effect is attributed to patent trading instead of other factors.

[Insert Table 6 Here.]

5.2.2 DDD analysis based on patent trading liquidity

The effect of trade hinges on the market liquidity. 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 a 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 Section 3.2, this measure of patent trading liquidity is a proxy of the likelihood that a firm's patents will be traded each year. Based on this liquidity measure, we further refine our treatment and control groups in Figure 3. In this figure, we divide firms in the treatment group into two sub-groups: high liquidity vs low liquidity group. A firm is included in the high (low) liquidity group if the average trading liquidity it faces during the sample period is above (below) the sample average of all firms. The vertical axis of Figure 3 is the average number of patents applied by firms in each sub-group of firms.

[Insert Figure 3 Here.]

As depicted in Figure 3, 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 in the high-liquidity group. Patenting output 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 output in the high-liquidity group accelerates once the patent exchange has been founded. The stark difference between high-liquidity and low-liquidity groups reflects the salient importance of trading liquidity. To evaluate the role of trading liquidity in a more rigorous manner, we estimate the following triple-difference regressions at the firm (i)-year (t) level:

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

In this equation, the sample construction, the dependent variable, the fixed effects, and the recurring variables are the same as those in our baseline estimations (i.e., Table 1). To capture the role of patent trading liquidity, we interact $\mathit{Treatment}_{i,t}$ with a dummy variable $\mathit{High\ Liquidity}_i$. We divide firms into two groups based on the patent trading liquidity that they are confronted with. A firm is classified into the high (low) liquidity group if the average trading liquidity it faces during the sample period is above (below) the sample average of all firms. The time-invariant dummy variable $\mathit{High\ Liquidity}_i$ takes the value of one if a firm is in the high liquidity group and zero otherwise. The cross term "$\mathit{Treatment}_{i,t} \times \mathit{High\ Liquidity}_i$" in equation (3) is introduced to conduct a comparison along three dimensions and β is the key regression coefficient of interest. 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).

We report the estimation results of this DDD analysis in Table 7. The results in this table demonstrates that the treatment effect is stronger for firms facing a liquid market for patent trading than their counterparts confronted with an illiquid market. In addition, the specialization pattern in our baseline estimations (i.e., Table 1) is also manifested in Table 7. Therefore, this DDD analysis lends further support to our findings that the treatment effect is attributed to patent trading instead of other factors.

[Insert Table 7 Here.]

5.3 Robustness checks

In this section, we conduct five additional tests to assess the validity and robustness of our findings. In Section 5.3.1, we undertake a placebo test by randomly assigning the treatment and control status to observations in our sample. Section 5.3.2 addresses the concern that our results could be driven by China's economic stimulus plan after the 2007–2008 global financial crisis. Section 5.3.3 examines the intensive-margin effect of patent trading. In Section 5.3.4, we redo our analysis using a firm's buyer-seller status during the period before the establishment of patent exchanges. Section 5.3.5 targets the concern for low quality patents.

5.3.1 Placebo test

One may be concerned that the establishments of patent exchanges may not be random and might coincide with other omitted variables driving our results. While our DDD analysis alleviates this concern to some extent, we also conduct a placebo test where a false treatment status is randomly assigned to observations in our sample while maintaining the true distribution of the event time. If the results in Table 1 are indeed driven by the establishment of patent exchanges (instead of by chance or other omitted shocks), such results should not be observed in this artificially treated sample.

We perform this placebo test one thousand times and use the pseudo-treated samples to re-estimate our baseline results. We plot the empirical distribution of the estimates of the key regression coefficients (i.e., *Treatment* and *Treatment* $\times$ *Net # of Patents Sold*) in Figure A4. In this figure, panel A4a, A4b, A4c, and A4d report the the empirical distribution of the coefficient estimates for regression (1), (2), (3), and (4) of our baseline results in Table 1. In each panel, we compare the true coefficient estimate with its empirical distribution and kernel density. Across all panels of Figure A4, the true positive coefficient estimates in Table 1 are well above the 99^{th} percentile of the distribution and the true negative estimate is below the 1^{th} percentile. Therefore, the results in this placebo test provide a vote of confidence that our findings are not driven by chance or other omitted shocks.

5.3.2 Government stimulus plan during the 2008 financial crisis

Some of the patent exchanges were established around the 2007–2008 global financial crisis. Though the financial crisis itself may not be able to explain the *increase* of patenting output, one could still be concerned that China's massive economic stimulus plan during the crisis may have contributed to higher patenting output. While this concern is mitigated by our DDD analysis and placebo test to some extent, we conduct further tests to explicitly control for government subsidy in Appendix Table A5–A7.

We gather the government subsidy information at the firm-year level from corporate financial statements. To capture the effects of the economic stimulus plan of the Chinese government, we include an additional control variable *Subsidy* in the regressions. To be concrete, *Subsidy* is the amount of government subsidy a firm receives scaled by firm assets. Incorporating *Subsidy* as a control variable, we reassess the buyer-seller specialization pattern in Appendix Table A5, the licensor-licensee specialization pattern in Appendix Table A6, and the R&D-efficiency-based specialization pattern in Appendix Table A7. As demonstrated by the estimation results in these tables, we observe the same specialization pattern when government subsidy is controlled for. Therefore, our findings are robust when the government stimulus plan associated with the global financial crisis is accounted for.

5.3.3 Intensive-margin analysis

When relying on the establishment of patent exchanges in our DiD estimations, we essentially focus on the effect of patent trading along the extensive margin. As a robustness check, we study the intensive-margin effects of patent trading liquidity in Appendix Table A8. To be specific, we replace the treatment indicator in our baseline analysis by a continuous variable of trading liquidity proxy, *Trading Liquidity*. As delineated in Section 3.2, *Trading Liquidity* is a proxy of the likelihood that a firm's patents will be traded each year.

According to regression (1) of Appendix Table A8, a one-standard-deviation increase in patent trading liquidity is associated with a 25.0% increase (14.3% decrease) of firm patenting output for patent sellers (buyers). Regression (2) of Table A8 indicates that a one-standard-deviation increase in patent trading liquidity is associated with an increase of advertisement expenditures by 93 million RMB (42.7% of sample mean) for patent buyers, but a decrease of 81 million RMB (37.2% of sample mean) for patent sellers. These results suggest that patent sellers (buyers) redirect more resources toward creating (commercializing) innovation when they face a more liquid market for patent trading. Therefore, the results of our intensive margin analysis strengthen our findings on how patent trading affects firm specialization.

5.3.4 Trading status before patent exchange establishments

In our baseline estimations, 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.[23] We recast our baseline estimations in Appendix Table A9 and the same specialization pattern is manifested in this table. Therefore, our findings are robust when using this time-invariant patent buyer-seller status during the period before the establishment of patent exchanges.

5.3.5 Low quality patents

As another concern, some patents are of low quality and of little values. Appendix Table A10 targets this concern for low quality patents. Following the strategies in previous studies (e.g., Akcigit et al. (2016)), we restrict our sample to patents that have been renewed at least three times.[24] We redo our baseline analysis and report the estimation results in Appendix Table A10. All our findings are robust when we focus on this sample of renewed patents.

[23]Since we focus on a firm's buyer-seller status during the period before the establishment of patent exchanges, we exclude firms that never file any patents during this period.

[24]To maintain patent validity in China, patent holders must pay an annual maintenance fee to renew their patents.

6 Implications of innovation specialization

In light of the effect of patent trading on firm specialization, what are the implications for firm performance and the industrial organization structure? To probe into 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

Built on our analysis of how patent trading affects firm specialization, we explore a "bottom line" question: How does patent trading affect firm performance? We investigate this question by assessing firm performance along four dimensions: innovation quality, firm productivity, profitability, and valuation. We report our DiD estimation results in Appendix Table A11.[25]

We use the relative citation strength of patents as a proxy of innovation quality in regression (1) of Table A11, firm TFP as a proxy of productivity in regression (2), firm ROA as a proxy of profitability in regression (3), and firm Tobin's Q as a proxy of valuation in regression (4). As demonstrated by regression (1) of Table A11, the quality of patents filed by the firms has improved after the establishment of patent exchanges. Combining the findings in Table A11 with our baseline estimation results (i.e., Table 1), patent trading boosts both the quantity and the quality of firm innovation. Regression (2) and (3) indicate that firm productivity and profitability have also improved after patent exchanges are established. According to our DiD estimations, the establishment of patent exchanges leads to an increase in firm TFP by 1.5% and an increase in firm ROA by 0.4 percentage points (11.9% of sample mean). Improvement in firm productivity and profitability are factored into rising firm valuation by the investors. According to regression (4), the establishment of patent exchanges contributes to a higher Tobin's Q by 0.049 (2.2% of sample mean). Taking stock of the estimation results in Table A11, our findings suggest patent trading enhances firm performance by promoting comparative-advantage-based specialization.

[25]To control for the persistence of the dependent variables, we include lagged dependent variables across all regressions in this table.

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 for 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 in creating (commercializing) innovation. In light of this, our analysis predicts increasing concentration of patenting activities and advertising activities after patent exchanges are established. To test this hypothesis, we estimate the following DiD regressions at the province (i)-year (t) level for the sample period of 2001–2016:

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

Following the common practice, we apply the Herfindahl-Hirschman index (HHI) as a measure of market concentration. The dependent variables in equation (4) are the province-level HHI for firm patenting activities and advertising expenditures. In equation (4), $\mathit{Treatment}_{i,t}$ equals one if a patent exchange has been established in province i by year t and zero otherwise. The effect of patent exchanges is captured by β, the key regression coefficient of interest. $X_{i,t}$ is a vector of control variables including GDP per capita and R&D-to-GDP ratio. γ_t (year fixed effect) is included to absorb the aggregate shocks and γ_i (province fixed effect) is incorporated to control for all time-invariant province heterogeneity. We report the estimation results in Appendix Table A12.

As demonstrated by the estimation results in Table A12, there has been a rise in both the patenting and advertising HHI after the patent exchanges are established. To be concrete, the establishment of patent exchanges in a province is associated with an increase of patenting HHI by 0.062 (23.5% of sample mean) and a raise in advertising HHI by 0.024 (14.4% of sample mean) in that province. Therefore, the results in Table A12 corroborate our hypothesis on how patent trading affects the industrial organization structure and reinforce our findings on the effects of the market for technology.

7 Conclusion

How does the market for technology affect the incentives of innovation and specialization? 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 records. A patent exchange facilitates patent trading by reducing search frictions and 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.

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 resources for innovation. Moreover, we find that patent trading contributes to higher innovation quality, higher firm productivity and profitability, and higher firm valuation. Therefore, we conclude that patent trading promotes comparative-advantage-based specialization and enhances firm performance. Our findings on patent exchanges shed light on how public policies can be designed to foster firm innovation and specialization.

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_ **and Jiajie Xu**, "Do Place-Based Policies Promote Local Innovation and Entrepreneurship?*," *Review of Finance*, 10 2021. rfab029.

Figure 1: **Patent exchanges and firm patenting activities**

We track firm patenting activities around the establishment of patent exchanges in this figure. Year 0 on the horizontal axis 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 vertical axis is the average number of patents applied by the firms in each group. The solid (dash) line is the average number of patents applied by the firms in the treatment (control) group.

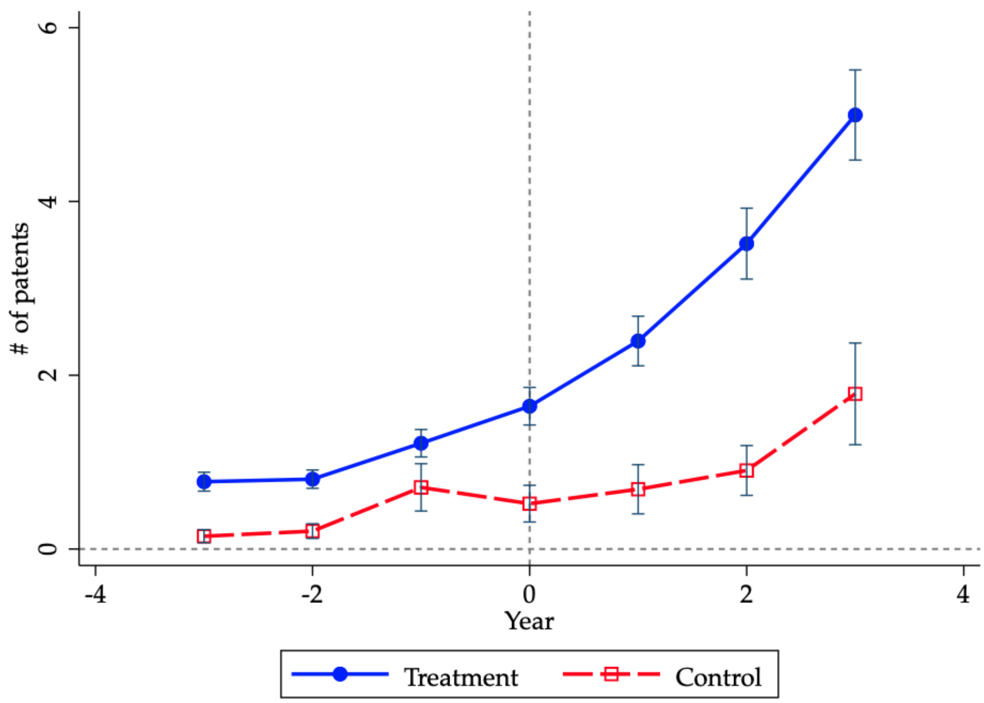


Figure 2: **Patent exchanges and firm patenting activities, traders vs non-traders**

We track firm patenting activities around the establishment of patent exchanges in this figure. In addition, we 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. We further categorize firms in the treatment group into three sub-groups: patent buyers, patent sellers, and 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 (smaller) than the number of patents it sold during our sample period. A firm in the treatment group is classified as a non-trader if it did not trade any patents during our sample period. The vertical axis is the average number of patents applied by the firms in each group.

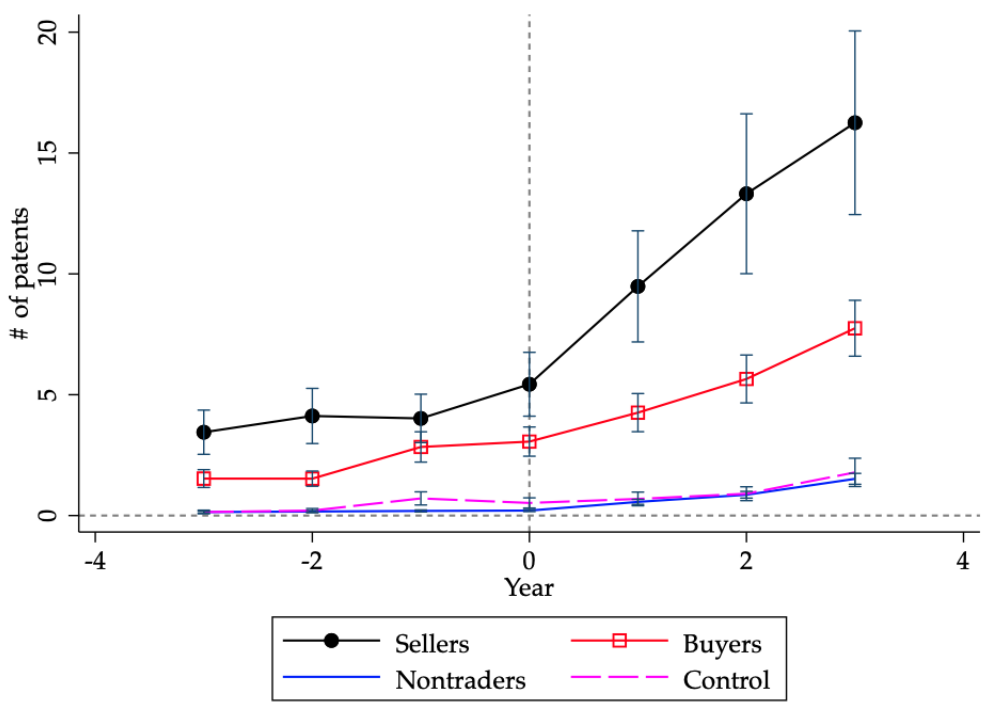


Figure 3: **Patent exchanges and patenting activities, high vs low trading liquidity**
We track firm patenting activities around the establishment of patent exchanges in this figure. In addition, we refine our treatment and control groups by distinguishing firms facing a liquid market for patent trading 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. Based on our measure of patent trading liquidity, we further divide firms in the treatment group into two sub-groups: high liquidity vs low liquidity group. A firm is included in the high (low) liquidity group if the average trading liquidity it faces during the sample period is above (below) the sample average of all firms. The vertical axis is the average number of patents applied by the firms in each group.

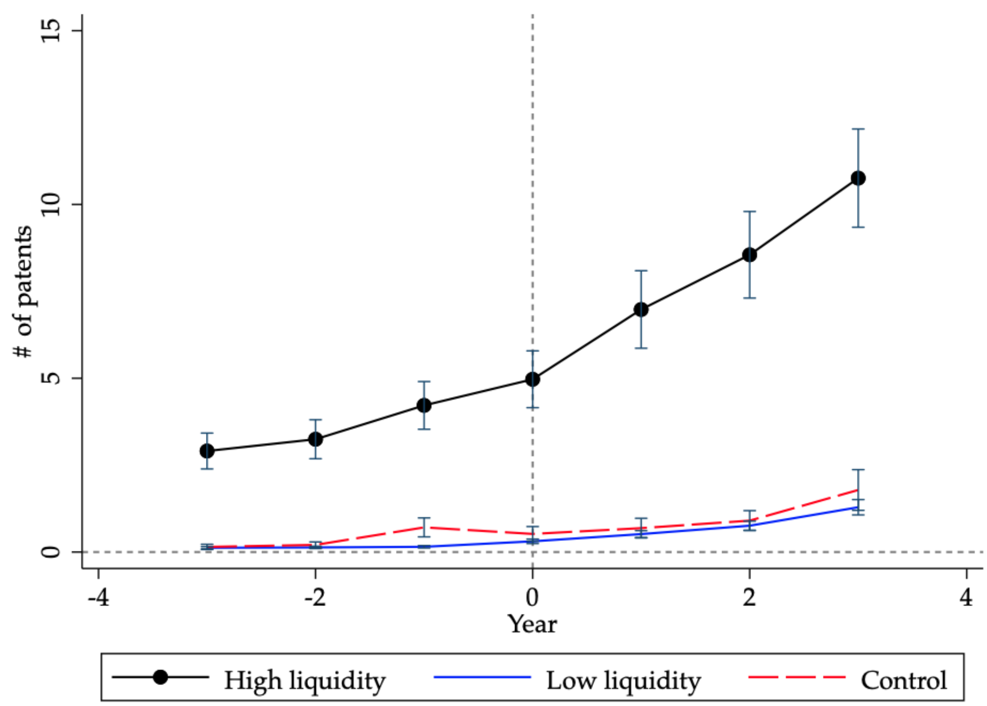


Table 1: DiD Regressions, Patent Trading and Firm Specialization

This table reports the estimation results for DiD regressions on the effects of patent trading. The variables are defined in Table A1. In all regressions, the independent variables are lagged by one year. All regressions 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.

	Innovation Output		*Advertising*	
	(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)
Assets	0.172***	0.169***	0.141***	0.141***
	(0.020)	(0.020)	(0.012)	(0.012)
R&D Intensity	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	-0.015	-0.013	0.087***	0.087***
	(0.061)	(0.060)	(0.031)	(0.031)
Age	0.029	0.028	-0.056***	-0.056***
	(0.024)	(0.024)	(0.013)	(0.013)
PP&E	0.227***	0.221***	0.008	0.007
	(0.072)	(0.071)	(0.036)	(0.035)
Capex	0.031	0.017	-0.085	-0.086
	(0.129)	(0.129)	(0.056)	(0.056)
Observations	26,770	26,770	26,770	26,770
Adjusted R^2	0.695	0.696	0.803	0.803
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Table 2: DiD Regressions, Patent Licensing and Firm Specialization

The regressions in this table examine the specialization pattern between patent licensors and licensees. All variables are defined in Table A1. In all regressions, the independent variables are lagged by one year. All regressions 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.

	Innovation Output	*Advertising*
	(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 Intensity	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	0.111***	0.186***
	(0.039)	(0.014)
Age	0.062***	-0.035***
	(0.015)	(0.005)
Observations	26,770	26,770
Adjusted R^2	0.691	0.790
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes

Table 3: R&D Efficiency and buyer-seller trading status

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. All other variables are defined in Table A1. In all regressions, the independent variables are lagged by one year. 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*$_t$		
R&D Efficiency	0.122***	0.141***	0.223**
	(0.046)	(0.048)	(0.088)
Assets	0.095***	0.057	-0.001
	(0.035)	(0.036)	(0.144)
R&D Intensity	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	0.105	0.151	-0.016
	(0.240)	(0.242)	(0.521)
Age	0.051	0.040	0.165
	(0.052)	(0.053)	(0.172)
PP&E	0.555**	0.531**	0.012
	(0.267)	(0.268)	(0.739)
Capex	-2.343***	-1.978**	-2.068
	(0.847)	(0.871)	(1.318)
Observations	15,224	15,224	15,224
Adjusted R^2	0.00355	0.00354	0.0711
Year fixed effect	No	Yes	Yes
Firm fixed effect	No	No	Yes

Table 4: DiD Regressions, Firm Specialization Based On R&D Efficiency

The regressions in this table examine the specialization pattern based on firm R&D efficiency. All variables are defined in Table A1. In all regressions, the independent variables are lagged by one year. All regressions 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.

	Innovation Output	*Advertising*
	(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)
Assets	0.097***	0.155***
	(0.030)	(0.020)
R&D Intensity	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	-0.048	0.132***
	(0.091)	(0.046)
Age	0.054*	-0.086***
	(0.032)	(0.018)
PP&E	0.047	0.051
	(0.114)	(0.056)
Capex	-0.164	-0.014
	(0.203)	(0.076)
Observations	15,224	15,224
Adjusted R^2	0.725	0.881
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes

Table 5: DiD Regressions, Dynamic Treatment Effects

This table reports the results of the dynamic DiD analysis. The variables are defined in Table A1. All independent variables (except for the dynamic treatment dummies) are lagged by one year . All regressions 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.

	Innovation Output		*Advertising*	
	(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)
Assets	0.171***	0.169***	0.141***	0.141***
	(0.010)	(0.010)	(0.003)	(0.003)
R&D Intensity	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	-0.014	-0.012	0.087***	0.087***
	(0.040)	(0.040)	(0.014)	(0.014)
Age	0.028*	0.027*	-0.056***	-0.056***
	(0.015)	(0.015)	(0.005)	(0.005)
PP&E	0.227***	0.220***	0.008	0.007
	(0.048)	(0.048)	(0.016)	(0.016)
Capex	0.030	0.018	-0.084**	-0.086**
	(0.101)	(0.100)	(0.034)	(0.034)
Observations	26,770	26,770	26,770	26,770
Adjusted R^2	0.695	0.696	0.803	0.803
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Table 6: 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. The variables are defined in Table A1. In all regressions, the independent variables are lagged by one 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.

	Innovation Output		*Advertising*	
	(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)
Assets	0.161***	0.159***	0.139***	0.139***
	(0.019)	(0.019)	(0.012)	(0.012)
R&D Intensity	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	0.010	0.011	0.092***	0.091***
	(0.059)	(0.059)	(0.031)	(0.031)
Age	0.027	0.027	-0.056***	-0.056***
	(0.024)	(0.024)	(0.013)	(0.013)
PP&E	0.220***	0.214***	0.007	0.006
	(0.069)	(0.069)	(0.035)	(0.035)
Capex	0.032	0.019	-0.085	-0.086
	(0.127)	(0.127)	(0.056)	(0.055)
Observations	26,770	26,770	26,770	26,770
Adjusted R^2	0.698	0.699	0.804	0.804
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Table 7: 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 in this regression specification. The variables are defined in Table A1. In all regressions, the independent variables are lagged by one 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.

	Innovation Output		*Advertising*	
	(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)
Assets	0.170***	0.169***	0.140***	0.140***
	(0.020)	(0.020)	(0.012)	(0.012)
R&D Intensity	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	-0.005	0.001	0.092***	0.091***
	(0.060)	(0.060)	(0.031)	(0.031)
Age	0.020	0.021	-0.061***	-0.061***
	(0.024)	(0.024)	(0.013)	(0.013)
PP&E	0.214***	0.206***	0.001	0.001
	(0.071)	(0.070)	(0.036)	(0.035)
Capex	0.048	0.027	-0.075	-0.075
	(0.129)	(0.128)	(0.056)	(0.056)
Observations	26,770	26,770	26,770	26,770
Adjusted R^2	0.696	0.698	0.805	0.805
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Appendix

FIGURE A1: **Shenzhen patent exchange**

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

Figure A2: **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 exhibited 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 the contract (e.g., trading or licensing) and contact information of the patent holder.

FIGURE A3: **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 to apply for exchange membership. After such applications are approved by the patent exchange, a patent holder can provide the information of patents for sale and a potential buyer can post the patent demand information. Based on such demand and supply information, the exchange matches the buyers with sellers and recommends a potential deal. The exchange can arrange a meeting if both parties are interested in the deal. 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.

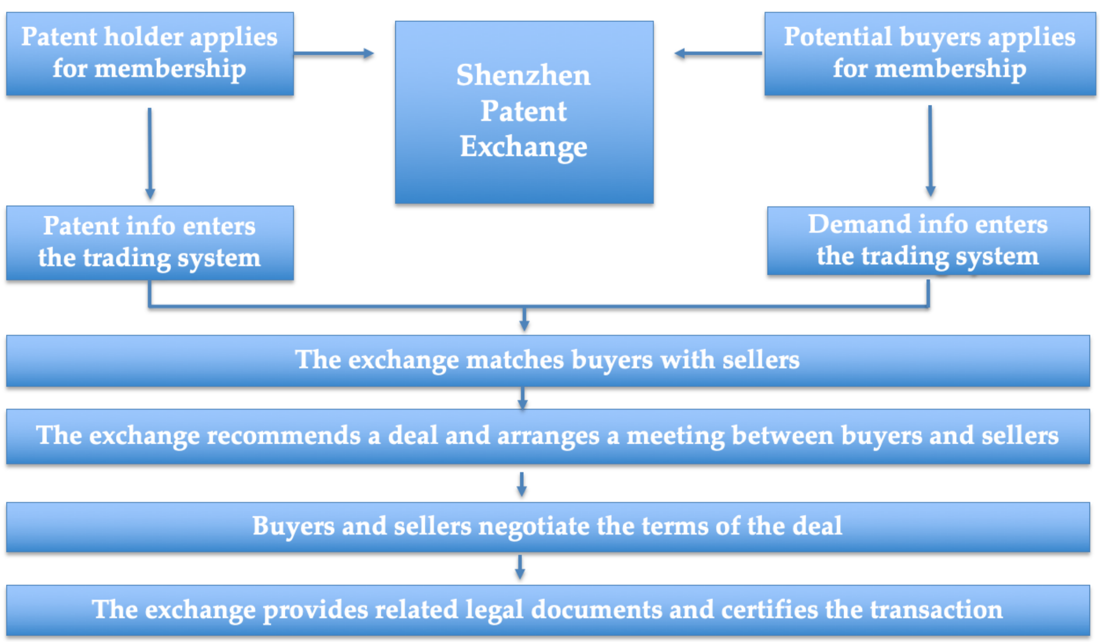
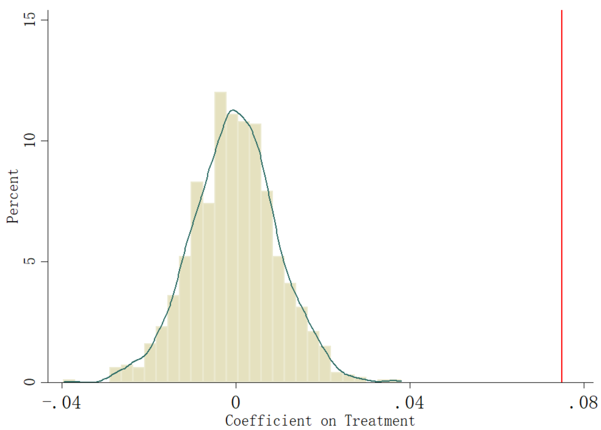
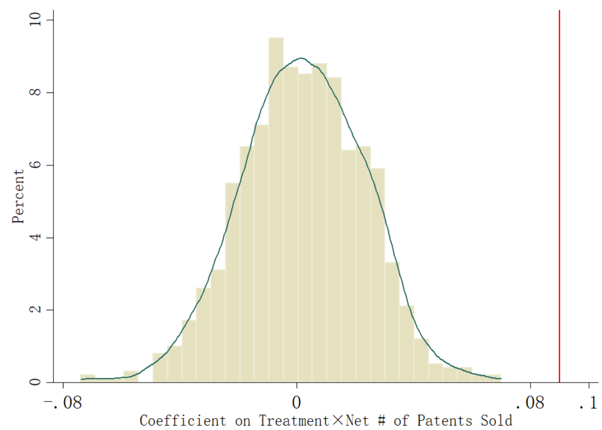


FIGURE A4: **Placebo test**

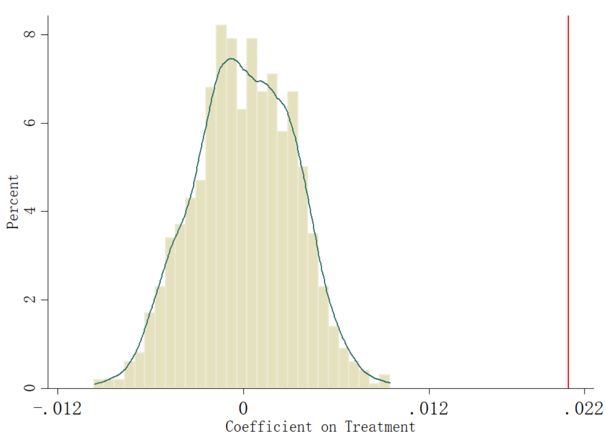
In this figure, we conduct a placebo test where the treatment and control status are randomly assigned to observations in our sample while maintaining the true distribution of the event years. We perform this placebo test one thousand times and use the pseudo-treated samples to re-estimate our baseline results. We plot the empirical distribution of the estimates of the key regression coefficients (i.e., *Treatment* and *Treatment* × *Net # of Patents Sold*) in this figure. Panel A4a, A4b, A4c, and A4d report the the empirical distribution of the coefficient estimates for regression (1), (2), (3), and (4) of our baseline results in Table 1. We also plot the kernel density of the coefficient estimates. The true coefficient estimate in each panel is marked by a red vertical line.



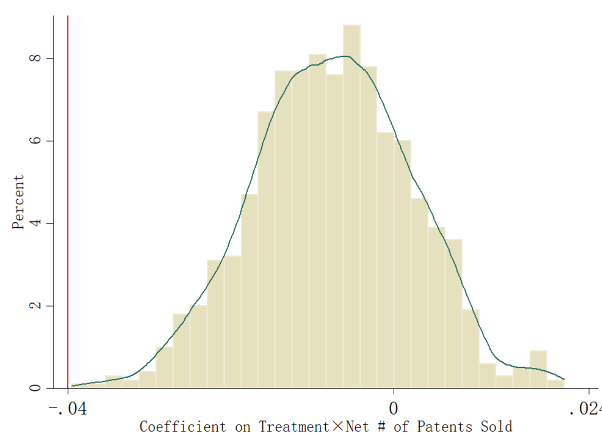
(A) INNOVATION REGRESSIONS, COEFFICIENT ON *Treatment*



(B) INNOVATION REGRESSIONS, COEFFICIENT ON *Treatment* × *Net # of Patents Sold*



(C) ADVERTISING REGRESSIONS, COEFFICIENT ON *Treatment*



(D) ADVERTISING REGRESSIONS, COEFFICIENT ON *Treatment* × *Net # of Patents Sold*

Table A1: Variable Definitions

Variable	Definition
Treatment	A treatment indicator that equals one in a year if a patent exchange has been established in the province where a firm is located by that year
Innovation Output	The natural logarithm of one plus the number of patent applications a firm files (and eventually granted)
Innovation Quality	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	Firm advertising expenditures
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 sells subtracted by the number of patents the firm buys
Net # of Patents Licensed Out	Number of a patents a firm licenses out subtracted by the number of patents the firm licenses in
R&D Efficiency	# of patent applications in a year divided by R&D capital
TFP	The natural logarithm of total factor productivity, estimated by the method of Ackerberg et al. (2015)
ROA	Net profit divided by book value of total assets
Assets	Natural logarithm of one plus book value of total assets
Age	Natural logarithm of one plus the number of years since a firm has been publicly listed
R&D Intensity	R&D expenditures divided by book value of total assets
Capex	Capital expenditures divided by book value of total assets
PP&E	Net value of property, plant, and equipment divided by book value of total assets
Leverage	Book value of total debt divided by book value of total assets
Tobin's Q	The ratio of the sum of the market value of equity and book value of debt to the sum of the book value of debt and equity
Subsidy	Government subsidy a firm receives divided by book value of total assets

Table A2: Descriptive Statistics

Our empirical analysis is based on publicly listed Chinese companies that have filed at least one patent between 2001 and 2016. The table reports the summary statistics of main variables that are defined in Table A1. To facilitate the economic interpretations of the following variables, we report the summary statistics of *Innovation Output* in terms of the number of patents, *Assets* and *Advertising* in terms of billions of RMB, and *Age* in terms of the number of years. All potentially unbounded variables are winsorized at the 1% extremes.

	Mean	Standard Deviation	Min	Median	Max	Observations
Innovation Output (number of patents)	7.291	21.35	0	1	160	26,770
Innovation Quality	0.541	0.953	0	0	4.927	26,770
Advertising (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
TFP	2.301	0.384	1.121	2.312	3.261	26,563
ROA	0.0337	0.0624	-0.264	0.0348	0.192	26,770
Assets (billion RMB)	7.459	18.24	0.216	2.288	137.2	26,770
Age (number of years)	8.102	5.873	0	7	22	26,770
R&D Intensity (%)	0.995	1.502	0	0.0679	7.395	26,770
Capex	0.0580	0.0553	0.000246	0.0414	0.264	26,770
PP&E	0.253	0.173	0.00331	0.220	0.743	26,770
Leverage	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 A3: Treated Regions and Treatment Time

The first column of this table reports the provinces treated based on the staggered establishments of patent exchanges. The second column is the treatment starting year.

Treated Provinces	Treatment Starting Year
Anhui	2006
Beijing	2006
Chongqing	2006
Fujian	2008
Gansu	2006
Guangdong	2006
Guizhou	2008
Hainan	2008
Henan	2006
Hubei	2006
Hunan	2007
Inner Mongolia	2008
Jiangsu	2008
Jiangxi	2007
Jilin	2006
Liaoning	2008
Ningxia	2009
Shaanxi	2006
Shandong	2006
Shanghai	2006
Shanxi	2008
Sichuan	2006
Tianjin	2006
Xinjiang	2009
Yunnan	2008
Zhejiang	2007

Table A4: Patent Exchanges and The Market For Technology, Logit Regressions

In this table, we assess the effect of patent exchanges on the market liquidity of patent trading and licensing in panel A and B, respectively. The regressions are based on a panel of patents that are valid between 2001 and 2016. The dependent variable in panel A (B) equals one in a year if a patent is traded (licensed) in that year and zero otherwise. *Treatment* equals one in a year if a patent exchange has been established in the province where the patent assignee is located by that year and zero otherwise. We add the relative citation strength of a patent to control for innovation quality. Patent assignees are classified into six types: individuals, corporations, universities, research institutions, government agencies, and other types. 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. 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
Control variable	Yes	Yes	Yes	Yes	Yes
Year fixed effect	No	Yes	Yes	Yes	Yes
Application year fixed effect	No	No	Yes	Yes	Yes
Technology class fixed effect	No	No	No	Yes	Yes
Patent assignee type fixed effect	No	No	No	No	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
Control variable	Yes	Yes	Yes	Yes	Yes
Year fixed effect	No	Yes	Yes	Yes	Yes
Application year fixed effect	No	No	Yes	Yes	Yes
Technology class fixed effect	No	No	No	Yes	Yes
Patent assignee type fixed effect	No	No	No	No	Yes

Table A5: DiD Regressions, Patent Trading and Firm Specialization

This table reports the estimation results for DiD regressions on the effects of patent trading, controlling for the amount of government subsidy a firm receives. All variables are defined in Table A1. In all regressions, the independent variables are lagged by one year. All regressions 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.

	Innovation Output		*Advertising*	
	(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**
		(0.034)		(0.019)
Net # of Patents Sold		-0.140***		0.027
		(0.032)		(0.018)
Assets	0.176***	0.173***	0.142***	0.142***
	(0.020)	(0.020)	(0.012)	(0.012)
R&D Intensity	0.079***	0.078***	0.029***	0.029***
	(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	0.096	0.096	0.105**	0.102**
	(0.114)	(0.114)	(0.048)	(0.048)
Leverage	-0.024	-0.022	0.085***	0.084***
	(0.060)	(0.060)	(0.031)	(0.031)
Age	0.029	0.028	-0.056***	-0.056***
	(0.024)	(0.024)	(0.013)	(0.013)
PP&E	0.212***	0.205***	0.005	0.004
	(0.072)	(0.071)	(0.036)	(0.036)
Capex	0.021	0.007	-0.087	-0.088
	(0.129)	(0.129)	(0.056)	(0.056)
Subsidy	0.043***	0.042***	0.010**	0.010**
	(0.013)	(0.013)	(0.004)	(0.004)
Observations	26,770	26,770	26,770	26,770
Adjusted R^2	0.695	0.696	0.803	0.804
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Table A6: DiD Regressions, Patent Licensing and Firm Specialization

The regressions in this table examine the specialization pattern between patent licensors and licensees, controlling for the amount of government subsidy a firm receives. All variables are defined in Table A1. In all regressions, the independent variables are lagged by one year. All regressions 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.

	Innovation Output	*Advertising*
	(1)	(2)
Treatment	0.082***	0.024***
	(0.025)	(0.009)
Treatment × *Net # of Patents Licensed Out*	0.094*	-0.033*
	(0.056)	(0.020)
Net # of Patents Licensed Out	-0.106*	0.043**
	(0.055)	(0.019)
R&D Intensity	0.078***	0.028***
	(0.006)	(0.002)
Tobin's Q	-0.023***	-0.015***
	(0.004)	(0.001)
ROA	0.396***	0.375***
	(0.092)	(0.032)
Leverage	0.106***	0.186***
	(0.039)	(0.014)
Age	0.062***	-0.035***
	(0.015)	(0.005)
Subsidy	0.032***	-0.001
	(0.008)	(0.003)
Observations	26,770	26,770
Adjusted R^2	0.691	0.790
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes

Table A7: DiD Regressions, Firm Specialization Based On R&D Efficiency

The regressions in this table examine the specialization pattern based on firm R&D efficiency, controlling for the amount of government subsidy a firm receives. All variables are defined in Table A1. In all regressions, the independent variables are lagged by one year. All regressions 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.

	Innovation Output	*Advertising*
	(1)	(2)
Treatment × R&D Efficiency	0.116**	-0.032**
	(0.046)	(0.014)
Treatment	-0.138	0.020
	(0.100)	(0.045)
R&D Efficiency	0.030	0.031**
	(0.041)	(0.012)
Assets	0.100***	0.157***
	(0.030)	(0.020)
R&D Intensity	0.019*	0.017***
	(0.011)	(0.004)
Tobin's Q	0.004	0.001
	(0.007)	(0.003)
ROA	0.451**	0.237***
	(0.212)	(0.086)
Leverage	-0.055	0.128***
	(0.091)	(0.046)
Age	0.056*	-0.085***
	(0.032)	(0.018)
PP&E	0.043	0.048
	(0.114)	(0.056)
Capex	-0.173	-0.020
	(0.203)	(0.076)
Subsidy	0.018	0.012**
	(0.017)	(0.005)
Observations	15,224	15,224
Adjusted R^2	0.725	0.881
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes

Table A8: Intensive Margin Analysis of Patent Trading

The regressions in this table perform the intensive-margin analysis of the effect of patent trading. All variables are defined in Table A1. In all regressions, the independent variables are lagged by one year. All regressions 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.

	Innovation Output	*Advertising*
	(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)
Assets	0.169***	0.140***
	(0.020)	(0.012)
R&D Intensity	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	-0.017	0.087***
	(0.060)	(0.031)
Age	0.016	-0.055***
	(0.024)	(0.013)
PP&E	0.209***	0.009
	(0.070)	(0.035)
Capex	0.015	-0.086
	(0.128)	(0.056)
Observations	26,770	26,770
Adjusted R^2	0.697	0.804
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes

Table A9: Buyer-Seller Status Before the Establishments of Patent Exchanges

In this table, we re-estimate our baseline results using the net number of patents a firm sold during the period *before* the establishment of patent exchanges. All variables are defined in Table A1. In all regressions, the independent variables are lagged by one year. All regressions 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.

	Innovation Output	*Advertising*
	(1)	(2)
Treatment	0.107***	0.003
	(0.031)	(0.012)
Treatment $\times$ *Net # of Patents Sold*	0.083**	-0.130***
	(0.034)	(0.014)
Assets	0.200***	0.168***
	(0.012)	(0.005)
R&D Intensity	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	-0.023	0.141***
	(0.050)	(0.020)
Age	0.020	-0.082***
	(0.019)	(0.008)
PP&E	0.212***	-0.021
	(0.063)	(0.025)
Capex	0.087	-0.095*
	(0.131)	(0.052)
Observations	18,700	18,700
Adjusted R^2	0.710	0.808
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes

Table A10: Renewed Patents

In light of the concern for low quality patents, we restrict our sample to patents that have been renewed at least three times and we re-estimate our baseline results. All variables are defined in Table A1. In all regressions, the independent variables are lagged by one year. All regressions 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.

	Innovation Output	*Advertising*
Treatment	0.079**	0.019*
	(0.035)	(0.011)
Treatment × Net # of Patents Sold	0.088**	-0.040**
	(0.035)	(0.020)
Net # of Patents Sold	-0.137***	0.027
	(0.033)	(0.018)
Assets	0.169***	0.141***
	(0.020)	(0.012)
R&D Intensity	0.081***	0.030***
	(0.010)	(0.005)
Tobin's Q	0.007	0.009***
	(0.005)	(0.002)
ROA	0.129	0.110**
	(0.113)	(0.048)
Leverage	-0.013	0.087***
	(0.060)	(0.031)
Age	0.028	-0.056***
	(0.024)	(0.013)
PP&E	0.220***	0.007
	(0.071)	(0.035)
Capex	0.017	-0.086
	(0.129)	(0.056)
Observations	26,770	26,770
Adjusted R^2	0.696	0.803
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes

Table A11: Patent Trading and Firm Performance

The regressions in this table evaluates how patent trading affects firm performance. All variables are defined in Table A1. In all regressions, the independent variables are lagged by one 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.

	Innovation Quality	*TFP*	*ROA*	*Tobin's Q*
	(1)	(2)	(3)	(4)
Treatment	0.037*	0.015***	0.004***	0.049*
	(0.022)	(0.005)	(0.001)	(0.027)
Assets	0.079***	0.020***	0.001***	-0.277***
	(0.005)	(0.001)	(0.000)	(0.007)
Age	-0.036***	-0.007***	-0.006***	0.035***
	(0.007)	(0.002)	(0.000)	(0.009)
Capex	0.363***	-0.151***	0.008	-0.728***
	(0.107)	(0.026)	(0.007)	(0.132)
Observations	26,770	26,563	26,730	26,665
Adjusted R^2	0.137	0.683	0.286	0.664
Lagged dependent variables	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Table A12: Concentration of Patenting Activities and Advertising Activities

The regressions in this table assess how patent exchanges affect the concentration of patenting and advertising activities. The dependent variable in regression (1) is the province-level Herfindahl-Hirschman Index (HHI) for firm patenting activities. The dependent variable in regression (2) is the HHI for advertising expenditures. *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. In all regressions, the independent variables are lagged by one year. All regressions in this table include year fixed effect and province 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.

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