Does Trading Spur Specialization? Evidence from Patenting[*]

Pengfei Han[†]
Guanghua School of Management, Peking University

Chunrui Liu[‡]
Business School, University of International Business and Economics

Xuan Tian[§]
PBC School of Finance, Tsinghua University

February 2023

Abstract

Exploiting staggered establishments of patent exchanges in China, we examine how patent trading affects firm innovation and specialization. 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. A firm shrinks its scope of innovation and invents in technological fields with greater proximity. Our findings suggest patent trading promotes comparative-advantage-based specialization and enhances firm performance. Relieving trading friction in the market for technology mitigates the negative consequences induced by capital market friction.

Keywords: Innovation, Market for Technology, Patent Trading, Patent Licensing, Specialization, R&D, Patent
JEL Classification Numbers: O31, O33, O34, G14

[*]We are grateful to Ufuk Akcigit, Li An, Ashish Arora, Salome Baslandze, Bo Bian, Murat Celik, Zhuo Chen, Lauren Cohen, Emin Dinlersoz, Lily Fang, Joao Gomes, Jeremy Greenwood, Bronwyn Hall, Zhiguo He, Sabrina Howell, Wei Jiang, Ben Jones, Chad Jones, Bill Kerr, Peter Klenow, Zonglai Kou, Josh Lerner, Bo Li, Bibo Liu, Yao Lu, Song Ma, Yifei Mao, Jun Qian, David Robinson, Carlos Serrano, Zheng (Mike) Song, Shang-Jin Wei, Wenfeng Wu, Han Xia, Bohui Zhang, Fabrizio Zilibotti, and participants of American Finance Association Annual Meeting, China Financial Research Conference, China Finance Scholar Forum, China International Conference in Finance, and Northern Finance Association Annual Meeting for helpful comments and suggestions. Han acknowledges financial support from China's Natural Science Foundation Grant (No. 72103003). Liu acknowledges financial support from China's Natural Science Foundation Grant (No. 72202034).

[†]Email: pengfeihan@gsm.pku.edu.cn. Address: Office 306, Guanghua School of Management, Peking University, Beijing, China.

[‡]Email: liuchunrui@uibe.edu.cn. Address: Office 531, Ningyuan Building, University of International Business and Economics, Beijing, China.

[§]Email: tianx@pbcsf.tsinghua.edu.cn. Address: Office 1-520, PBC School of Finance, Tsinghua University, Beijing, China.

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 for 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 a 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 is not in the best position to create innovations but is 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 firm in-house 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 innovation specialization? 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 in *creating* innovation. In contrast, some firms (e.g., an established pharmaceutical company equipped with abundant experienced sales representatives) feature a comparative advantage in *commercializing* innovation. When patents can be easily traded, a firm with a comparative advantage in creating innovation can specialize in patenting its technological achievement and sell its patents to others. Analogously, a firm with a comparative advantage in commercializing innovation can buy patents from the market and specialize in advertising its products. Hence, we expect to observe that patent sellers redirect their resources toward creating innovation when opportunities for patent trading arise, whereas patent buyers switch their effort toward commercializing innovation. Does patent trading spur such a pattern of specialization? To investigate this question, we exploit the unique institutional setting of patent exchanges in China to evaluate the effect of patent trading on firm innovation and specialization.

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 spending, the value of technology transfer transactions is 9.7% of aggregate corporate R&D between 2001 and 2017.[2] 8.6% of the patents granted in China between 2001 and 2017 have been traded at least once during this period. Corporations in China are actively participating in patent

[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.

[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.

trading. 53.0% of the patent-filing publicly listed firms have 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 of the endogeneity concern for patent trading. 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 transactions (i.e., the reverse causality concern). The institutional arrangement of patent exchanges in China provides us with a unique setting to address the endogeneity concern and establish causality. A patent exchange in China is a facility where patents can be traded or licensed. A patent exchange also organizes technology trade fairs where patent holders can showcase their technologies and potential buyers can search for technology suppliers. Patent trading is rife with search friction and information friction. As a focal point of patent trading and a major organizer of technology trade fairs, a patent exchange reduces search friction in patent trading and enhances matching efficiency of market participants. A patent exchange also reduces information friction of patent trading by screening[3] and gathering commercialization information on the patents.[4] 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 another advantage because it alleviates a common identification concern 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).[5]

We compile a unique dataset on patent exchanges in China and assemble a novel database that contains elaborate micro-level information on firms' financial statements, patent filings, patent trading, and patent licensing records. Exploiting staggered establishments of patent exchanges in

[3]For example, a patent exchange deters potential fraud by verifying whether a patent is authentic and valid.

[4]For instance, a patent exchange requests from the patent holders for elaborate information on the technical attributes and potential commercial applications of their patents.

[5]In light of the recent econometric studies (e.g., de Chaisemartin and D'Haultfuille (2020)) on the caveats of interpreting the results of two-way fixed effects difference-in-differences (DiD) regressions, we also conduct robustness checks along the suggested lines of Baker et al. (2022) and our findings are robust.

China, we conduct a difference-in-differences (DiD) analysis to assess how patent trading affects firm innovation and specialization.

Our baseline DiD estimation results suggest that enhanced patent trading (facilitated by the establishment of patent exchanges) is associated with 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 21.2% 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. The effect of patent trading on a firm's advertising expenditures is also starkly different between patent buyers and sellers. An average patent buyer expands its advertising expenditures by 98 million RMB (45.1% of the sample mean) after a patent exchange is established, whereas an average patent seller cuts its advertising expenditures by 43 million RMB (19.6% of the sample mean). Hence, our findings indicate 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.

Analogous to the effects of patent trading on specialization, we find that patent licensing 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, patent licensees switch their effort from patenting to advertising activities. As complementary evidence to refine our analysis, we also adopt a firm's R&D efficiency measure as a more direct proxy for its competitive advantage in creating innovation. We find that a firm with high R&D efficiency specializes in creating innovation as a response to an emerging market for technology, whereas a firm with low R&D efficiency specializes in commercializing innovation.

To delve further into the process of creating innovation, we investigate firm specialization in terms of the scope of innovation. We gauge the scope of innovation by the measure of technological distance developed in Akcigit et al. (2016). Through the lens of this technological distance measure, inventing in more closely related technological fields signals a more focused scope of innovation and a higher level of innovation specialization. We find that a patent filed after the establishment of patent exchanges is technologically closer to its owner's patent portfolio. Such a decline in the technological distance indicates that a firm shrinks its scope of innovation and invents in technological fields with greater proximity after the patent exchanges are established. These findings constitute consistent evidence that the market for technology promotes innovation specialization by inducing the firms to focus their innovating activity on their core business lines.

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 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. To address the concerns for reverse causality, we examine the dynamic treatment effects 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 event. According to our dynamic treatment analysis, however, no pre-existing trends are manifested: Firms in the treatment group and the control group are not characterized by any significant differences in patenting before the patent exchanges are established. As further supporting evidence, our regional-level dynamic treatment analysis indicates that the treated and control regions do not significantly differ in the size and development level of the regional economy, the regional R&D and patenting activities, and the fiscal capacity of the local governments before the event. In contrast, the treatment effects start to be significant after the patent exchanges are established and the effects persist in the long run. Therefore, the findings of the dynamic treatment analysis reject the reverse causality argument and alleviate the concern that the establishment of patent exchanges might correlate with regional-level characteristics.

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 examine the heterogeneity of the treatment effects based on the following intuition. To the extent that patent exchanges affect firm innovation and specialization, the effect should be (i) stronger for patent traders than non-traders, and (ii) stronger for firms facing a liquid market for patent trading than their counterparts confronted with an illiquid market. Our findings suggest that the treatment effects are indeed more pronounced for patent traders than non-traders and more salient for firms facing a more liquid market for patent trading. In addition, our findings are robust when accounting for other potentially related innovation policies and China's economic stimulus plan during the 2007–2008 global financial crisis. These findings provide a vote of confidence that the treatment effects are indeed attributed to patent trading instead of other factors.

As evidence of a subtle interplay between technology market friction and capital market friction, we find that the effect of patent trading on specialization is more pronounced when a firm is more financially constrained. Capital market friction can impose limitations on specialization: Since a financially constrained firm is confronted with a limited amount of resources, it may not be able to achieve its desired level of R&D and advertising spending. In contrast to the specialization-retarding role played by capital market friction, the market for technology facilitates firm specialization in accordance with their comparative advantages and the effects are more salient for more financially constrained firms.[6] Our findings shed light on how technology market friction interacts with capital

[6] In response to an emerging market for technology, a firm with a comparative advantage in creating innovation can sell the patents instead of commercializing the technologies by itself. Since selling the patents expedites the process of financially harvesting the fruit of R&D and frees up resources spent on commercialization, it allows the firm to better focus on creating innovation; this strategy contributes to a higher level of firm specialization in creating

market friction: Relieving trading friction in the market for technology can be instrumental in mitigating the negative consequences induced by capital market friction.

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 find that enhanced patent trading is associated with an improvement in firm innovation quality. Firm innovation has also become more explorative (in the sense that a firm's technological advancement relies more on exploring new knowledge) and a firm is more likely to achieve radical breakthroughs in its technological discoveries. Enhanced patent trading is also associated with rising firm productivity, profitability, and market valuation. These findings indicate that patent trading enhances firm performance by promoting comparative advantage-based specialization. As complementary evidence at the regional level, we find that the establishment of patent exchanges in a region is associated with improved performance of the regional economy. Our findings shed light on how the market for technology contributes to the aggregate economy via the specialization-promoting channel.

Our paper contributes to two strands of studies 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 endogenous growth model to quantify the impact of ideas misallocation. 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.

Second, our paper is related to a growing body of literature that studies innovation in developing countries, particularly 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

innovation and the effects are stronger for more financially constrained firms. Analogously, a firm with a comparative advantage in commercializing innovation can buy patents from the market instead of inventing the technologies by itself. Since buying the patents saves the time and resources required in the innovation process, the firm is better able to concentrate on commercializing the technologies; this strategy enables a higher level of firm specialization in commercializing innovation and the effects are more salient when a firm is more financially constrained.

after hiring directors with foreign experience and talent emigration can lead to brain gain. Chen (2015) studies how property rights protection affects the size and composition of corporate boards of Chinese firms. Fang et al. (2017) and Tan et al. (2020) find that innovation output increases after China's state-owned enterprises (SOEs) are privatized. Cong and Howell (2021) find that policy uncertainty associated with initial public offering has discouraged corporate innovation in China. 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 of 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 elaborate and solid empirical evidence on the effects of patent trading on innovation specialization, especially for developing countries with rudimentary patent systems. We contribute to the literature on the market for technology by providing likely causal evidence on how the market for technology 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)).[7] We also add to the emerging literature that aims to unveil the innovation ecosystem in developing countries. We compile a unique dataset on patent exchanges in China and assemble a novel micro-level database that combines firm accounting information with patent trading and licensing information. Exploiting China's unique institutional setting of patent exchanges to establish causality, our study is instrumental in illuminating the effects of the market for technology in general. Our findings also shed light on how public policies can be designed to foster firm innovation and specialization,

[7]While our measure of technological distance is based on Akcigit et al. (2016), our conceptual framework of studying patent trading is different. In Akcigit et al. (2016), firms do not feature any differences in their comparative advantages in creating versus commercializing innovation and the patent-to-firm distance is exogenously drawn from the empirical distance distribution. In contrast, we focus on how a firm's comparative advantage shapes its incentives to trade patents and how the market for technology spurs specialization in creating vs commercializing innovation in accordance with a firm's comparative advantage. In particular, our analysis suggests that firms with high (low) R&D efficiency are sellers (buyers) in patent trading and specialize in creating (commercializing) innovation in response to an emerging market for technology. While Akcigit et al. (2016) is primarily based on a quantitative-theoretical approach to studying patent trading, we aim to uncover the causal effects of the market for technology.

especially for developing economies with under-developed patent systems.

The rest of the paper is organized as follows. Section 2 describes the institutional background of patent exchanges and patent trading in China. We conduct a DiD analysis in Section 3 to study how the market for technology affects firm innovation and specialization. To strengthen our identification strategy, Section 4 reports the results for dynamic DiD analysis, heterogeneous treatment effect analysis, and a battery of robustness checks. We assess the effect of patent trading on firm performance and the industrial organization structure in Section 5. Section 6 concludes our paper.

2 Institutional background and data

2.1 Patent exchanges in China

The institutional background of patent exchanges and patent trading in China is delineated in this section. Section 2.1.1 provides an overview of patent exchanges and Section 2.1.2 elaborates on trading rules and procedures. We highlight how patent exchanges facilitate patent trading in Section 2.1.3.

2.1.1 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 of the market for 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.[8] 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;

[8]Before the establishment of patent exchanges, patent trading had to rely on decentralized transactions and the market was remarkably less liquid.

(ii) the number of technology trade fairs organized by the exchange and the number of participants in such events. As a consequence of persistent poor performance, a patent exchange can be shut down.

2.1.2 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.

Internet Appendix Figure IA1 is a snapshot of the website of Shenzhen Patent Exchange. As illustrated by this figure, 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 sale and a patent holder can look for patent demand information.[9] For instance, Internet Appendix Figure IA2 will pop up when a potential buyer starts searching for patents available for sale. As shown at the 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 Internet Appendix Figure IA2. The patent on the left is titled "An Account Management System Based on Cloud Service" and it can be used in the area of information digitalization. The patent on the right is titled "A Gear Cutter For 3D Printing Waste" and it is classified into the category of instruments and apparatuses. When clicking each patent available for sale, the buyer will be directed to further information about the patents.[10]

How do buyers and sellers participate in trading at the patent exchange? The procedures of patent trading are delineated in Internet Appendix Figure IA3. To participate in patent trading,

[9]Though the information on the exchange website is instrumental in initiating negotiations, such information is typically not sufficient to strike a deal. For instance, a patent holder may not post the suggested trading price on the exchange website. Built on such website information, most patent trading transactions still rely heavily on subsequent in-person meetings and negotiations at the exchange. We will elaborate on this issue when discussing how the establishment of patent exchanges can be exploited as a quasi-experiment for empirical analysis in Section 3.

[10]One may wonder if patents purchased from the patent exchange may not be immediately convertible into final products. Even if some patents may not immediately translate into final products, buying patents from the exchange still relieves a firm of particular R&D burden (associated with creating the technologies underlying these patents purchased), enables the firm to better focus on further developing and commercializing the technologies, and brings the firm closer to the final products. Hence, the establishment of a patent exchange still facilitates innovation specialization even if some patents purchased from the exchange may not be immediately convertible into final products.

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 about patents for sale and a potential buyer can post the patent demand information. Based on such demand and supply information, the exchange matches 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.

2.1.3 How patent exchanges facilitate patent trading

The rules and procedures of patent trading suggest that a patent exchange facilitates patent trading by reducing search friction and information friction of trading. We discuss both friction reduction roles of a patent exchange in this section.

Patent trading is rife with search friction. It is challenging for a patent holder 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 friction exceed the benefits of trade. As demonstrated by Akcigit et al. (2016), such friction is of vital importance in how the market for technology functions. Designed as a focal point for patent trading, a patent exchange facilitates patent trading by reducing search friction and enhancing matching efficiency of market participants. Patent holders can provide information about their patents to the exchange and specify preliminary terms of trade to initiate the negotiation. Buyers can also enunciate their specific technical requirements and commercial needs on the exchange. As another channel to foster matchmaking, the exchange also organizes technology trade fairs to facilitate communication between buyers and sellers. In addition, the exchange can recommend a potential deal to buyers and sellers based on the 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. Patent exchanges standardize the transaction process and provide professional intermediary services to aid market participants and lubricate their transactions.

Apart from search friction, information friction also poses 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 patent create and 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 technological and commercial uncertainties, asymmetric information between buyers and sellers can also be a major barrier to patent trading. Since a patent owner sometimes possesses private information about her inventions, evaluating the exact value of a patent can be more challenging for the buyers and such information asymmetry may lead to adverse selection (Chatterjee and Rossi-Hansberg (2012)). Such information asymmetry and adverse selection problems threaten the functioning of the market. A patent exchange is instrumental in alleviating information friction of patent trading and addressing the “lemons problem” via the following strategies. First, both patent holders and potential buyers are required to apply for exchange membership and disqualified applicants are excluded from trading. In addition, the exchange verifies the authenticity and validity of the patents posted for sale. Moreover, the exchange requests from patent holders a technical report of the elaborate technological attributes of the patents. Furthermore, 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 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. Because of such screening and information-gathering functions, patent exchanges contribute to addressing imperfect information problems associated with technological and commercial uncertainty, as well as asymmetric information problems between buyers and sellers.

2.2 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 firm accounting and patenting information. Section 2.2.1 describes the databases used in our analysis, Section 2.2.2 delineates how the variables are constructed, and Section 2.2.3 provides summary statistics for the firms in our sample.

2.2.1 Data description

To study patent trading in China, we obtain a comprehensive dataset of patents granted at the Chinese National Intellectual Property Administration (CNIPA).[11] 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.

Following Serrano (2010), 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 inventors to their employers. We single out such inventor-employer patent 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.[12]

To gather firm accounting information, we focus on publicly traded companies in China.[13] To combine firm accounting information with patenting information, we merge the CSMAR database

[11] Analogous to the patent application 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 we focus on invention patents (subsequently referred to as "patents") in this study.

[12] To alleviate the concern for invalid patent reassignment information, we 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. This data cleaning process builds on Serrano (2010).

[13] Following the common practice in the literature, we exclude firms in the financial industry.

with the CNIPA patent database. Data merging is accomplished by matching company names in these two datasets while accounting for the unique features of the Chinese language during the merging process. Our merged dataset contains elaborate micro-level information on firms' financial statements, patent filings, and patent trading records.

2.2.2 Variable construction

The main variables in our study are defined in Appendix Table A1. Following the common practice in the literature, we examine a firm's patenting activity as a proxy for its innovation output in our baseline analysis.[14] To be specific, *Innovation Output* is the natural logarithm of one plus the number of patent applications a firm files and eventually granted. *Advertising* is a firm's advertising expenditures, a proxy for its effort to commercialize innovation. *Innovation Output* and *Advertising* are the main dependent variables in our analysis of innovation specialization.

Following Hochberg et al. (2018), we calculate the *Trading Liquidity* measure to assess the market liquidity of patent trading. *Trading Liquidity* is a proxy for the likelihood that a firm's patents are traded each year.[15] Following Hirshleifer et al. (2013), we construct the *R&D Efficiency* proxy to evaluate a firm's efficiency of creating innovation. *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, *R&D Efficiency* of firm i in year t is defined as follows:

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

$Patent_{i,t}$ 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 $t-2$, respec-

[14] In our baseline analysis of firm innovating performance, we focus on a firm's patenting activity (a proxy for innovation output) as the outcome variable while controlling for a firm's R&D expenditures (a proxy for innovation input) in the regressions. In addition, we also examine a firm's R&D expenditures as the outcome variable in Section (4.3).

[15] 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 in the same technology class) that are traded 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 across all patents in a firm's patent portfolio.

tively. *R&D Efficiency* gauges the efficiency of transforming a firm's innovation input (i.e., R&D expenditures) into innovation output (i.e., patents) and this measure captures a firm's competitive advantage in creating innovation.

In our analysis of firm specialization in terms of the scope of innovation, we follow Akcigit et al. (2016) to construct a measure of technological distance between patents. Based on patent citation information, the technological distance between technology classes X and Y is defined as

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

$d(X, Y)$ refers to the technological distance between technology classes X and Y. $\#(X \cap Y)$ denote the number of patents that cite patents from technology classes X and Y simultaneously. $\#(X \cup Y)$ refer to the number of patents that cite patents in either technology class X and/or Y. $d(X, Y)$ is bounded between 0 and 1 and a higher value of $d(X, Y)$ indicates that X and Y are technologically more distant from each other.

Built on $d(X, Y)$, the distance of a patent p to the patent portfolio of firm f is defined as

$$d_\iota(p, f) = \left(\frac{1}{\|P_f\|} \sum_{p' \in P_f} d(X_p, Y_{p'})^\iota \right)^{1/\iota} \tag{2}$$

ι is a weighting parameter and $0 < \iota \leq 1$. P_f denotes the set of patents of firm f prior to patent p and $\|P_f\|$ refers to its cardinality. $d_\iota(p, f)$ is bounded between 0 and 1 and a higher value of $d_\iota(p, f)$ indicates that patent p is technologically more distant to the patent portfolio of firm f. When $\iota = 1$, $d_1(p, f)$ is the average distance of patent p to each patent in the patent portfolio of firm f. Following the literature (e.g., Akcigit et al. (2016), Brav et al. (2018), Ma et al. (2019)), we also examine the technological distance metric with $\iota = \frac{2}{3}$ and $\iota = \frac{1}{3}$ in our analysis.

As a measure of firm productivity, *TFP* is the natural logarithm of a firm's total factor productivity. To gauge firm TFP, we follow Ackerberg et al. (2015) to estimate a Cobb–Douglas production function.[16] The proxy variables in our TFP estimation follow Giannetti et al. (2015).[17]

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

[17] To be specific, output is proxied by a firm's total revenue, labor is proxied by the total number of employees,

As a proxy for firm profitability, *ROA* is a firm's return on assets (i.e., a firm's earnings before interest and taxes divided by its book value of assets).

The following variables are included as 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* 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. *Tobin's Q* is 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.

2.2.3 Descriptive statistics

Our baseline analysis is based on publicly listed Chinese companies that have filed at least one patent between 2001 and 2017.[18] We provide summary statistics for firms in the sample in Appendix Table A2. All potentially unbounded variables are winsorized at the 1% extremes unless otherwise specified.

As reported in Appendix Table A2, the average firm in the sample has gone public for about 8 years, has an asset of 7.5 billion RMB, and a return on asset of 5.3%. 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 in the sample spends 218 million RMB on advertising expenditures (amounting to 3.8% of firm assets) and features a Tobin's Q of 2.2.

The average firm in the sample files approximately seven successful patent applications each year. Regarding patent trading activities, the average firm in the sample has traded about five patents during the sample period and some active market participants have traded 86 patents.[19]

capital is proxied by total assets, and intermediate inputs are proxied by cash payments for raw materials and services.

[18] Following the common practice in the literature, we focus on patent-filing firms in our baseline analysis. We also conduct the analysis based on R&D-performing firms (i.e., firms reporting positive R&D expenditures) as a robustness check. Our findings are robust in these tests and more details are reported in Section 3.2.

[19] The summary statistics in this table correspond to the total number of patents traded and licensed by each firm during the sample period. Since the total number of patents traded and licensed is a firm-level variable, the number of observations for these variables is smaller than other firm-year-level variables.

The average firm in the sample is involved in about three patent licensing transactions and some active market participants have licensed 41 patents during the sample period.

3 The market for technology and innovation specialization

A patent exchange facilitates patent trading and licensing by reducing search friction and information friction. As a response to rising opportunities for patent trading, 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 innovation specialization in this section. We discuss how the staggered establishments of patent exchanges can be exploited as a quasi-experiment to establish causality in Section 3.1. Section 3.2 reports our baseline analysis of specialization between patent buyers and sellers. We extend our analysis to specialization between patent licensors and licensees in Section 3.3 and specialization based on a firm's R&D efficiency in Section 3.4. We delve further into the process of creating innovation and investigate firm specialization in terms of the scope of innovation in Section 3.5.

3.1 Establishment of patent exchanges as a quasi-experiment

As highlighted in Section 2.1, 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 with a unique and ideal setting to address the endogeneity problem and establish causality.

One may wonder whether the physical presence of a patent exchange in the local market matters because the website of a patent exchange has already provided some information about the patents. Though the information on the exchange website is instrumental in initiating negotiations, such information is typically not sufficient to strike a deal.[20] Built on such website information, most

[20]For instance, a patent holder may not post the suggested trading price on the exchange website.

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; the 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 the 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 face-to-face negotiation and the physical presence of a patent exchange matters.

One may also wonder whether firms can rely on remote instead of local patent exchanges to complete patent transactions. Note that the physical presence of a patent exchange in the local market does have binding implications for local market participants for two reasons. First, there has been a wealth of empirical evidence demonstrating the crucial importance of geographic proximity (e.g., Tian (2011)). In the context of patent trading, traveling to remote patent exchanges entails significant financial costs (especially for small businesses) and time costs (especially for executives of large enterprises). In addition, a local patent exchange is also instrumental in gathering and aggregate information (especially "soft" information) about the local trading participants and the patents in the local market. Hence, a local patent exchange enjoys major costs and information advantages against remote ones for local trading participants. Second, it is well documented that inter-regional trading activities in China are fragmented along the provincial borders (e.g., Bai et al. (2004), Poncet (2005)).[21] In the specific context of patent trading, the market is remarkably localized at the province level: 85.6% of the transactions before the establishments of patent exchanges was attributed to intra-provincial trade. This pattern of province-based patent trading is in part due to the province-based intellectual property system in China and the notorious difficulty of addressing legal disputes across the provincial borders.[22] In light of this, the establishment of a

[21] McCallum (1995) pioneer in documenting the home bias in international trade and subsequent studies find that such home bias is also manifested in inter-regional trade within a country (e.g., see Wolf (2000) for inter-state trade in the United States). In the context of China, it is well documented that local-protectionism-motivated trade barriers erected by the provincial governments are responsible for the fragmentation of inter-regional trade along the provincial borders in China (e.g., Bai et al. (2004), Poncet (2005)).

[22] According to the Supreme People's Court of China, patent-related litigations in China are stipulated to be filed at the province-level court in each province. In particular, when legal disputes arise after patent trading transactions, such litigations are stipulated to be filed at the province-level court of the defendant. Due to local

patent exchange has a binding implication for local market participants and our empirical findings indicate that it has enhanced the market liquidity of patent trading in the local market.[23] In view of China's institutional setting of trade and intellectual property system, we adopt two strategies to categorize the treatment and control groups in our DiD analysis. First, we classify the treatment group based on whether a patent exchange is established in the province where a firm is located. Second, we categorize the treatment group based on the geographic distance between a firm and its closest patent exchange.

3.2 Specialization between patent buyers and sellers

Exploiting the staggered establishments of patent exchanges as a quasi-experiment, we evaluate how patent trading affects firm innovation and specialization in the following firm-year-level panel regressions:

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

Our regression sample covers all publicly listed Chinese companies that have filed at least one patent between 2001 and 2017.[24] The subscript i in equation (3) indexes for firms and t indexes for years. The dependent variable $y_{i,t+1}$ is either *Innovation Output* or *Advertising* as defined in

protectionism of the provincial governments in China, however, addressing legal disputes and enforcing intellectual property rights across provinces are notorious difficult, as frequently underscored during the legislative process in China. For instance, see the speech of Cao Xianghong (an academician of Chinese Academy of Engineering and a member of Chinese People's Political Consultative Conference) during the second session of the twelfth National Committee of the Chinese People's Political Consultative Conference, as publicized by People's Daily (the largest newspaper group in China) in an article titled "Local Protectionism in Enforcing Intellectual Property Rights," March 10, 2014. As another high-profile example, see the speech of Cai Jinchai (the CEO of Fujian Panpan Food Group and a member of Chinese People's Political Consultative Conference) during the second session of the thirteenth National Committee of the Chinese People's Political Consultative Conference, as publicized by People's Daily in an article titled "Strengthening Inter-provincial Intellectual Property Rights Protection," March 8, 2019. To the extent that inter-provincial patent trading is discouraged by the province-based intellectual property system and the difficulty of addressing legal disputes across provinces, such factors are responsible for the fragmentation of patent trading along the provincial borders in China.

[23] According to our DiD estimations reported in Internet Appendix Table IA1, the establishments of patent exchanges contribute to improving the odds for a patent to be traded by 7.0%.

[24] Following the common practice in the literature, we focus on patent-filing firms in our baseline analysis. As a robustness check, we report the results based on R&D-performing firms (i.e., firms reporting positive R&D expenditures) in Internet Appendix Table IA2 and our findings are robust.

Section 2.2.2.[25] The treatment event is based on the establishment of patent exchanges.[26] Based on China's institutional setting of trade and intellectual property system (as delineated in Section 3.1), the treatment group in our baseline analysis is classified by whether a patent exchange is established in the province where a firm is located. To be specific, the dummy variable $Treatment_{i,t}$ equals one if a patent exchange has been established in the province where firm i is located by year t and zero otherwise.[27] $X_{i,t}$ is a vector of control variables including standard firm characteristics, as delineated at the end of Section 2.2.2.[28] 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.[29] $\epsilon_{i,t}$ in equation (3) is the error term. We cluster standard errors at the firm level in our baseline

[25]In our baseline analysis of firm innovating performance, we focus on a firm's patenting activity (a proxy for innovation output) as the outcome variable while controlling for a firm's R&D expenditures (a proxy for innovation input) in the regressions. In addition, we also examine a firm's R&D expenditures as the outcome variable in Section (4.3).

[26]Since the timing of the event is based on the establishment of patent exchanges, one may wonder whether the operation of a patent exchange could lag its establishment. In fact, the patent exchanges are expected to be ready for operation by the time they are established. Patent exchanges are typically affiliated with larger intellectual property organizations. They receive various government support, but they must be certified to gain such public support (as delineated in Section 2.1). In order to be certified, their parent organizations must demonstrate that they have satisfied the eligibility conditions (e.g., having enough capital, space, professional working staff, and elaborate operation plans). Hence, the patent exchanges are expected to be ready for operation by the time they are certified and the event timing is based on their establishment year. Nevertheless, one could still be concerned that the treatment effects could take time to realize. One may also wonder whether patent exchanges could already have an effect before the event (because their parent organizations must demonstrate their eligibility in order to satisfy the certification requirements). To address these concerns, we conduct the dynamic DiD analysis in Section 4.1. We find that the treatment group and the control group are not characterized by any significant differences before the establishment of patent exchanges. The treatment effects start to be statistically significant one year after the event and its magnitude tends to increase over time. In light of these findings, though full-fledged treatment effects may take time to unfold, the establishment year of patent exchanges captures the advent of the treatment event and the dynamic DiD analysis traces how the treatment effects evolve over time.

[27]The treated provinces and the treatment time are delineated in Internet Appendix Table IA3. One may be concerned that the timing of treatment events across some provinces is close to each other. To strengthen our identification, we refine the treatment and control groups and examine the heterogeneity of the treatment effects in Section 4.2. To further alleviate this concern, 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 in Section 4.3.5. Our findings are robust in all these tests.

[28]To be specific, the control variables are *Assets* (the natural logarithm of one plus a firm's book value of assets), *Age* (the natural logarithm of one plus the number of years since a firm has been publicly listed), *R&D* (the ratio of a firm's R&D expenditures to its book value of assets), *Capex* (the ratio of a firm's capital expenditures to its book value of assets), *PP&E* (the net value of property, plant, and equipment divided by a firm's book value of assets) *Leverage* (a firm's book value of total debt divided by the book value of total assets), and *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).

[29]We also report the results incorporating the industry-year fixed effects in Internet Appendix Table IA4 and our findings are robust.

analysis.[30] β captures the treatment effects of the patent exchanges, and, thus, is the key regression coefficient of interest. We report the results of our baseline DiD estimations in Table 1. Odd-numbered regressions in Table 1 report the estimation results without control variables and we add the control variables to even-numbered regressions in this table.

[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. The positive estimates for the treatment indicator in Table 1 imply that the complementarity effect of patent trading is on average stronger than its substitution effect. Hence, patent trading enhances in-house innovation for the average firm. According to our DiD estimate in regression (2) with control variables, the establishment of patent exchanges induces a 7.5% increase in firm patenting output.[31]

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. Hence, 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 a pattern of 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 of patents sold indicates that a firm is a

[30] In our baseline estimations, we cluster standard errors at the firm level to account for potential serial dependence of the error terms. Our findings are robust when the standard errors are clustered at the province level.

[31] As surveyed in Baker et al. (2022), recent econometric studies suggest that two-way fixed effects DiD regressions are embedded with a "bad comparison" problem (i.e., the earlier-treated groups are used as controls for the later-treated groups). Following the recommendations of Baker et al. (2022), we also conduct a robustness check based on Callaway and Sant'Anna (2021) and our findings are robust. We find that the treatment effects are positive for all treatment cohorts and the average treatment effect (weighted by the sample share of each treatment cohort) on firm innovation output is 11.9%.

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 our analysis in this section focuses on specialization between patent buyers and sellers based on a firm's net number of patents sold, we also adopt a more direct proxy for a firm's competitive advantage in Section 3.4. Our analysis in this section is based on the net number of patents a firm sells each year, and we also conduct the analysis based on the net number of patents sold by a firm during the pre-event period (i.e., before the establishment of patent exchanges) in Section 4.3.

Regression (4) of Table 1 suggests that the interaction 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).[32] While the establishment of patent exchanges contributes to a 21.2% 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 patent sellers, whereas they are substitutes for 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 (5)–(8) of Table 1, where we apply a firm's advertising expenditures as a proxy for 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 regression (8) of Table 1, an average patent buyer expands its advertising expenditures by 98 million RMB (45.1% of the sample mean) after the patent exchange is established, whereas an average patent seller cuts its advertising expenditures by 43 million RMB (19.6% of the sample mean).[33]

[32] 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 sells. The mean value of the number of patents bought (sold) is 1.96 (1.48) for the patent buyers (sellers) in our sample.

[33] One may wonder if patents purchased from the patent exchange may not be immediately convertible into final

While we categorize the treatment group by a firm's province in our baseline analysis, Appendix Table A3 reports the results where the treatment group is based on the geographic distance between a firm and its closest patent exchange. The empirical setup of the regressions in this table is the same as equation (3), except that the treatment indicator takes the value of one if a patent exchange has been established within 60 miles of the firm and zero otherwise.[34] As demonstrated by the results in this table, our findings are robust under this alternative classification of the treatment group.

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) decreases (increases) advertising expenditures of a patent seller (buyer). These findings indicate that patent sellers (buyers) redirect more resources toward creating (commercializing) innovation. This observation constitutes suggestive evidence that patent sellers (buyers) specialize in creating (commercializing) innovation when opportunities for patent trading arise.

3.3 Specialization between patent licensors and licensees

A patent can be both traded and licensed in a patent exchange. 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 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

products. Even if this is true in some scenarios, buying patents from the exchange still relieves a firm of particular R&D burden (associated with creating the technologies underlying these patents purchased), enables the firm to better focus on further developing and commercializing the technologies, and brings the firm closer to the final products. Hence, the establishment of a patent exchange still facilitates innovation specialization even if some patents purchased from the exchange may not immediately translate into final products.

[34]This threshold value of 60 miles is based on the average distance between patent buyers and sellers during the pre-event period (i.e., before the establishment of patent exchanges). Our findings are robust when applying a smaller or larger threshold to classify the treatment group. For instance, we report the results based on a threshold value of 90 miles in Internet Appendix Table IA5 and our findings are robust.

licensing transactions.

[Insert Table 2 Here.]

Echoing the findings in Table 1, the interaction 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).[35] Regression (2) of Table 2 suggests that the establishment of patent exchanges contributes to a 28.0% boost in patenting output for an average licensor, whereas it leads to a 10.1% decline in patenting output for the average licensee. According to regression (4) of Table 2, an average licensor cuts its advertising expenditures by 25 million RMB (11.3% of the sample mean) after a patent exchange is established, whereas the average licensee expands its advertising expenditures by 59 million RMB (27.1% of the 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 observation provides suggestive evidence that patent licensors (licensees) specialize in creating (commercializing) innovation when a market for technology emerges.

3.4 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,

[35] 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 1.65 (1.45) for the licensors (licensees) in our sample.

we adopt a firm's R&D efficiency as a more direct proxy for 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 3.4.1. 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 3.4.2.

3.4.1 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 Internet Appendix Table IA6 where the sample construction, the fixed effects, and the recurring variables are the same as those in Table 1.[36] The dependent variable in Table IA6 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.

The regressions in Table IA6 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 2.2.2, this R&D efficiency measure gauges the efficiency of transforming a firm's innovation input (i.e., R&D expenditures) into innovation output (i.e., patents) and it captures a firm's competitive advantage in creating innovation. Across all regressions in Table IA6, 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 is fairly large. According to regression (4) of Table IA6, 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).[37] 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

[36]Since the R&D efficiency information is missing in some cases, the number of observations in Table IA6 is smaller than that in Table 1.

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

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, and, thus, establish a link between the buyer-seller-based specialization pattern in the previous section and the R&D-efficiency-based specialization pattern in the next section.

3.4.2 R&D efficiency and firm specialization

As a complement to our study of buyer-seller-based specialization, we adopt a firm's R&D efficiency measure as a more direct proxy for 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 3.[38]

The results in Table 3 indicate that the interaction 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 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).[39] According to regression (2) of Table 3, the establishment of patent exchanges contributes to a 38.3% increase in patenting output for a firm with high R&D efficiency, whereas it leads to an 11.8% decrease in patenting output for the average firm. Regression (4) of Table 3 suggests that a firm with high R&D efficiency cuts its advertising expenditures by 124 million RMB (56.9% of the sample mean) after a patent exchange is established, whereas the average firm expands its advertising expenditures by 13 million RMB (6.0% of the sample mean). Our findings indicate 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.

[38]Since the R&D efficiency information is missing in some cases, the number of observations in Table 3 is smaller than that in Table 1.

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

[Insert Table 3 Here.]

Taking stock of our DiD analysis in Section 3, 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 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.

3.5 Specialization in terms of the scope of innovation

In our previous analysis of firm specialization, we focus on how firms choose between two types of activities (i.e., creating versus commercializing innovation). In this subsection, we delve further into the process of creating innovation and investigate firm specialization in terms of the scope of innovation. We gauge the scope of innovation by the measure of technological distance as delineated in Section (2.2.2).[40] Through the lens of this technological distance measure, inventing in more closely related technological fields signals a more focused scope of innovation and a higher level of innovation specialization. We trace how the distance between a patent and its assignee's patent portfolio evolves in the patent-level regressions in Table 4.

The regressions in Table 4 are based on patents granted between 2001 and 2017. The dependent variable *Distance* is the technological distance of a patent to the patent assignee's patent portfolio prior to this patent. *Distance* in column (1) is the average distance of a patent to its assignee's patent portfolio (i.e., $\iota = 1$ in equation 2). Following the literature (e.g., Akcigit et al. (2016), Brav et al. (2018), Ma et al. (2019)), we also examine the technological distance metric with $\iota = \frac{2}{3}$ and

[40]Echoing Akcigit et al. (2016), we find that a patent owner is more likely to sell patents that are more technologically distant and the patents are technologically closer to the buyers than to the sellers. We elaborate on these findings in Internet Appendix Section (IA0.1).

$\iota = \frac{1}{3}$ in columns (2) and (3). The *Treatment* indicator takes the value of 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 control for the number of citations received by the patent, the patent stock of the patent assignee and its patenting experience (i.e., the number of years since its first successful patent application). We incorporate patent application year fixed effects to absorb the aggregate shocks and we include patent assignee fixed effects to control for all time-invariant heterogeneity at the assignee level.

Since the coefficient for the *Treatment* indicator is negative across all regressions in Table 4, a patent filed after the establishment of patent exchanges is technologically closer to its owner's patent portfolio. Such a decline in the technological distance suggests that a firm shrinks its scope of innovation and invents in technological fields with greater proximity after the patent exchanges are established. These findings constitute consistent evidence that the market for technology promotes innovation specialization by inducing the firms to focus their innovating activity on their core business lines.

[Insert Table 4 Here.]

4 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 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 4.1 and we examine the heterogeneity of the treatment effects to address the second concern in Section 4.2. In addition, we conduct ten additional tests to assess the validity and robustness of our findings in Section 4.3.

4.1 Dynamic difference-in-differences analysis

To trace out the dynamic effects of the patent exchanges, we conduct a dynamic DiD analysis at the firm level in Section 4.1.1. Parallel to the firm-level analysis, we preform a province-level dynamic DiD analysis in Section 4.1.2 to examine whether the establishment of patent exchanges might correlate with regional characteristics.

4.1.1 Firm-level analysis

A potential concern for our DiD specification is reverse causality, i.e., a patent exchange may be chosen to be established in provinces characterized by vigorous patenting activities. This is because more patent filings in these regions imply a higher demand for patent trading and a patent exchange may be founded to meet such demand. To address the concerns for reverse causality, we study the dynamic treatment effects 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. $Treatment(0)$ in Table 5 is defined with respect to the year when the patent exchange is established. $Treatment(-\tau)$ and $Treatment(\tau)$ correspond to τ years before and after the establishment of patent exchanges, respectively. $Treatment(3+)$ refers to three and more years after the patent exchanges are established.

[Insert Table 5 Here.]

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 are tiny. Therefore, we do not observe any significant differences between the treatment and control groups before the event and hence no pre-existing trends are manifested. In contrast, the treatment indicators start to gain both statistical and economic significance after the establishment of the patent exchanges and the treatment effects persist in the long run (significant at the 1% level). In addition, the magnitude of the estimates of the treatment indicators after the event are remarkably larger than their counterparts before the event. Therefore, the findings in Table 5 reject the demand-driven interpretation of our results and rule out the reverse causality argument.

4.1.2 Province-level analysis

Though no pre-existing trends are manifested in the firm-level analysis, one may still wonder if the establishment of patent exchanges might correlate with province-level characteristics. Parallel to the firm-level analysis, we address this concern by conducting a dynamic DiD analysis at the province level in Table 6.

The empirical setup of the regressions in Table 6 is the same as that in Table 5, except that the analysis is based on province-year-level panel regressions. As proxies for the size and development level of the regional economy, the dependent variables *GDP* and *GDP pc* in regression (1) and (2) are the province-level GDP and per capita GDP, respectively. *R&D* in regression (3) refers to the province-level expenditures on research and development. *Innovation Output* in regression (4) refers to the natural logarithm of the number of patent filings in each province. As proxies for the fiscal capacity of the local governments, the dependent variables in regression (5) and (6) are the province-level fiscal expenditures and fiscal revenue.[41] We control for the province-level population and investments in fixed assets across all regressions. We include year fixed effects in all regressions to absorb the aggregate time trend and we incorporate province fixed effects to control for all time-invariant unobserved heterogeneity at the province level.

[Insert Table 6 Here.]

Before the establishment of patent exchanges, the treated and control provinces do not signif-

[41] Except for the number of patents (for which no inflation adjustment is needed), other variables in this table are expressed in terms of inflation-adjusted real values. GDP is measured in trillions of RMB, per capita GDP in one hundred thousand RMB, R&D in ten billion RMB, and fiscal expenditures and fiscal revenue in one hundred billion RMB.

icantly differ in the size and development level of the regional economy, the regional R&D and patenting activities, and the fiscal capacity of the local governments. The absence of pre-existing trends at the province level rejects the reverse causality argument and alleviates the concern that the establishment of patent exchanges might correlate with province-level characteristics. In addition, the results in Table 6 indicate that the establishment of patent exchanges is associated with a long-run improvement in regional GDP, per capita GDP, R&D and patenting activities, and fiscal capacity of the local governments. As will be demonstrated in Section 5.1, the market for technology enhances firm performance by promoting comparative-advantage-based specialization. In light of these findings, enhanced firm performance has eventually translated into improved performance of the regional economy in the long run.[42] Our findings shed light on how the market for technology contributes to the aggregate economy via the specialization-promoting channel.

4.2 Heterogeneity of the treatment effects

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 examine the heterogeneity of the treatment effects to strengthen our DiD analysis.[43] In Section 4.2.1, we refine our DiD analysis 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 4.2.2. To examine how capital market friction interact with trading friction in the market for technology, we assess the role of financial constraints in Section 4.2.3.

4.2.1 Patent traders vs non-traders

If the treatment effects on firm innovation and specialization are attributed to patent trading, the effect must be more pronounced for patent traders than non-traders. In light of this, we distinguish

[42] Significant treatment effects in Table 6 arise later than that in Table 5. This may be due to the time needed for the changes in firm specialization strategy to translate into enhanced firm performance and the time needed for the firm-level changes to significantly affect the regional-level aggregate outcomes.

[43] In this section, we focus on examining the heterogeneity of the treatment effects to address this concern. As further tests, we evaluate whether the results could be driven by other potentially related innovation policies and China's economic stimulus plan during the 2007–2008 global financial crisis in Section 4.3. We also undertake a placebo test in Section 4.3 to assess whether our findings could be driven by chance or other omitted shocks.

patent traders from non-traders in the following regressions at the firm(i)-year(t) level:

$$y_{i,t+1} = Treatment_{i,t} \times \alpha + Treatment_{i,t} \times Trader_i \times \beta + \delta' X_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{4}$$

In this equation, the sample construction, the dependent variable, the fixed effects, and the recurring variables are the same as those in our baseline setup (i.e., equation 3). To capture potentially different effects of patent trading on traders and non-traders, we interact "$Treatment_{i,t}$" with a dummy variable "$Trader_i$" in equation (4). "$Trader_i$" takes the value of one if a firm has traded any patents and zero otherwise.[44] The interaction term "$Treatment_{i,t} \times Trader_i$" in equation (4) 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 has been established (relative to provinces where no patent exchanges exist), and (iii) in the years after the exchange has been established (relative to the years before its establishment).

We report the results in Table 7 and we incorporate interaction terms with the net number of patents sold by a firm in even-numbered regressions.[45] As demonstrated by the results in this table, the treatment effects are stronger for patent traders than non-traders and we observe the same pattern of specialization as that documented in Section 3.[46] Hence, the heterogeneous treatment effects in Table 7 provide further supporting evidence that the treatment effects are attributed to patent trading instead of other factors.

[44] We assess a firm's trading status during both the full sample period and the pre-event period (i.e., before the establishment of patent exchanges). To be specific, the dummy variable "*Trader*" is based on a firm's trading activity during the full sample period in Table 7 and it is based on a firm's trading activity during the pre-event period in Internet Appendix Table IA9. Our findings are robust in both tables. In Section 4.3, we also conduct an analysis where the net number of patents sold by a firm is based on the pre-event information and our findings are robust as well.

[45] Since "*Trader*" in Table 7 is based on a firm's trading activity during the full sample period, the term "*Trader* $\times$ *Net # of Patents Sold*" is subsumed because it is always equal to "*Net # of Patents Sold*." In contrast, since "*Trader*" in Internet Appendix Table IA9 is based on a firm's trading activity during the pre-event period, the term "*Trader* $\times$ *Net # of Patents Sold*" is not subsumed because it is not always equal to "*Net # of Patents Sold*" (note that some non-traders during the pre-event period may start trading patents after the patents exchanges are established).

[46] The estimate of the triple interaction term (with the net number of patents sold) is positive in regression (2) and the estimate of the triple interaction term is negative in regression (4). These results suggest that patent sellers redirect their resources from advertising to patenting activities, whereas patent buyers switch their effort from patenting to advertising activities. This observation provides suggestive evidence that patent sellers and buyers specialize in creating and commercializing innovation, respectively.

[Insert Table 7 Here.]

4.2.2 Heterogeneity by patent trading liquidity

The effect of trade hinges on the market liquidity. Despite 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 more liquid market for patent trading. In light of this, we examine the role of patent trading liquidity in the following regressions at the firm(i)-year(t) level:

$$y_{i,t+1} = \mathit{Treatment}_{i,t} \times \alpha + \mathit{Treatment}_{i,t} \times \mathit{High\ Liquidity}_i \times \beta + \delta' X_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{5}$$

In this equation, the sample construction, the dependent variable, the fixed effects, and the recurring variables are the same as those in our baseline setup (i.e., equation 3). To capture the role of patent trading liquidity, we interact "$\mathit{Treatment}_{i,t}$" with a dummy variable "$\mathit{High\ Liquidity}_i$" in equation (5). We construct a measure of patent trading liquidity based on the method of Hochberg et al. (2018).[47] We divide firms into two groups based on the patent trading liquidity that they face. A firm is classified into the high (low) liquidity group if the average trading liquidity it faces 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.[48] The interaction term "$\mathit{Treatment}_{i,t} \times \mathit{High\ Liquidity}_i$" in equation (5) 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 has been established (relative to provinces where no patent exchanges exist) and (iii) in the years after

[47] As delineated in Section 2.2.2, this measure of patent trading liquidity is a proxy for the likelihood that a firm's patents are traded.

[48] We assess the trading liquidity a firm faces during both the full sample period and the pre-event period (i.e., before the establishment of patent exchanges). To be specific, the dummy variable "*High Liquidity*" is based on the average trading liquidity a firm faces during the full sample period in Table 8 and it is based on the average trading liquidity a firm faces during the pre-event period in Internet Appendix Table IA10. Our findings are robust in both tables.

the exchange has been established (relative to the years before its establishment).

We report the results in Table 8 and we incorporate interaction terms with the net number of patents a firm sells in even-numbered regressions. The results in this table demonstrate that the treatment effects are stronger for firms facing a liquid market for patent trading than their counterparts confronted with an illiquid market. In addition, the specialization pattern documented in Section 3 is also manifested in Table 8.[49] Therefore, the heterogeneous treatment effects in Table 8 lend further support to our findings that the treatment effects are attributed to patent trading instead of other factors.

[Insert Table 8 Here.]

4.2.3 Heterogeneity by financial constraints

Apart from trading friction in the market for technology, a firm may also be confronted with friction in the capital market. How does capital market friction interact with the effects of trade on specialization? We explore this question in the following regressions at the firm(i)-year(t) level:

$$y_{i,t+1} = \textit{Treatment}_{i,t} \times \alpha + \textit{Treatment}_{i,t} \times \textit{Constrained}_i \times \beta + \delta' X_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{6}$$

In this equation, the sample construction, the dependent variable, the fixed effects, and the recurring variables are the same as those in our baseline setup (i.e., equation 3). We introduce financial constraints into this equation by interacting "$\textit{Treatment}_{i,t}$" with a dummy variable "$\textit{Constrained}_i$" in equation (6). Our measure of financial constraints is based on the SA index developed in Hadlock and Pierce (2010).[50] We divide firms into two groups based on the financial constraints that they

[49] According to the positive estimate of the triple interaction term (with the net number of patents sold) in regression (2) and the negative estimate of the triple interaction term in regression (4), patent sellers and buyers redirect more resources toward creating and commercializing innovation, respectively, and the effects are more salient for firms facing a more liquid market for patent trading.

[50] To be specific, the SA index is computed as $-0.737 \times \textit{Size} + 0.043 \times \textit{Size}^2 - 0.040 \times \textit{Age}$. *Size* refers to the natural logarithm of inflation-adjusted book value of assets and *Age* is the number of years since a firm has gone public. Following the recommendation of Hadlock and Pierce (2010), *Size* is winsorized at the natural logarithm of \$4.5 billion and *Age* is winsorized at 37 years. Since the prevailing proxies for financial constraints are primarily based on the U.S. listed firms, it is intrinsically challenging to adapt these proxies to the Chinese context. We adopt the SA measure in this study because it is arguably less susceptible to cross-country differences, compared to other alternative proxies for financial constraints (e.g., the KZ index and the WW index). Though the factor loadings in the SA measure are developed in the U.S. context, the economic reasoning underlying the SA measure is presumably

are confronted with. A firm is classified into the financially constrained (unconstrained) group if the average financial constraints it faces is above (below) the sample average of all firms; the time-invariant financial constraint indicator "$Constrained_i$" takes the value of one if a firm is in the constrained group and zero otherwise.[51] We report the results in Table 9 and we incorporate interaction terms with the net number of patents sold by a firm in even-numbered regressions in this table.

[Insert Table 9 Here.]

The estimation results exhibit the same specialization pattern as that documented in Section 3 and the effects are more pronounced for more financially constrained firms.[52] Capital market friction can impose limitations on firm specialization. Though having a comparative advantage in creating innovation, a financially constrained firm is confronted with a limited amount of resources, and, thus, may not be able to achieve its desired level of R&D spending, particularly considering that commercializing an innovation also entails various expenses (e.g., advertising expenditures).[53] Commercialization is inherently risky and a firm may fail in transitioning its technologies from its research laboratory to the marketplace. Even if a firm eventually succeeds in bringing its products to the market, commercialization could be a time sink for firms without the marketing expertise. Hence, a firm with a comparative advantage in creating innovation may not be able to achieve its optimal innovation specialization level and such limitations on specialization are more severe when

also valid in the Chinese context and the main factors (i.e., size, size-squared, and age) in the SA measure are arguably less susceptible to cross-country differences than other firm characteristics used to construct the KZ and WW measures. Like other proxies for financial constraints, the SA measure is also subject to various caveats (e.g., see Farre-Mensa and Ljungqvist (2015)). To the extent that all proxies for financial constraints inevitably feature particular limitations along certain dimensions, our findings can be viewed as a first-order approximation and we leave a more thorough investigation for future research.

[51]We assess the financial constraints a firm faces during both the full sample period and the pre-event period (i.e., before the establishment of patent exchanges). To be specific, the dummy variable "*Constrained*" is based on the average financial constraints a firm faces during the full sample period in Table 9 and it is based on the average financial constraints a firm faces during the pre-event period in Internet Appendix Table IA11. Since some firms have not gone public during the pre-event period, their financial constraints information is missing, and, thus, the number of observations in Table IA11 is smaller than that in Table 9. Our findings are robust in both tables.

[52]As demonstrated by the positive estimate of the triple interaction term (with the net number of patents sold) in regression (2) and the negative estimate of the triple interaction term in regression (4), patent sellers and buyers specialize in creating and commercializing innovation, respectively, and the effects are more pronounced for more financially constrained firms.

[53]Financial constraints and dependence on external finance have been demonstrated to have significant influence on corporate innovation (e.g., Cornaggia et al. (2015), Acharya and Xu (2017), Moshirian et al. (2021)).

a firm is more financially constrained. Analogously, since R&D spending is essential to create an innovation in the first place and the innovation process is intrinsically risky and time-consuming, a firm with a comparative advantage in commercializing innovation may not be able to attain its desired level of advertising expenditures when it is financially constrained.

In contrast to the specialization-retarding role played by capital market friction, the market for technology facilitates firm specialization in accordance with their comparative advantages and the effects are more pronounced for more financially constrained firms. In response to an emerging market for technology, a firm with a comparative advantage in creating innovation can sell the patents instead of commercializing the technologies by itself. Since selling the patents expedites the process of financially harvesting the fruit of R&D and frees up resources spent on commercialization, it allows the firm to better focus on creating innovation; this strategy contributes to a higher level of firm specialization in creating innovation and the effects are stronger for more financially constrained firms. Analogously, a firm with a comparative advantage in commercializing innovation can buy patents from the market instead of inventing the technologies by itself. Since buying the patents saves the time and resources required in the innovation process, the firm is better able to concentrate on commercializing the technologies; this strategy enables a higher level of firm specialization in commercializing innovation and the effects are more salient when a firm is more financially constrained.

Our findings shed light on how capital market friction interacts with trading friction in the market for technology. As revealed by our findings, increasing specialization after the establishment of patent exchanges is more salient for more financially constrained firms. This finding implies that more financially constrained firms suffer from more severe limitations on specialization *before* the event. This observation constitutes suggestive evidence that capital market friction may have impeded firm specialization before the establishment of patent exchanges. Since the effects of trade on specialization are more pronounced for more financially constrained firms, an emerging market for technology is a particular blessing for firms afflicted with capital market friction. Therefore, our findings provide suggestive evidence on a subtle interplay between technology market friction and capital market friction: Relieving trading friction in the market for technology can be instrumental in mitigating the negative consequences induced by capital market friction.

4.3 Robustness checks

In this section, we conduct ten additional tests to assess the validity and robustness of our findings. We control for other potentially related innovation policies in Section 4.3.1. We address the concern that our results might be affected by China's economic stimulus plan after the 2007–2008 global financial crisis in Section 4.3.2. We perform estimations based on Poisson regression models in Section 4.3.3. We focus on firms that never trade any patents with trading counterparties in other provinces in Section 4.3.4. We undertake a placebo test by randomly assigning the treatment and control status to observations in our sample in Section 4.3.5. We redo our analysis using a firm's buyer-seller status during the pre-event period (i.e., before the establishment of patent exchanges) in Section 4.3.6. We examine a firm's R&D expenditures as the outcome variable in Section 4.3.7. We address the concern that our findings may be driven by low-quality patents in Section 4.3.8. We adopt alternative measures of a firm's net number of patents sold in Section 4.3.9. We conduct a robustness check to exclude firms in China's innovation hubs in Section 4.3.10.

4.3.1 Other innovation policies

One may wonder if our findings could be contaminated by other confounding innovation policies. To alleviate this concern, we control for other potentially related innovation policies: (i) government subsidies for patents, (ii) government support for pledging patents as collateral for financing, (iii) tax cuts for new product development, and (iv) government support for small and medium-sized high-tech enterprises. Controlling for these innovation policies, we reassess the buyer-seller specialization pattern in Appendix Table A4, the licensor-licensee specialization pattern in Appendix Table A5, and the R&D-efficiency-based specialization pattern in Appendix Table A6.

We exploit the regional variation of these innovation policies in these tables. To be specific, "*Patent Subsidy*" is a dummy variable for the policy of government subsidies for patents. That is to say, "*Patent Subsidy*" takes the value of one for a firm in a year if there are government subsidies for patents (either patent applications or grants) in the province where this firm is located in that year, and zero otherwise. Analogously, "*Patents as Collateral*" is a dummy variable for government supporting policies for pledging patents as collateral for financing, "*Tax Cut*" is a dummy variable for tax cuts for new product development, and "*Tech SMEs*" is a dummy variable for government supporting policies for small and medium-sized high-tech enterprises. As demonstrated by the results in Appendix Table A4–A6, our findings are robust when controlling for these innovation policies.

4.3.2 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 firm patenting output, one could still be concerned that China's massive economic stimulus plan during the crisis may have contributed to higher patenting output.[54] To capture the effects of the economic stimulus plan of the Chinese government, we include an additional control variable *Subsidy* in the regressions and we report the results in Internet Appendix Table IA12–IA14. To be concrete, *Subsidy* is the amount of government subsidy a firm receives scaled by firm assets.[55] Our findings are robust when the government subsidy is accounted for.

4.3.3 Poisson regressions

Since the distribution of firm patenting output is skewed to the right, we follow the common practice in the literature to use the natural logarithm of one plus the number of patents as the dependent variables in our baseline estimations. To evaluate the sensitivity of our findings, we perform estimations based on the Poisson regression models and report the results in Internet Appendix Tables IA15–IA17. Our findings are robust in these Poisson regressions as well.

[54] It is well-documented (e.g., Agarwal et al. (2020)) that the Chinese government has significant influence on channeling financial resources to corporations in China.

[55] We gather the government subsidy information at the firm-year level from corporate financial statements.

4.3.4 Excluding inter-provincial trade

Based on China's institutional setting of trade and intellectual property system (as delineated in Section 3.1), the treatment group in our baseline analysis is classified by whether a patent exchange is established in the province where a firm is located or the geographic distance between a firm and its closest patent exchange.[56] Nevertheless, one may wonder if a firm could rely on patent exchanges in other provinces. To address this concern, we focus on firms that never trade any patents with trading counterparties in other provinces and we report the results in Internet Appendix Table IA18. Our findings are robust to excluding all these firms with inter-provincial trade.

4.3.5 Placebo test

To assess the robustness of our findings, we conduct a placebo test of randomly assigning a false treatment status to observations in our sample while maintaining the true distribution of the event time. If the findings 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 1,000 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 1. In this figure, panels 1a, 1b, 1c, and 1d report the empirical distribution of the coefficient estimates for regressions (2), (4), (6), and (8) in Table 1 (i.e., our baseline estimations with control variables). In each panel, we compare the true coefficient estimate with its empirical distribution and kernel density. Across all panels of Figure 1, 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^{st} percentile. Therefore, the results in this placebo test provide a vote of confidence that our findings are unlikely to be driven by chance or other omitted shocks.

[56] In particular, the market of patent trading is remarkably localized at the province level: 85.6% of the transactions before the establishments of patent exchanges was attributed to intra-provincial trade. This pattern of province-based patent trading is in part due to the province-based intellectual property system in China and the notorious difficulty of addressing legal disputes across the provincial borders. More detailed discussions can be found in Section 3.1).

[Insert Figure 1 Here.]

4.3.6 Buyer-seller status based on pre-event information

A firm's buyer-seller status in our baseline analysis is based on the net number of patents a firm sells each year. To assess the robustness of our findings, we recast the analysis using the net number of patents sold by a firm during the pre-event period (i.e., before the establishment of patent exchanges). We report the results in Internet Appendix Table IA19 and our findings are robust when the net number of patents sold by a firm is based on the pre-event information.[57]

4.3.7 Firm R&D as an outcome variable

In our baseline analysis of firm innovating performance, we focus on a firm's patenting activity (a proxy for innovation output) as the outcome variable while controlling for a firm's R&D expenditures (a proxy for innovation input) in the regressions. In addition, we also examine a firm's R&D expenditures as the outcome variable in Internet Appendix Table IA20. As delineated in Section 2.2.2, *R&D* (the dependent variable in this table) is the ratio of a firm's R&D expenditures to its book value of assets.[58] As demonstrated by the results in this table, our findings are robust when firm R&D is adopted as a proxy for firm innovating activity.

4.3.8 Excluding low-quality patents

One may be concerned that some patents are of low quality and little value and one may wonder if these low-quality patents could drive our results. Internet Appendix Table IA21 addresses this concern. Following previous studies (e.g., Akcigit et al. (2016)), we restrict our sample to patents that have been renewed at least three times.[59] We redo our baseline analysis and report the estimation results in Internet Appendix Table IA21. Our findings are robust to excluding low-

[57] Since the net number of patents sold by a firm is based on the pre-event information, it becomes a firm-specific variable and is absorbed by the firm fixed effects.

[58] Since *R&D* is the dependent variable in this table, it is no longer incorporated as a control variable in these regressions.

[59] Similar to the patent renewal policy at the USPTO, patent holders in China must pay a renewal fee to maintain the validity of their patents. Patents renewal and expiration information has been frequently used in the innovation studies based on patent data (e.g., Serrano (2010), Akcigit et al. (2016)).

quality patents.

4.3.9 Alternative measures of net number of patents sold

In our baseline analysis, our measure of the net number of patents sold is based on a firm's trading activity each year. As a robustness check, we adopt an alternative measure of the net number of patents sold based on a firm's cumulated trading activity by the end of each year.[60] We report the results in Internet Appendix Table IA22 and our findings are robust. While our measure of the net number of patents sold is based on the number of patent counts in our baseline analysis, we also apply an alternative patent-value-weighted measure of the net number of patents sold where the weight is the number of citations received by each patent (a widely used proxy for patent value). We report the results in Internet Appendix Table IA23 and our findings are robust as well.

4.3.10 Innovation hubs

One may wonder if our findings could be driven by innovation-intensive firms in China's innovation hubs (i.e., Beijing, Shanghai, and Shenzhen). One may also wonder if some firms are headquartered in these innovation hubs but operate in multiple provinces. To attenuate these concerns, we exclude firms headquartered in these innovation hubs (i.e., Beijing, Shanghai, and Shenzhen) in the regressions in Internet Appendix Table IA24 and our findings are robust.

5 Implications of innovation specialization

In light of the effect of patent trading on firm specialization, we evaluate how patent trading affects firm performance in Section 5.1 and we study its effects on the industrial organization structure in Section 5.2.

[60] To the extent that a firm's competitive advantage is persistent, a firm's cumulated net number of patents sold constitutes an alternative proxy for a firm's revealed competitive advantage.

5.1 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 in the DiD regressions in Internet Appendix Table IA25. We evaluate a firm's innovating performance in Panel A of this table and we examine firm productivity, profitability, and market valuation in Panel B.

As in previous sections, the treatment indicator in Internet Appendix Table IA25 equals one for a firm in a year if a patent exchange has been established in the province where this firm is located by that year, and zero otherwise. The dependent variable *Innovation Quality* in regression (1) refers to the relative citation strength of patents.[61] 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 the same cohort (i.e., patents applied in the same year and in the same technology class).[62] The results in regression (1) suggest that the quality of a firm's patents has improved after the establishment of patent exchanges. Combining these results with the findings in Table 1, patent trading contributes to both higher quantity and higher quality of firm innovation.

We delve further into a firm's innovating performance in regression (2)–(4) of Panel A. The dependent variables *Explorative Innovation* and *Exploitative Innovation* in regression (2) and (3) of Table IA25 refer to the natural logarithm of one plus the number of explorative patents and exploitative patents filed by the firms. Following the common practice in the literature (e.g., Brav et al. (2018), Hsu et al. (2021)), we categorize a patent to be exploitative if at least 80% of its citations are based on the firm's existing knowledge (i.e., belong to the patents filed by the firm or the patents cited by the firm's patents filed in the past five years). We categorize a patent to be explorative if at least 80% of its citations are based on new knowledge (i.e., do not belong to the patents filed by the firm and the patents cited by the firm's patents filed in the past five years).[63] Exploitative patents hinge heavily on existing knowledge and explorative

[61]To control for the persistence of the dependent variables, lagged dependent variables are included across all regressions in this table.

[62]This measure of relative citation strength facilitates quality comparison of patents from different time vintages and technology classes.

[63]Note that a patent can be neither explorative nor exploitative.

patents rely crucially on new knowledge. According to regression (2) and (3) of Panel A, a firm's explorative patent filings have increased by 8.4% (significant at the 1% level) after the establishment of patent exchanges and its exploitative patent filings have not significantly changed. The dependent variable *Breakthrough Innovation* in regression (4) of Panel A is the natural logarithm of one plus the number of breakthrough patents filed by the firms. Following Kerr (2010), we categorize a breakthrough patent as the top ten percent most cited patents in its cohort (i.e., patents applied in the same year and in the same technology class). The results in regression (4) suggest that a firm's breakthrough patents have increased by 4.2% (significant at the 1% level) after the patent exchanges are established.

As revealed by the findings in Panel A of Table IA25, a firm's innovation has become more explorative after the establishment of patent exchanges and it is more likely to achieve radical breakthroughs in its technological discoveries. Apart from the efficiency gain originating from comparative-advantage-based specialization, serendipitous discoveries could be another factor underlying the changes in firm explorative and breakthrough innovations. Because of the intrinsic uncertainty entailed during the innovation process, the innovation outcome may be associated with serendipitous discoveries outside the scope of a firm's intended use, especially when a firm explores new knowledge or seeks radical technological breakthroughs (e.g., Akcigit et al. (2016)). Since a market for technology facilitates a firm to sell or license out such serendipitous discoveries to other firms with a higher valuation, the establishment of patent exchanges incentivizes the firms to pursue explorative innovation and breakthrough innovation.

In Panel B of Table IA25, we turn our focus to firm productivity, profitability, and market valuation. Regression (1) and (2) in Panel B suggest that firm productivity (measured by TFP) and profitability (measured by ROA) have been bolstered after the patent exchanges are established. According to these regressions, the establishment of patent exchanges is associated with an increase in firm TFP by 1.4% (significant at the 1% level) and an increase in firm ROA by 0.2 percentage points (4.7% of the sample mean). The improvement in firm innovating performance, productivity, and profitability are factored into rising firm valuation by the investors. According to regression (3) in Panel B, the establishment of patent exchanges contributes to a higher Tobin's Q by 0.049 (2.2%

of the sample mean). Taking stock of the results in Table IA25, our findings indicate that patent trading enhances firm performance by promoting comparative-advantage-based specialization.

5.2 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 patenting (advertising) activities to 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 the 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 2001–2017:

$$y_{i,t+1} = \mathit{Treatment}_{i,t} \times \beta + \delta' X_{i,t} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{7}$$

Following the common practice, we adopt the Herfindahl-Hirschman index (HHI) as a measure of market concentration. The dependent variables in equation (7) are the province-level HHI for firm patenting activities and advertising expenditures. In equation (7), $\mathit{Treatment}_{i,t}$ 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 province-level 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 heterogeneity at the province level.

We report the results in Internet Appendix Table IA26.[64] As demonstrated by the results in

[64] Sine the HHI information for patenting activities becomes missing when some provinces have no patent filings in some years, the number of observations in regression (1) of this table is smaller than that in regression (2).

this table, both patenting and advertising HHI have witnessed a major increase after the patent exchanges are established. To be concrete, the establishment of patent exchanges in a province is associated with a rise in patenting HHI by 0.062 (23.5% of the sample mean) and a raise in advertising HHI by 0.024 (14.4% of the sample mean) in that province. Therefore, the results in Internet Appendix Table IA26 corroborate our hypothesis on how patent trading affects the industrial organization structure and reinforce our findings on the effects of the market for technology.

6 Conclusion

How does the market for technology affect the incentives for innovation and specialization? The unique institutional arrangement of patent exchanges in China provides an ideal setting to investigate this question. We compile a unique dataset on patent exchanges in China and we assemble a novel dataset that contains elaborate micro-level information on firms' financial statements, patent filings, patent trading, and patent licensing records. A patent exchange facilitates patent trading by reducing search friction and information friction of trading transactions. Exploiting staggered establishments of patent exchanges in China, we examine the causal effect of patent trading on firm innovation and specialization.

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 the market for technology spurs specialization based on a firm's comparative advantage in creating versus commercializing innovation. In addition, the effect of patent trading is stronger for traders than non-traders, more salient for firms facing a more liquid market for patent trading, and more pronounced for more financially constrained firms. Our findings suggest that there is a subtle interplay between technology market friction and capital market friction: Relieving trading friction in the market for technology can be instrumental in mitigating the negative consequences induced by capital market friction. Moreover, we find that an emerging market for technology is associated with enhanced firm efficiency and improved performance of the regional economy. These findings constitute suggestive evidence on how the market for technology contributes to the aggregate economy via the specialization-promoting channel. Our findings shed light on how public policies can be designed to foster firm innovation and specialization, especially for developing economies with rudimentary patent systems.

References

Acharya, Viral and Zhaoxia Xu, "Financial dependence and innovation: The case of public versus private firms," *Journal of Financial Economics*, 2017, *124* (2), 223–243.

Ackerberg, Daniel A., Kevin Caves, and Garth Frazer, "Identification Properties of Recent Production Function Estimators," *Econometrica*, 2015, *83* (6), 2411–2451.

Agarwal, Sumit, Wenlan Qian, Amit Seru, and Jian Zhang, "Disguised corruption: Evidence from consumer credit in China," *Journal of Financial Economics*, 2020, *137* (2), 430–450.

Akcigit, Ufuk, Murat Alp Celik, and Jeremy Greenwood, "Buy, Keep, or Sell: Economic Growth and the Market for Ideas," *Econometrica*, 2016, *84* (3), 943–984.

Bai, Chong-En, Yingjuan Du, Zhigang Tao, and Sarah Y. Tong, "Local protectionism and regional specialization: evidence from China's industries," *Journal of International Economics*, 2004, *63* (2), 397–417.

Baker, Andrew C., David F. Larcker, and Charles C.Y. Wang, "How much should we trust staggered difference-in-differences estimates?," *Journal of Financial Economics*, 2022, *144* (2), 370–395.

Brav, Alon, Wei Jiang, Song Ma, and Xuan Tian, "How does hedge fund activism reshape corporate innovation?," *Journal of Financial Economics*, 2018, *130* (2), 237–264.

Callaway, Brantly and Pedro H.C. Sant'Anna, "Difference-in-Differences with multiple time periods," *Journal of Econometrics*, 2021, *225* (2), 200–230. Themed Issue: Treatment Effect 1.

Chatterjee, Satyajit and Esteban Rossi-Hansberg, "Spin-offs and the Market for Ideas," *International Economic Review*, 2012, *53* (1), 53–93.

Chen, Tao, "Institutions, board structure, and corporate performance: Evidence from Chinese firms," *Journal of Corporate Finance*, 2015, *32*, 217–237.

Cong, Lin William and Sabrina T. Howell, "Policy Uncertainty and Innovation: Evidence from Initial Public Offering Interventions in China," *Management Science*, 2021, *67* (11), 7238–7261.

Cornaggia, Jess, Yifei Mao, Xuan Tian, and Brian Wolfe, "Does banking competition affect innovation?," *Journal of Financial Economics*, 2015, *115* (1), 189–209.

de Chaisemartin, Clment and Xavier D'Haultfuille, "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects," *American Economic Review*, September 2020, *110* (9), 2964–96.

Fang, Lily H., Josh Lerner, and Chaopeng Wu, "Intellectual Property Rights Protection, Ownership, and Innovation: Evidence from China," *The Review of Financial Studies*, 04 2017, *30* (7), 2446–2477.

Farre-Mensa, Joan and Alexander Ljungqvist, "Do Measures of Financial Constraints Measure Financial Constraints?," *The Review of Financial Studies*, 09 2015, *29* (2), 271–308.

Galasso, Alberto, Mark Schankerman, and Carlos J. Serrano, "Trading and enforcing patent rights," *The RAND Journal of Economics*, 2013, *44* (2), 275–312.

Giannetti, Mariassunta, Guanmin Liao, and Xiaoyun Yu, "The Brain Gain of Corporate Boards: Evidence from China," *The Journal of Finance*, 2015, *70* (4), 1629–1682.

Hadlock, Charles J. and Joshua R. Pierce, "New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index," *The Review of Financial Studies*, 03 2010, *23* (5), 1909–1940.

Han, Pengfei, Wei Jiang, and Danqing Mei, "Mapping U.S.-China Technology Decoupling, Innovation, and Firm Performance," *unpublished manuscript*, 2021.

He, Jie (Jack) and Xuan Tian, "Finance and Corporate Innovation: A Survey," *Asia-Pacific Journal of Financial Studies*, 2018, *47* (2), 165–212.

_ **and** _ , "Institutions and Innovation," *Annual Review of Financial Economics*, 2020, *12* (1), 377–398.

Hirshleifer, David, Po-Hsuan Hsu, and Dongmei Li, "Innovative efficiency and stock returns," *Journal of Financial Economics*, 2013, *107* (3), 632–654.

Hochberg, Yael V., Carlos J. Serrano, and Rosemarie H. Ziedonis, "Patent collateral, investor commitment, and the market for venture lending," *Journal of Financial Economics*, 2018, *130* (1), 74–94.

Hsu, Po-Hsuan, Yiqing Lu, Hong Wu, and Yuhai Xuan, "Director Job Security and Corporate Innovation," *unpublished manuscript*, 2021.

Kerr, William R., "Breakthrough inventions and migrating clusters of innovation," *Journal of Urban Economics*, 2010, *67* (1), 46–60. Special Issue: Cities and Entrepreneurship.

Ma, Song, Joy Tianjiao Tong, and Wei Wang, "Selling Innovation in Bankruptcy," *unpublished manuscript*, 2019.

McCallum, John, "National Borders Matter: Canada-U.S. Regional Trade Patterns," *The American Economic Review*, 1995, *85* (3), 615–623.

Moshirian, Fariborz, Xuan Tian, Bohui Zhang, and Wenrui Zhang, "Stock market liberalization and innovation," *Journal of Financial Economics*, 2021, *139* (3), 985–1014.

Poncet, Sandra, "A Fragmented China: Measure and Determinants of Chinese Domestic Market Disintegration," *Review of International Economics*, 2005, *13* (3), 409–430.

Serrano, Carlos J., "The dynamics of the transfer and renewal of patents," *The RAND Journal of Economics*, 2010, *41* (4), 686–708.

Tan, Yongxian, Xuan Tian, Xinde Zhang, and Hailong Zhao, "The real effect of partial privatization on corporate innovation: Evidence from China's split share structure reform," *Journal of Corporate Finance*, 2020, *64*, 101661.

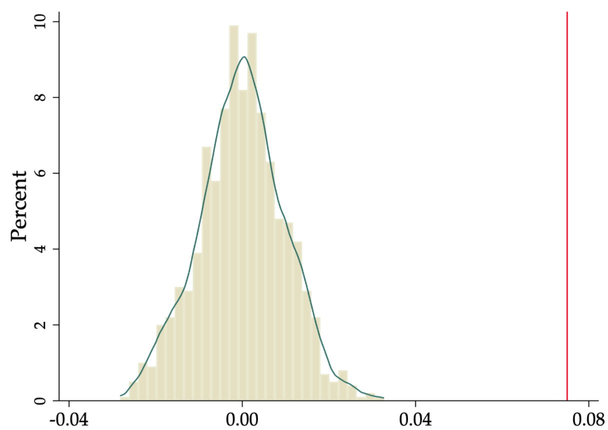
Tian, Xuan, "The causes and consequences of venture capital stage financing," *Journal of Financial Economics*, 2011, *101* (1), 132–159.

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

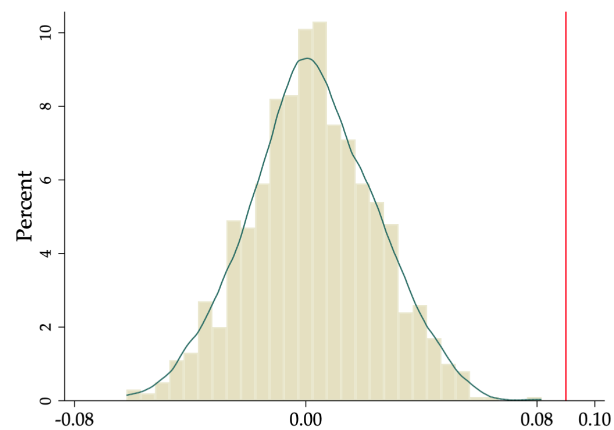
Wolf, Holger C., "Intranational Home Bias in Trade," *The Review of Economics and Statistics*, 11 2000, *82* (4), 555–563.

Figure 1: **Placebo test**

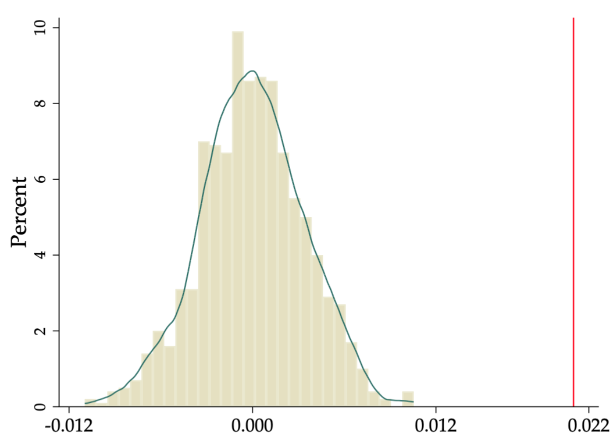
In this figure, we conduct a placebo test where the treatment and control status are randomly assigned to observations in our sample while maintaining the true distribution of the event years. We perform this placebo test 1,000 times and use the pseudo-treated samples to re-estimate our baseline results. 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. Panels 1a, 1b, 1c, and 1d report the the empirical distribution of the coefficient estimates for regressions (2), (4), (6), and (8) in Table 1 (i.e., our baseline estimations with control variables). We also plot the kernel density of the coefficient estimates. The true coefficient estimate in each panel is marked by a red vertical line.



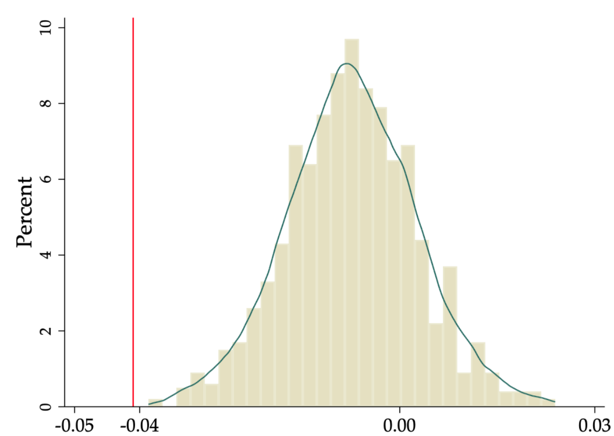
(a) Innovation regressions, coefficient on *Treatment*



(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 1: Patent Trading and Firm Specialization

We report the DiD estimation results on the effects of patent trading in this table. Odd-numbered regressions in this table report the estimation results without control variables and we add the control variables to even-numbered regressions. The control variables are delineated at the end of Section 2.2.2. The variables are defined in Table A1. All regressions include firm fixed effects and year fixed effects. 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)	(5)	(6)	(7)	(8)
Treatment	0.084**	0.075**	0.089**	0.079**	0.025**	0.021*	0.022*	0.018*
	(0.038)	(0.036)	(0.038)	(0.035)	(0.012)	(0.011)	(0.012)	(0.011)
Treatment × *Net # of Patents Sold*			0.092**	0.090***			-0.038*	-0.041**
			(0.038)	(0.035)			(0.021)	(0.019)
Net # of Patents Sold			-0.150***	-0.140***			0.020	0.027
			(0.036)	(0.032)			(0.020)	(0.018)
Observations	26,770	26,770	26,770	26,770	26,770	26,770	26,770	26,770
Adjusted R-squared	0.687	0.695	0.689	0.696	0.784	0.803	0.785	0.803
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes	No	Yes	No	Yes

Table 2: Patent Licensing and Firm Specialization

We examine the specialization pattern between patent licensors and licensees in this table. Odd-numbered regressions in this table report the estimation results without control variables and we add the control variables to even-numbered regressions. The control variables are delineated at the end of Section 2.2.2. The variables are defined in Table A1. All regressions include firm fixed effects and year fixed effects. 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 × Net # of Patents Licensed Out	0.122*	0.123*	-0.029*	-0.027*
	(0.069)	(0.066)	(0.017)	(0.016)
Treatment	0.087**	0.077**	0.024*	0.020*
	(0.038)	(0.036)	(0.012)	(0.011)
Net # of Patents Licensed Out	-0.112*	-0.117*	0.045***	0.040***
	(0.067)	(0.064)	(0.015)	(0.015)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.688	0.695	0.784	0.802
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table 3: Firm Specialization Based On R&D Efficiency

We assess the specialization pattern based on firm R&D efficiency in this table. Odd-numbered regressions in this table report the estimation results without control variables and we add the control variables to even-numbered regressions. The control variables are delineated at the end of Section 2.2.2. All variables are defined in Table A1. All regressions include firm fixed effects and year fixed effects. 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 × *R&D Efficiency*	0.109**	0.117**	-0.044***	-0.032**
	(0.048)	(0.046)	(0.013)	(0.014)
Treatment	-0.138	-0.140	0.013	0.019
	(0.102)	(0.100)	(0.048)	(0.045)
R&D Efficiency	0.026	0.028	0.020*	0.030**
	(0.042)	(0.041)	(0.011)	(0.012)
Observations	15,224	15,224	15,224	15,224
Adjusted R-squared	0.724	0.725	0.871	0.881
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table 4: Specialization in terms of the scope of innovation

In this table, we trace how the distance between a patent and its assignee's patent portfolio evolve in patent-level regressions. The dependent variable *Distance* is the technological distance of a patent to the patent assignee's patent portfolio prior to this patent. As delineated in Section (2.2.2), the measure of technological distance follows Akcigit et al. (2016). *Distance* in column (1) is the average distance of a patent to its assignee's patent portfolio (i.e., $\iota = 1$ in equation 2). Following the literature, we also examine the technological distance metric with $\iota = \frac{2}{3}$ and $\iota = \frac{1}{3}$ in columns (2) and (3). The *Treatment* indicator takes the value of 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. The control variables are delineated in Section (3.5). All regressions include patent application year fixed effects and patent assignee fixed effects. Robust 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.

	Distance		
	(1)	(2)	(3)
Treatment	-0.0056***	-0.0064***	-0.0075***
	(0.0017)	(0.0019)	(0.0022)
Observations	1,927,596	1,927,596	1,927,596
Adjusted R-squared	0.596	0.512	0.373
Distance metric	$\iota = 1$	$\iota = \frac{2}{3}$	$\iota = \frac{1}{3}$
Patent assignee fixed effect	Yes	Yes	Yes
Application year fixed effect	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

Table 5: Dynamic DiD analysis at the firm level

We report the results of the dynamic DiD analysis at the firm level in this table. $Treatment(0)$ is defined with respect to the year when the patent exchange is established. $Treatment(-\tau)$ and $Treatment(\tau)$ correspond to τ years before and after the establishment of patent exchanges, respectively. $Treatment(3+)$ refers to three and more years after the patent exchanges are established. Other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. *** 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)	0.048	0.047	-0.001	-0.001
	(0.033)	(0.033)	(0.013)	(0.013)
Treatment(−1)	0.048	0.048	0.008	0.008
	(0.034)	(0.034)	(0.012)	(0.012)
Treatment(0)	0.058	0.057	0.013	0.013
	(0.038)	(0.037)	(0.013)	(0.013)
Treatment(1)	0.137***	0.136***	0.027**	0.027**
	(0.040)	(0.040)	(0.013)	(0.013)
Treatment(2)	0.090**	0.088**	0.029**	0.029**
	(0.042)	(0.042)	(0.013)	(0.013)
Treatment(3+)	0.154***	0.156***	0.050***	0.048***
	(0.042)	(0.041)	(0.014)	(0.014)
Treatment(3+) × *Net # of Patents Sold*		0.043*		-0.024**
		(0.026)		(0.011)
Net # of Patents Sold		-0.099***		0.007
		(0.024)		(0.010)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.691	0.692	0.788	0.789
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table 6: Dynamic DiD analysis at the province level

We report the results of the dynamic DiD analysis at the province level in this table. $Treatment(0)$ is defined with respect to the year when the patent exchange is established. $Treatment(-\tau)$ and $Treatment(\tau)$ correspond to τ years before and after the establishment of patent exchanges, respectively. $Treatment(3+)$ refers to three and more years after the patent exchanges are established. *GDP* and *GDP pc* in regression (1) and (2) are the province-level GDP and per capita GDP. *R&D* in regression (3) refers to the province-level expenditures on research and development. *Innovation Output* in regression (4) refers to the natural logarithm of the number of patent filings in each province. *Fiscal Expenditures* and *Fiscal Revenue* in regression (5) and (6) are the province-level fiscal expenditures and revenue. The control variables are delineated in Section 4.1.2. All regressions include province fixed effects and year fixed effects. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	GDP	*GDP pc*	*R&D*	*Innovation Output*	*Fiscal Expenditures*	*Fiscal Revenue*
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment(−2)	-0.086	-0.006	-0.346	0.022	-0.124	-0.061
	(0.158)	(0.013)	(0.471)	(0.091)	(0.209)	(0.179)
Treatment(−1)	-0.057	0.003	-0.268	0.082	-0.099	-0.003
	(0.168)	(0.014)	(0.501)	(0.097)	(0.223)	(0.190)
Treatment(0)	-0.009	0.008	-0.198	0.084	-0.043	0.068
	(0.183)	(0.015)	(0.545)	(0.105)	(0.242)	(0.207)
Treatment(1)	0.088	0.019	0.054	0.128	0.113	0.215
	(0.190)	(0.015)	(0.566)	(0.109)	(0.252)	(0.215)
Treatment(2)	0.165	0.026	0.236	0.170	0.245	0.324
	(0.196)	(0.016)	(0.583)	(0.112)	(0.259)	(0.222)
Treatment(3+)	0.475***	0.039***	1.133**	0.195**	0.749***	0.687***
	(0.169)	(0.014)	(0.502)	(0.097)	(0.223)	(0.191)
Observations	496	496	496	496	496	496
Adjusted R-squared	0.840	0.961	0.775	0.969	0.879	0.830
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Patent Traders vs Non-Traders

We distinguish patent traders from non-traders in this table. The dummy variable "*Trader*" takes the value of one for patent traders and it equals zero for non-traders. All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. Since "*Trader*" in this table is based on a firm's trading activity during the full sample period, the term "*Trader* × *Net # of Patents Sold*" is subsumed because it is always equal to "*Net # of Patents Sold*." All regressions include firm fixed effects and year fixed effects. 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*	0.472***	0.470***	0.089***	0.086***
	(0.041)	(0.041)	(0.022)	(0.022)
Treatment × *Trader* × *Net # of Patents Sold*		0.119***		-0.038**
		(0.035)		(0.019)
Treatment	-0.227***	-0.220***	-0.036**	-0.037**
	(0.040)	(0.039)	(0.016)	(0.016)
Net # of Patents Sold		-0.156***		0.024
		(0.033)		(0.018)
Treatment × *Net # of Patents Sold*		-0.002		0.001
		(0.005)		(0.002)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.700	0.701	0.804	0.804
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table 8: Patent trading liquidity

In this table, we distinguish firms facing a liquid market for patent trading from their counterparts confronted with an illiquid market. The dummy variable "*High Liquidity*" takes the value of one if the patent trading liquidity a firm faces is above the sample average of all firms and zero otherwise. All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. 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***	0.202***	0.113***	0.107***
	(0.050)	(0.050)	(0.026)	(0.025)
Treatment × *High Liquidity* × *Net # of Patents Sold*		0.142***		-0.045*
		(0.043)		(0.027)
Treatment	-0.009	-0.005	-0.026*	-0.026*
	(0.040)	(0.040)	(0.014)	(0.013)
Net # of Patents Sold		-0.172***		-0.013
		(0.037)		(0.014)
Treatment × *Net # of Patents Sold*		-0.012***		0.002
		(0.005)		(0.002)
High Liquidity × *Net # of Patents Sold*		-0.074*		0.025
		(0.042)		(0.026)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.696	0.697	0.805	0.805
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table 9: Firm financial constraints

We assess the role of financial constraints in this table. The dummy variable "*Constrained*" takes the value of one if the financial constraints a firm faces is above the sample average of all firms and zero otherwise. All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. 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 × *Constrained*	0.188***	0.191***	0.175***	0.171***
	(0.046)	(0.046)	(0.021)	(0.021)
Treatment × *Constrained* × *Net # of Patents Sold*		0.140***		-0.070*
		(0.053)		(0.036)
Treatment	-0.025	-0.023	-0.072***	-0.072***
	(0.041)	(0.041)	(0.013)	(0.013)
Net # of Patents Sold		-0.059***		-0.003
		(0.016)		(0.006)
Treatment × *Net # of Patents Sold*		-0.001		0.001
		(0.005)		(0.002)
Constrained × *Net # of Patents Sold*		-0.116**		0.044
		(0.051)		(0.034)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.696	0.697	0.807	0.807
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Appendix

Table A1: Variable Definitions

Variable	Definition
Treatment	A dummy variable that equals one in a year if a patent exchange has been established in the province where a firm is located by that year and zero otherwise
Innovation Output	Natural logarithm of one plus the number of patent applications a firm files and eventually granted
Advertising	Firm advertising expenditures
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
Trading Liquidity	A measure of patent trading liquidity, constructed as a proxy for the likelihood that a firm's patents are traded each year
R&D Efficiency	Number of patent applications divided by the weighted average of R&D expenditures in recent years
Distance	Technological distance of a patent to the patent assignee's patent portfolio prior to this patent, the measure of technological distance is based on Akcigit et al. (2016)
TFP	Natural logarithm of total factor productivity, estimated by the method of Ackerberg et al. (2015)
ROA	Earnings before interest and taxes divided by book value of assets
Assets	Natural logarithm of one plus book value of assets
Age	Natural logarithm of one plus the number of years since a firm has been publicly listed
R&D	R&D expenditures divided by book value of assets
Capex	Capital expenditures divided by book value of assets
PP&E	Net value of property, plant, and equipment divided by book value of 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 assets
Innovation Quality	The number of citations a patent receives divided by the average number of citations received by patents in the same cohort (i.e., patents applied in the same year and in the same technology class)
Breakthrough Innovation	Natural logarithm of one plus the number of breakthrough patents. A breakthrough patent is defined to be the top ten percent most cited patents in its cohort (i.e., patents applied in the same year and in the same technology class)
Explorative Innovation	Natural logarithm of one plus the number of explorative patents. A patent is categorized to be explorative if at least 80% of its citations are based on new knowledge (i.e., do not belong to the patents filed by the firm and the patents cited by the firm's patents filed in the past five years)
Exploitative Innovation	Natural logarithm of one plus the number of exploitative patents. A patent is categorized to be exploitative if at least 80% of its citations are based on the firms existing knowledge (i.e., belong to the patents filed by the firm or the patents cited by the firm's patents filed in the past five years)

Table A2: Descriptive Statistics

Our empirical analysis is based on publicly listed Chinese companies that have filed at least one patent between 2001 and 2017. This table reports the summary statistics of the main variables as 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. *Patents Traded* and *Patents Licensed* refer to the total number of patents traded and licensed by each firm during the sample period. Since the total number of patents traded and licensed is a firm-level variable, the number of observations for these variables is smaller than other firm-year-level variables. Since the R&D efficiency information is missing in some cases, the number of observations is smaller for this variable. The number of observations is smaller for *TFP* and *ROA* because of missing firm accounting information. All potentially unbounded variables are winsorized at the 1% extremes.

	Mean	Standard Deviation	Min	Median	Max	Observations
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation Output (number of patents)	7.291	21.35	0	1	160	26,770
Advertising (billion RMB)	0.218	0.526	0	0.0553	3.730	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
Patents Traded	4.674	12.49	0	1	86	2,801
Patents Licensed	2.595	6.319	0	0	41	2,801
R&D Efficiency	0.187	0.563	0	0.0389	4.468	15,224
TFP	2.667	0.370	1.541	2.675	3.603	26,556
ROA	0.0527	0.0620	-0.207	0.0503	0.236	26,014
R&D(%)	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
Tobin's Q	2.203	2.001	0.224	1.596	11.53	26,770

Table A3: Treatment based on distance between firms and patent exchanges

The treatment indicator (i.e., *Treatment*) in this table is based on the geographic distance between a firm and its closest patent exchange. *Treatment* in this table takes the value of one if a patent exchange is established within 60 miles of the firm and zero otherwise. This threshold value of 60 miles is based on the average distance between patent buyers and sellers during the pre-event period (i.e., before the establishment of patent exchanges). All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. *** 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***	0.081***	0.018**	0.013*
	(0.021)	(0.021)	(0.007)	(0.007)
Treatment × *Net # of Patents Sold*		0.064***		-0.046***
		(0.018)		(0.006)
Net # of Patents Sold		-0.110***		0.018***
		(0.015)		(0.005)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.688	0.689	0.786	0.786
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table A4: Patent Trading and Firm Specialization, Controlling for other potentially related innovation policies

This table reports the DiD estimation results on the effects of patent trading while controlling for other potentially related innovation policies. *Patent Subsidy* is a dummy variable for government subsidies for patents, *Patents as Collateral* is a dummy variable for government supporting policies for pledging patents as collateral for financing, *Tax Cut* is a dummy variable for tax cuts for new product development, and *Tech SMEs* is a dummy variable for government supporting policies for small and medium-sized high-tech enterprises. All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. *** 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	0.072***	0.076***	0.018**	0.016*
	(0.026)	(0.026)	(0.009)	(0.009)
Treatment × Net # of Patents Sold		0.090***		-0.040***
		(0.028)		(0.010)
Net # of Patents Sold		-0.139***		0.027***
		(0.027)		(0.009)
Patent Subsidy	0.054***	0.054***	0.006	0.006
	(0.019)	(0.019)	(0.007)	(0.007)
Tax Cut	-0.024	-0.023	0.000	0.000
	(0.018)	(0.018)	(0.006)	(0.006)
Tech SMEs	0.071***	0.071***	-0.009	-0.009
	(0.018)	(0.018)	(0.006)	(0.006)
Patents as Collateral	-0.035**	-0.034**	-0.006	-0.005
	(0.017)	(0.017)	(0.006)	(0.006)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.695	0.696	0.803	0.803
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table A5: Patent Licensing and Firm Specialization, Controlling for other potentially related innovation policies

The regressions in this table examine the specialization pattern between patent licensors and licensees while controlling for other potentially related innovation policies. *Patent Subsidy* is a dummy variable for government subsidies for patents, *Patents as Collateral* is a dummy variable for government supporting policies for pledging patents as collateral for financing, *Tax Cut* is a dummy variable for tax cuts for new product development, and *Tech SMEs* is a dummy variable for government supporting policies for small and medium-sized high-tech enterprises. All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. 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 × Net # of Patents Licensed Out	0.126*	-0.027*
	(0.067)	(0.016)
Treatment	0.074**	0.018
	(0.036)	(0.011)
Net # of Patents Licensed Out	-0.120*	0.040***
	(0.065)	(0.015)
Patent Subsidy	0.053*	0.007
	(0.032)	(0.016)
Tax Cut	-0.021	0.000
	(0.031)	(0.017)
Tech SMEs	0.070**	-0.009
	(0.033)	(0.017)
Patents as Collateral	-0.039	-0.003
	(0.028)	(0.012)
Observations	26,770	26,770
Adjusted R-squared	0.695	0.802
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table A6: Firm Specialization Based On R&D Efficiency, Controlling for other potentially related innovation policies

The regressions in this table assess the specialization pattern based on firm R&D efficiency while controlling for other potentially related innovation policies. *Patent Subsidy* is a dummy variable for government subsidies for patents, *Patents as Collateral* is a dummy variable for government supporting policies for pledging patents as collateral for financing, *Tax Cut* is a dummy variable for tax cuts for new product development, and *Tech SMEs* is a dummy variable for government supporting policies for small and medium-sized high-tech enterprises. All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. 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 $\times$ *R&D Efficiency*	0.116**	-0.031**
	(0.046)	(0.014)
Treatment	-0.108	0.018
	(0.099)	(0.044)
R&D Efficiency	0.030	0.029**
	(0.041)	(0.012)
Patent Subsidy	-0.043	-0.043
	(0.077)	(0.029)
Tax Cut	0.099**	-0.014
	(0.040)	(0.018)
Tech SMEs	0.066	0.009
	(0.059)	(0.024)
Patents as Collateral	-0.021	-0.009
	(0.030)	(0.011)
Observations	15,224	15,224
Adjusted R-squared	0.725	0.881
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Internet appendix for

“Does Trading Spur Specialization? Evidence from Patenting”

(not to be published)

In this Internet Appendix, we provide supplemental evidence and robustness tests to the main results presented in “Does Trading Spur Specialization? Evidence from Patenting.”

IA0.1 Stylized facts about patent trading

Since our measure of technological distance is based on Akcigit et al. (2016), we also replicate the main empirical analysis of the stylized facts about patent trading in Akcigit et al. (2016) in the Chinese context.

We examine how the decision to sell a patent relates to the technological distance measure in the patent-level regressions in Internet Appendix Table IA7. These regressions are based on patents granted between 2001 and 2017 and the empirical specification follows Akcigit et al. (2016). The dependent variable *Patent Sold* takes the value of one if a patent has been sold by the end of the sample period and zero otherwise. The main explanatory variable *Distance* is the technological distance of a patent to the patent assignee's patent portfolio prior to this patent. *Distance* in column (1) is the average distance of a patent to its assignee's patent portfolio (i.e., $\iota = 1$ in equation 2). Following the literature (e.g., Akcigit et al. (2016), Brav et al. (2018), Ma et al. (2019)), we also examine the technological distance metric with $\iota = \frac{2}{3}$ and $\iota = \frac{1}{3}$ in columns (2) and (3). We control for the number of citations received by the patent, the patent stock of the patent assignee and its patenting experience (i.e., the number of years since its first successful patent application). We incorporate patent application year fixed effects to absorb the aggregate shocks and we include patent assignee fixed effects to control for all time-invariant heterogeneity at the assignee level. The results in this table indicate that a patent is more likely to be sold if it is more distant to its owner. Echoing Akcigit et al. (2016), we also find that patents traded are technologically closer to the buyers than to the sellers (the average difference in the distance (buyer minus seller) is -0.002).

In the patent assignee-year level regressions in Internet Appendix Table IA8, we track how the patent portfolios of innovators evolve between 2001 and 2017.[65] The dependent variable is the distance-weighted patent stock (i.e., each patent is weighted by the distance to its assignee's patent portfolio). As in our previous analysis, the distance metric in column (1) is based on the average distance of a patent to its assignee's patent portfolio (i.e., $\iota = 1$ in equation 2). We also examine the technological distance metric with $\iota = \frac{2}{3}$ and $\iota = \frac{1}{3}$ in columns (2) and (3). The *Treatment* indicator takes the value of 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 control for the patent assignee's patent stock and we incorporate year fixed effects and patent assignee fixed effects throughout the regressions. The negative estimate of the *Treatment* indicator indicates that the establishments of patent exchanges are negatively associated with the distance-weighted patent stock (while controlling for the unadjusted patent stock). Reinforcing the findings of our baseline analysis of specialization, the results in Table IA8 indicate that an emerging market for technology is associated with more specialized and less diversified patent portfolios of innovators.

[65] Since we focus on the listed firms in the firm-year level regressions (e.g., Table 1), the number of observations in those regressions is smaller than that in Table IA8.

Figure IA1: **Shenzhen patent exchange**

This figure is a snapshot of the website of the Shenzhen Patent Exchange. As illustrated by this figure, 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 sale and a patent holder can look for patent demand information.

FIGURE IA2: **Patents available for sale**

This figure will pop up when a potential buyer starts searching for patents available for sale. As shown at the 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" and it can be used in the area of information digitalization. The patent on the right is titled "A Gear Cutter For 3D Printing Waste" and it is classified into the category of instruments and apparatuses. When clicking each patent available for sale, the buyer will be directed to further information about the patents.

FIGURE IA3: **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.

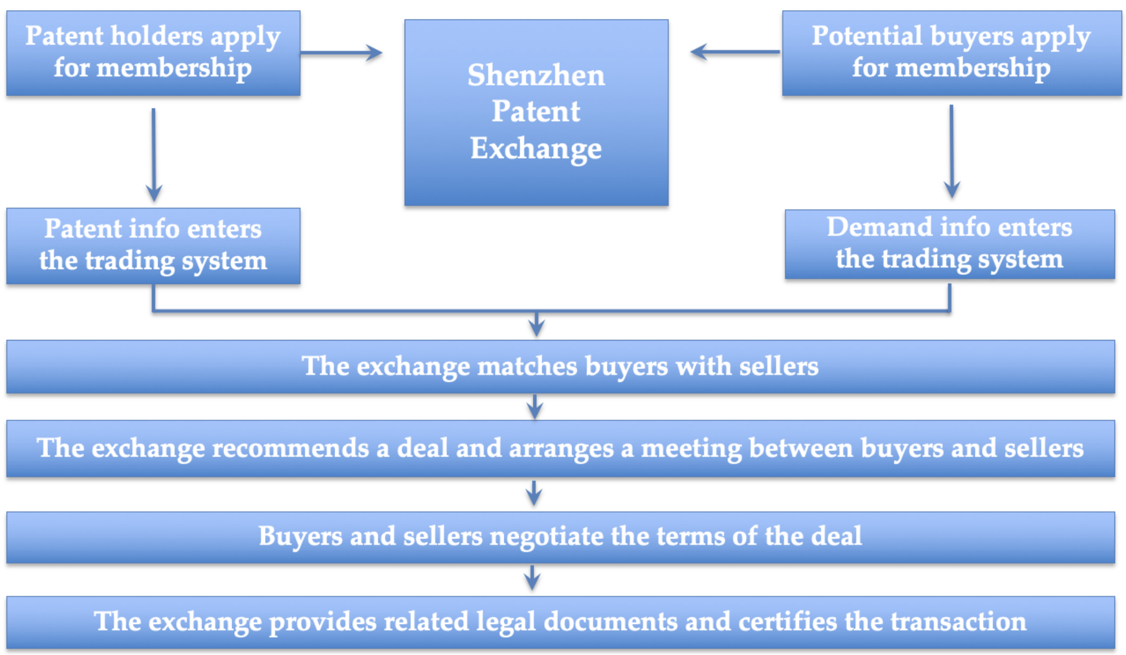


Table IA1: Patent Exchanges and The Market For Technology

In this table, we examine how patent exchanges affect the market liquidity of patent trading in patent-level regressions. The dependent variable *Patent Traded* takes the value of one if a patent has been traded and zero otherwise. The *Treatment* indicator takes the value of 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. All regressions include patent application year fixed effects and patent assignee fixed effects. In column (2), we control for the number of citations received by the patent, the patent stock of the patent assignee and its patenting experience (i.e., the number of years since its first successful patent application). Robust 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.

	1{Patent Traded}	
	(1)	(2)
Treatment	0.0038**	0.0042**
	(0.0019)	(0.0019)
Observations	1,927,596	1,927,596
Adjusted R-squared	0.366	0.366
Patent assignee fixed effect	Yes	Yes
Application year fixed effect	Yes	Yes
Controls	No	Yes

Table IA2: Alternative sample based on R&D-performing firms

We report the results based on R&D-performing firms (i.e., firms reporting positive R&D expenditures) in this table. Odd-numbered regressions in this table report the estimation results without control variables and we add the control variables to even-numbered regressions. The control variables are delineated at the end of Section 2.2.2. The variables are defined in Table A1. All regressions include firm fixed effects and year fixed effects. *** 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)	(5)	(6)	(7)	(8)
Treatment	0.098***	0.092***	0.102***	0.096***	0.021**	0.021**	0.018*	0.018*
	(0.029)	(0.029)	(0.029)	(0.029)	(0.010)	(0.010)	(0.010)	(0.010)
Treatment × *Net # of Patents Sold*			0.085***	0.083***			-0.040***	-0.042***
			(0.029)	(0.029)			(0.010)	(0.010)
Net # of Patents Sold			-0.128***	-0.124***			0.022**	0.024**
			(0.028)	(0.028)			(0.010)	(0.009)
Observations	23,189	23,189	23,189	23,189	23,189	23,189	23,189	23,189
Adjusted R-squared	0.689	0.692	0.690	0.692	0.794	0.798	0.794	0.798
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes	No	Yes	No	Yes

Table IA3: Treated Regions and Treatment Time

The first column of this table reports the treated provinces where the patent exchanges are established. The second column reports the starting year of the treatment event.

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 IA4: Incorporating industry-year fixed effects

We incorporate the industry-year fixed effects in this table. The variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects, year fixed effects, and industry-year fixed effects. *** 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	0.069***	0.073***	0.018**	0.016*
	(0.025)	(0.025)	(0.009)	(0.009)
Treatment $\times$ *Net # of Patents Sold*		0.086***		-0.032***
		(0.027)		(0.009)
Net # of Patents Sold		-0.136***		0.021**
		(0.027)		(0.009)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.722	0.723	0.820	0.820
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table IA5: Treatment based on distance between firms and patent exchanges

The treatment indicator (i.e., *Treatment*) in this table is based on the geographic distance between a firm and its closest patent exchange. *Treatment* in this table takes the value of one if a patent exchange is established within 90 miles of the firm and zero otherwise. All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. *** 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	0.111***	0.117***	0.021***	0.015*
	(0.022)	(0.022)	(0.008)	(0.008)
Treatment × *Net # of Patents Sold*		0.065***		-0.056***
		(0.020)		(0.007)
Net # of Patents Sold		-0.115***		0.029***
		(0.018)		(0.006)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.688	0.689	0.786	0.786
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table IA6: 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. Standard errors are reported in the parentheses and are clustered at the firm level when firm fixed effects are included in regression (3). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Net Number of Patents Sold / Patent Stock		
	(1)	(2)	(3)
R&D Efficiency	0.119**	0.143***	0.224**
	(0.046)	(0.048)	(0.088)
Assets	0.073**	0.036	-0.027
	(0.032)	(0.034)	(0.142)
R&D	0.108***	0.107***	0.003
	(0.021)	(0.022)	(0.044)
Tobin's Q	-0.014	-0.046*	-0.080*
	(0.021)	(0.024)	(0.042)
Leverage	0.271	0.277	0.112
	(0.223)	(0.224)	(0.482)
Age	0.059	0.043	0.167
	(0.052)	(0.052)	(0.172)
PP&E	0.632**	0.583**	0.068
	(0.266)	(0.268)	(0.736)
Capex	-2.567***	-2.092**	-2.139
	(0.845)	(0.869)	(1.319)
Observations	15,224	15,224	15,224
Adjusted R-squared	0.003	0.003	0.071
Firm fixed effects	No	No	Yes
Year fixed effects	No	Yes	Yes
Control variables	Yes	Yes	Yes

Table IA7: Technological distance and patent sale

In this table, we examine how the decision to sell a patent relates to the technological distance measure in patent-level regressions. The dependent variable *Patent Sold* takes the value of one if a patent has been sold by the end of the sample period and zero otherwise. The main explanatory variable *Distance* is the technological distance of a patent to the patent assignee's patent portfolio prior to this patent. As delineated in Section (2.2.2), the measure of technological distance follows Akcigit et al. (2016). *Distance* in column (1) is the average distance of a patent to its assignee's patent portfolio (i.e., $\iota = 1$ in equation 2). Following the literature, we also examine the technological distance metric with $\iota = \frac{2}{3}$ and $\iota = \frac{1}{3}$ in columns (2) and (3). The control variables are delineated in Section (IA0.1). All regressions include patent application year fixed effects and patent assignee fixed effects. Robust 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.

	Patent Sold		
	(1)	(2)	(3)
Distance	0.0017**	0.0015**	0.0013**
	(0.0007)	(0.0006)	(0.0005)
Observations	1,927,596	1,927,596	1,927,596
Adjusted R-squared	0.366	0.366	0.366
Distance metric	$\iota = 1$	$\iota = \frac{2}{3}$	$\iota = \frac{1}{3}$
Patent assignee fixed effect	Yes	Yes	Yes
Application year fixed effect	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

Table IA8: Patent portfolio adjusted by technological distance

In this table, we track how patent portfolios of the innovators evolve in patent assignee-year level regressions. The dependent variable is the distance-weighted patent stock (i.e., each patent is weighted by the technological distance to its assignee's patent portfolio). As delineated in Section (2.2.2), the measure of technological distance follows Akcigit et al. (2016). The technological distance measure in column (1) is based on the average distance of a patent to its assignee's patent portfolio (i.e., $\iota = 1$ in equation 2). Following the literature, we also examine the technological distance metric with $\iota = \frac{2}{3}$ and $\iota = \frac{1}{3}$ in columns (2) and (3). The *Treatment* indicator takes the value of 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. The control variables are delineated in Section (IA0.1). All regressions include year fixed effects and patent assignee fixed effects. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance-Weighted Patent Stock		
	(1)	(2)	(3)
Treatment	-0.6740**	-0.5232**	-0.3083**
	(0.2735)	(0.2224)	(0.1542)
Patent Stock	9.2775***	7.5423***	5.2457***
	(0.0620)	(0.0504)	(0.0350)
Observations	172,608	172,608	172,608
Adjusted R-squared	0.654	0.657	0.664
Distance metric	$\iota = 1$	$\iota = \frac{2}{3}$	$\iota = \frac{1}{3}$
Patent assignee fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

Table IA9: Patent Traders vs Non-Traders, pre-event information

In this table, we distinguish patent traders from non-traders. The dummy variable "*Trader*" takes the value of one for patent traders and it equals zero for non-traders. "*Trader*" in this table is based on a firm's trading activity during the pre-event period (i.e., before the establishment of patent exchanges). All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. Since "*Trader*" in this table is based on a firm's trading activity during the pre-event period, the term "*Trader* × *Net # of Patents Sold*" is not subsumed because it is not always equal to "*Net # of Patents Sold*" (note that some non-traders during the pre-event period may start trading patents after the patents exchanges are established). All regressions include firm fixed effects and year fixed effects. *** 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*	0.065**	0.105***	0.130***	0.119***
	(0.031)	(0.032)	(0.041)	(0.011)
Treatment × *Trader* × *Net # of Patents Sold*		0.327***		-0.103***
		(0.091)		(0.031)
Treatment	0.065**	0.063**	-0.001	-0.001
	(0.026)	(0.026)	(0.013)	(0.009)
Net # of Patents Sold		-0.075***		-0.007**
		(0.010)		(0.004)
Treatment × *Net # of Patents Sold*		0.000		0.000
		(0.003)		(0.001)
Trader × *Net # of Patents Sold*		-0.102		0.040
		(0.082)		(0.028)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.702	0.704	0.804	0.805
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table IA10: Patent trading liquidity, pre-event information

We distinguish firms facing a liquid market for patent trading from their counterparts confronted with an illiquid market in this table. The dummy variable "*High Liquidity*" takes the value of one if the patent trading liquidity a firm faces is above the sample average of all firms and zero otherwise. "*High Liquidity*" in this table is based on the trading liquidity a firm faces during the pre-event period (i.e., before the establishment of patent exchanges). All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. 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*	0.102**	0.122**	0.122***	0.102***
	(0.052)	(0.052)	(0.027)	(0.025)
Treatment × *High Liquidity* × *Net # of Patents Sold*		0.199***		-0.132***
		(0.058)		(0.034)
Treatment	0.036	0.037	-0.025**	-0.024*
	(0.039)	(0.039)	(0.012)	(0.012)
Net # of Patents Sold		-0.052***		-0.004
		(0.015)		(0.006)
Treatment × *Net # of Patents Sold*		-0.001		0.001
		(0.004)		(0.002)
High Liquidity × *Net # of Patents Sold*		-0.146***		0.068***
		(0.049)		(0.026)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.695	0.696	0.805	0.806
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table IA11: Firm financial constraints, pre-event information

The regressions in this table evaluate the role of financial constraints. The dummy variable "*Constrained*" takes the value of one if the financial constraints a firm faces is above the sample average of all firms and zero otherwise. "*Constrained*" in this table is based on the financial constraints a firm faces during the pre-event period (i.e., before the establishment of patent exchanges). The variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. *** 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 × *Constrained*	0.155***	0.157***	0.208***	0.203***
	(0.023)	(0.023)	(0.009)	(0.009)
Treatment × *Constrained* × *Net # of Patents Sold*		0.105*		-0.103***
		(0.062)		(0.025)
Treatment	0.003	0.003	-0.070***	-0.071***
	(0.027)	(0.027)	(0.011)	(0.011)
Net # of Patents Sold		-0.091***		-0.006
		(0.014)		(0.006)
Treatment × *Net # of Patents Sold*		0.001		0.000
		(0.003)		(0.001)
Constrained × *Net # of Patents Sold*		-0.073		0.062**
		(0.061)		(0.024)
Observations	18,613	18,613	18,613	18,613
Adjusted R-squared	0.701	0.702	0.791	0.792
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table IA12: Patent Trading and Firm Specialization, Controlling for government subsidies

This table reports the DiD estimation results on the effects of patent trading while controlling for *Subsidy* (i.e., the amount of government subsidy a firm receives scaled by firm assets). Other variables are defined in Table A1 and other control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. 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	0.0746**	0.0790**	0.0207*	0.0183*
	(0.0358)	(0.0351)	(0.0113)	(0.0111)
Treatment × *Net # of Patents Sold*		0.0899***		-0.0405**
		(0.0346)		(0.0194)
Net # of Patents Sold		-0.1395***		0.0269
		(0.0324)		(0.0180)
Subsidy	0.0017**	0.0015**	0.0008**	0.0008**
	(0.0008)	(0.0008)	(0.0003)	(0.0003)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.695	0.696	0.803	0.803
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table IA13: Patent Licensing and Firm Specialization, Controlling for government subsidies

The regressions in this table examine the specialization pattern between patent licensors and licensees while controlling for *Subsidy* (i.e., the amount of government subsidy a firm receives scaled by firm assets). Other variables are defined in Table A1 and other control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. 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 × *Net # of Patents Licensed Out*	0.1229*	-0.0269*
	(0.0657)	(0.0162)
Treatment	0.0775**	0.0195*
	(0.0355)	(0.0113)
Net # of Patents Licensed Out	-0.1170*	0.0401***
	(0.0639)	(0.0147)
Subsidy	0.0017**	0.0008**
	(0.0008)	(0.0004)
Observations	26,770	26,770
Adjusted R-squared	0.695	0.802
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Control variables	Yes	Yes

Table IA14: Firm Specialization Based On R&D Efficiency, Controlling for government subsidies

The regressions in this table assess the specialization pattern based on firm R&D efficiency while controlling for *Subsidy* (i.e., the amount of government subsidy a firm receives scaled by firm assets). Other variables are defined in Table A1 and other control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. 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*	0.1161**	-0.0326**
	(0.0462)	(0.0136)
Treatment	-0.1397	0.0197
	(0.1000)	(0.0446)
R&D Efficiency	0.0294	0.0308**
	(0.0411)	(0.0122)
Subsidy	0.0032	0.0026*
	(0.0068)	(0.0015)
Observations	15,224	15,224
Adjusted R-squared	0.725	0.881
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Control variables	Yes	Yes

Table IA15: Poisson Regressions, Patent Trading

We report the estimation results based on Poisson regression models in this table. The dependent variable is the number of patent applications a firm files and eventually granted. All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Patents			
	(1)	(2)	(3)	(4)
Treatment	0.226***	0.197***	0.259***	0.235***
	(0.021)	(0.021)	(0.022)	(0.022)
Treatment $\times$ *Net # of Patents Sold*			0.118***	0.126***
			(0.010)	(0.010)
Net # of Patents Sold			-0.150***	-0.150***
			(0.010)	(0.010)
Observations	23,996	23,996	23,996	23,996
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table IA16: Poisson Regressions, Patent Licensing

The regressions in this table are based on Poisson regression models. The dependent variable is the number of patent applications a firm files and eventually granted. All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Patents	
	(1)	(2)
Treatment × *Net # of Patents Licensed Out*	0.192***	0.207***
	(0.020)	(0.020)
Treatment	0.234***	0.203***
	(0.021)	(0.021)
Net # of Patents Licensed Out	-0.214***	-0.227***
	(0.020)	(0.020)
Observations	23,996	23,996
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Control variables	No	Yes

Table IA17: Poisson Regressions, R&D Efficiency

This table reports the estimation results based on Poisson regression models. The dependent variable is the number of patent applications a firm files and eventually granted. All other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Patents	
	(1)	(2)
Treatment × *R&D Efficiency*	0.195***	0.218***
	(0.022)	(0.022)
Treatment	0.043	-0.006
	(0.041)	(0.041)
R&D Efficiency	-0.024	-0.003
	(0.019)	(0.019)
Observations	14,111	14,111
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	No	Yes

Table IA18: Excluding inter-provincial trade

In this table, we focus on firms that never trade any patents with trading counterparties in other provinces. The variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Innovation Output	*Advertising*
	(1)	(2)
Treatment × *Net # of Patents Sold*	0.117*	-0.030*
	(0.063)	(0.018)
Treatment	0.075***	0.015**
	(0.026)	(0.007)
Net # of Patents Sold	-0.233***	0.018
	(0.060)	(0.017)
Observations	23,389	23,389
Adjusted R-squared	0.664	0.785
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control Variables	Yes	Yes

Table IA19: Net number of patents sold, pre-event information

The results in this table are based on the net number of patents sold by a firm during the pre-event period (i.e., before the establishment of patent exchanges). The variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Innovation Output	*Advertising*
	(1)	(2)
Treatment × *Net # of Patents Sold*	0.070**	-0.046***
	(0.031)	(0.005)
Treatment	0.069***	-0.004
	(0.024)	(0.004)
Observations	26,770	26,770
Adjusted R-squared	0.674	0.826
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA20: Firm R&D as the outcome variable

In this table, *R&D* (the dependent variable) is the ratio of a firm's R&D expenditures to its book value of assets. Other variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. Since *R&D* is the dependent variable in this table, it is no longer incorporated as a control variable in these regressions. All regressions include firm fixed effects and year fixed effects. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	R&D	
	(1)	(2)
Treatment	0.042*	0.044*
	(0.025)	(0.025)
Treatment × *Net # of Patents Sold*		0.013**
		(0.006)
Net # of Patents Sold		-0.014**
		(0.006)
Observations	26,770	26,770
Adjusted R-squared	0.721	0.721
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA21: Renewed Patents

The results in this table are based on patents that have been renewed at least three times. The variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. 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 × Net # of Patents Sold	0.0900**	0.0871**	-0.0379*	-0.0409**
	(0.0381)	(0.0349)	(0.0213)	(0.0196)
Treatment	0.0885**	0.0787**	0.0224*	0.0183*
	(0.0377)	(0.0352)	(0.0122)	(0.0111)
Net # of Patents Sold	-0.1481***	-0.1368***	0.0196	0.0268
	(0.0362)	(0.0327)	(0.0198)	(0.0181)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.689	0.696	0.785	0.803
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table IA22: Net number of patents sold based on cumulated trading activity

In this table, we adopt an alternative measure of the net number of patents sold based on a firm's cumulated trading activity by the end of each year. The variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. *** 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	0.094***	0.085***	0.019**	0.015*
	(0.026)	(0.025)	(0.009)	(0.009)
Treatment × Net # of Patents Sold	0.037***	0.036***	-0.016***	-0.018***
	(0.010)	(0.010)	(0.004)	(0.003)
Net # of Patents Sold	-0.054***	-0.046***	-0.003	0.003
	(0.010)	(0.010)	(0.003)	(0.003)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.688	0.695	0.788	0.805
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table IA23: Net number of patents sold, patent-value-weighted measure

In this table, we apply an alternative patent-value-weighted measure of the net number of patents sold where the weight is the number of citations received by each patent (a widely used proxy for patent value). The variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. 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	0.088**	0.079**	0.023*	0.019*
	(0.038)	(0.035)	(0.012)	(0.011)
Treatment × *Net # of Patents Sold*	0.044**	0.043**	-0.018*	-0.020**
	(0.021)	(0.019)	(0.010)	(0.009)
Net # of Patents Sold	-0.077***	-0.072***	0.008	0.012
	(0.020)	(0.018)	(0.010)	(0.009)
Observations	26,770	26,770	26,770	26,770
Adjusted R-squared	0.689	0.696	0.785	0.803
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table IA24: Excluding firms in innovation hubs

In this table, we exclude firms in China's innovation hubs (i.e., Beijing, Shanghai, and Shenzhen). All variables are defined in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions include firm fixed effects and year fixed effects. 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	0.069*	0.075*	0.022*	0.021*
	(0.039)	(0.038)	(0.012)	(0.012)
Treatment × *Net # of Patents Sold*		0.110***		-0.027**
		(0.038)		(0.013)
Net # of Patents Sold		-0.156***		0.010
		(0.034)		(0.011)
Observations	20,772	20,772	20,772	20,772
Adjusted R-squared	0.667	0.668	0.772	0.772
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table IA25: Patent Trading and Firm Performance

We evaluate a firm's innovating performance in Panel A of this table and we examine firm productivity, profitability, and market valuation in Panel B. *Innovation Quality* is the number of citations a patent receives divided by the average number of citations received by patents in its cohort. *Explorative Innovation* is the natural logarithm of one plus the number of explorative patents a firm files. *Exploitative Innovation* is the natural logarithm of one plus the number of exploitative patents a firm files. *Breakthrough Innovation* is the natural logarithm of one plus the number of breakthrough patents a firm files. *TFP* is the natural logarithm of firm total factor productivity. *ROA* is a firm's return on assets (i.e., a firm's earnings before interest and taxes divided by its book value of assets). *Tobin's Q* is 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. More details about variable definitions can be found in Table A1. The control variables are delineated at the end of Section 2.2.2. All regressions in this table include industry fixed effects and year fixed effects. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Panel A. Firm innovating performance

	Innovation Quality	*Explorative Innovation*	*Exploitative Innovation*	*Breakthrough Innovation*
	(1)	(2)	(3)	(4)
Treatment	0.0372*	0.0835***	0.0293	0.0418***
	(0.0223)	(0.0285)	(0.0193)	(0.0141)
Observations	26,770	10,234	10,234	26,770
Adjusted R-squared	0.137	0.631	0.585	0.580
Control variables	Yes	Yes	Yes	Yes

Panel B. Firm productivity, profitability, and market valuation

	TFP	*ROA*	*Tobin's Q*
	(1)	(2)	(3)
Treatment	0.0143***	0.00247*	0.0490*
	(0.00543)	(0.00132)	(0.0275)
Observations	26,556	26,014	26,665
Adjusted R-squared	0.666	0.300	0.664
Control variables	Yes	Yes	Yes

Table IA26: Patent Exchanges and Industrial Organization Structure

The dependent variable in regression (1) of this table is the province-level Herfindahl-Hirschman Index (HHI) of firm patenting activities. The dependent variable in regression (2) is the province-level HHI of advertising expenditures. *Treatment* equals one in a year if a patent exchange has been established in a province by that year and zero otherwise. The control variables are delineated in Section 5.2. All regressions in this table include province fixed effects and year fixed effects. *** 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-squared	0.577	0.810
Control variable	Yes	Yes