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(not to be published)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."

IA1.1 Further information about the institutional background

Patent exchanges receive various government support (e.g., favorable policies for financing and land use), but they must be certified to gain such support. In order to be certified, the applicants must demonstrate that they have satisfied the eligibility conditions. In particular, the applicants must demonstrate that the space of the patent exchange is above 400 square meters and they have invested more than 500 thousand RMB on the facility in the exchange; the patent exchange must have at least six qualified intellectual property professionals, as well as elaborate operation goals and plans for at least five years (endorsed by external intellectual property experts). The process of application and certification is the same for all applicants and it is accomplished fairly quickly.

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 the local protectionism of the provincial governments in China, however, addressing legal disputes and enforcing intellectual property rights across provinces are notoriously difficult, as frequently underscored during the legislative process in China. For instance, see the speech of Cao Xianghong (an academician of the Chinese Academy of Engineering and a member of the 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 the 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. In light of this, inter-provincial patent trading in China is discouraged by the province-based intellectual property system and the difficulty of addressing legal disputes and enforcing intellectual property rights across provinces.

IA1.2 Further information about firm innovating performance

Built on our analysis of how patent trading affects firm specialization, we explore a "bottom line" question: How does patent trading affect firm innovating performance? We investigate this question in the firm-year level regressions reported in Internet Appendix Table IA7.

As in other sections, the *Treatment* indicator in Internet Appendix Table IA7 takes the value of one if a patent exchange has been established in the firm's province and zero otherwise. In column (1), the dependent variable *Innovation Quality* is 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).[31] The results in column (1) suggest that the establishment of patent exchanges is associated with improved quality of firm innovation.

We delve further into a firm's innovating performance in columns (2)–(4) of Internet Appendix Table IA7. In light of the recent studies on count data (e.g., Cohn et al. (2022)), we conduct the analysis based on Poisson regressions in columns (2)–(4) of this table. The dependent variables *Explorative Innovation* and *Exploitative Innovation* in columns (2) and (3) of Table IA7 refer to 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. (2023)), 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).[32] Exploitative patents hinge heavily on existing knowledge

[31] This measure facilitates quality comparison of patents from different time vintages and technology classes.
[32] Note that a patent can be neither explorative nor exploitative.

of the firms and explorative patents rely crucially on new knowledge. According to the results in columns (2) and (3), a firm's explorative patent filings have ratcheted up after the establishment of patent exchanges and its exploitative patent filings have not significantly changed. In column (4), the dependent variable *Breakthrough Innovation* is 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 column (4) indicate that the establishment of patent exchanges is associated with rising breakthrough innovation of the firms.

According to the findings in Internet Appendix Table IA7, 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 innovation and breakthrough innovation. 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 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.

IA1.3 Further information about patent trading

Since our measure of technological distance is based on Akcigit et al. (2016), we also replicate the empirical analysis of the main 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 reported in Internet Appendix Table IA8. These regressions are based on patents granted between 2001 and 2019 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. Following the existing literature (e.g., Akcigit et al. (2016), Brav et al. (2018), Ma et al. (2022)), we examine the technological distance metric with $\iota = \frac{2}{3}$ in column (1) and $\iota = \frac{1}{3}$ in column (2). We control for the number of citations received by the patent and the patent assignee's patent stock and patenting experience (i.e., the number of years since its first successful patent application), as well as provincial GDP, population, R&D, and fiscal revenue (a proxy for fiscal capacity of the government). We incorporate patent application year fixed effects to absorb the aggregate shocks, and we include technology class fixed effects and patent assignee fixed effects to control for all time-invariant heterogeneity at the technology class level and patent assignee level. The results in this table indicate that a patent is more likely to be sold if it is technologically more distant from its owner. Echoing Akcigit et al. (2016), we also find that patents traded are technologically closer to the buyers than to the sellers.[33] Parallel to the study of patent trading, we also conduct the analysis of patent licensing and the findings are similar to those about patent trading.[34]

In the patent assignee-year level regressions reported in Internet Appendix Table IA10, we track how the patent portfolios of the corporate assignees evolve between 2001 and 2019.[35] The dependent variable is the distance-weighted patent stock (i.e., each patent is weighted by the distance to the patent portfolio of the patent owners). Following the existing literature (e.g., Akcigit et al. (2016), Brav et al. (2018), Ma et al. (2022)), we examine the technological distance metric with $\iota = \frac{2}{3}$ in column (1) and $\iota = \frac{1}{3}$ in column (2). The *Treatment* indicator takes the value of one in a year if a patent exchange has been established in the patent assignee's province by that year, and zero otherwise. We control for the patent assignee's patent stock and patenting experience (i.e., the number of years since its first successful patent application), and we incorporate year fixed effects and patent assignee fixed effects into the regressions. The significantly negative coefficient

[33] In particular, the average difference in the technological distance (buyer minus seller) is -0.012.

[34] In particular, parallel to our analysis of patent trading (as reported in Internet Appendix Table IA8), we also carry out an analogous analysis of patent licensing and we report the results in Internet Appendix Table IA9. The results in this table suggest that a patent is more likely to be licensed out if it is technologically more distant from its owner.

[35] 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 IA10.

estimate of the treatment indicator suggests that the establishment of patent exchanges is negatively associated with the distance-weighted patent stock (while controlling for the unadjusted patent stock). The findings in this table indicate that an emerging market for technology is associated with more specialized and less diversified patent portfolios of the patent owners.

In the patent-level regressions reported in Internet Appendix Table IA11, we examine the technological distance of the patents traded to the buyer's patents. The dependent variable in this table is the technological distance of a patent to the buyer's patents in each patent trading transaction.[36] Following the existing literature (e.g., Akcigit et al. (2016), Brav et al. (2018), Ma et al. (2022)), we examine the technological distance metric with $\iota = \frac{2}{3}$ in column (1) and $\iota = \frac{1}{3}$ in column (2). The *Treatment* indicator in this table takes the value of one in a year if a patent exchange has been established in the patent buyer's province by that year, and zero otherwise. We control for the number of citations received by the patent and the patent assignee's patent stock and patenting experience (i.e., the number of years since its first successful patent application), as well as provincial GDP, population, R&D, and fiscal revenue (a proxy for fiscal capacity of the government). We incorporate patent application year fixed effects to absorb the aggregate shocks, and we include technology class fixed effects and patent assignee fixed effects to control for all time-invariant heterogeneity at the technology class level and patent assignee level. Since the coefficient estimate of the treatment indicator is significantly negative in the regressions in this table, a patent traded is technologically closer to the buyer's patents after the establishment of patent exchanges. These findings constitute consistent evidence that the market for technology reduces trading friction and enhances the matching efficiency and matching quality of market participants.

IA1.4 Further information about the financial constraint measure

In the analysis of the interplay between technology market friction and capital market friction, the measure of financial constraints is based on the WW index and the SA index. We follow Whited and Wu (2006) and Hadlock and Pierce (2010) to construct the WW index and the SA index, respectively. To be specific, the WW index is computed as $-0.091 \times CF - 0.062 \times DIVPOS +$

[36] When the patent buyers do not have any patents before the patent trading transactions, the dependent variable is unavailable and such transactions are dropped in the regressions in this table.

$0.021 \times TLTD - 0.044 \times LNTA + 0.102 \times ISG - 0.035 \times SG$, where CF is the ratio of cash flow to total assets, $DIVPOS$ is an indicator that takes the value of one if the firm pays cash dividends, $TLTD$ is the ratio of the long-term debt to total assets, $LNTA$ is the natural logarithm of total assets, ISG is the growth rate of sales at the level of the firm's industry, and SG is the growth rate of sales at the level of the firm. The SA index is computed as $-0.737 \times \mathit{Size} + 0.043 \times \mathit{Size}^2 - 0.040 \times \mathit{Age}$, where *Size* is the natural logarithm of the 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.

IA1.5 Robustness checks

In this subsection, we report more details about the robustness tests outlined in Section (4.4).

IA1.5.1 Excluding inter-provincial trade

Based on China's institutional setting of trade and intellectual property system, the treatment group in our baseline analysis is classified by whether a patent exchange is established in the firm's province or the geographic distance between a firm and its closest patent exchange. 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 IA13. As shown by the results in this table, our findings are robust to excluding inter-provincial trade.

IA1.5.2 Firm operation across multiple provinces

One may wonder if firms could have operations in multiple provinces with different exposure to the treatment event. To capture firm operations across multiple provinces, we assess a firm's exposure to the treatment event based on the share of patents filed by a firm and its subsidiaries across provinces. We report the results in Internet Appendix Table IA14. To capture a firm's exposure to the treatment event, the variable *Treatment Exposure* in this table is the weighted average treatment indicator across provinces where the weight for a province is the share of patents filed by a firm and its subsidiaries in that province during the pre-event period (i.e., before the establishment of patent exchanges). The results in this table suggest that our findings are robust when the analysis is based on a firm's exposure to the treatment event while taking firm operations across multiple provinces into account.

IA1.5.3 Stacked regressions

We follow the recommendations of Baker et al. (2022) to address the "bad comparisons" concern in the context of staggered treatment timing and treatment effect heterogeneity. Specifically, we conduct the stacked regression analysis (e.g., Cengiz et al. (2019)) and report the results in Internet Appendix Table IA15. To be concrete, we follow Cengiz et al. (2019) to create event-specific "clean 2×2" datasets combining each treated cohort with clean control cohorts. In columns (1) and (2), the clean control cohorts are the not-yet-treated groups. In columns (3) and (4), the clean control cohorts are the never-treated groups. We conduct the analysis by stacking these event-specific datasets together (and each dataset is indexed by a dataset-specific identifier).[37] The pre-event period is five years before the event and the post-event period is ten years after the event across all events in this test. The results in Internet Appendix Table IA15 suggest that our findings are robust.

IA1.5.4 Placebo test

We conduct a placebo test based on the never-treated groups (i.e., provinces without any patent exchanges) and report the results in Internet Appendix Table IA16. In this placebo test, we assign an artificial "pseudo-treatment" starting year to each province without any patent exchanges. Specifically, we apply the propensity score matching (PSM) method to match each province without any patent exchanges with a province in the treated group.[38] In each pair of matched provinces, we assign the treatment starting year of the treated province to the province without any patent exchanges. Based on this pseudo-treatment starting year, we artificially assign a false treatment

[37] Since these event-specific datasets are stacked together (and each dataset is indexed by a dataset-specific identifier) in the regressions, the number of observations in Internet Appendix Table IA15 is greater than that in our baseline analysis. More detailed explanations can be found in Cengiz et al. (2019).

[38] This PSM matching is based on the pre-event provincial GDP, population, and R&D expenditure.

status to firms in provinces without any patent exchanges. We conduct the DiD analysis accordingly and report the results in Internet Appendix Table IA16. In this table, the *Treatment* indicator takes the value of one for firms in such pseudo-treated provinces (i.e., those without any patent exchanges) and during the years after their (artificially assigned) pseudo-treatment starting years, and zero otherwise. The pseudo-control group in these regressions comprises of firms in treated provinces but during the pre-event period before the firms receive any treatment (i.e., before a patent exchange has been established in the firm's province). Hence, neither the pseudo-treated group nor the pseudo-control group in these regressions has received any treatment, and, thus, we do not expect to observe any treatment effects. Since no treatment effects are manifested in the regressions in Internet Appendix Table IA16, the absence of any treatment effects in this placebo test provides a vote of confidence to strengthen our findings.

IA1.5.5 Mergers and acquisitions

We control for a firm's mergers and acquisitions (M&As) activities in the regressions reported in Internet Appendix Table IA17. In this table, the control variable *M&A* takes the value of one in a year if a firm acquires another company or is involved in a merger in that year and zero otherwise. The results in this table suggest that our findings are robust to controlling for a firm's M&A activities.

IA1.5.6 Firm R&D as an outcome variable

In our baseline analysis of innovation specialization, 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 expenditure (a proxy for innovation input) in the regressions. In addition, we also examine a firm's R&D expenditure as the outcome variable in Internet Appendix Table IA18. 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.

IA1.5.7 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 IA19 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.[39] We redo our baseline analysis and report the results in Internet Appendix Table IA19. The results in this table suggest that our findings are robust to excluding low-quality patents.

IA1.5.8 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 as follows: (i) government subsidies for patents, (ii) tax cuts for new product development, and (iii) government support for small and medium-sized high-tech enterprises. We exploit the regional variation of these innovation policies and report the results in Internet Appendix Table IA20. Specifically, *Patent Subsidy* in this table 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 firm's province in that year, and zero otherwise. Analogously, *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 shown by the results in this table, our findings are robust to controlling for these innovation policies.

IA1.5.9 Government stimulus plan during the 2008 financial crisis

Some of the patent exchanges were established around the 2007–2008 global financial crisis and one may wonder if the results could be driven by China's massive economic stimulus plan during the crisis.[40] To capture the effects of the economic stimulus plan of the government, we include an

[39]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. Patent renewal and expiration information has been widely used in the innovation studies based on patent data (e.g., Serrano (2010), Akcigit et al. (2016)).

[40]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.

additional control variable *Subsidy* in the regressions and report the results in Internet Appendix Table IA21. To be concrete, *Subsidy* is the amount of government subsidy a firm receives scaled by firm assets. The results in this table suggest that our findings are robust when the government subsidy is accounted for.

IA1.5.10 Random assignment of treatment status

We conduct a placebo test by randomly assigning a false treatment status to observations in our sample while maintaining the true distribution of the event time. If our baseline 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 conduct this placebo test 1,000 times and we use the pseudo-treated samples to perform our baseline estimations. Since the effects of patent trading on innovation specialization are captured by the interaction term (i.e., "*Treatment* × *Net # of Patents Sold*"), we plot the empirical distribution of the coefficient estimates of the interaction term in Figure IA2. In this figure, panels IA2a and IA2b report the empirical distribution of the coefficient estimates of the interaction term in columns (2) and (4) of 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. In both panels of Figure IA2, the true positive coefficient estimate in Table 1 is well above the 95^{th} percentile of the distribution and the true negative estimate is below the 5^{th} percentile. Therefore, the results of this placebo test provide a vote of confidence that our findings are unlikely to be driven by chance or other omitted shocks.

Figure IA1: **Patents available for sale**

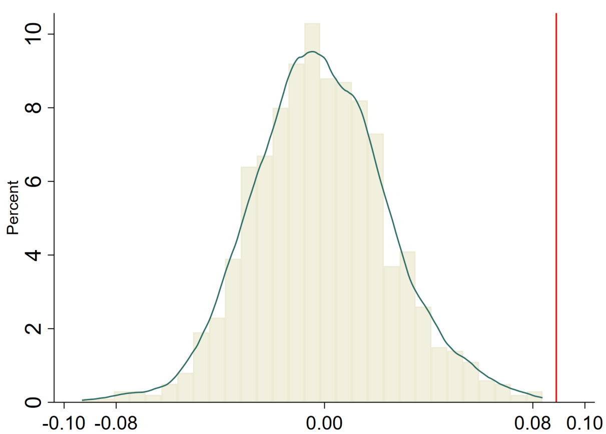
This figure is an example of patents posted for sale on the website of the Fujian Patent Exchange. We have added the English translation for the original information in Chinese.

(Patent title)	专利名	一种治疗肝炎的药物及其生产工艺	(A drug for treating hepatitis and its production process)
(Industry classification)	行业分类:	生物与医药技术	(Biotechnology and pharmaceutical technology)
(Brief introduction)	简介:	本发明是关于一种治疗肝炎的药物及其生产工艺，其公开了由茵陈、龙胆、黄芩、猪胆膏、栀子、白芍、当归、甘草为原料按一定比例精制而成。该发明茵胆平肝胶囊属纯中药制剂，具有清热利湿，消黄，保肝降酶的功效，用于肝胆湿热所致的肋痛、口苦、尿黄、身目发黄；急、慢性肝炎见上述证候者，相对市场上的其它类似具有显著的疗效且无毒副作用。	
(Patent number)	专利号:	00107729.5	
(Patent applicant/assignee)	申请(专利权)人:	漳州片仔癀药业股份有限公司	(Zhangzhou Pientzehuang Pharmaceutical Co., Ltd)

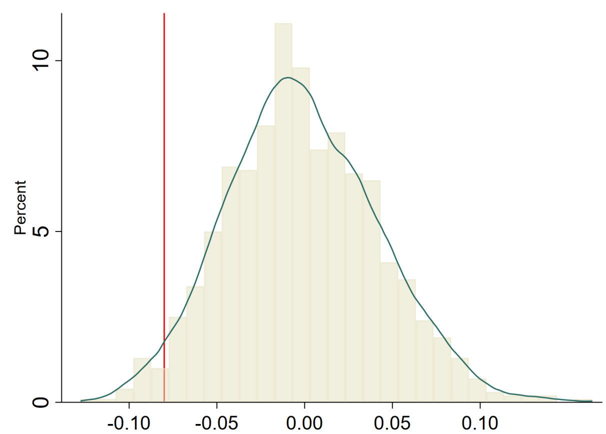
(This is an invention about a drug for treating hepatitis and its production process. The ingredients of the drug are artemisia, gentiana, scutellaria baicalensis, pig bile extract, gardenia jasminoides, white peony, angelica sinensis, and licorice. This invention of yindan pinggan capsule is a pure traditional Chinese medicine preparation. This drug has the effects of clearing heat and promoting dampness, eliminating jaundice, protecting the liver and lowering enzymes. This drug can be used for treating rib pain, bitter mouth, yellow urine, and the yellowing of the body and eyes caused by dampness and heat in the liver and gallbladder, as well as acute and chronic hepatitis with such symptoms. Compared to similar drugs on the market, this drug has significant therapeutic effects and no toxic side effects.)

Figure IA2: Random assignment of treatment status

In this figure, we conduct a placebo test by randomly assigning a false treatment status to observations in our sample while maintaining the true distribution of the event time. We perform this placebo test 1,000 times and we use the pseudo-treated samples to perform our baseline estimations. Since the effects of patent trading on innovation specialization are captured by the interaction term (i.e., "*Treatment* $\times$ *Net # of Patents Sold*"), we plot the empirical distribution of the coefficient estimates of the interaction term in this figure. Specifically, panels IA2a and IA2b report the empirical distribution of the coefficient estimates of the interaction term in columns (2) and (4) of Table 1 (i.e., our baseline estimations with control variables). We also plot the kernel density of the coefficient estimates in this figure. The true coefficient estimate in each panel is marked by a red vertical line.



(a) Innovation output



(b) New product introduction

Table IA1: Patent exchanges and patent trading

We examine the market liquidity of patent trading in the patent-level regressions in this table. The dependent variable *Patent Traded* takes the value of one if a patent has been traded by the end of the sample period and zero otherwise. The *Treatment* indicator takes the value of one in a year if a patent exchange has been established in the patent assignee's province by that year, and zero otherwise. The control variables are delineated in Section (3.4). The results in column (2) suggest that the establishment of patent exchanges contributes to improving the odds for a patent to be traded by 1.15 percentage points (12.7% of the average odds for a patent to be traded). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Patent Traded	
	(1)	(2)
Treatment	0.0146***	0.0115***
	(0.0025)	(0.0025)
Observations	1,897,584	1,897,584
Adjusted R-squared	0.4154	0.4158
Patent assignee fixed effects	Yes	Yes
Technology class fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	No	Yes

Table IA2: Number of new product introductions

We examine a firm's number of new product introductions as an outcome variable in this table. Specifically, the dependent variable in this table is the natural logarithm of one plus the number of a firm's new product announcements with positive CARs each year. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. Column (1) reports the results without control variables and we add the control variables to column (2). The control variables are delineated in Section (2.4). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Number of New Products	
	(1)	(2)
Treatment × *Net # of Patents Sold*	-0.016***	-0.014**
	(0.006)	(0.006)
Treatment	-0.014	-0.015
	(0.011)	(0.011)
Observations	32,688	32,688
Adjusted R-squared	0.2004	0.2017
Firm fixed effects	Yes	Yes
Industry × Year fixed effects	Yes	Yes
Control variables	No	Yes

Table IA3: Average CARs per new product introduction

We examine the shareholder value added by each new product introduction of the firms in this table. Specifically, the dependent variable in this table is the average cumulative abnormal returns (CARs) of a firm's new product introductions each year. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. Column (1) reports the results without control variables and we add the control variables to column (2). The control variables are delineated in Section (2.4). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Average CARs Per New Product	
	(1)	(2)
Treatment × *Net # of Patents Sold*	-0.066*	-0.062*
	(0.034)	(0.034)
Treatment	-0.043	-0.049
	(0.075)	(0.075)
Observations	32,688	32,688
Adjusted R-squared	0.1058	0.1067
Firm fixed effects	Yes	Yes
Industry × Year fixed effects	Yes	Yes
Control variables	No	Yes

Table IA4: Treated Regions and Treatment Time

The treated regions and the treatment time are delineated in this table. The first column of this table reports the treated regions where the patent exchanges are established. The second column reports the starting year of the treatment event.

Treated regions	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 IA5: Treatment based on distance to a patent exchange

The *Treatment* indicator in this table is based on the geographic distance between a firm and its closest patent exchange. Specifically, *Treatment* in this table takes the value of one if a patent exchange is established within 90 miles of the firm and zero otherwise. *Innovation Output* is the number of patent applications a firm files and eventually granted. The analysis is based on Poisson regressions when the dependent variable is *Innovation Output*. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. Odd-numbered regressions in this table report the results without control variables and we add the control variables to even-numbered regressions. The control variables are delineated in Section (2.4). Standard errors are clustered at the province 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		*CARs of New Product*	
	(1)	(2)	(3)	(4)
Treatment × *Net # of Patents Sold*	0.107**	0.105**	-0.085**	-0.082**
	(0.053)	(0.048)	(0.036)	(0.036)
Treatment	0.207	0.168	-0.024	-0.036
	(0.152)	(0.144)	(0.073)	(0.072)
Observations	24,005	24,005	32,688	32,688
Pseudo/Adjusted R-squared	0.7727	0.7790	0.1187	0.1195
Firm fixed effects	Yes	Yes	Yes	Yes
Industry × Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table IA6: R&D Efficiency and buyer-seller trading status

The regressions in this table examine how a firm's buyer-seller status in patent trading is related to its R&D efficiency. The dependent variable is the net number of patents sold by a firm (i.e., the number of patents a firm sells subtracted by the number of patents the firm buys) during the sample period. The main explanatory variable *R&D Efficiency* is the average R&D efficiency of the firm. Column (1) reports the results without control variables and we add the control variables (as delineated in Section 2.4) to column (2). Standard errors are clustered at the province level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Net # of Patents Sold	
	(1)	(2)
R&D Efficiency	2.016*	2.238*
	(1.156)	(1.270)
Observations	2,533	2,533
R-squared	0.0156	0.0171
Control variables	No	Yes

Table IA7: Patent trading and firm innovating performance

We evaluate a firm's innovating performance in this table. The *Treatment* indicator takes the value of one if a patent exchange has been established in the firm's province and zero otherwise. *Innovation Quality* is 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). *Explorative Innovation*, *Exploitative Innovation*, and *Breakthrough Innovation* refer to the number of explorative patents, exploitative patents, and breakthrough patents of the firms. The analysis is based on Poisson regressions in the last three columns. The control variables are delineated in Section (2.4). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Innovation Quality	*Explorative Innovation*	*Exploitative Innovation*	*Breakthrough Innovation*
	(1)	(2)	(3)	(4)
Treatment	0.084**	0.322***	0.152	0.233*
	(0.034)	(0.088)	(0.151)	(0.127)
Observations	24,005	7,046	7,046	20,250
Adjusted/Pseudo R-squared	0.1859	0.7089	0.4635	0.6212
Firm fixed effects	Yes	Yes	Yes	Yes
Industry × Year fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table IA8: Technological distance and patent sale

We examine how the decision to sell a patent relates to the technological distance measure in the patent-level regressions in this table. The empirical specification of the regressions 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. Following the existing literature (e.g., Akcigit et al. (2016), Brav et al. (2018), Ma et al. (2022)), we examine the technological distance metric with $\iota = \frac{2}{3}$ in column (1) and $\iota = \frac{1}{3}$ in column (2). The control variables are delineated in Section (IA1.3). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Patent Sold	
Distance metric	$\iota = \frac{2}{3}$	$\iota = \frac{1}{3}$
	(1)	(2)
Distance	0.0035***	0.0026***
	(0.0008)	(0.0006)
Observations	1,897,584	1,897,584
Adjusted R-squared	0.4158	0.4158
Patent assignee fixed effects	Yes	Yes
Technology class fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA9: Technological distance and patent licensing

We examine how the decision to license out a patent relates to the technological distance measure in the patent-level regressions in this table. The empirical specification of the regressions follows Akcigit et al. (2016). The dependent variable *Patent Licensed Out* takes the value of one if a patent has been licensed out 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. Following the existing literature (e.g., Akcigit et al. (2016), Brav et al. (2018), Ma et al. (2022)), we examine the technological distance metric with $\iota = \frac{2}{3}$ in column (1) and $\iota = \frac{1}{3}$ in column (2). The control variables are delineated in Section (IA1.3). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Patent Licensed Out	
Distance metric	$\iota = \frac{2}{3}$	$\iota = \frac{1}{3}$
	(1)	(2)
Distance	0.0018***	0.0020***
	(0.0003)	(0.0003)
Observations	1,897,584	1,897,584
Adjusted R-squared	0.0259	0.0259
Technology class fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA10: Patent portfolio adjusted by technological distance

We track how the patent portfolios of the corporate assignees evolve in the patent assignee-year level regressions in this table. The dependent variable is the distance-weighted patent stock (i.e., each patent is weighted by the distance to the patent portfolio of the patent owners). Following the existing literature (e.g., Akcigit et al. (2016), Brav et al. (2018), Ma et al. (2022)), we examine the technological distance metric with $\iota = \frac{2}{3}$ in column (1) and $\iota = \frac{1}{3}$ in column (2). The *Treatment* indicator takes the value of one in a year if a patent exchange has been established in the patent assignee's province by that year, and zero otherwise. The control variables are delineated in Section (IA1.3). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance-Weighted Patent Stock	
Distance metric	$\iota = \frac{2}{3}$	$\iota = \frac{1}{3}$
	(1)	(2)
Treatment	-1.0315*	-0.7637*
	(0.5773)	(0.4584)
Observations	141,099	141,099
Adjusted R-squared	0.7107	0.7092
Patent assignee fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA11: Technological distance to buyer's patents

In this table, we examine the technological distance of the patents traded to the buyer's patents in patent-level regressions. The dependent variable in this table is the technological distance of a patent to the buyer's patents in each patent trading transaction. Following the existing literature (e.g., Akcigit et al. (2016), Brav et al. (2018), Ma et al. (2022)), we examine the technological distance metric with $\iota = \frac{2}{3}$ in column (1) and $\iota = \frac{1}{3}$ in column (2). The *Treatment* indicator takes the value of one in a year if a patent exchange has been established in the patent buyer's province by that year, and zero otherwise. The control variables are delineated in Internet Appendix Section (IA1.3). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance to Buyer's Patents	
Distance metric	$\iota = \frac{2}{3}$	$\iota = \frac{1}{3}$
	(1)	(2)
Treatment	-0.0253*	-0.0344*
	(0.0150)	(0.0177)
Observations	88,690	88,690
Adjusted R-squared	0.6755	0.6544
Patent assignee fixed effects	Yes	Yes
Technology class fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA12: Specialization by scope of innovation and financial constraints

In this table, we investigate the pattern of specialization in terms of the scope of innovation while accounting for the role of financial constraints. Specifically, we trace how the technological distance between a patent and its assignee's patent portfolio evolves around the establishment of patent exchanges 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. Following the existing literature (e.g., Akcigit et al. (2016), Brav et al. (2018), Ma et al. (2022)), we examine the technological distance metric with $\iota = \frac{2}{3}$ in column (1) and $\iota = \frac{1}{3}$ in column (2). The *Treatment* indicator takes the value of one in a year if a patent exchange has been established in the patent assignee's province by that year, and zero otherwise. The dummy variable *Constrained* in this table takes the value of one if the financial constraint a firm faces during the pre-event period (i.e., before the establishment of patent exchanges) is above the sample average of all firms and zero otherwise. The control variables are delineated in Section (3.4). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance	
Distance metric	$\iota = \frac{2}{3}$	$\iota = \frac{1}{3}$
	(1)	(2)
Treatment × *Constrained*	-0.0515***	-0.0483***
	(0.0020)	(0.0022)
Treatment	-0.0245***	-0.0312***
	(0.0052)	(0.0057)
Observations	150,559	150,559
Adjusted R-squared	0.1691	0.1147
Technology class fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA13: Excluding inter-provincial trade

In this table, we focus on firms that never trade any patents with trading counterparties in other provinces. *Innovation Output* is the number of patent applications a firm files and eventually granted. The analysis is based on Poisson regressions when the dependent variable is *Innovation Output*. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. Odd-numbered regressions in this table report the results without control variables and we add the control variables to even-numbered regressions. The control variables are delineated in Section (2.4). Standard errors are clustered at the province 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		*CARs of New Product*	
	(1)	(2)	(3)	(4)
Treatment × *Net # of Patents Sold*	0.300*	0.315*	-0.156*	-0.148*
	(0.180)	(0.169)	(0.078)	(0.085)
Treatment	0.083	0.087	-0.003	-0.014
	(0.127)	(0.112)	(0.103)	(0.106)
Observations	22,590	22,590	31,212	31,212
Pseudo/Adjusted R-squared	0.7983	0.8029	0.1169	0.1180
Firm fixed effects	Yes	Yes	Yes	Yes
Industry × Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table IA14: Firm operation across multiple provinces

In light of potential firm operations across multiple provinces, we assess a firm's exposure to the treatment event based on the share of patents filed by a firm and its subsidiaries across provinces in this table. To capture a firm's exposure to the treatment event, the variable *Treatment Exposure* in this table is the weighted average treatment indicator across provinces, where the weight for a province is the share of patents filed by a firm and its subsidiaries in that province during the pre-event period (i.e., before the establishment of patent exchanges). *Innovation Output* is the number of patent applications a firm files and eventually granted. The analysis is based on Poisson regressions when the dependent variable is *Innovation Output*. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. Odd-numbered regressions in this table report the results without control variables and we add the control variables to even-numbered regressions. The control variables are delineated in Section (2.4). Standard errors are clustered at the province 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		*CARs of New Product*	
	(1)	(2)	(3)	(4)
Treatment Exposure × *Net # of Patents Sold*	0.106**	0.091*	-0.088**	-0.083**
	(0.045)	(0.050)	(0.037)	(0.038)
Treatment Exposure	0.247	0.165	-0.018	-0.031
	(0.154)	(0.147)	(0.093)	(0.093)
Observations	24,005	24,005	32,688	32,688
Pseudo/Adjusted R-squared	0.7959	0.8018	0.1187	0.1195
Firm fixed effects	Yes	Yes	Yes	Yes
Industry × Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table IA15: Stacked regressions

In this table, we follow the recommendations of Baker et al. (2022) to address the "bad comparisons" concern in the context of staggered treatment timing and treatment effect heterogeneity. Specifically, we conduct the stacked regression analysis (e.g., Cengiz et al. (2019)) and report the results in this table. To be concrete, we follow Cengiz et al. (2019) to create event-specific "clean 2×2" datasets combining each treated cohort with clean control cohorts. In columns (1) and (2), the clean control cohorts are the not-yet-treated groups. In columns (3) and (4), the clean control cohorts are the never-treated groups. We conduct the analysis by stacking these event-specific datasets together (and each dataset is indexed by a dataset-specific identifier). *Innovation Output* is the number of patent applications a firm files and eventually granted. The analysis is based on Poisson regressions when the dependent variable is *Innovation Output*. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. *Treat* takes the value of one for the treated cohorts and *Post* takes the value of one after the treatment starting year. The control variables are delineated in Section (2.4). Standard errors are clustered at the province × sub-experiment level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Control cohort: not-yet treated		*Control cohort: never treated*	
	Innovation Output	*CARs of New Product*	*Innovation Output*	*CARs of New Product*
	(1)	(2)	(3)	(4)
Treat × Post × Net # of Patents Sold	0.150***	-0.181***	0.093*	-0.192***
	(0.052)	(0.048)	(0.049)	(0.049)
Treat × Post	-0.131	-0.119	-0.192	-0.091
	(0.091)	(0.071)	(0.120)	(0.084)
Post × Net # of Patents Sold	-0.027	0.119***	0.038	0.131***
	(0.045)	(0.028)	(0.040)	(0.028)
Observations	23,996	33,262	22,405	29,361
Adjusted/Pseudo R-squared	0.3814	0.1168	0.4288	0.1237
Firm × sub-experiment fixed effects	Yes	Yes	Yes	Yes
Province × sub-experiment fixed effects	Yes	Yes	Yes	Yes
Year × sub-experiment fixed effects	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes

Table IA16: Placebo test

In this table, we conduct a placebo test based on the never-treated groups (i.e., provinces without any patent exchanges). In this placebo test, we assign an artificial treatment starting year to each province without any patent exchanges. Specifically, we apply the propensity score matching (PSM) method to match each province without any patent exchanges with a province in the treated group. In each pair of matched provinces, we assign the treatment starting year of the treated province to the province without any patent exchanges. Based on this treatment starting year, we artificially assign a false treatment status to firms in provinces without any patent exchanges. The *Treatment* indicator takes the value of one for firms in such pseudo-treated provinces (i.e., those without any patent exchanges) and during the years after their (artificially assigned) treatment starting years, and zero otherwise. The pseudo-control group in these regressions comprises of firms in treated provinces but during the pre-event period before the firms receive any treatment. Hence, neither the pseudo-treated group nor the pseudo-control group in these regressions has received any treatment. *Innovation Output* is the number of patent applications a firm files and eventually granted. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. The control variables are delineated in Section (2.4). Standard errors are clustered at the province level and reported in the parentheses. ***, **, * denote significance at the 1%, 5%, and 10% level.

	Innovation Output	*CARs of New Product*
	(1)	(2)
Treatment × *Net # of Patents Sold*	0.023	0.024
	(0.084)	(0.015)
Treatment	-0.042	-0.138
	(0.167)	(0.168)
Observations	2,995	6,644
Pseudo/Adjusted R-squared	0.7054	0.0796
Firm fixed effects	Yes	Yes
Industry × Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA17: M&A

We control for a firm's mergers and acquisitions (M&As) activities in the regressions reported in this table. Specifically, the control variable *M&A* takes the value of one in a year if a firm acquires another company or is involved in a merger in that year and zero otherwise. *Innovation Output* is the number of patent applications a firm files and eventually granted. The analysis is based on Poisson regressions when the dependent variable is *Innovation Output*. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. Other control variables are delineated in Section (2.4). Standard errors are clustered at the province 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	*CARs of New Product*
	(1)	(2)
Treatment × Net # of Patents Sold	0.089*	-0.077*
	(0.051)	(0.038)
Treatment	0.148	-0.043
	(0.138)	(0.096)
M&A	0.016	0.480***
	(0.034)	(0.046)
Observations	24,005	32,688
Pseudo/Adjusted R-squared	0.8018	0.1238
Firm fixed effects	Yes	Yes
Industry × Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA18: Firm R&D as outcome variable

We examine a firm's R&D expenditure as the outcome variable in this table. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. Standard errors are clustered at the province level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	R&D	
	(1)	(2)
Treatment × *Net # of Patents Sold*	0.018***	0.010***
	(0.004)	(0.004)
Treatment	0.394	0.294
	(0.272)	(0.280)
Observations	25,828	25,828
Pseudo R-squared	0.9005	0.9104
Firm fixed effects	Yes	Yes
Industry × Year fixed effects	Yes	Yes
Control variables	No	Yes

Table IA19: Renewed patents

We focus on patents that have been renewed at least three times in this table. *Innovation Output* is the number of patent applications a firm files and eventually granted. The analysis is based on Poisson regressions when the dependent variable is *Innovation Output*. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. Odd-numbered regressions in this table report the results without control variables and we add the control variables to even-numbered regressions. The control variables are delineated in Section (2.4). Standard errors are clustered at the province 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		*CARs of New Product*	
	(1)	(2)	(3)	(4)
Treatment × *Net # of Patents Sold*	0.107**	0.093*	-0.086**	-0.081**
	(0.044)	(0.050)	(0.037)	(0.037)
Treatment	0.242	0.155	-0.032	-0.040
	(0.172)	(0.138)	(0.097)	(0.097)
Observations	23,818	23,818	32,688	32,688
Pseudo/Adjusted R-squared	0.7965	0.8022	0.1187	0.1195
Firm fixed effects	Yes	Yes	Yes	Yes
Industry × Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table IA20: Controlling for other potentially related innovation policies

We control for other potentially related innovation policies in this table while exploiting the regional variation of these innovation policies in the regressions. Specifically, *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 firm's province in that year, and zero otherwise. Analogously, *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. Other control variables are delineated in Section (2.4). Standard errors are clustered at the province 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	*CARs of New Product*
	(1)	(2)
Treatment × *Net # of Patents Sold*	0.101*	-0.081**
	(0.055)	(0.037)
Treatment	0.182	-0.044
	(0.127)	(0.094)
Patent Subsidy	0.130	-0.007
	(0.106)	(0.057)
Tax Cut	-0.151	0.044
	(0.103)	(0.062)
Tech SMEs	0.106	-0.039
	(0.164)	(0.075)
Observations	24,005	32,688
Pseudo/Adjusted R-squared	0.7897	0.1194
Firm fixed effects	Yes	Yes
Industry × Year fixed effects	Yes	Yes
Other control variables	Yes	Yes

Table IA21: Controlling for government subsidies

In this table, we control for *Subsidy* (i.e., the amount of government subsidy a firm receives scaled by firm assets) in the regressions. *Innovation Output* is the number of patent applications a firm files and eventually granted. The analysis is based on Poisson regressions when the dependent variable is *Innovation Output*. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. Other control variables are delineated in Section (2.4). Standard errors are clustered at the province 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	*CARs of New Product*
	(1)	(2)
Treatment × *Net # of Patents Sold*	0.088*	-0.080**
	(0.051)	(0.037)
Treatment	0.147	-0.039
	(0.137)	(0.097)
Subsidy	0.018	-0.016
	(0.030)	(0.020)
Observations	24,005	32,688
Firm fixed effects	Yes	Yes
Industry × Year fixed effects	Yes	Yes
Other control variables	Yes	Yes

Table IA22: Excluding non-traders

In this table, we exclude the non-traders (i.e., firms that do not trade any patents) from the regressions. *Innovation Output* is the number of patent applications a firm files and eventually granted. The analysis is based on Poisson regressions when the dependent variable is *Innovation Output*. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. Odd-numbered regressions in this table report the results without control variables and we add the control variables to even-numbered regressions. The control variables are delineated in Section (2.4). Standard errors are clustered at the province 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		*CARs of New Product*	
	(1)	(2)	(3)	(4)
Treatment × *Net # of Patents Sold*	0.101**	0.087*	-0.070*	-0.072*
	(0.044)	(0.051)	(0.036)	(0.037)
Treatment	0.252	0.142	0.055	0.042
	(0.193)	(0.154)	(0.123)	(0.123)
Observations	15,618	15,618	17,446	17,446
Pseudo/Adjusted R-squared	0.8022	0.8083	0.1137	0.1150
Firm fixed effects	Yes	Yes	Yes	Yes
Industry × Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table IA23: Incubator services

We assess the role of incubator services provided by some patent exchanges in the patent-level regressions in this table. The dependent variable *Patent Traded* takes the value of one if a patent has been traded by the end of the sample period and zero otherwise. The *Treatment* indicator takes the value of one in a year if a patent exchange has been established in the patent assignee's province by that year, and zero otherwise. The *Incubator* indicator takes the value of one in a year if a patent exchange has been established in the patent assignee's province by that year and the patent exchange provides incubator services, and zero otherwise. The control variables are delineated in Section (3.4). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Patent Traded	
	(1)	(2)
Treatment $\times$ *Incubator*	0.0044*	0.0107***
	(0.0026)	(0.0026)
Treatment	0.0118***	0.0058**
	(0.0029)	(0.0029)
Observations	1,871,248	1,871,248
Adjusted R-squared	0.4174	0.4176
Patent assignee fixed effects	Yes	Yes
Technology class fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	No	Yes

Table IA24: Intellectual property rights

We assess the role of intellectual property rights (IPRs) in this table. The dummy variable *Strong IPRs* in this table is based on the average values of the IPRs proxy in Fang et al. (2017) during the pre-event period (i.e., before the establishment of patent exchanges). Specifically, *Strong IPRs* takes the value of one if the IPRs score of a firm's province is above the average score across all provinces and zero otherwise. *Innovation Output* is the number of patent applications a firm files and eventually granted. The analysis is based on Poisson regressions when the dependent variable is *Innovation Output*. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. The control variables are delineated in Section (2.4). Standard errors are clustered at the province 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	*CARs of New Product*
	(1)	(2)
Treatment × Net # of Patents Sold × Strong IPRs	0.414*	-0.206***
	(0.240)	(0.064)
Treatment × Net # of Patents Sold	-0.276	0.144**
	(0.222)	(0.055)
Treatment × Strong IPRs	-0.352	0.071
	(0.222)	(0.109)
Treatment	0.487*	-0.108
	(0.266)	(0.144)
Observations	22,681	30,722
Pseudo/Adjusted R-squared	0.8043	0.1210
Firm fixed effects	Yes	Yes
Industry × Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA25: Number of Patents Sold

We conduct a dynamic DiD analysis at the province-year level in this table. The dependent variable is the number of patents sold in a province and the analysis is based on Poisson regressions. $Treatment(-\tau)$ and $Treatment(\tau)$ correspond to τ years before and after the establishment of patent exchanges, respectively. $Treatment(4-)$ refers to four or more years before the event, and $Treatment(4+)$ refers to four or more years after the event. In column (2), we control for the patent stock that could be sold in a province, GDP per capita, and the ratio of R&D to GDP. ***, **, * denote significance at the 1%, 5%, and 10% level.

	Number of Patents Sold	
	(1)	(2)
Treatment(4−)	0.106	0.035
	(0.420)	(0.402)
Treatment(−3)	0.261	0.217
	(0.427)	(0.479)
Treatment(−2)	0.180	0.136
	(0.171)	(0.202)
Treatment(−1)	0.105	0.094
	(0.237)	(0.218)
Treatment(1)	0.330**	0.425***
	(0.136)	(0.142)
Treatment(2)	0.297*	0.459**
	(0.156)	(0.184)
Treatment(3)	0.724**	0.972***
	(0.300)	(0.324)
Treatment(4+)	0.525***	0.820***
	(0.176)	(0.209)
Observations	589	589
Pseudo R-squared	0.9666	0.9691
Province fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	No	Yes

Table IA26: Small vs large firms

We distinguish between small and large firms in this table. The dummy variable *Smaller Firms* in this table is based on the average value of firm assets during the pre-event period (i.e., before the establishment of patent exchanges). Specifically, *Smaller Firms* takes the value of one if a firm's assets are below the average value across all firms and zero otherwise. *Innovation Output* is the number of patent applications a firm files and eventually granted. The analysis is based on Poisson regressions when the dependent variable is *Innovation Output*. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. Odd-numbered regressions in this table report the results without control variables and we add the control variables to even-numbered regressions. The control variables are delineated in Section (2.4). Since firm accounting information during the pre-event period is missing in some cases, the number of observations in this table is smaller than that of the baseline analysis. Standard errors are clustered at the province level and reported in the parentheses. ***, **, * denote significance at the 1%, 5%, and 10% level.

	Innovation Output		*CARs of New Product*	
	(1)	(2)	(3)	(4)
Treatment × *Net # of Patents Sold* × *Smaller Firms*	0.478**	0.510***	-0.042*	-0.044*
	(0.203)	(0.196)	(0.021)	(0.022)
Treatment × *Net # of Patents Sold*	0.013***	0.007*	-0.008*	-0.008*
	(0.004)	(0.004)	(0.004)	(0.004)
Treatment × *Smaller Firms*	0.211	0.258	0.070	0.074
	(0.312)	(0.320)	(0.048)	(0.047)
Treatment	0.178	0.080	-0.053	-0.055
	(0.194)	(0.158)	(0.091)	(0.092)
Observations	17,120	17,120	23,504	23,504
Firm fixed effects	Yes	Yes	Yes	Yes
Industry × Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table IA27: Firm advertising expenditure

We examine firm advertising expenditure as an outcome variable in this table. In columns (1) and (2), the dependent variables are a firm's advertising expenditure. In columns (3) and (4), the dependent variables are the natural logarithm of one plus a firm's advertising expenditure. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. Odd-numbered regressions in this table report the results without control variables and we add the control variables to even-numbered regressions. The control variables are delineated in Section (2.4). Standard errors are clustered at the province level and reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Advertising		*Log Advertising*	
	(1)	(2)	(3)	(4)
Treatment × *Net # of Patents Sold*	-0.086**	-0.082**	-0.092**	-0.076**
	(0.037)	(0.036)	(0.034)	(0.032)
Treatment	0.004	0.005	-0.181	-0.173
	(0.023)	(0.022)	(0.114)	(0.117)
Observations	32,688	32,688	32,688	32,688
Adjusted R-squared	0.7583	0.7623	0.7479	0.7536
Firm fixed effects	Yes	Yes	Yes	Yes
Industry × Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table IA28: Patent trading and innovation specialization

We study the innovation specialization pattern between patent buyers and sellers in this table. *Innovation Output* is the number of patent applications a firm files and eventually granted. The analysis is based on Poisson regressions when the dependent variable is *Innovation Output*. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. *Patent Seller* (*Patent Buyer*) is a dummy variable that takes the value of one for patent sellers (buyers) and zero otherwise. The control variables are delineated in Section (2.4). Standard errors are clustered at the province 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	*CARs of New Product*
	(1)	(2)
Treatment × *Patent Seller*	0.445*	-0.364*
	(0.268)	(0.192)
Treatment × *Patent Buyer*	-0.560**	0.239**
	(0.219)	(0.110)
Treatment	0.240	0.012
	(0.284)	(0.092)
Observations	24,005	32,688
Pseudo/Adjusted R-squared	0.8152	0.1195
Firm fixed effects	Yes	Yes
Industry × Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA29: Patent licensing and innovation specialization

We examine the innovation specialization pattern between patent licensors and licensees in this table. *Innovation Output* is the number of patent applications a firm files and eventually granted. The analysis is based on Poisson regressions when the dependent variable is *Innovation Output*. *CARs of New Product* is the cumulative abnormal return of firm new product announcements. The *Treatment* indicator takes the values of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. *Patent Licensor* (*Patent Licensee*) is a dummy variable that takes the value of one for patent licensors (licensees) and zero otherwise. The control variables are delineated in Section (2.4). Standard errors are clustered at the province 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	*CARs of New Product*
	(1)	(2)
Treatment × *Patent Licensor*	0.659**	-0.274*
	(0.289)	(0.155)
Treatment × *Patent Licensee*	-0.357**	0.321**
	(0.174)	(0.156)
Treatment	-0.060	-0.036
	(0.148)	(0.093)
Observations	24,005	32,688
Pseudo/Adjusted R-squared	0.7281	0.1235
Firm fixed effects	Yes	Yes
Industry × Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA30: Specialization in terms of the scope of innovation

In this table, we investigate the pattern of specialization in terms of the scope of innovation. The dependent variable *Distance* is the technological distance of a patent to the patent assignee's patent portfolio prior to this patent. Following the existing literature (e.g., Akcigit et al. (2016), Brav et al. (2018), Ma et al. (2022)), we examine the technological distance metric with $\iota = \frac{2}{3}$ in column (1) and $\iota = \frac{1}{3}$ in column (2). The *Treatment* indicator takes the value of one in a year if a patent exchange has been established in the patent assignee's province by that year, and zero otherwise. *Patent Seller* (*Patent Buyer*) is a dummy variable that takes the value of one for patent sellers (buyers) and zero otherwise. The control variables are delineated in Section (3.4). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Distance	
Distance metric	$\iota = \frac{2}{3}$	$\iota = \frac{1}{3}$
	(1)	(2)
Treatment × *Seller*	-0.0133***	-0.0156***
	(0.0040)	(0.0045)
Treatment × *Buyer*	-0.0093***	-0.0095***
	(0.0032)	(0.0035)
Treatment	-0.0016	0.0008
	(0.0035)	(0.0040)
Observations	1,897,584	1,897,584
Adjusted R-squared	0.6462	0.5680
Patent assignee fixed effects	Yes	Yes
Technology class fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA31: Firm productivity, profitability, and valuation

In this table, the dependent variable is a firm's total factor productivity in column (1), a firm's return on assets in column (2), and a firm's Tobin's Q in column (3). The TFP estimation, following Ackerberg et al. (2015), is based on a Cobb–Douglas production function where output is proxied by a firm's total revenue. Inputs include capital and labor, approximated by total assets and total number of employees. Intermediate inputs are approximated by cash payments for raw materials and service, following Giannetti et al. (2015). Tobin's Q refers to the ratio of the sum of the market value of equity and the book value of debt to the sum of the book value of debt and equity. The *Treatment* indicator in this table takes the value of one in a year if a patent exchange has been established in the firm's province by that year and zero otherwise. The control variables are delineated in Section (2.4). *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	TFP	*ROA*	*Tobin's Q*
	(1)	(2)	(3)
Treatment	0.012*	0.005***	0.046**
	(0.006)	(0.002)	(0.023)
Observations	32,252	32,252	32,252
Adjusted R-squared	0.5407	0.2014	0.4761
Industry × Year fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes