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(not to be published)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 patent trading

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 IA4. 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 during 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.

In the patent assignee-year level regressions reported in Internet Appendix Table IA5, we track how the patent portfolios of the corporate assignees evolve between 2001 and 2019.[20] The dependent variable is the distance-weighted patent stock (i.e., each patent is weighted by the distance to the

[20] We focus on the listed firms in the firm-year level regressions (e.g., Table 1), and the number of observations in those regressions is smaller than that in Table IA5.

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 estimate of the treatment indicator suggests that the establishment of patent exchanges is negatively associated with the distance-weighted patent stock (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.

IA1.2 Robustness checks

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

IA1.2.1 Excluding inter-provincial trade

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 IA6. As shown by the results in this table, our findings are robust to excluding inter-provincial trade.

IA1.2.2 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 IA7. 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 and taking firm operations across multiple provinces into account.

IA1.2.3 Stacked regressions

We follow the recommendations of Baker et al. (2022) to address the "bad comparisons" concern in the context of staggered treatment timing. Specifically, we conduct the stacked regression analysis (e.g., Cengiz et al. (2019)) and report the results in Internet Appendix Table IA8. To be concrete, we follow Cengiz et al. (2019) to create event-specific "clean 2×2" datasets combining each treated cohort with the never-treated groups (as clean control cohorts). We conduct the analysis by stacking these event-specific datasets together (and each dataset is indexed by a dataset-specific identifier). The results in Internet Appendix Table IA8 suggest that our findings are robust.

IA1.2.4 Mergers and acquisitions

We control for a firm's mergers and acquisitions (M&As) activities in the regressions reported in Internet Appendix Table IA9. 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.

IA1.2.5 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, 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 IA10 and our findings are robust.

IA1.2.6 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 IA11 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.[21] We redo our baseline analysis and report the results in Internet Appendix Table IA11. The results in this table suggest that our findings are robust to excluding low-quality patents.

IA1.2.7 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 IA12. Specifically, *Patent Subsidy* in this table takes the value of one for a firm in a year if there are government subsidies for patents 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.

IA1.2.8 Government stimulus plan during the 2008 financial crisis

One may wonder if the results could be driven by China's massive economic stimulus plan during the 2007–2008 global financial crisis.[22] To capture the effects of the economic stimulus plan of the government, we include an additional control variable *Subsidy* in the regressions and report the results in Internet Appendix Table IA13. To be concrete, *Subsidy* is the amount of government

[21] 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.

[22] 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.

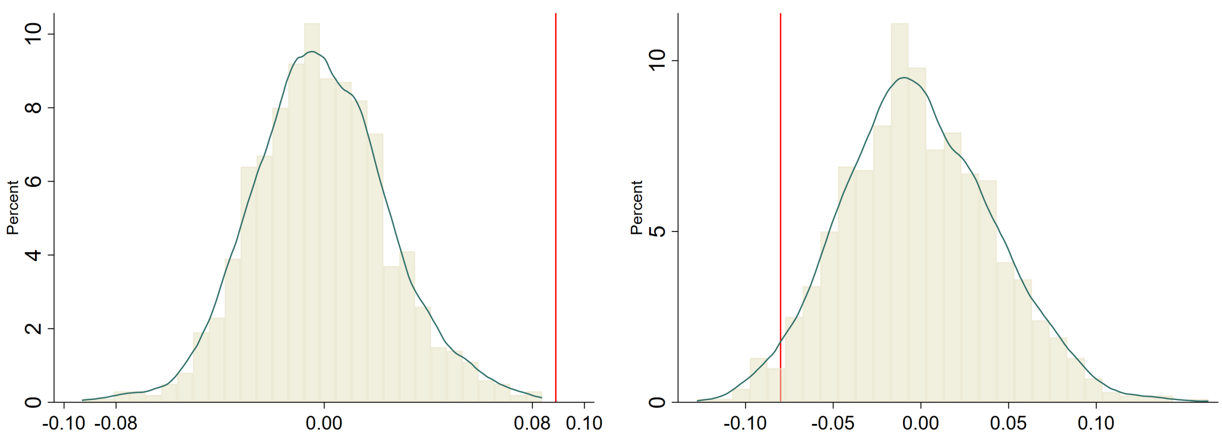
subsidy a firm receives scaled by firm assets. The results in this table suggest that our findings are robust when the government subsidy is accounted for.

IA1.2.9 Random assignment of treatment status

We conduct a placebo test by randomly assigning a false treatment status to observations in our sample and maintaining the true distribution of the event time. If the 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 the baseline estimations. The effects of patent trading on innovation specialization are captured by the interaction term (i.e., "*Treatment* × *Net # of Patents Sold*"), and we plot the empirical distribution of the coefficient estimates of the interaction term in Figure IA1. In this figure, panels IA1a and IA1b report the empirical distribution of the coefficient estimates of the interaction term in columns (2) and (4) of Table 1 (i.e., the 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 IA1, 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: 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 and 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 the baseline estimations. The effects of patent trading on innovation specialization are captured by the interaction term (i.e., "*Treatment* × *Net # of Patents Sold*"), and we plot the empirical distribution of the coefficient estimates of the interaction term in this figure. Specifically, panels IA1a and IA1b report the empirical distribution of the coefficient estimates of the interaction term in columns (2) and (4) of Table 1 (i.e., the 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 during 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 1.16 percentage points (12.8% 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***	0.0116***
	(0.0025)	(0.0025)
Observations	1,897,579	1,897,579
Adjusted R-squared	0.4154	0.4159
Patent assignee fixed effects	Yes	Yes
Technology class fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	No	Yes

Table IA2: 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 IA3: Treatment based on distance to 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 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). *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*	0.100*	0.094**	-0.066*	-0.065*
	(0.054)	(0.047)	(0.035)	(0.035)
Treatment	0.153	0.096	0.043	0.028
	(0.168)	(0.169)	(0.076)	(0.076)
Observations	24,005	24,005	32,688	32,688
Pseudo/Adjusted R-squared	0.7726	0.7789	0.1186	0.1195
Firm fixed effects	Yes	Yes	Yes	Yes
Industry × Year fixed effects	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes

Table IA4: 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 during 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 (IA1.1). *** 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	0.0034***	0.0025***
	(0.0008)	(0.0006)
Observations	1,897,579	1,897,579
Adjusted R-squared	0.4159	0.4159
Patent assignee fixed effects	Yes	Yes
Technology class fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA5: 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 (IA1.1). *** 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	-1.0325*	-0.7651*
	(0.5772)	(0.4586)
Observations	141,099	141,099
Adjusted R-squared	0.7107	0.7091
Patent assignee fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA6: 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 IA7: Firm operation across multiple provinces

In this table, 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. 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 IA8: Stacked regressions

We conduct the stacked regression analysis in this table. Specifically, we follow Cengiz et al. (2019) to create event-specific "clean 2 × 2" datasets combining each treated cohort with the never-treated groups (as clean control cohorts). 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 × cohort 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)
Treat × Post × Net # of Patents Sold	0.093*	-0.192***
	(0.049)	(0.049)
Treat × Post	-0.192	-0.091
	(0.120)	(0.084)
Post × Net # of Patents Sold	0.038	0.131***
	(0.040)	(0.028)
Observations	22,405	29,361
Pseudo/Adjusted R-squared	0.4288	0.1237
Firm × cohort fixed effects	Yes	Yes
Province × cohort fixed effects	Yes	Yes
Year × cohort fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA9: 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 $\times$ *Net # of Patents Sold*	0.089*	-0.080**
	(0.051)	(0.037)
Treatment	0.149	-0.040
	(0.136)	(0.097)
M&A	0.014	-0.026
	(0.031)	(0.045)
Observations	24,005	32,688
Pseudo/Adjusted R-squared	0.8018	0.1195
Firm fixed effects	Yes	Yes
Industry $\times$ Year fixed effects	Yes	Yes
Control variables	Yes	Yes

Table IA10: 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 IA11: 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 IA12: Controlling for other potentially related innovation policies

In this table, we control for other potentially related 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 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 IA13: 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
Control variables	Yes	Yes