Technological Decoupling? The Impact on Innovation of US Restrictions on Chinese Firms

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Abstract

Recent U.S.-China tensions have raised the specter of technological decoupling. This paper examines the impact of U.S. export restrictions and technology licensing on Chinese firms' innovation. It finds that U.S. sanctions reduce the quantity and quality of patent outputs of targeted Chinese firms, primarily due to decreased collaboration with U.S. inventors. However, firms with strong preexisting innovation capacities—such as a higher initial patent stock or those in sectors closer to the U.S. technology frontier—experience less severe reductions in patent output. Sanctions in specific technology fields lead to a decline in the patent output of both Chinese firms with U.S. collaborators and U.S. firms with Chinese collaborators.

Keywords: Innovation, Entity List, Decoupling

JEL Codes: O33, O38, O47

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1 Introduction

China has made significant strides in innovation since joining the WTO and opening its markets to international trade, investment, and knowledge flows. This integration catalyzed rapid growth, with foreign firms playing a pivotal role in facilitating the diffusion of advanced technologies and enhancing China's innovation capacity (Branstetter et al. 2023; Fang et al. 2020; Jiang et al. 2024 and Wei et al. 2017). The share of patents filed by Chinese assignees in the United States Patent and Trademark Office (USPTO) rose from 0.2% in 2000 to 7.2% in 2022.[1] This surge in patent activity, underscores the importance of global integration and international collaboration for China's innovation ecosystem.

However, technology has become a source of tension between the U.S. and China – raising the prospect of technological decoupling. The U.S. Department of Commerce has increasingly used the Entity List to regulate technology transfers and restrict exports of goods containing U.S. components to Chinese entities. The Entity List subjects selected foreign entities to licensing requirements for exporting, reexporting, and/or transferring certain technologies and goods. For example, Huawei's inclusion in the Entity List in 2019 prohibited Google from providing its services to Huawei, directly affecting Huawei's smartphone business and prompting the company to develop its own operating system (Reuters 2019). The number of Chinese firms on this list has increased dramatically from 3 in 2010 to 345 in 2022, with a significant increase in 2018. Despite the extensive discussion of these U.S. sanctions in the media, there is little research that has explored the effects on Chinese firms' innovation.

This paper examines how inclusion in the U.S. Entity List affects the innovation activities of Chinese firms. Data from PATSTAT, a patent database, is used to measure firms' innovation output and its quality by examining patent applications and citations. The key finding is that inclusion on the Entity List reduces the quantity and quality of a firm's patent output. The result is robust to a variety of empirical strategies - difference-in-differences and event study design accounting for staggered treatment (following Callaway and Sant'Anna 2021) - where sanctioned firms are matched to non-sanctioned firms with similar initial firm characteristics and patent portfolios using propensity score weights.[2] The event study plots suggest common (pre-sanction) trends between

[1]Based on data from WIPO IP Statistics Data Center.
[2]Sanctions and Entity List are used interchangeably in this paper.

our treatment and matched control group firms, and we also show balance in covariate levels.

To investigate the underlying mechanism, we draw on literature emphasizing the importance of U.S. collaborations for Chinese research (Veugelers 2017; Aghion et al. 2024). We first show that Chinese firms' innovation output is positively associated with collaboration with U.S. inventors, more so than collaboration with inventors in Europe or advanced East Asia. Secondly, inclusion in the Entity List reduces collaborations of Chinese firms with U.S. inventors. Finally, the decline in patent output due to inclusion on the Entity List is driven primarily by Chinese firms with prior U.S. collaborators.

We also investigate whether domestic innovation capacity can mitigate the effect of sanctions and find some evidence in support of this hypothesis. Specifically, more innovative firms, i.e., those with a higher initial patent stock, suffer a smaller decrease in patent output following the imposition of U.S. sanctions. In addition, we examine the role of technological distance from the U.S., comparing the stock of Chinese patents relative to the U.S. following Akcigit et al. 2024, and the importance of cross-border technology sourcing, following Bian et al. 2024. Sanctioned firms in sectors with a smaller technology distance to the U.S., or firms in sectors that are less dependent on foreign technology experienced a smaller decline in patent output compared to sanctioned firms in other sectors.

After examining the impact on sanctioned firms, we consider spillovers to non-sanctioned firms in China and firms in the U.S. that operate in the same primary technology fields as sanctioned firms.[3] We find that the influence of the U.S. Entity List extends beyond the directly targeted firms. The treatment group consists of firms operating in the sanctioned field, while the control group includes similar firms in non-sanctioned fields matched using propensity score matching. Our empirical analysis shows a modest but significant negative spillover effect on the innovation output of Chinese firms in sanctioned technology fields. No comparable spillover effect was detected for U.S. firms. However, Chinese firms with previous U.S. collaborators and U.S. firms with previous Chinese collaborators both saw a significant decrease in patent activity following the sanctioning of their primary technology fields.

The potential spillover effect is not limited to firms in the sanctioned technology fields but could

[3] To estimate these spillover effects, we assign firms to a single technology field using the most common field of their patents. Sanctioned technology fields are defined using the sanctioned firms' primary technology fields.

also affect firms in unsanctioned technology fields through the innovation network. Using patent citations, we map out forward and backward linkages of each technology field within the innovation network. We find that Chinese firms in downstream technology fields – those using technologies produced by sanctioned fields – experience a decline in patent output. However, Chinese firms in upstream fields – those producing technologies utilized by the sanctioned fields – saw a modest increase in their patent output. This finding suggests that U.S. sanctions may stimulate domestic innovation in sectors positioned upstream of sanctioned technologies.

This paper contributes to two main areas of existing literature. First, it estimates the impact of the intensifying tension between the U.S. and China on innovation. Most existing research has focused on the academic output of scientists and research publications (for instance, see Aghion et al. 2024, Flynn et al. 2024, and Jia et al. 2024). Both Aghion et al. 2024 and Jia et al. 2024 examine the impact of the "China Initiative" launched by the Trump administration, with the former focusing on the impact on Chinese scientists and the latter on U.S. scientists.[4] Our study focuses on the innovation output of Chinese firms targeted by the Entity List. As such, this paper complements the evidence from Han et al. 2024, who identified adverse effects on the performance of Chinese firms' operating within sanctioned technology fields. We add to their analysis by considering the direct consequences for the firms targeted by Entity List sanctions and examining how these sanctions could affect targeted firms.

Additionally, this study contributes to the literature on the importance of international collaboration in fostering innovation, especially the collaboration and innovation networks between the U.S. and China. Previous studies suggested that collaborating with inventors from technologically more advanced economies can provide firms in less developed economies access to cutting-edge knowledge, thereby enhancing their innovation capacity (Montobbio and Sterzi 2013, Giuliani et al. 2016). These collaborations also bring long-term benefits by enabling inventors to continually produce high-impact innovations (Branstetter et al. 2015, Azoulay et al. 2021). Prior research highlights the importance of U.S. connections for Chinese researchers (for example, Veugelers 2017).[5]

[4]The U.S. Department of Justice describes its "China Initiative" as reflecting the strategic priority of countering Chinese national security threats and reinforcing the President's overall national security strategy. The U.S. Administration seeks to reach multiple goals through the Initiative: (i) identifying and prosecuting those engaged in trade secret theft, hacking, and economic espionage; (ii) protecting critical infrastructure against external threats through foreign direct investment and supply chain compromises; and (iii) combating covert efforts to influence the American public and policymakers without proper transparency.

[5]Qiu et al. 2024 and Qiu et al. 2025 highlight frictions in the dissemination of Chinese scientific research beyond

Xie and Freeman 2023 find that U.S.-China collaborations are linked to a higher quality of both U.S. and Chinese research.[6] They note that the previously growing share of U.S. or Chinese papers with U.S.-China collaborations has fallen since 2018. Flynn et al. 2024 find that since 2016, Chinese scientific researchers were less likely to cite U.S. papers (compared to UK papers), which they attribute to rising U.S.-China geopolitical tensions.[7] Aghion et al. 2024 document a decline in publications by Chinese researchers who previously collaborated with U.S. colleagues following the "China Initiative". Our paper expands on these findings by analyzing the impact on innovation at the firm and sector levels, evaluating the importance of U.S. collaborations for Chinese firms' innovation.

The remainder of the paper is structured as follows. Section 2 gives an overview of China's innovation trends and collaboration patterns. Section 3 discusses the data used in the analysis. Section 4 presents empirical evidence on the impact of U.S. sanctions on Chinese firms' innovation. Section 5 discusses the potential mechanism. Section 6 tests the spillover effect on indirectly affected firms and section 7 concludes.

2 Recent Trends in Chinese Patenting

China has rapidly enhanced its innovation capability since 2006 (Figure 1). Chinese applicants filed fewer than 140 thousand patent applications annually in the 1990s. However, this figure surged to nearly 1.6 million by 2022, with 120 thousand patents filed abroad. In 2022, almost 14% of patents filed to the European Patent Office (EPO), United States Patent and Trademark Office (USPTO), and under the Patent Cooperation Treaty (PCT) were filed by Chinese applicants. The literature suggests that the liberalization of domestic markets and foreign direct investment have significantly contributed to the surge in patent filings among Chinese firms (Hu and Jefferson 2009). Knowledge spillovers from multinational companies have increased the innovation capacities of domestic Chinese applicants through either direct technology transfers or collaborations (Holmes et al. 2015).

China, as Chinese research demonstrates a strong home-bias in citations and is less likely to be cited by U.S. papers compared to similar quality research from other countries.

[6]For Chinese research, having returnee Chinese co-authors previously educated in the U.S. is associated with higher citations (a proxy for quality). A positive correlation is observed also with Chinese diaspora co-authors, for U.S. research.

[7]Note Flynn et al. 2024 do not observe a decline in Chinese citations from U.S. research.

Figure 1 goes here

The quality of Chinese innovation has also seen a consistent upward trajectory. The proportion of Chinese patents (i.e., patents filed by Chinese applicants) among the top 1% most cited patents granted by the EPO, USPTO, and under PCT has increased from a mere 0.2% in 1998 to approximately 8% in 2020 (Figure 2, left panel). The improvement in the quality of Chinese patents varies across technology fields (Figure 2, right panel). Overall, the median relative quality of Chinese patents – measured by the average number of citations each Chinese patent receives relative to U.S. patents – has shown significant growth from 2007 to 2016 across all technology fields. The slight decline in median patent quality after 2016 may be a consequence of the escalating US-China tension. Nevertheless, in technology sectors where China has already surpassed the U.S., China continues to exhibit rapid growth in quality. Patents in fields such as autonomous vehicles, computer vision, and battery technology are approaching the highest quality innovation worldwide (Bergeaud and Verluise 2022).

Figure 2 goes here

The patterns of Chinese collaboration have shifted recently. During the 2000s, Chinese innovation was heavily reliant on collaborations with U.S. inventors, which contributed to around 6% of Chinese patents granted in CNIPA and 33% of Chinese patents granted in EPO, USPTO, and under PCT (Figure 3, left panel) from 2002 to 2012. However, since 2012, there has been a noticeable change in the dynamics of U.S. and other foreign collaborations. The relative importance of U.S. collaborators has declined, with Chinese applicants increasingly turning to inventors from advanced East Asia and Europe (Figure 3, right panel). The importance of inventors from these regions has grown, especially after 2016, implying a diversification in China's international collaboration network possibly in response to the intensified tension with the U.S..

Figure 3 goes here

3 Data

3.1 Data Source and Sample

We analyze the impact of being included in the Entity List on a firm's innovation output. The primary data source used in our analysis is the PATSTAT Global 2022 Spring Version. PATSTAT categorizes patent applicants as government entities, companies, individuals, or unknowns. For applicants labeled as unknown, we employ firm-specific identifiers (such as "company", "group", "ltd") in their name to determine their status as firms. For our analysis, we only retain entities identified as firms.

There are three major patent categories granted globally: invention, utility models, and industry design. We exclude industrial design patents from our analysis due to their limited scientific value. Given the varied grant requirements and the absence of utility models in certain patent offices (e.g., USPTO and Canada), our analysis focuses solely on invention patents. Furthermore, China implemented a significant reform in its intellectual property and patent system in 2006. To mitigate the potential impact of these policy changes on our analysis, we only consider patent applications filed after 2006.

Our sample primarily includes firms that engage in ongoing innovation activities. We exclude firms that have not filed patents and those with fewer than three years of patenting activities (which need not be consecutive) from 2006 to 2021. Additionally, firms that had not filed patents in the Chinese patent office during this period were also dropped. After the data cleaning, our sample consists of approximately 28 thousand Chinese firms.

To estimate the impact of U.S. sanctions, we rely on the Entity List issued by the U.S. Department of Commerce. The Entity List is an important part of the U.S. export control system. The U.S. government uses it to impose sanctions against foreign persons or entities, including government organizations, research institutes, companies, and individuals. Entities included in the Entity List must fulfill U.S. license requirements to receive certain exports, reexports, or transfers of items (including technologies) from the U.S.. We obtained the historical Entity List from the Federal Register from 1997 to 2021.

Entities/persons are typically included in the Entity List if they are believed to be involved in activities contrary to U.S. national security interests. After cleaning, we have 375 unique Chinese entities, including firms, universities, research institutes, and government agencies. The Entity List covers entities operating in various domains. For example, China's biggest smartphone vendor, Huawei, and 68 of its non-U.S. affiliates were added to the List in 2019. That year, HiSilicon, Huawei's chip design arm, was also added to the List. These measures have cut access to newer chipsets from the most advanced chipset makers such as TSMC and Samsung, eroding market shares of Huawei and HiSilicon. In 2021, seven supercomputers manufacturers were added to the blacklist: Tianjin Phytium Information Technology, Sunway Microelectronics, Shanghai Center for High-Performance Integrated Circuit Design, and the National Supercomputer Centers of Jinan, Shenzhen, Wuxi, Zhengzhou.

We match the Entity List to the PATSTAT dataset using entity names. To identify the affected corporations, we match the exact entities on the Entity List, as well as their subsidiaries or affiliated entities mentioned on the Entity List. For example, China Aerospace Science and Industry Corporation (CASIC) was added to the Entity List in 2018. We identified all PATSTAT-listed firms associated with CASIC as a sanctioned entity from 2018 onwards. Since our primary focus is on changes in sanctioned firms' innovation behavior, we drop all research institutes and government agencies in our sample. However, if the research institutes or government agencies have affiliated firms or subsidiaries identified as firms, these subsidiaries or affiliated firms are included in our sample and identified as sanctioned firms. After matching, we identify 182 sanctioned firms in PATSTAT.

3.2 Outcome Variable

We use the patent count at time t to measure innovation outcomes in that year. Applicants can file patents across multiple patent offices, such as JPO, EPO, USPTO, and WIPO. Using patents filed in one patent office might not fully reflect applicants' innovation activities. To avoid double counting in patent counts, we track the earliest filing ID of each patent, ensuring the uniqueness of patents in our count. This means a patent's initial filing ID is used to calculate a firm's annual patent filings. Moreover, being added to the Entity List could distinctively impact a firm's patent filing domestically and in foreign offices. The inclusion in the Entity List may reduce a firm's market share internationally, potentially reducing its incentive to file patents in foreign patent offices. To understand these dynamics, we analyze a firm's patent applications in its home country, as well as in the USPTO, EPO, and WIPO.

We also evaluate the U.S. sanction's impact on the scientific significance of a firm's patent filings. We count each firm's yearly most important patent filings using three proxies. First, we consider the number of high-technology patents, classified according to the EPO criteria based on each patent's IPC code. Second, we count "triadic patents", that are concurrently filed in the EPO, USPTO, and JPO. These patents, known for their high novelty standards, represent a firm's most important inventions annually. Relatively few Chinese firms have filed "triadic patents". As an alternative measure, we use international patents, i.e., patents filed either at EPO, USPTO, or WIPO.

Patent counts could be an imperfect proxy for innovation outcomes due to the varying difficulty and criteria involved in obtaining a patent across different technology fields. We also use quality-adjusted patent counts, to compare patents across different technology fields and levels of technological complexities. We use patent-forward citations to measure a patent's quality and scientific value. Patent citation accumulation trajectory varies across industries, nations, and patent offices, due to factors like truncation issues (i.e., more recent patents have less time to accumulate citations), heterogeneous examination practices, home bias (because of patent-examination officers' bias, or because domestic inventors are more likely to cite patents applied to the home country office), language barriers, etc. (Boeing and Mueller 2016). To address truncation issues, a patent's citation is calculated as the total number of forward citations each patent received within three years of its publication date.[8] We evaluate patent quality based on filings in the USPTO, EPO, and WIPO only, due to their more comprehensive patent citation records. To account for heterogeneity in citation accumulation, we further adjust patent citation by dividing mean citation per patent in the same application-year-tech-class-patent-office-domestic cohort. This normalization controls for the truncation and home bias problems. It also adjusts for the shifts in accumulation trajectory caused by patent policy and technological fluctuation.

Patent stock is calculated as a deflated sum of past citation-adjusted patent applications up to that year. We use the application year instead of the granted year as the knowledge is already embodied when an applicant applies for patents. We also discard patent applications before 1945 and after 2019 to avoid truncation issues at the beginning and end of the sample. Following Hall

[8]We also use a five-year window as a robustness check, and the results are qualitatively similar.

et al. 2001, we calculate a patent stock using a 15% depreciation rate. Further details on the data construction are given in Appendix A.

3.3 Descriptive Statistics

The patenting activity of firms in and outside the Entity List differs (see Table A.2 in the Appendix). We thus rely on propensity score matching to ensure the treatment (sanctioned firms) and control groups are comparable.[9] We match each firm in the Entity List with a firm in the same sector that shares similar patent trajectories as the sanctioned firm before the treated firm is included in the Entity List. We use a firm's patent age, log of patent stock, and log of the previous year's patent applications to characterize its patent trajectory. We use weights computed based on the entropy balancing method in Hainmueller and Xu 2013 to improve the balance between the treatment and control groups.

In Table 1, we present the (pre-treatment) summary statistics for our matched treatment and control firms. The last two columns perform a t-test between the two groups and reveal that the sanctioned firms and unsanctioned firms have similar patent outcomes before sanctions. We do not observe statistically significant differences in quality adjusted patents overall, or quality adjusted international, triadic or high-tech patents. We also do not observe significant differences in any of the measures of patent counts, with the exception of some difference in triadic patents. In addition, the mean and variance of control variables are almost identical between the sanctioned and unsanctioned firms after re-weighting.

Table 1 goes here

4 Results

In this section, we present our empirical approach and results. We first present our benchmark difference-in-differences estimates of U.S. Entity List sanctions on the log patents of Chinese firms. The second subsection presents robustness to alternatives to the log patents specification.

[9] As a limited number of firms were added to the Entity List before 2013, we could not build a comparable control group for those added to the Entity List before 2013. Thus, we drop firms added to the Entity List before 2013, in our analysis.

4.1 Benchmark Empirical Models

Our benchmark model estimates the impact of U.S. sanctions on Chinese firms' innovation output, and log patents, through a difference-in-differences strategy. We estimate this specification:

$$y_{ijt} = \beta \times T_{ij} \times Post_{ijt} + \gamma X_{ij,t-1} + \psi_i + \delta_{jt} + \varepsilon_{it} \quad (1)$$

where $y_{i,jt}$ is the log of patents' applications at time t for firm i in sector j, reflecting either the firm's total patent applications, or international, triadic or high-tech patent applications.[10] $T_{i,j}$ is a dummy variable equal to 1 if firm i of sector j has been added to the Entity List during the period 2013-2019; $Post_{ij,t}$ is a dummy variable equal to 1 since the year firm i has been added to the Entity List; $X_{i,jt}$ is a set of controls including the log of firm i of sector j's patent stock at time $t-1$, a dummy variable that equals 1 if firm i of sector j has patented at year $t-1$; ψ_i is the firm fixed effect to capture the unobserved firm characteristics. $\delta_{j,t}$ is the sector-year fixed effect to capture the unobserved sector-year changes that affect firms' patenting activity and standard errors are clustered at the sector level (consistent with the level of the treatment variable).[11]

Callaway and Sant'Anna 2021 warn about potential biases in staggered difference-in-differences in the presence of dynamic treatment effects. These challenges result from the two-way fixed effect (TWFE) estimator making "forbidden comparisons" between treated firms and those previously treated (as well as those not yet treated). Past treated units may not have a parallel trend to the current treated group, because of dynamic treatment effects. These biases can be large when there is a large proportion of treated units, which is fortunately not the case in our context - fewer than 1% of treated firms in our data (see Table A.2) and fewer than 20% after matching (see Table 1). Callaway and Sant'Anna 2021 present an event study estimator that compares each cohort of firms entering the Entity List, against a control group that comprises those firms that are never or not yet treated.

To explore possible mechanisms, we examine how treatment effects differ across groups of firms

[10] We add one to patent applications to avoid dropping zeros and also examine robustness to this by employing the negative binomial model that retains zero observations, as well as considering separately outcomes for the propensity to patent (extensive margin) and the intensity of patenting conditional on non-zero patents (intensive margin).

[11] Other U.S. policies like the "China Initiative" might also affect a firm's patenting and collaboration. To avoid potential influence on policies that focus on specific industries, we control for sector-year fixed effects to isolate the treatment effect of the Entity List on sanctioned firms only.

(e.g., those with existing U.S. collaborations), introducing a triple difference. Unfortunately Callaway and Sant'Anna 2021 cannot estimate triple difference (or continuous) treatment effects, and therefore we retain the two-way fixed effects model as our baseline and verify the robustness to employing the Callaway and Sant'Anna 2021 estimator.

The identifying assumption of our difference-in-differences analysis is that the patent activity in both the treatment and control groups follows the same trend before sanctioned firms are added to the Entity List. Figure 4 shows that the sanctioned and unsanctioned firms exhibited parallel trends before the sanctioned firms were added to the Entity List (using the Callaway and Sant'Anna 2021 estimator). Kahn-Lang and Lang 2020 argue that tests of parallel trends may be under-powered and suggest verifying also differences in pre-treatment levels between the treatment and control groups. As discussed in the previous section, in Table 1 we are unable to reject balance in the level of (pre-treatment) patent outcomes and (pre-treatment) covariates.

Figure 4 goes here.

Figure 4 shows a slightly negative effect of U.S. sanctions on sanctioned Chinese firms' total (left) and high technology (right) patent applications, compared to non-sanctioned firms. The decline is significant and magnified for patent applications in high technology fields two years after the inclusion in the Entity List.[12]

Table 2 goes here.

Our baseline results (estimated via difference-in-differences in equation 1) are reflected in Table 2. These show the average treatment effect of the U.S. sanctions on sanctioned firms' patent applications, with (lower panel) and without (upper panel) adjusting for patent quality. Sanctioned firms experienced a significant decline in total patent applications after being added to the Entity List. The results are qualitatively similar with or without quality adjustment corrections, but quantitatively larger when accounting for quality adjustments. Sanctioned firms experience a 9.9% reduction in their total patents and a 14.0% reduction when patents are quality-adjusted.[13]

[12] We also do not observe pre-trends in international and triadic patenting, but do not find as clear graphical evidence for post-sanction changes, see Figure A.4 in the Appendix.

[13] The 9.9% reduction in patent counts is calculated as exp(-0.104)-1, the 14.0% reduction in quality adjusted patents is calculated similarly.

The effect is generally qualitatively similar across different patent categories. U.S. sanctions slightly lower firms' patent applications in high-technology patents. However, U.S. sanctions significantly discourage firms' international patent applications.

Table 3 goes here.

The estimated average treatment on treated (ATT) for sanctioned firms in Table 3 is the staggered treatment effect, based on the Callaway and Sant'Anna 2021 method. The estimated ATT is consistent with our estimated coefficient β in Table 2, estimated via difference-in-differences. Thus is appears the staggered treatment concerns are not a major bias in our setting. We observe a strong decline in patent applications in most patent categories, including the total number of patents, and the number of high-tech and triadic patent applications.[14]

4.2 Robustness

The log transformation of outcome variables in the presence of zeroes can cause a bias in estimating and interpreting the average treatment effect (Chen and Roth 2024). Following their suggestions, we conduct three robustness checks for our benchmark regression.

In the first robustness check, we estimate the average treatment effect in levels, as the percentage changes from the controlled mean using a negative binomial, which includes the zero patenting firms in the analysis, but note it is not possible to include firm fixed effects. Notice that we do not use Poisson regression as in Chen and Roth 2024, due to the over-dispersion of the patent data. The negative binomial regression results are qualitatively consistent with our benchmark regression, but larger in magnitude (Table A.7). The third row of Table A.7 calculates the implied average treatment effect in percentage changes. It shows that U.S. sanctions significantly decrease firms' patent applications in all patent categories, albeit with slightly larger magnitudes than our baseline specification.

When the outcome variable is well-defined at zero and there are many zeros in the sample, the estimated treatment effect on the whole sample mixes the extensive and the intensive margins' effects. That is, the U.S. sanctions might have different impacts on firms' decisions regarding

[14]Table 3 present patent counts, but similar results are obtained using quality-adjusted patents, which are available upon request.

"whether to file patents" and "how many patents should be filed conditional on filing patents". In our second robustness analysis, we separately estimate the treatment effect on intensive and extensive margins. Specifically, we re-run the regression on a set of firms with positive patent applications at time t, to assess the intensive margin. To quantify the extensive margin, we replace the count variable $y_{ij,t}$ with a dummy variable that equals 1 if firm i in sector j filed a patent at time t.

The estimated average treatment effect is qualitatively consistent with our benchmark regression (see Table A.8). On the intensive margin, among firms that patent in a given year, the U.S. sanctions significantly reduce the number of patents the firm files in total and high technology field. However, since only a limited number of firms file triadic patents, the estimated average treatment effect on triadic patents is noisy and not significant.

In the third robustness check, we focus only on firms that patented before 2013. Thus, the estimated coefficient does not account for the impact on the firm's decision to start to patent for the first time. We re-run the regression 1 on a set of firms that were already patenting. Table A.9 shows the estimated coefficients. Among firms that had already started their patenting activity, the estimated average treatment effect is again qualitatively similar to our benchmark regression.

5 Mechanism

In this section, we explore the underlying mechanism which could explain the decline in firms' patent applications. We first consider whether Chinese firms with prior U.S. collaborations are disproportionately affected by the sanctions, and then examine the extent to which Chinese innovation capacity insulates firms from the sanction shock.

5.1 Collaboration with the U.S.

Previous literature has shown that knowledge can spillover across nations through various channels such as trade flows (Grossman and Helpman 1990, Grossman and Helpman 1991, Coelli et al. 2022), foreign investment (Liu 2008, Lee 2006, Gorodnichenko et al. 2014), and more direct interactions like R&D collaborations (Alnuaimi et al. 2012, Kerr and Kerr 2018, König et al. 2019).

International collaborations are an important channel for the transfer of knowledge from advanced to developing countries (Montobbio and Sterzi 2013, Giuliani et al. 2016). First, collaborating with inventors from advanced countries provides firms in developing regions access to frontier knowledge, improving their capacity for innovation (Giuliani et al. 2016). Additionally, such collaborations introduce a diversity of knowledge that can spark creativity. When inventors from varied geographical regions collaborate, they can more effectively integrate dispersed knowledge, which in turn facilitates the identification and exploitation of new innovation opportunities (Singh and Fleming 2010). Lastly, cross-border collaborations do not only boost current invention rates but also offer long-term benefits by enabling inventors to continually produce high-impact patents (Branstetter et al. 2015, Alnuaimi et al. 2012).

Before considering the effect of the sanctions, as motivation, we first assess the importance of U.S. collaborators in Chinese firms' innovation output. We contrast the correlation between patenting and collaboration with U.S. inventors and inventors from Europe+ or advanced Asian economies or other regions, by estimating the following equation:[15]

$$y_{ijt} = \sum_{r=US,Europe+,AdvAsia,other} \beta_r \times col_{rijt} + \gamma X_{ij,t-1} + \psi_i + \delta_{jt} + \varepsilon_{it} \tag{2}$$

where $y_{ij,t}$ captures innovation output: total patent applications, and high-tech patent applications. $col_{r,ijt}$ is the log of the number of current or past collaborations with inventors from different regions. Since past collaborations are highly correlated with patent stock, we drop the patent stock from the vector of covariates $X_{ij,t-1}$. The coefficient β_r is the r region collaboration elasticity of patent applications. To eliminate the impact on U.S. sanctions, we focus only on non-sanctioned firms.

Table 4 goes here

International collaboration matters for Chinese patenting activity (Table 4). Current collaboration with U.S., and European+ inventors is significantly correlated with Chinese total and high-tech inventions, but to a varying degree.[16] Patenting has a stronger association with collaborating with

[15] The "Europe+" group includes advanced European countries (Ireland, Norway, Demark, Spain, Belgium, Austria, Finland, Iceland, Netherlands, Italy, Sweden, Switzerland, Germany, France, UK, Portugal, Czechia, Greece, and Luxembourg) plus Canada and Australia. The advanced Asia region includes the Republic of Korea; Japan; Singapore; Hong Kong SAR, China; and Taiwan, China.

[16] In our sample, the average U.S., Europe+, advanced Asian economies collaborator per patent is 0.11, 0.009, and 0.081, respectively. The average other region collaborator per patent is only 0.002. In addition, less than 1% of firms had collaborations with inventors from other regions.

Americans than collaborating with European inventors or those in advanced Asian countries or countries in other regions. This relationship holds across various types of patents including total, international, or high-tech patents. Past collaborations with U.S. innovators are also more strongly correlated with patenting activity than collaborations with other advanced economies. The elasticity of patent applications remains significant and higher for U.S. collaborators, past or present.

Next, we examine how inclusion in the Entity list affects Chinese firms' decisions to collaborate with the U.S. in their future patenting. We first consider this for all firms, and second examine heterogeneity for firms with prior U.S. collaborations using a triple-difference estimation. To do so, we estimate the following regression:

$$col_{ijt} = \beta \times T_{ij} \times Post_{ijt} + \alpha \times T_{ijt} \times Post_{ij,t} \times PreCol_{US,ij} + \psi_i + \delta_{jt} + \varepsilon_{it} \qquad (3)$$

where $col_{ij,t}$ is the measure of collaborations with inventors in the U.S.; Europe+; and Advanced Asia. Collaboration is measured by the average number of inventors from a given region, per patent.[17] The other variables are the same as equation 1. $PreCol_{US,ij}$ is a dummy variable that equals 1 if the firm has collaborated with a U.S. inventor before time t. Table 5 displays the regression results.

Table 5 goes here

The imposition of sanctions leads these firms to reduce their collaborations with the U.S. inventors (see column 1 of Table 5). Collaborations with European+ inventors also declined but by a smaller amount (column 2). The impact on collaborations with inventors from advanced Asian economies is much more muted. Collaborations with Asian inventors decline slightly, only for Chinese sanctioned firms with pre-existing ties with U.S. inventors. (see column 6 of Table 5).

Sanctioned firms with pre-sanction U.S. collaborations experienced a significant decline in post-sanction U.S. collaboration (column 4) and post-sanction advanced Asian collaborations. There is a significant increase in the U.S. and advanced Asia collaborations of sanctioned firms that did not collaborate with the U.S. previously. In contrast, post-sanction Chinese-Europe+ collabora-

[17] Patents reflect total patents. Section A.2 describes the construction of this variable and the other two different measures on the degree of collaboration between Chinese firms and foreign inventors.

tion increased among sanctioned firms with prior U.S. collaboration, whereas it decreased among sanctioned firms without U.S. collaboration.

The results in this section suggest that (i) collaborating with the U.S. is positively related to firm innovation, and (ii) sanctions lead firms with prior U.S. collaborations to subsequently reduce their U.S. collaborations. A natural question is therefore whether the sanction-induced reduction in patenting was disproportionately concentrated in firms with prior (pre-sanction) U.S. collaborations. We examine this question by estimating regression 3 but considering firm patent applications as an outcome.

Table 6 goes here

Table 6 shows the decline in sanctioned firms' patent applications is due primarily to those Chinese firms with prior (pre-sanction) U.S. collaborations (noted earlier in Table 2). Columns 4 to 6 show that, among firms already patenting at a given year t, the impact of sanctions on the patents of firms without prior U.S. collaborations (reflected by the first row) is not significantly different from zero, and the estimated coefficients are positive. However, columns 1 and 3 indicate that, among firms without prior U.S. collaborations, sanctions lead to an overall increase in total and high-tech patents. The difference between columns 4 and 1 may reflect that firms do not rely on U.S. knowledge (measured by collaboration), and sanctions may incentivize those firms to patent more frequently (i.e., at the extensive margin). In contrast, firms with prior U.S. sanctions significantly reduce their innovation (both on intensive and extensive margins) in terms of total, international, or high-tech patent applications.

5.2 Chinese Innovation Capacity

Firms with greater innovation capacity might be less dependent on U.S. knowledge and thus less affected by the U.S. sanction. We first examine whether top innovating firms are less affected by the U.S. sanctions. We define top innovating firms as those among the top 10% largest quality-adjusted patent stock within a given industry at the year they are being sanctioned. We estimate:

$$y_{ijt} = \beta \times T_{ij} \times Post_{ijt} + \alpha \times T_{ij} \times Top_{ij} + \gamma X_{ij,t-1} + \psi_i + \delta_{jt} + \varepsilon_{it} \quad (4)$$

where Top_{ij} is a dummy reflecting top innovating firms. Other variables are defined as equation 1. We find evidence that the top innovating firms are somewhat more insulated from the effects of the sanctions (see columns 1 to 3 of Table 7). The estimated coefficient α is significant and positive for total patents at both extensive and intensive margins and for high-tech patents at intensive margins only. Among firms patenting in a given year, U.S. sanctions are not as effective at curbing top innovators' overall and high-tech patenting. However, they appear similarly effective in deterring international patents, regardless of the firm's patenting capacity.

Table 7 goes here

We further explore whether firms in sectors close to the global knowledge frontier or more reliant on indigenous innovations are less affected by the U.S. sanctions. To measure the distance to the knowledge frontier, we follow the approach of Akcigit et al. 2024, computing the ratio of triadic patents filed by Chinese firms to the total triadic patents filed by either Chinese or U.S. firms in each 2-digit ISIC sector.[18] To examine sector-level indigenous innovation, we explore the cross-border diffusion of technology through three channels that were identified in the previous literature: learning from prior foreign technology (Jaffe et al. 1993; Thompson 2006), direct adoption (Eaton and Kortum 1999), and learning from foreign collaboration (Giuliani et al. 2016; Kerr and Kerr 2018). We use the "sourcing", "adoption" and "collaboration" measures developed by Archibugi and Michie 1995 and Bian et al. 2024 to reflect the degree of domestic innovation at sector level.

Patent citations are a well-established metric for assessing knowledge spillovers and sourcing (see Keller 2004 and Bloom et al. 2019 for review). A larger share of citations to foreign patents suggests a significant reliance on foreign "prior art". Our first measure, "sourcing", captures the importance of domestic knowledge sourcing as the share of citations made to Chinese patents in each 2-digit ISIC sector. To assess the direct adoption of foreign knowledge, we track a patent's priority number and count the number of patents previously granted in a foreign patent office but reapplied for in the domestic office at each 2-digit ISIC sector, which could indicate the degree of technology transfer (Holmes et al. 2015). "Adoption" is measured as one minus the share of

[18] Patents in PATSTAT are assigned with IPC code. We first use the concordance table provided by PATSTAT to convert each IPC code into NACE version 2, and then use the concordance table in `https://unstats.un.org/unsd/classifications/Econ`, to covert NACE version 2 into ISIC revision 4. Patents used to compute knowledge distance are then classified into the 2-digit ISIC sector.

patents that were first applied outside of China. Previous sections have shown the importance of direct cross-border collaboration in encouraging domestic innovations. Therefore, we measure the dependence on domestic inventors, "collaboration", as the proportion of patents applied by Chinese firms developed by Chinese inventors only.

We test our conjecture on the relationship between innovation capacity and the impact of U.S. sanctions, we estimate:

$$y_{ij,t} = \beta \times T_{ij} \times Post_{ij,t} + \alpha \times T_{ij} \times Post_{ij,t} \times InnovCap_j + \gamma X_{ij,t-1} + \psi_i + \delta_{jt} + \varepsilon_{it}$$

where $InnovCap_j$ is the measure of the innovation capacity of sector j at the time firm i in sector j was added to the Entity List. α measures the degree to which domestic innovation capacity could alter the treatment effect of U.S. sanctions. We also find evidence that firms in sectors closer to the knowledge frontier and that rely more on domestic knowledge and domestic collaborators are less adversely affected by the sanctions (see columns 1 to 4 of Table 8). The mediating effect is much stronger for high-tech patents (see table A.12).

Table 8 goes here

6 Spillover Effects: Indirectly Connected Firms

Thus far we have focused on the effects on the sanctioned Chinese firms. In this section, we examine potential spillovers to non-sanctioned firms. We first consider spillovers to firms operating in the same technology fields as the sanctioned firms and then consider downstream and upstream impacts through forward and backward citation linkages.

6.1 Chinese firms in the sanctioned technology field

The U.S. Entity List only sanctions specific firms. However, such a policy may have a spillover effect at the technology level if the sanctioned firms are important contributors to the technology in their sectors. In this section, we examine spillovers of sanctions to other (non-sanctioned) firms within the same technological field.

We identify the IPC fields affected by the Entity List sanctions through the following procedure.

First, we classify firms into technology fields based on their patent applications' main IPC code at the 4-digit level. We then compute each sanctioned firm's number of patent applications in each IPC code before being added to the Entity List. A firm's technology field is defined as the IPC field hosting most of its patents. Second, we match each sanctioned firm in the Entity List to PATSTAT and identify its technology field using the method in the first step. We then define these IPC codes as "sanctioned IPC field" if (1) the sanctioned firms are among the top 10% of Chinese innovating firms in their primary IPC field, or (2) the sanctioned firms patent more than 10% of total patents in their primary IPC field.[19] We have 40 sanctioned IPC fields in our sample, with 22 added after 2018.[20] Most of the sanctioned IPC fields are under the electric communication technique (H04) and measurementtesting technique (G01). Firms patenting in sanctioned IPC fields file significantly more patents overall, and in high-tech fields than other firms in our sample.

We define our treatment group as the set of firms whose primary IPC field is being sanctioned. In our sample, firms can switch among different IPC fields over the years. To eliminate potential bias caused by firms that switch their treatment status, we drop firms that switch in/out of the sanctioned IPC field after the IPC field was sanctioned. Figure 5 shows the total number of firms patenting under the sanctioned IPC field each year. The majority of firms are in the technology field of Computing and Information, Electronics, and Electric Technology.

Figure 5 goes here

As in our benchmark analysis, we use propensity score matching to construct a comparable control group, due to the significant difference in patent trajectory between firms in sanctioned and unsanctioned IPC fields. For each firm's primary IPC field being affected at year t, we find firms in an unaffected IPC field that share a similar patent trajectory before year t. We use a firm's patent age, log of patent stock, and log of the previous year's patent application to characterize its patent trajectory. Summary statistics for these firms before and after matching are presented in Tables A.3

[19] For example, consider firm ABC: it was added to the Entity List in 2017, and its primary IPC field is G08B. If ABC is not among the top 10% of Chinese innovating firms whose primary IPC fields are G08B and its granted patents are less than 10% of total granted patents in G08B up to the year 2017, we do not consider G08B as a sanctioned IPC field. Conversely, if ABC is among the top 10% of Chinese innovating firms, or its granted patents are more than 10% of the total granted patents in G08B, we treat G08B as a sanctioned IPC field.

[20] Our classification method differs slightly from Han et al. 2024, as they classify a sanctioned IPC field as the primary technology field of the entity sanctioned. The classified IPC field is at the 3-digit level. The defined sanctioned IPC fields using our method are thus much stricter.

and A.4. After matching we cannot reject the balance of covariates, but do reject similarity in the levels of several pre-sanction patent measures (see Table A.4), which caveats the spillover results in this section. After the matching, we use entropy balancing to re-weight all control variables. In addition, to remove the direct impact of U.S. sanctions, we drop firms in the Entity List. We then estimate the following equation:

$$y_{ijt} = \beta \times T_{ij} \times Post_{ijt} + \alpha \times T_{ij} \times Post_{ijt} \times PreCol_{US,ij} + \gamma X_{ij,t-1} + \psi_i + \delta_{jt} + \varepsilon_i t \qquad (5)$$

where T_{ij} is a dummy variable that equals 1 if firm i's primary technology field is identified as a sanctioned IPC field. $Post_{ijt}$ is a dummy variable that equals 1 if firm i's primary technology field is added to the Entity List. $PreCol_{US,ij}$ is a dummy variable that equals 1 if the firm has collaborated with a U.S. inventor before time t. y_{ijt} is the log of patents' applications or the number of collaborators from the given region per patent. Other variables are defined as in regression 1.

Table 9 goes here

The regression results in Table 9 (columns 1 to 3) suggest there are negative spillovers of the Entity List sanctions to non-sanctioned firms. We find negative effects of sanctions for firms within the same IPC field (as those targeted by the sanctions) in terms of their total, international, and high-tech patenting. The negative spillover effect on firms in the sanctioned IPC field in Table 9 is slightly smaller than the earlier negative firms on the directly sanctioned firms (in Table 2).

In columns 4 to 6 of Table 9 we examine whether U.S. sanctions affect Chinese firms' collaboration networks. Unlike the earlier effects observed on directly sanctioned firms (see Table 5), U.S. sanctions do not significantly affect Chinese firms' collaboration with inventors from the U.S. and Europe+ . In contrast, there is a significant increase in the number of advanced Asia inventors per patent (column 5).

Next, we examine whether firms with prior-sanction U.S. collaboration are disproportionately affected by the negative spillovers observed thus far. Firms that had U.S. collaboration before the sanction observed a significant drop in both post-sanction patenting and U.S. collaborations, relative to firms without prior U.S. collaborations, as demonstrated by the triple-interaction term (Table 10). These firms reduce their total or high-tech patenting or patenting at international offices. In addition, they are less likely to continue collaborating with U.S. inventors. However, they do increase their collaborations with inventors from Europe+ and advanced Asian countries. The regression results are consistent with our hypothesis that cross-border collaborations are important determinants in firms' innovation output.

Table 10 goes here

6.2 Firms in the upstream and downstream technology fields

The U.S. sanctions may lead to varied spillover effects across the technology network. Particularly, firms located upstream and downstream of the technology value chain could face different impacts from the U.S. sanctions even if their technology field is not directly sanctioned. To examine the different spillover effects on these firms, we adopt the methodology proposed by Han et al. 2024, quantifying each unsanctioned technology field's indirect linkage to the sanctioned technology field at the four-digit IPC level through the citation network. We define the downstream measure of an IPC field j in year t as the weighted sum of sanction indicators, where the weights are the proportion of citations IPC field j makes to each sanctioned field n. Similarly, the upstream measure of technology field j in year t is calculated as the weighted sum of sanction indicators, with weights based on the proportion of citations made by each sanctioned field n to field j.[21]

$$\begin{aligned} Downstream_{jt} &= \sum_{n \neq j} \frac{\text{Citations made by } j \text{ to } n}{\text{total citations made by } j} \times sanction_{nt} \\ Upstream_{jt} &= \sum_{n \neq j} \frac{\text{Citations made by } n \text{ to } j}{\text{total citations to } j} \times sanction_{nt} \end{aligned} \tag{6}$$

where $sanction_{nt}$ is a dummy variable that equals 1 if the IPC field is sanctioned at time t. The upstream and downstream measure allows us to estimate the significance of the sanctioned fields in the innovation process of indirectly exposed technology fields. For instance, if the semiconductor sector is sanctioned by the U.S., firms heavily dependent on semiconductor innovations (i.e., firms in the downstream sectors) may experience negative impacts due to the interruption of technology flows from the U.S.. Conversely, such sanctions may foster domestic innovations and increase the

[21] Since citation data is not often consistently available from China's and other regional patent offices, when measuring IPC-to-IPC citations, we only consider patents that were applied for in EPO, USPTO, or WIPO, where the citation information is complete and consistent over time

demand for inventions from the technology field that the semiconductor sector is dependent on (i.e., firms in the upstream sectors). The direction and magnitude of network spillover effects of U.S. sanctions are estimated using the following regressions:

$$y_{ijt} = \beta_1 Downstream_{jt} + \beta_2 Upstream_{jt} + \gamma X_{ij,t-1} + \psi_i + \delta_{jt} + \varepsilon_{it} \tag{7}$$

$$y_{ijt} = \beta DummyDownstream_{j,t} + \gamma X_{ij,t-1} + \psi_i + \delta_{jt} + \varepsilon_{it} \tag{8}$$

where $DummyDownstream_{jt}$ is a dummy variable that equals 1 for firms in the downstream sector (i.e. its downstream measure is larger than the upstream measure). Table 11 shows the estimates of equation (7) in columns 1 to 3 and the estimates of equation (8) in columns 4 to 6. These estimates are largely consistent with our hypothesis. Firms in sectors that are located downstream of the sanctioned sectors experience a significant decline in patenting, whereas firms in sectors upstream of the sanctioned sectors increase their patent activity. However, due to data limitations, it is hard for us to test whether the decrease in patenting among those downstream firms was caused by a reduction in technology access and transfer.

Table 11 goes here

6.3 U.S. firms in the sanctioned technology field

U.S. sanctions, while primarily targeting Chinese firms, may inadvertently affect U.S. firms as well, through the innovation network. For example, when the U.S. imposes sanctions on Huawei, U.S. companies that depend on Huawei's products may find their supply chain disrupted and hard to get critical components that could be useful in their R&D. In addition, the U.S. sanctions could hinder the previous collaboration between U.S. companies and Chinese partners. These factors could lead to a decrease in innovation activity among U.S. firms, delaying their R&D processes and reducing their patent output. On the other hand, sanctions could also create opportunities for U.S. firms. By restricting technology transfers from the U.S. to China and limiting Chinese firm's access to U.S. technologies, the Entity List could reduce Chinese firms' competitiveness and market share. Therefore, U.S. firms could be incentivized to invest more in R&D to capture the market share that was previously occupied by Chinese firms.

To examine the impact of U.S. sanctions on U.S. firms, we re-run equation 4 on the sample of U.S. firms. As in our previous analysis, we use propensity score matching to construct a comparable control group, due to the significant difference in patent trajectory between firms in sanctioned and unsanctioned IPC fields. After the matching, we use entropy balancing to re-weight all the control variables.

Table 12 goes here

In general, there are no significant changes in innovation activity for U.S. firms in the sanctioned technology field (see columns 1 to 3 of Table 12). However, U.S. firms that had prior-sanction collaborations with Chinese inventors experienced a significant decline in patenting after being sanctioned (reflected by the triple interaction term in columns 4 to 6).

7 Conclusion

This paper presents evidence that inclusion in the U.S. Entity List negatively impacts the innovation output of targeted Chinese firms, and other Chinese firms operating within the same technology fields. The negative effect primarily stems from Chinese firms that previously collaborated with U.S. inventors. However, this negative effect could be mitigated by domestic innovation capacity – sanctioned firms with higher initial patent stocks or operating in sectors with a smaller technological distance to the U.S., incurred a smaller innovation penalty. In addition, firms in the technology fields located upstream of the sanctioned technology areas experienced a slight increase in their innovation output. While the U.S. sanctions do not significantly affect U.S. firms in the sanctioned technology fields overall, they do lead to a reallocation of innovation output away from firms with prior Chinese collaborations and towards other firms.

There is widespread concern that U.S. and Chinese policies could lead to costly economic divisions. Some recent analyses have suggested that extreme forms of decoupling, such as the division of trade and technology into blocs of East and West, could have severe consequences (Cerdeiro et al. 2023, Garcia-Macia and Goyal 2020, Góes and Bekkers 2022, and Jinji and Ozawa 2024). We find evidence suggesting that even less extreme policy measures, such as the inclusion of some firms on the U.S. Entity List, can have significant adverse effects. U.S. sanctions led to large reductions in innovation of both Chinese firms that previously collaborated with the U.S. and U.S. firms that collaborated with China, undermining mutual gains from bilateral collaboration.

Furthermore, Chinese firms are shifting their collaboration away from the U.S. and Europe, and toward Asia. One potential extension to our study is to investigate the spillover effect of technological distancing on a broader set of countries. As China is approaching the technology frontier and becoming a major contributor to global innovation, any impact on Chinese firms' innovation activity could affect other countries through its production and research network.

Our empirical analysis is necessarily constrained by the recent timing of these policies, meaning many of their longer-term effects may be yet to materialize. Future quantitative evaluation of such policies could assess their impact on targeted countries' innovation efficiency and aggregate productivity. Our research indicates a marginally positive effect of U.S. sanctions on the innovation output of Chinese firms located upstream of the sanctioned fields. This suggests that U.S. sanctions may encourage China's effort to bolster its domestic innovation and reduce its technology dependence on the U.S. With the increase in China's innovation capacity, U.S. sanctions may not have a strong long-run negative impact on Chinese firms' innovation output.

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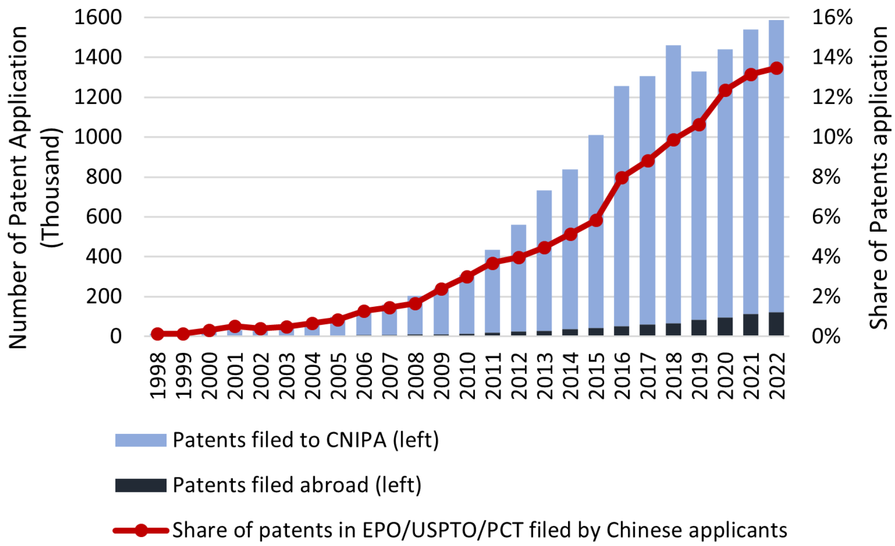
Figures

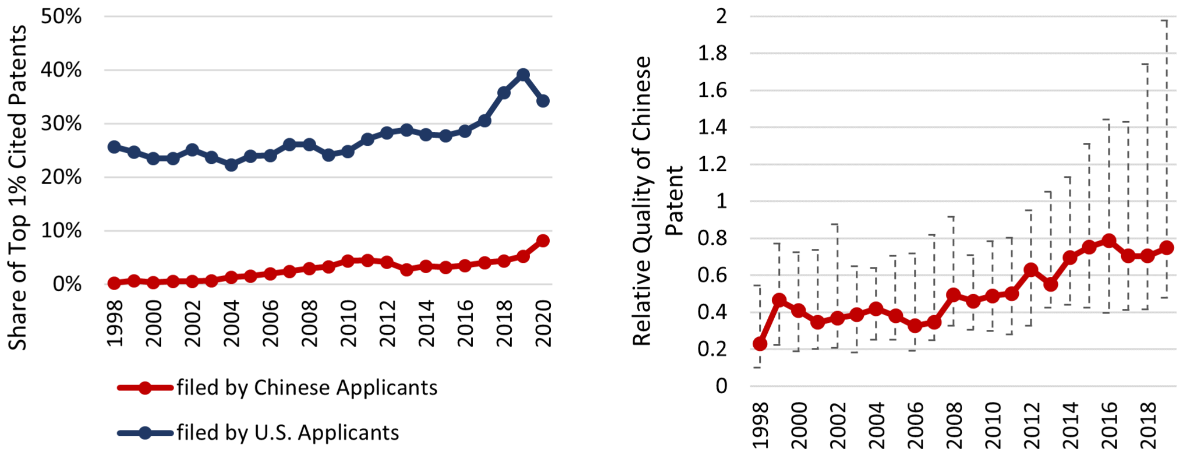
Figure 1: Rapid growth in China's innovation



Source: WIPO IP Statistics Data Center.

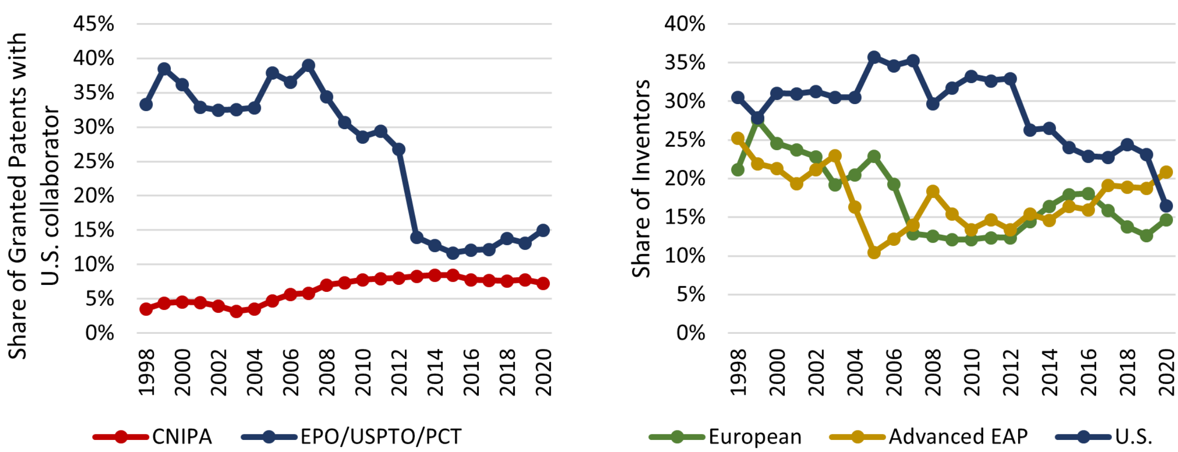
Notes: The blue and black bar shows the number of patents filed by Chinese applicants to the Chinese National Intellectual Property Administration (CNIPA) and all foreign patent offices respectively. The red line is the share of patents filed by Chinese applicants to the European Patent Office (EPO), United States Patent and Trademark Office (USPTO), and under the Patent Cooperation Treaty (PCT).

Figure 2: The quality of Chinese patents has rapidly converged to U.S. quality levels



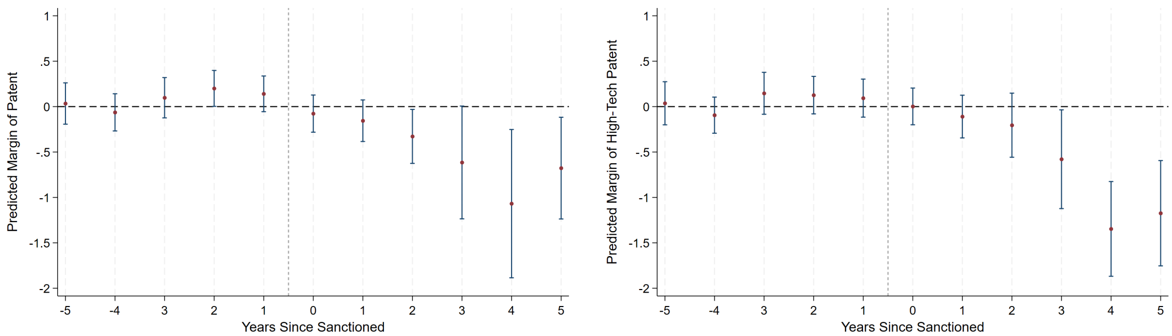
Source: PATSTAT Dataset, Spring 2022 version.
Notes: The left panel shows the number of top 1% cited patents applied by Chinese/U.S. applicants to the total number of top 1% cited patents. The top 1% cited patents are computed within granted patents registered in EPO/USPTO/PCT and adjusted by the technology domains and the year when it applied (following Lerner and Seru 2021). The right panel shows the relative quality of Chinese patents in each technology domain (IPC 3 digit) registered in EPO/USPTO/PCT. The relative quality is measured by the average number of citations each patent received relative to the average number of citations each U.S. patent (i.e., patents filed by U.S. applicants) received. The red dots are the median of relative quality, and the whiskers reflect the top quarter and the bottom quarter of relative quality across all technology domains.

Figure 3: The importance of U.S. collaboration decreased in the most recent decade



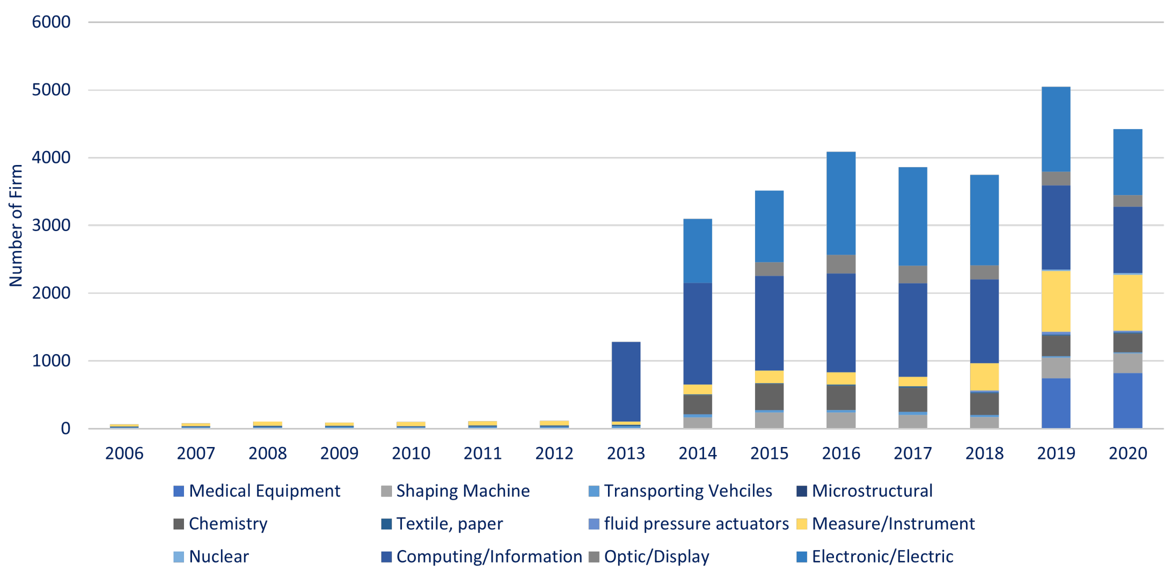
Source: PATSTAT Dataset, Spring 2022 version.
Notes: The left panel shows the share of granted Chinese patents registered in CNIPA (red solid line) and EPO/USPTO/PCT (black solid line) that have collaborated with U.S. inventors. The right panel shows the average share of inventors per patent, measured as the number of inventors from each region to the total number of inventors per patent. The right panel focuses only on Chinese-granted patents registered in EPO/USPTO/PCT and jointly developed with foreigners.

Figure 4: Effect of U.S. sanctions on patent applications



Source: PATSTAT Dataset, Spring 2022 version.
Notes: The red dots are the estimated differences in the number of patent applications (i.e. patent counts) between sanctioned and unsanctioned firms five years before and after the sanctioned firms were added to the Entity List. The left panel shows the results for all patents, and the right panel focuses on high-tech patents. The blue bar is the 95% confidence interval. The estimates reflect staggered difference-in-differences using the method by Callaway and Sant'Anna 2021.

Figure 5: Number of Chinese Patenting Firms Under Sanctioned IPC Field



Source: PATSTAT Dataset, Spring 2022 version.
Notes: The bar charts show the number of firms in the newly added sanctioned IPC fields across different years and different technology fields. We identified 40 sanctioned 4-digit IPC fields, and then regrouped these IPC fields into 12 broader technology fields listed in the legend

Tables

Table 1: Summary Statistics after matching and balancing

	Sanctioned Firm		**Unsanctioned Firm**		**Difference**	
	Mean	Std. Dev	Mean	Std. Dev	Diff	Std
Patent Counts						
Total Patents	30.63	62.78	27.99	63.12	2.63	(3.60)
High-Tech Patents	14.38	28.25	12.01	29.95	2.37	(1.67)
EPO/USPTO/PCT Patents	4.90	15.56	3.65	18.96	1.26	(0.99)
Triadic Patents	0.51	2.97	0.22	1.51	0.29**	(0.13)
Quality-adjusted Patents						
Total Patents	22.62	49.51	24.5	68.54	-1.88	(3.42)
High-Tech Patents	9.03	19.13	10.37	35.05	-1.34	(1.62)
EPO/USPTO/PCT Patents	5.77	20.28	5.57	30.98	0.20	(1.50)
Triadic Patents	1.05	6.25	0.57	5.36	0.48	(0.33)
Controls						
Patent Age	5.07	3.08	5.07	3.16	0.00	(0.18)
Patent Stock (log)	2.53	1.68	2.53	1.65	0.00	(0.10)
Prior Average Patent App.	0.47	0.54	0.48	0.57	0.00	(0.00)
Dummy Patent	0.78	0.42	0.78	0.42	0.00	(0.02)
Lagged Total Patent App (log)	2.02	1.58	2.02	1.60	0.00	(0.09)
No of Observations	1,080			5,254		

Note: This Table compares the mean and standard deviation of sanctioned and unsanctioned firms before firms are sanctioned. The prior average patent applications are computed as the annual patent filings for each firm before 2002. It reflects a firm's pre-sample innovation capacity. Patent is a dummy variable that equals 1 if a firm at year t has also patented at $t-1$. Lagged Total Patent App (log) represents the the log of one plus the patent count (from total patents) at $t-1$. The last column is the standard error of the t-test. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table 2: Post-Sanction Innovation Performance among Sanctioned Firms

	(1) Total	(2) International	(3) Triadic	(4) High-Tech
Panel A: Patent Count				
Treatment×Post	-0.104***	-0.171***	-0.077***	-0.036
	(0.026)	(0.012)	(0.013)	(0.037)
Panel B: Quality-Adjusted Patents				
Treatment×Post	-0.151***	-0.193***	-0.092***	-0.102*
	(0.05)	(0.012)	(0.024)	(0.053)
No. Obs.	6,334	6,334	6,334	6,334

Note: We estimate the coefficients in columns 1 to 4 using difference-in-differences. Sector-year and firm FEs are included. The dependent variable is the log of one plus (total / international / triadic / high-tech) patent applications, with panel A reflecting patent application counts and panel B quality adjusted patent applications. Treatment is a dummy reflecting whether the firm is included in the Entity List, with Post reflecting the periods after their inclusion. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table 3: Estimated Average Treatment on the Treated

	(1) Total	(2) International	(3) Triadic	(4) High-Tech
Treatment×Post	-0.275***	-0.107	-0.046***	-0.235***
	(0.107)	(0.075)	(0.047)	(0.116)
No. Obs.	6,370	6,370	6,370	6,370
Sector-year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Note: Columns 1 to 4 are the staggered difference-in-differences estimates using the method by Callaway and Sant'Anna (2021). The dependent variable is the log of one plus (total / international / triadic / high-tech) patent application counts. Treatment is a dummy reflecting whether the firm is included in the Entity List, with Post reflecting the periods after their inclusion. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table 4: Estimated Patent Elasticity on Collaboration

	(1)	(2)	(3)	(4)	(5)	(6)
	Current Collaborators			**Past Collaborators**		
	Total	Intl	High-Tech	Total	Intl	High-Tech
U.S.	0.147***	0.057***	0.130***	0.472***	0.129***	0.428***
	(0.010)	(0.010)	(0.011)	(0.021)	(0.028)	(0.017)
Euro+	0.102***	0.082***	0.068***	0.087*	0.121***	0.138***
	(0.026)	(0.006)	(0.006)	(0.046)	(0.017)	(0.024)
Adv. Asia	0.143***	0.074***	0.123***	0.239***	0.111***	0.208***
	(0.028)	(0.011)	(0.024)	(0.014)	(0.013)	(0.036)
other	0.110	0.054	0.092	0.402***	0.332***	0.346***
	(0.127)	(0.130)	(0.135)	(0.044)	(0.031)	(0.059)
No. Obs.	5,317	5,317	5,317	5,317	5,317	5,317
R-Squared	0.687	0.652	0.706	0.716	0.658	0.730
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences on a set of firms that had positive patenting during the sample period. The dependent variable is the log of one plus (total / international / high-tech) patent application counts. In columns 1 to 3, the independent variable is log of one plus the number of collaborators at the current year t. In columns 4 to 6, the independent variable is log of one plus the total number of past collaborators up to the current year t. The "Euro+" group includes advanced European countries (Ireland, Norway, Demark, Spain, Belgium, Austria, Finland, Iceland, Netherlands, Italy, Sweden, Switzerland, Germany, France, UK, Portugal, Czechia, Greece, and Luxembourg) plus Canada and Australia. The Advanced Asia region includes the Republic of Korea; Japan; Singapore; Hong Kong SAR, China; and Taiwan, China. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table 5: Post-Sanction Collaboration among Sanctioned Firms

	(1)	(2)	(3)	(4)	(5)	(6)
	Average Collaborator per Patent					
	U.S.	Euro+	Adv. Asia	U.S.	Euro+	Adv. Asia
Treatment×Post	-0.115***	-0.041***	0.012	0.257**	-0.070**	0.305***
	(0.038)	(0.009)	(0.052)	(0.091)	(0.023)	(0.124)
Treatment×Post×pre-US				-0.446***	0.035*	-0.351**
				(0.134)	(0.019)	(0.158)
No. Obs.	5,442	5,442	5,442	5,442	5,442	5,442
R-squared	0.367	0.174	0.398	0.379	0.198	0.399
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences on a set of firms that had positive patenting. The dependent variable is log of one plus average number of collaborators (from U.S. / Euro+ / Advanced Asia) per patent. $pre - US$ is a dummy variable that equals 1 if the firm had collaborated with U.S. prior to the year it was sanctioned. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table 6: Prior U.S. Collaboration and Post-Sanction Innovation Performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent Application			**Patent Application (Intensive Margin)**		
	Total	Intl.	High-Tech	Total	Intl.	High-Tech
Treat×Post	0.444***	-0.025	0.553***	0.096	0.134	0.073
	(0.126)	(0.036)	(0.137)	(0.102)	(0.102)	(0.081)
Treat×Post×pre-US	-0.650***	-0.173***	-0.698***	-0.267**	-0.432***	-0.296***
	(0.153)	(0.052)	(0.145)	(0.104)	(0.104)	(0.075)
No. Obs	6,334	6,334	6,334	5,442	2,040	3,690
R-squared	0.631	0.611	0.647	0.653	0.516	0.610
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences. The dependent variable is the log of one plus (total / international / high-tech) patent application counts. Columns 4 to 6 focus on the set of firms with positive patenting at t. $pre-US$ is a dummy variable that equals 1 if the firm had collaborated with U.S. prior to the year it was sanctioned. Standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table 7: Innovation Capacity and Post-Sanction Innovation Performance

	(1)	(2)	(3)
	Patent Application		
	Total	Intl.	High-Tech
Treatment×Post	-0.163***	-0.223***	-0.058
	(0.040)	(0.039)	(0.267)
Treatment×Post×Top	0.156***	0.140*	0.060
	(0.037)	(0.078)	(0.046)
No. Obs	6,334	6,334	6,334
R-squared	0.63	0.611	0.645
Firm FE	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences. The dependent variable is the log of one plus (total / international / high-tech) patent application counts. Top is a dummy variable that equals 1 if the firm ranks within the top 10% in terms of quality-adjusted patent stock in its industry in the year when it is sanctioned. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table 8: Knowledge Distance and Post-Sanction Innovation Performance

	(1)	(2)	(3)	(4)
	Patent Application			
Treatment×Post	-0.666***	-1.416**	-3.199**	-8.297*
	(0.195)	(0.511)	(1.417)	(4.290)
Treatment×Post×TechDist	0.033***			
	(0.009)			
Treatment×Post×Sourcing		0.023**		
		(0.008)		
Treatment×Post×Adoption			0.039**	
			(0.017)	
Treatment×Post×Collaboration				0.087*
				(0.045)
No. Observation	6,334	6,334	6,334	6,334
R-Squared	0.631	0.631	0.631	0.630
Firm FE	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences. The dependent variable is the log of one plus total patent application counts. *TechDist* is measured as the ratio of triadic patents filed by Chinese firms to the total triadic patents filed by either Chinese or U.S. firms in each 2-digit ISIC sector. *Sourcing* is measured as the share of citations made to Chinese patents in each 2-digit ISIC sector. *Adoption* is measured as 1 minus the share of patents that first applied outside of China. *Collaboration* is measured as the proportion of patents applied by Chinese firms developed by Chinese inventors only. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table 9: Post-sanction Innovation Performance among Firms in the Sanctioned Technology Field

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent Application			**Average Collaborator per Patent**		
	Total	Intl.	High-Tech	U.S.	Euro+	Adv. Asia
Treatment×Post	-0.069**	-0.095***	-0.035***	-0.025	0.001	0.030**
	(0.026)	(0.011)	(0.012)	(0.015)	(0.004)	(0.010)
No. Obs	193,851	193,851	193,851	158,421	158,421	158,421
R-squared	0.410	0.425	0.481	0.409	0.269	0.390
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences. In columns 1 to 3, the dependent variable is the log of one plus (total / international / high-tech) patent application counts. In columns 4 to 6, the dependent variable is log of one plus average number of collaborators (from U.S. / Euro+ / Advanced Asia) per patent. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table 10: Pre-Sanction U.S. Collaboration and Post-Sanction Innovation Performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent Application			**Average Collaborator per Patent**		
	Total	Intl.	High-Tech	U.S.	Euro+	Adv. Asia
Treatment×Post	0.041	0.125***	0.084**	0.357***	-0.015***	-0.066
	(0.026)	(0.034)	(0.035)	(0.025)	(0.005)	(0.042)
Treatment×Post×pre-US	-0.134**	-0.268***	-0.146**	-0.464***	0.020**	0.116**
	(0.055)	(0.033)	(0.055)	(0.026)	(0.009)	(0.051)
No. Obs	193,851	193,851	193,851	158,421	158,421	158,421
R-squared	0.410	0.428	0.481	0.410	0.269	0.390
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences. In columns 1 to 3, the dependent variable is the log of one plus (total / international / high-tech) patent application counts. In columns 4 to 6, the dependent variable is log of one plus average number of collaborators (from U.S. / Euro+ / Advanced Asia) per patent. Estimates in columns 1 to 3 are based on a set of firms that started patenting before 2013 and estimates in columns 4 to 6 are based on a set of firms that have positive patenting. $pre-US$ is a dummy variable that equals 1 if the firm had collaborated with U.S. prior to the year it was sanctioned. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table 11: Spillover through Innovation Network

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent Application					
	Total	Intl.	High-Tech	Total	Intl.	High-Tech
Downstream	-0.547**	-0.171	0.034			
	(0.278)	(0.190)	(0.220)			
Upstream	0.531**	0.237	0.003			
	(0.248)	(0.168)	(0.192)			
DummyDownstream				-0.034***	-0.004	-0.023***
				(0.008)	(0.005)	(0.006)
No. Observation	192,262	192,262	192,262	192,262	192,262	192,262
R-squared	0.411	0.426	0.484	0.411	0.426	0.484
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences. The dependent variable is the log of one plus (total / international / high-tech) patent application counts. *Downstream* measures the relative frequency of a technology field j cites the sanctioned technology fields. *Upstream* measures the relative frequency of a technology field j being cited by the sanctioned technology fields. See equation (6) for detail. *DummyDownstream* is a dummy variable that equals 1 if the technology field j is more frequently cites the sanctioned technology fields than being cited by the sanctioned technology fields. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table 12: Pre-Sanction Chinese Collaboration and Post-Sanction Innovation Performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent Application					
	Total	Intl.	High-Tech	Total	Intl	High-Tech
Treatment×Post	-0.003	-0.016	-0.006	0.209***	0.218***	0.177***
	(0.012)	(0.017)	(0.010)	(0.018)	(0.018)	(0.024)
Treatment×Post×Pre-CN				-0.266***	-0.293***	-0.229***
				(0.014)	(0.011)	(0.022)
No. Obs.	219,728	219,728	219,728	219,728	219,728	219,728
R-squared	0.224	0.232	0.362	0.226	0.236	0.365
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

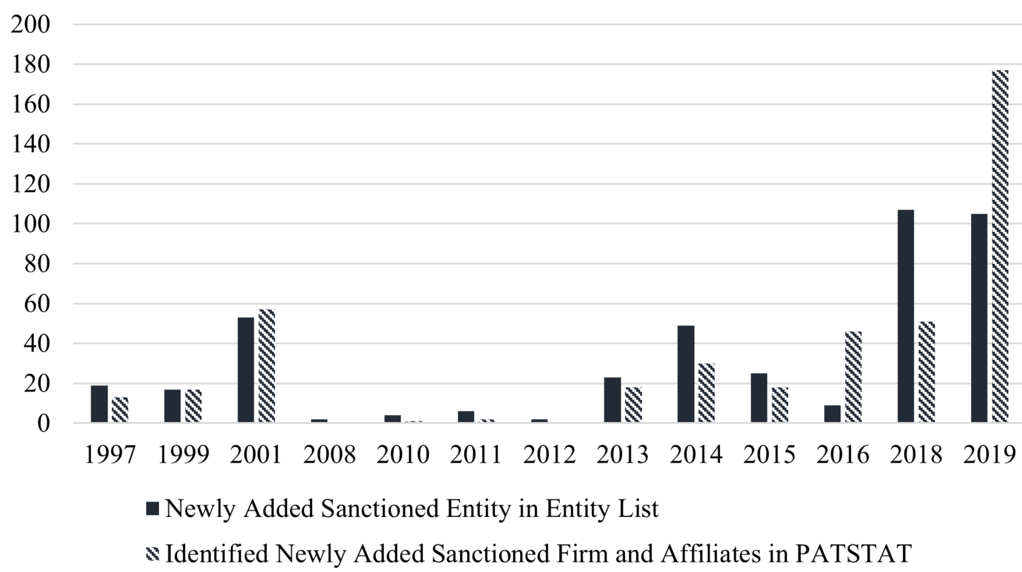
Note: We estimate the coefficients using difference-in-differences. The dependent variable is the log of one plus (total / international / high-tech) patent application counts. $pre - CN$ is a dummy variable that equals 1 if the firm had collaborated with China prior to the year it was sanctioned. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

A Appendix: Data and Sample

A.1 Details in Construction of the Sample

Data Source. The analysis is based on data from PATSTAT Global 2022 Spring Version, and information on sanctioned entities from the Entity List issued by the U.S. Department of Commerce. We rely on `https://www.federalregister.gov/` to obtain the announcement date and sanctioned firms' information. We match the entity list to the PATSTAT using entity names. To identify the affected corporations, we match the exact entities as well as their subsidiaries or affiliated institutes. The affiliated institutes/companies are identified using firm names. For example: China Electronics Technology Group Corp (CETC) 54th Research Institute was added to the Entity List in 2001, we identified all PATSTAT-listed firms under the name CETC or China Electronics Technology Group Corp as sanctioned entities. For instance: 54th Research Institute of CETC, CETC No. 2 Research Institutes. Table 1 shows the number of sanctioned entities and identified sanctioned entities in the PATSTAT.

Figure A.1: Annual Distribution of Firms Added to the Entity List Over Time



Source: PATSTAT Dataset, Spring 2022 version. Federal Registry
Notes: Each dark blue bar shows the number of newly added sanctioned entities in the Entity List. The dashed blue bar is the number of these entities and their affiliates we can match to PATSTAT.

Imputing Country of Residence One limitation of the PATSTAT dataset is the absence of location information. For example, patent applications filed at the Chinese patent office, around

37% of patent applicants/inventors have missing information on their country of residence. To address this gap, we utilize the methodology proposed by De Rassenfosse et al. (2013) and Menon and Tarasconi (2017) to recover and assign country codes to each inventor/applicant with missing location information using the following steps.

First, we use the location information associated with each inventor/applicant ID to recover their country of residence. Next, we utilize the standardized names by PATSTAT. Due to variations in how names are recorded across different patent offices, the same inventors/applicants may appear under different names. PATSTAT regroups name that likely represents the same individual under a unique standardized name and assigns them a unique PSN ID. Inventors/applicants linked by the same PSN ID are assumed to reside in the same country within a specific year. If some inventors/applicants id lack country information, but others under the same PSN ID have, we infer the missing country information based on the available location information. In some rare cases, multiple country codes are associated with a single PSN ID, and the country code corresponding to the highest number of patents is selected for all linked inventors/applicants.

Second, we use the priority patent information, when, for example, a patent filed in China lacks the location data of its applicants/inventors, but its priority filings in EPO contain the location information. The location information recorded by EPO is used to infer the country of residence of applicants/inventors who lack location information in China. When the first filing lacks location information whereas the subsequent filings contain the location information, we use the country code in the subsequent filings to impute country information for applicants/inventors.

Lastly, for the rest of the applicants/inventors with missing country codes, we use the information on patent office locations. Following Rassenfosse and Seliger (2021), we assume that inventors/applicants would first file patents in their domestic patent office. Therefore, the location of the patent office for the applicants/inventors' first filing is used as a proxy for their country of residence. Table A.1 shows the imputation of country code using each method

A.2 Construction of Sample and Measurement

Matched Sample. To ensure the validity of our difference-in-differences analysis, it is crucial that the comparison between sanctioned firms (treatment group) and unsanctioned firms (control group) is based on comparable firm characteristics before the sanctions.

Table A.1: Imputed Country Code and Method

	(1)	(2)	(3)	(4)	(5)	(6)
	Applicants' Location			**Inventors' Location**		
Imputation Method	Total	U.S.	China	Total	U.S.	China
Recorded	1,121,609	99,403	955,141	1,843,834	159,644	1,536,147
Address and PSN name	90,907	8,458	75,671	104,103	15,269	77,917
Priority and Subsequent filings	48,116	7,665	33,672	43,176	9,145	22,828
First Filings and Patent Office	372,996	3,480	363,888	1,791,780	5,388	1,663,120

Note: This Table lists the number of applicants/inventors with recorded country codes (first row) and the number of country codes we imputed using different methods (row 2 to row 4). Columns (2), (3), (5), and (6) lists the number of Chinese/U.S. applicants/inventors imputed using each method.

Table A.2 presents descriptive statistics for our sample, before matching. On average, sanctioned firms (firms on the Entity List from 1997 to 2021) filed notably more patents between 2006 and 2017, both domestically and internationally, compared to other Chinese firms in our sample. We also observe higher filing rates in triadic patents and high-technology patents for sanctioned firms. This indicates that sanctioned firms have a stronger focus on global innovation and have a broader global market presence. This trend also suggests larger R&D capabilities in sanctioned firms compared to their unsanctioned counterparts

To achieve this comparability, we implement the two steps following suggestions in Hainmueller and Xu (2013). First, for each firm being sanctioned at year t, we use propensity score matching to find "matched" control firms that have similar patent trajectories before year t. We estimate the propensity score using logit regressions, which is defined as $p_{x,T} = Pr(D_i = 1|X, T) = G(X, T, \text{sector dummy})$, where X is firm-level controls includes patent age, log of patent stock, log of patent, pre-sample average patent applications (i.e. average patent applications before 2003), a dummy variable that equals 1 if firms patent at $t-1$ and log of patent applications at $t-1$. Second, we use entropy balancing to re-weight data to further balance out the covariates. The entropy balancing adjusts the weights of the control group (unsanctioned firms) to align the moments of covariates, means, and variance, with that of the treated group (sanctioned firms).

Table 1 provides summary statistics after matching, of the variables used in matching and the patenting outcomes (before sanctions). The mean and variance of control variables (X) are similar between the sanctioned and unsanctioned firms after re-weighting. The last two columns perform a t-test between the two groups and reveal that the sanctioned firms and unsanctioned firms have similar patent outcomes before sanctions.

Table A.2: Summary Statistics

	Sanctioned Firms			**Other Firms**		
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Total Patents	81.46	6.00	501.43	14.08	2.00	108.95
Domestic Patents	79.87	5.00	486.94	13.90	2.00	108.54
EPO/USPTO/PCT Patents	39.60	0.00	339.22	1.65	0.00	18.23
High-Tech Patents	46.59	1.00	324.80	4.21	0.00	39.59
Triadic Patents	3.51	0.00	37.41	0.19	0.00	2.27
Patent Stock	120.77	4.87	898.56	23.10	4.43	187.56
Patent Quality	1.28	0.91	1.38	1.64	1.00	3.31
Priori Ave. Patent App.	0.79	0.00	8.20	0.23	0.00	2.97
Patent Age	9.08	9.00	3.60	12.16	10.00	7.22
No of Observations	2,138			347,521		

Note: Table compares the patenting of firms in our treatment group (firms included in the Entity list) and control groups (other firms) over the period 2006-2017, before matching and using the entropy balancing method.

Table A.3 compares summary statistics of firms in the identified sanctioned IPC field and unsanctioned IPC field. We find firms in the sanctioned IPC fields file significantly higher patents than firms in other IPC fields. Hence, we use a similar matching method to construct a comparable control group and then apply entropy balancing to reweigh the control group observations. More specifically, for each firm i of the sanctioned IPC field j, we find firms in the unsanctioned IPC field that share the same patent trajectories before field j being sanctioned. Table A.4 provides summary statistics of the variables used in matching and main outcomes variables (i.e. patent counts) before sanctions.

Measurement of Collaboration. To examine how cross-border collaboration affects innovation outcomes among Chinese firms, we develop three measures to assess the strength of the partnership at the applicant-inventor level rather than between applicants. Given the share of cross-border co-application is relatively small in our sample, [22] we instead focus on the regional distribution of inventors of patents applied by Chinese firms. We group the inventor's locations into five regions: China, U.S., Advanced Asia, Europe+, and others. Advanced Asia includes the Republic of Korea; Japan; Singapore; Hong Kong SAR, China; and Taiwan, China. Europe+ includes advanced European countries (Ireland, Norway, Demark, Spain, Belgium, Austria, Finland, Iceland, Netherlands,

[22] During the sample period 2006-2020, only 4.6% of patents applied by Chinese firms have foreign firms as their co-applicants, whereas 13.7% of patents applied by Chinese firms collaborate with foreign inventors.

Table A.3: Summary Statistics for firms in IPC fields

	Firms in the Sanctioned IPC fields			**Firms in other IPC fields**		
	Mean	Medium	Std. Dev.	Mean	Medium	Std. Dev.
Total Patents	25.34	3	181.99	10.96	2	78.50
Domestic Patents	24.97	2	179.62	10.81	2	78.32
EPO/USPTO/PCT Patents	3.69	0	60.48	1.17	0	7.26
High-tech Patents	10.30	1	81.98	2.11	0	17.17
Triadic Patents	0.33	0	6.27	0.13	0	0.93
Patent Stock	46.59	5.30	397.23	21.26	5.13	133.96
Patent Quality	1.57	0.92	3.83	1.74	1.00	3.35
Priori Average Patent App.	0.20	0.00	1.45	0.31	0.00	5.02
Patenting Age	8.87	7	7.51	9.23	8	7.74
No. of Observations	104,813			244,846		

Note: Table compares the patenting of firms in our treatment group (firms included in the sanctioned IPC fields) and control groups (other firms) over the period 2006-2017, before matching and using the entropy balancing method. Each firm's average patent quality per year was calculated as the ratio of citation-adjusted to total unadjusted patent counts. The prior average patent applications are computed as the annual patent filings for each firm before 2002.

Italy, Sweden, Switzerland, Germany, France, UK, Portugal, Czechia, Greece, and Luxembourg) and other advanced economies like Canada and Australia.

The first measurement of collaboration strength is an inventor location dummy D_{pr}, which equals 1 if patent p has at least one inventor from region r. We then use this variable to quantify the share of patents applied for by firm i in year t that involve collaborators from region r. This measurement reflects the relative degree of collaboration across different regions at the extensive margin. However, the dummy variable alone does not capture the relative scale of cross-regional collaborative efforts within each patent. For instance, consider a patent developed by five inventors where three are from the U.S., one from Japan, and one from China. Using a dummy variable, won't reveal the extent to which region contributes more to the patent.

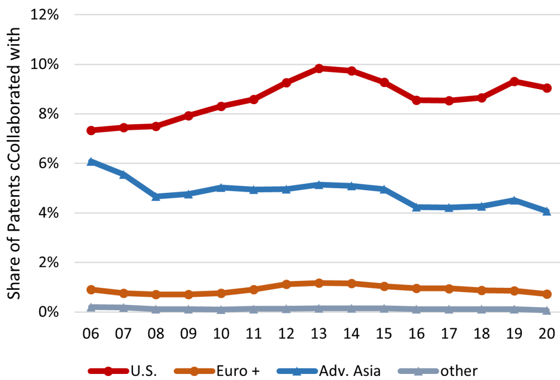
To capture the intensive margin of cross-regional collaboration, that is, to measure each region's relative contribution, the second measurement we use is the average number of inventors per patent. For each patent p, we compute Col_{pr} as the number of inventors from region r. We then average this number across all patents applied for by firm i in year t to get the average number of inventors per patent for each region. This measurement further helps us assess the depth of cross-region collaboration. Figure A.2 shows the trends of share of patents collaborated, and average inventors per patent across different regions for all patents in our sample.

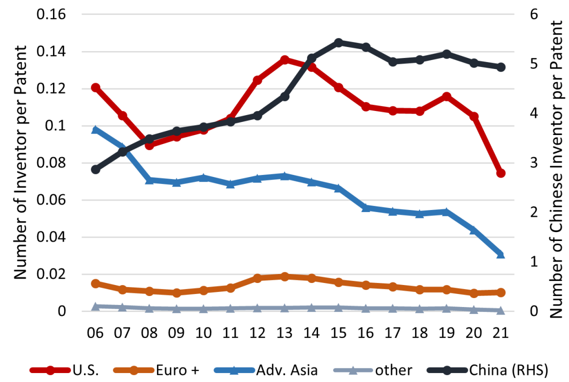
Table A.4: Summary Statistics after matching and balancing

	Firms in Sanctioned IPC fields		**Firms in other IPC fields**		**Difference**	
	Mean	Std. Dev	Mean	Std. Dev	Diff	Std
Patent Counts						
Total Patents	5.18	7.91	5.08	8.19	0.10**	(0.05)
High-Tech Patents	2.00	3.73	1.01	2.5	0.99***	(0.02)
EPO/USPTO/PCT Patents	1.35	2.91	0.85	2.39	0.5***	(0.02)
Triadic Patents	0.2	0.87	0.12	0.63	0.08***	(0.00)
Quality-adjusted Patents						
Total Patents	4.82	21.31	4.71	10.66	0.11	(0.10)
High-Tech Patents	2.02	20.03	0.95	3.45	1.08***	(0.09)
EPO/USPTO/PCT Patents	2.17	20.35	1.38	6.15	0.79***	(0.09)
Triadic Patents	0.8	19.65	0.34	2.7	0.45***	(0.08)
Controls						
Patent Age	9.61	6.84	9.60	7.48	0.01	(0.04)
Patent Stock (log)	1.80	0.99	1.80	1.01	0.00	(0.01)
Prior Average Patent App.	0.17	0.30	0.17	0.35	0.00	(0.00)
Dummy Patent	0.75	0.43	0.75	0.43	0.00	(0.00)
Lagged Total Patent App (log)	1.20	0.95	1.2	0.96	0.00	(0.01)
No of Observations	87,401			106,450		

Note: This Table compares the mean and standard deviation of firms in sanctioned and unsanctioned sectors before the sector is sanctioned. The prior average patent applications are computed as the annual patent filings for each firm before 2002. It reflects a firm's pre-sample innovation capacity. Patent is a dummy variable that equals 1 if a firm at year t has also patented at $t-1$. Lagged Total Patent App (log) represents the the log of one plus the patent count (from total patents) at $t-1$. The last column is the standard error of the t-test. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Figure A.2: Trends of Collaboration Strength





Source: PATSTAT Dataset, Spring 2022 version.
Notes: The trend is computed using all patents applied for by Chinese firms in our sample from 2006 to 2021. The left panel shows the share of patents that collaborated with inventors from different regions. The right panel shows the average inventors per patent from different regions

The third measurement we use is the "collaboration stock", which reflects the cumulative impact of historical collaborations. To compute this, we first calculate the total number of inventors from each region for each patent p filed by firm i: Col_{rpi}. Next, we aggregate these totals for all patents applied for by firm i in each year y as: $Coly_{riy} = \sum_{p=1}^{N_{ip}} col_{i,pr,y}$. To account for the diminishing impact of past collaboration on current innovation, we aggregate these annual collaborations across all years up to $t-1$, with an annual depreciation rate of 15%, the same as the depreciation rate of the patent stock. That is, the past collaboration stock of firm i at time t with region r is computed as: $colstk_{rit} = \sum_{y=1}^{t-1}(1-0.15)^{y-1} \times Coly_{riy}$. Table A.5 provides the summary statistics of these three collaboration measures for sanctioned and unsanctioned firms in our matched sample.

Table A.5: Summary Statistics for Collaborations Strength (mean)

	(1)	(2)	(3)	(4)	(5)	(6)
	Sanctioned Firms			**un-Sanctioned Firm**		
	Collab. Dummy	Ave. Inventor per Patent	Collab. Stock (log)	Collab. Dummy	Ave. Inventor. per Patent	Collab. Stock (log)
U.S.	0.503	0.107	1.637	0.442	0.118	1.443
European+	0.085	0.007	0.263	0.088	0.009	0.283
Adv. Asia	0.312	0.037	0.947	0.318	0.081	1.105
others	0.018	0.001	0.046	0.015	0.002	0.050

Note: This Table compares the mean of different collaboration measures between sanctioned and unsanctioned firms. Columns 1 and 4 use a dummy variable that indicates whether a patent has at least one inventor from region region. Columns 2 and 5 show the average inventor per patent. Columns 3 and 6 are log of collaboration stock as defined above.

Measure of Innovation Capacity and Innovation Network. We assess the innovation capacity at the 2-digit ISIC sector level using four measurements derived from previous literature (see section 5.2 for details). For each sector j in year t, we calculate the following:

1. Relative knowledge: computed as the ratio of triadic patents filed by Chinese firms to the total number of triadic patents filed by either Chinese or U.S. firms up to year t. This measurement aims to gauge the sector's distance to the global technology frontier

2. Domestic knowledge sourcing: computed as the share of citations that Chinese firms make to Chinese patents out of the total citations made by these firms up to year t. This measurement reflects each sector's reliance on domestic knowledge.

3. Degree of indigenous innovation: computed as the proportion of patents first applied for in China. We first track the priority number of each patent to identify those that have been previously granted or submitted an application at a foreign patent office by the end of year t. We then calculate the share of these patents by dividing their number by the total number of patent applications in the Chinese patent office up to year t. The degree of indigenous innovation is then defined as 1 minus this share. This measurement indicates the level of innovation originating within China.

4. Dependence on domestic inventor: computed as the proportion of patents applied for by Chinese firms that are developed by Chinese inventors up to year t. This measurement captures the sector's reliance on domestic human capital for developing innovation.

We use IPC-to-IPC citations to measure each IPC's exposure to the sanctioned IPC. We define the upstream exposure of an IPC field j in year t to the sanctioned IPC fields as the weighted sum of sanction indicators, where the weights are the proportion of citations IPC field j makes to each sanctioned field n. Similarly, the downstream exposure of technology field j in year t to the sanctioned IPC fields is calculated as the weighted sum of sanction indicators, with weights based on the proportion of citations made by each sanctioned field n to field j. Hence, the downstream firms (i.e., firms dependent on technology from sanctioned IPC) have higher upstream exposure. And the upstream firms (i.e. firms in sectors the sanctioned IPC relies on) have higher downstream exposure.

Table A.6 summarizes the means and standard deviations of these measures, and the mean of innovation capacity at the year when firms/IPC fields are being sanctioned.

Table A.6: Summary Statistics for Innovation Capacity and Upstream/Downstream Exposure

	(1)	(2)	(3)	(4)
	Total		**Sanctioned Year**	
	Mean	Std. Dev	Mean	Std. Dev
Relative knowledge (percentage %)	7.40	6.07	15.02	6.12
Domestic knowledge sourcing (percentage %)	42.62	21.63	58.21	9.12
Degree of indigenous innovation (percentage %)	74.43	15.63	81.70	5.16
Dependence on domestic inventor (percentage %)	93.63	4.09	94.90	1.61
Downstream measure ($\times 100$)	0.86	3.15	1.89	3.76
Upstream measure ($\times 100$)	0.85	3.49	1.91	4.36

Note: This Table compares the mean and standard deviation of different innovation capacity measures at the sector level. Columns 3 and 4 are the mean and standard deviations of sectors where the sanctioned firms (or firms in the sanctioned IPC fields in the last two rows) are located when they are added to the Entity List (or added into the sanctioned IPC fields).

B Appendix: Robustness and Additional Results

B.1 Parallel Trend and TWFE

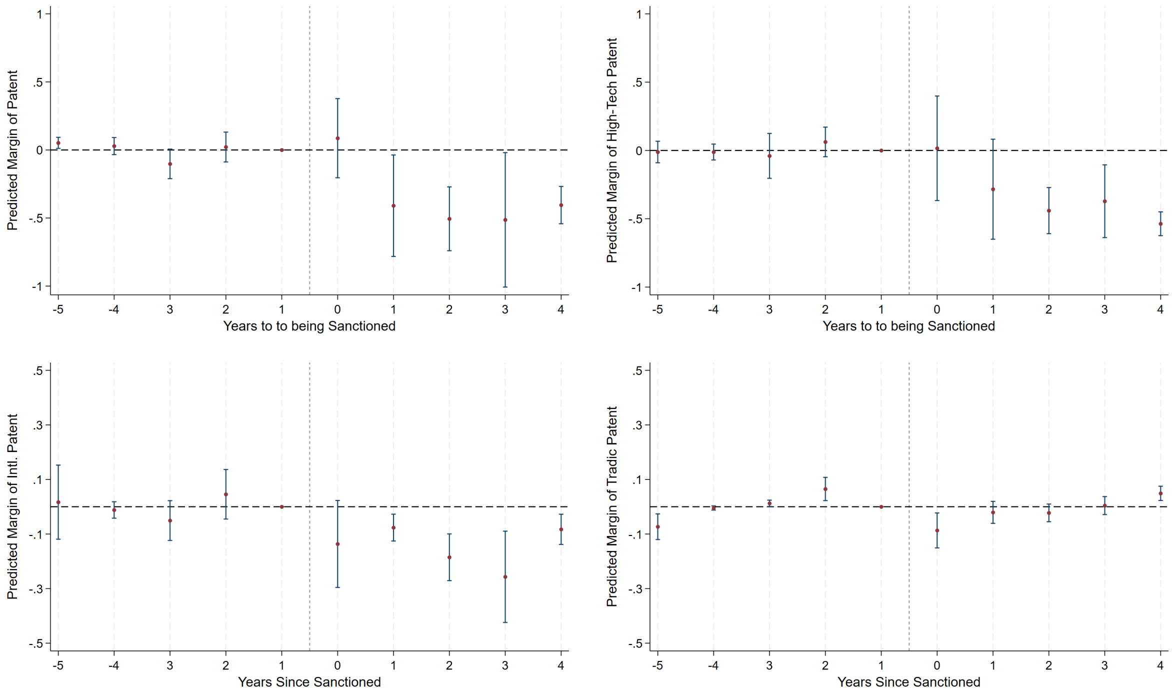
The identifying assumption of our DID analysis is that the patent activity in both the treatment and control groups follows the same trend before sanctioned firms are added to the Entity List. The assumption of parallel trends, central in the TWFE approach, is violated if firms enter the treatment group at different stages. We test the presence of parallel trends and estimate this dynamic event study equation:

$$y_{ij,t} = \sum_{k=-5}^{k=-1} \alpha_k T_{ij} \times Pre_{ij,t+k} + \sum_{k=0}^{k=5} \beta_k T_{ij} \times Post_{ij,t+k} + \gamma X_{ij,t-1} + \psi_i + \delta_{jt} + \varepsilon_{it}$$

where $Pre_{ij,t+k}$ (or $Post_{ij,t+k}$)is a dummy variable that equals 1 if k year before (or after) the year when firm i of sector j has been added into the Entity List. $X_{ij,t-1}$ is a set of controls including the log of firm i of sector j's patent stock at time $t-1$, a dummy variable that equals 1 if firm i of sector j has patented at year $t-1$; ψ_i is the firm fixed effect to capture the unobserved firm characteristics. δ_{jt} is the sector-year fixed effect to capture the unobserved sector-year changes that affect firms' patenting activity. Figure A.3 confirms the sanctioned and unsanctioned firms had parallel trends over all patent categories before the sanctioned firms were added to the Entity List. The estimates show a negative effect of U.S. sanctions on sanctioned Chinese firms' total, high-tech, and international patent applications, compared to non-sanctioned firms. The decline is significant and magnified for those patent applications two years after the inclusion of the firms in the Entity List. However, the treatment effect is insignificant for triadic patent applications.

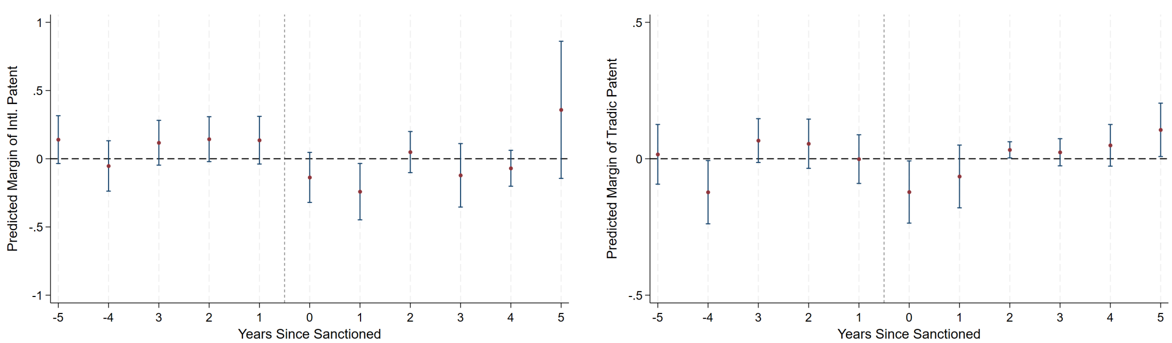
Callaway and Sant'Anna (2021) warn about potential heterogenous treatment effects. Our two-way fixed effect (TWFE) estimates would be biased if we compared firms recently added to the Entity List to firms already subject to U.S. sanctions. We re-ran the event study analysis using Callaway and Sant'Anna (2021)'s estimator. Figure 4 shows the estimated coefficient on total patent applications and high-tech patent applications. Figure A.4 below shows the same estimator on international patent applications and triadic patent applications. The Callaway and Sant'Anna (2021)'s estimates are qualitatively similar to the TWFE estimates, except that the treatment effect on international patent applications is insignificant.

Figure A.3: Effect of U.S. sanctions on patent applications



Source: PATSTAT Dataset, Spring 2022 version.
Notes: The red dots are the estimated differences in the number of patent applications between sanctioned and unsanctioned firms five years before and after the sanctioned firms were added to the Entity List. The top left figure shows the results for total patents, top right high-tech patents, bottom left international patents, bottom right triadic patent applications. The blue bar is the 95% confidence interval. The estimates are based on a two way fixed effects "event study" regression, with sector, firm, and year fixed effects.

Figure A.4: Effect of U.S. sanctions on patent applications



Source: PATSTAT Dataset, Spring 2022 version.
Notes: The red dots are the estimated differences in the number of patent applications (i.e. patent counts) between sanctioned and unsanctioned firms five years before and after the sanctioned firms were added to the Entity List. The left panel shows the results for international patents, and the right panel focuses on triadic patents. The blue bar is the 95% confidence interval. The estimates reflect staggered difference-in-differences using the method by Callaway and Sant'Anna 2021.

B.2 Robustness

In the first robustness check, we estimate the average treatment effect in levels as percentage changes from the controlled mean using a negative binomial. Specifically, we estimate the following model:

$$y_{ijt} = exp(\beta \times T_{ij} \times Post_{ijt} + \psi T_{ij} + \gamma X_{ij,t-1} + \eta Z_i + \delta_{jt} + \varepsilon_{it}) \tag{9}$$

where y_{ijt} is the count number of patent applications. Z_i is the number of pre-determined, time-invariant firm characteristics that might affect firms' patenting capability. Following Blundell et al. (1999), we use the average pre-sample patent applications to control for firms' fixed effects in the negative binomial model. We use the firm's patent age and patent stock to approximate firm's i patent capability. Table A.7 displays the estimated coefficients and the implied average treatment effect, $exp(\beta + \psi) - 1$.

Table A.7: Estimated Average Treatment Effect using Negative Binomial

	(1)	(2)	(3)	(4)
	Patent Application			
	Total	International	Triadic	High-Tech
Treatment×Post	-0.365***	-1.249***	-3.389***	-0.571***
	(0.057)	(0.299)	(0.360)	(0.108)
Treatment	0.125***	0.266**	0.561***	0.400***
	(0.040)	(0.135)	(0.051)	(0.108)
Implied ATE	-0.213***	-0.630***	-0.941***	-0.157*
	(0.022)	(0.077)	(0.023)	(0.086)
No. Obs.	6,377	6,377	6,377	6,377
R-squared	0.110	0.065	0.089	0.109
Sector-year FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No

Note: We estimate the coefficients using negative binomial regressions. We control for firm fixed effects using the pre-sample patent applications. Implied ATE is calculated as $exp(\beta + \psi) - 1$. Robust standard errors clustered at the 2-digit ISIC level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

In our second robustness analysis, we estimate the treatment effect on intensive and extensive margins separately. Specifically, we re-run the regression 1 on a set of firms with positive patent applications at time t, to assess the intensive margin. To quantify the extensive margin, we replace y_{ijt} in equation (1) with a dummy variable that equals 1 if firm i of sector j filed a patent at time

t. [23] As only a limited number of firms applied for triadic patents after being sanctioned, we focus our analysis on total patents, high-tech patents, and international patent applications.

Table A.8: Post-Sanction Innovation Performance among Sanctioned Firms

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent Application (Intensive Margin))			**Patent Application (Extensive Margin))**		
Treatment×Post	-0.127***	-0.239	-0.176***	-0.025**	-0.050**	-0.040***
	(0.027)	(0.147)	(0.059)	(0.011)	(0.023)	(0.008)
No. Obs	5,442	2,040	3,690	6,334	6,334	6,334
R-squared	0.653	0.516	0.610	0.242	0.487	0.287
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: We estimate the coefficient using difference-in-differences. Columns 1 to 3 use a set of firms with positive patent filing in each category. Robust standard errors clustered at the 2-digit ISIC level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

In the third robustness check, we focus only on firms that already had patents before 2013 and repeat our baseline regression 1 on this sample. Our analysis focuses only on firms that were sanctioned after 2013. The results from our benchmark regression may conflate the treatment effects on the number of firms that start patenting with the impact on the number of patent applications filed by these firms. Therefore, in this robustness check, we isolate and estimate the treatment effect solely on the number of patent applications filed by each firm.

Table A.9: Post-Sanction Innovation Performance among Sanctioned Firms (Patenting Firm)

	(1)	(2)	(3)	(4)
		Patent Application		
	Total	International	Triadic	High-Tech
Treatment×Post	-0.110***	-0.205***	-0.103	-0.066*
	(0.030)	(0.022)	(0.214)	(0.033)
No. Obs.	6,245	3,786	1,307	5,255
R-squared	0.628	0.536	0.329	0.610
Sector-year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Note: We estimate the coefficients in columns 1 to 5 using difference-in-differences on a set of firms that start filing patents in specific categories before 2013. Robust standard errors are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

[23] We use a linear probability model to estimate the extensive margin in our regression, which includes firm fixed effects and sector-year fixed effect. Using non-linear regression models like logit or probit in this context could lead to incidental parameter problems. Moreover, our primary interest is the marginal effects of sanctions, and the LPM provides reliable estimates for these effects (Wooldridge 2010).

B.3 Additional Results

Different collaboration measurement. Section A.2 describes three different measures on the degree of collaboration between Chinese firms and foreign inventors: inventor location dummy D_{pr}, the share of patents collaborated with an inventor from region r, and the average inventor from region r per patent. Table 5 shows the impact of U.S. sanctions on the average inventor per patent. The following tables re-ran similar regressions and estimated the impact of U.S. sanctions on the probability of collaborating, as well as the share of patents collaborated with inventors from different regions.

Table A.10: Post-Sanction Collaboration among Sanctioned Firms

	(1)	(2)	(3)	(4)	(5)	(6)
	Probability of Collaborating with Inventors from					
	U.S.	Euro+	Adv. Asia	U.S.	Euro+	Adv. Asia
Treatment×Post	-0.047***	-0.057***	-0.017	0.077**	-0.052***	0.059
	(0.009)	(0.015)	(0.039)	(0.028)	(0.014)	(0.051)
Treatment×Post×pre-US				-0.148***	-0.006	-0.091
				(0.038)	(0.013)	(0.082)
No. Obs.	5,442	5,442	5,442	5,442	5,442	5,442
R-squared	0.312	0.196	0.388	0.402	0.311	0.388
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using a linear probability model. $pre-US$ is a dummy variable that equals 1 if the firm had collaborated with U.S. prior to the year it was sanctioned. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Innovation Capacity and High-Tech patent applications. Table 8 shows how an increase in innovation capacity at the sector level could mitigate the negative impact of US sanctions on total patent applications of Chinese firms. We re-ran the regression (5.2) using patent applications in the high-technology field as the dependent variable. Table A.12 shows that firms in sectors with higher innovation capacity are less adversely affected by the sanctions. Compared to the estimates in table 8, the mediating effect is much stronger for high-tech patents.

Table A.11: Post-Sanction Collaboration among Sanctioned Firms

	(1)	(2)	(3)	(4)	(5)	(6)
	Share of Patents with Inventors from					
	U.S.	Euro+	Adv. Asia	U.S.	Euro+	Adv. Asia
Treatment×Post	-0.117***	-0.048***	0.028	0.259**	-0.068**	0.311***
	(0.038)	(0.011)	(0.070)	(0.090)	(0.022)	(0.123)
Treatment×Post×pre-US				-0.451***	0.025	-0.339**
				(0.129)	(0.019)	(0.174)
No. Obs.	5,442	5,442	5,442	5,442	5,442	5,442
R-squared	0.401	0.198	0.377	0.368	0.195	0.377
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences. $pre-US$ is a dummy variable that equals 1 if the firm had collaborated with U.S. prior to the year it was sanctioned. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table A.12: Knowledge Distance and Post-Sanction Innovation Performance

	(1)	(2)	(3)	(4)
	High-Tech Patent Application			
Treatment×Post	-0.750***	-1.633***	-3.568***	-10.720***
	(0.216)	(0.368)	(0.786)	(2.777)
Treatment×Post×TechDist	0.042***			
	(0.008)			
Treatment×Post×Sourcing		0.028***		
		(0.006)		
Treatment×Post×Adoption			0.044***	
			(0.009)	
Treatment×Post×Collaboration				0.113***
				(0.030)
No. Observation	6,334	6,334	6,334	6,334
R-Squared	0.646	0.646	0.646	0.646
Firm FE	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences. $TechDist$ is measured as the ratio of triadic patents filed by Chinese firms to the total triadic patents filed by either Chinese or U.S. firms in each 2-digit ISIC sector. *Sourcing* is measured as the share of citations made to Chinese patents in each 2-digit ISIC sector. *Adoption* is measured as 1 minus the share of patents that first applied outside of China. *Collaboration* is measured as the proportion of patents applied by Chinese firms developed by Chinese inventors only. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Results on the intensive margin. In our benchmark regression, we estimate the treatment effect using log transformation of the dependent variable, i.e. $log(patent + 1)$. The log transformation of outcome variables that are well defined at zero might cause a bias in estimating and interpreting the average treatment effect (Chen and Roth 2024), particularly when the treatment affects the extensive margin. Hence, in this section, we re-ran all the regressions focusing only on firms that applied for patents each year. The coefficients estimated in the following tables reflect the treatment effect at an intensive margin only.

Table A.13: Innovation Capacity and Post-Sanction Innovation Performance

	(1)	(2)	(3)
	Patent Application (Intensive Margin)		
	Total	Intl.	High-Tech
Treatment×Post	-0.237***	-0.260**	-0.214***
	(0.042)	(0.107)	(0.064)
Treatment×Post×Top	0.260***	0.033	0.083***
	(0.039)	(0.070)	(0.027)
No. Obs	5,442	2,040	3,690
R-squared	0.653	0.515	0.610
Firm FE	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences on a set of patenting firms. *Top* is a dummy variable that equals 1 if the firm ranks within the top 10% in terms of quality-adjusted patent stock in its industry in the year when it is sanctioned. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table A.14: Knowledge Distance and Post-Sanction Innovation Performance

	(1)	(2)	(3)	(4)
	Patent	**Application**	**(Intensive**	**Margin)**
Treatment×Post	-0.851***	-2.107***	-4.193***	-12.987***
	(0.238)	(0.543)	(1.375)	(4.246)
Treatment×Post×TechDist	0.042**			
	(0.010)			
Treatment×Post×Sourcing		0.035***		
		(0.009)		
Treatment×Post×Adoption			0.052***	
			(0.016)	
Treatment×Post×Collaboration				0.136***
				(0.044)
No. Observation	5,442	5,442	5,442	5,442
R-Squared	0.654	0.655	0.654	0.653
Firm FE	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences on a set of patenting firms. *TechDist* is measured as the ratio of triadic patents filed by Chinese firms to the total triadic patents filed by either Chinese or U.S. firms in each 2-digit ISIC sector. *Sourcing* is measured as the share of citations made to Chinese patents in each 2-digit ISIC sector. *Adoption* is measured as 1 minus the share of patents that first applied outside of China. *Collaboration* is measured as the proportion of patents applied by Chinese firms developed by Chinese inventors only. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table A.15: Pre-Sanction U.S. Collaboration and Post-Sanction Innovation Performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent Application (Intensive Margin)			**Patent Application (Intensive Margin)**		
	Total	Intl.	High-Tech	U.S.	Euro+	Adv. Asia
Treatment×Post	-0.065***	-0.131***	-0.061***	-0.091***	0.075	-0.006
	(0.021)	(0.012)	(0.010)	(0.027)	(0.069)	(0.035)
Treatment×Post×pre-US				0.031	-0.221***	-0.064
				(0.052)	(0.070)	(0.050)
No. Obs.	158,421	56,574	80,605	158,421	56,574	80,605
R-squared	0.441	0.296	0.391	0.441	0.297	0.391
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences on a set of patenting firms. Estimates in columns 1 to 3 are based on a set of firms that started patenting before 2013 and estimates in columns 4 to 6 are based on a set of firms that have positive patenting. $pre - US$ is a dummy variable that equals 1 if the firm had collaborated with U.S. prior to the year it was sanctioned. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table A.16: Spillover through Innovation Network

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent Application (Intensive Margin)					
	Total	Intl.	High-Tech	Total	Intl.	High-Tech
Downstream	-0.036	-0.191	-0.204			
	(0.254)	(0.446)	(0.299)			
Upstream	-0.024	0.144	0.184			
	(0.226)	(0.388)	(0.273)			
DummyDownstream				-0.015**	-0.011	-0.020**
				(0.007)	(0.013)	(0.009)
No. Observation	157,266	56,376	79,991	157,266	56,376	79,991
R-squared	0.442	0.294	0.391	0.442	0.294	0.391
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences on a set of patenting firms. $Downstream$ measures the relative frequency of a technology field j cites the sanctioned technology fields. $Upstream$ measures the relative frequency of a technology field j being cited by the sanctioned technology fields. See 6 for detail. $DummyDownstream$ is a dummy variable that equals 1 if the technology field j is more frequently cites the sanctioned technology fields than being cited by the sanctioned technology fields. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.

Table A.17: Pre-Sanction Chinese Collaboration and Post-Sanction Innovation Performance

	(1)	(2)	(3)	(4)	(5)	(6)
	Patent Application (Intensive Margin)					
	Total	Intl.	High-Tech	Total	Intl	High-Tech
Treatment×Post	-0.044***	-0.050***	-0.046***	0.037**	0.039**	0.045***
	(0.008)	(0.007)	(0.006)	(0.016)	(0.016)	(0.010)
Treatment×Post×Pre-CN				-0.101***	-0.112***	-0.112***
				(0.012)	(0.016)	(0.010)
No. Obs.	160,000	157,011	96,309	160,000	157,011	96,309
R-squared	0.217	0.215	0.214	0.218	0.216	0.215
Sector-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: We estimate the coefficients using difference-in-differences on a set of patenting firms. $pre-CN$ is a dummy variable that equals 1 if the firm had collaborated with China prior to the year it was sanctioned. Robust standard errors clustered at the 2-digit ISIC sector level are in parentheses. ***, **, and * indicate significance at levels 1 percent, 5 percent, and 10 percent, respectively.