Mapping U.S.–China Technology Decoupling: Policies, Innovation, and Firm Performance

Pengfei Han,[a,*] **Wei Jiang,**[b,c,d] **Danqing Mei**[e,*]

[a] Guanghua School of Management, Peking University, Beijing 100871, China; [b] Goizueta Business School, Emory University, Atlanta, Georgia 30322; [c] National Bureau of Economic Research, Cambridge, Massachusetts 02138; [d] ECGI, 1040 Brussels, Belgium; [e] Department of Finance, Cheung Kong Graduate School of Business, Beijing 100738, China

*Corresponding authors

Contact: pengfeihan@gsm.pku.edu.cn, https://orcid.org/0000-0001-5798-4934 (PH); wei.jiang@emory.edu,

propensity for domestic patents in a technology area to cite foreign patents relative to citing their own. In simplified language, the extreme situation of “perfect decoupling” implies that patents filed in one country never cite any patents in the other country, suggesting two segregated ecosystems of innovation. In the other extreme of “perfect integration,” there is an utter absence of a “home bias” in patent citations as if there were no national borders in technology. Although the extent of decoupling is symmetric with respect to both countries, one nation might depend more on the technology of the other than the other way around. A related measure of China’s technological dependence on the United States (which is the negative value of U.S. dependence on China) is based on the propensity of Chinese patents citing U.S. ones relative to citations in the reverse direction.

Applying the measures at the aggregate level, we discover that U.S.–China technology decoupling has been declining steadily since 2000, the year before China acceded to the World Trade Organization (WTO). In other words, growing integration of the two technological systems has been the dominant theme in the twenty-first century. China’s technological dependence on the United States, on the other hand, is hump shaped, peaking in 2009 at the end of the Great Recession. Therefore, from China’s perspective, 2000–2009 was a decade of dependence-deepening integration with the United States, whereas the next decade featured dependence-relaxing integration. Toward the last two years of our sample (2020–2021, the coronavirus disease 2019 (COVID-19) era), we observe signs of decreasing decoupling sectors. As the downstream becomes captive to domestic technologies and supplies after facing restrictions in accessing U.S. technologies and inputs, firms in the focal sector thrive in performance and produce more breakthrough innovations. Our findings indicate that U.S. sanctions can instigate broader impact than was envisioned by the policy makers and prompt potentially unintended consequences via the network spillovers.

Our paper contributes to two broad strands of literature. The first is on U.S.–China economic relations. Most of the studies on U.S.–China economic relations work in areas related to production and trade.[4] Although trade is a crucial aspect of the U.S.–China relationship, technological interdependence between the two countries has seen rising importance in the new economy, which we believe, would welcome a new study to provide empirical evidence based on combined data from both countries. The second literature is on innovation, which has been largely based on single-country (usually U.S.) experience, even in a crosscountry setting such as building on shocks from foreign sources.[5] The literature on innovation in China has also been emerging.[6] As we indicated earlier, this study is the first to quantify technology decoupling and the implications of government policies in both countries for technology decoupling and dependence, as well as on the operating and innovative performance of firms.[7]

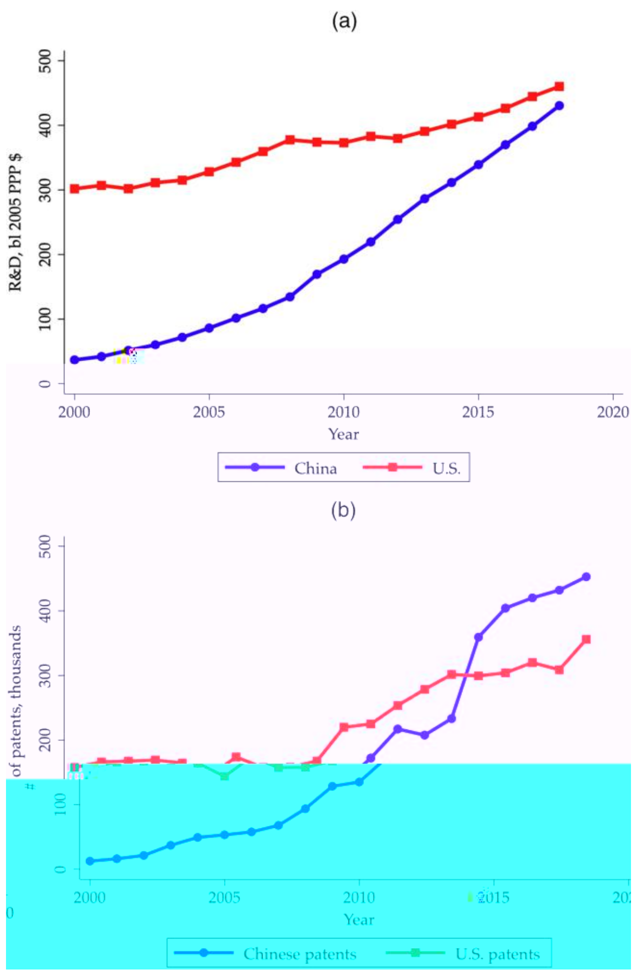
The rest of the paper is organized as follows. Section 2 describes both patent systems and develops measures quantifying U.S.–China technology decoupling and China's technological dependence on the United States. Section 3 evaluates the relationship between U.S.–China technology decoupling and firm performance. In Section 4, we study how government interventions from both countries (China's industrial policies and U.S. sanctions against China) affect U.S.–China technology decoupling and the performance of firms, especially Chinese firms. Section 5 concludes.

2. Measuring Technology Decoupling and Dependence Between the United States and China

2.1. Overview: Patenting in the United States and China

The most crucial data inputs of this study are the combined patent-level databases from the two countries based on the full records from the U.S. Patent and Trademark Office (USPTO) and the Chinese National Intellectual Property Administration (CNIPA). We focus on "utility patents" granted at the USPTO ("U.S. patents" hereafter), which cover inventions that function in a unique manner to produce a useful result and are commonly considered the default form of patents.[8] The counterparts in the CNIPA system are "invention patents" ("Chinese patents" hereafter).[9] Despite differences in many details, the patent examination procedures at USPTO and CNIPA are mostly comparable. USPTO and CNIPA grant patents to both domestic and foreign assignees, and neither of them discriminate based on the citizenship of applicants in regard to eligibility for patent applications. Filing patents at a foreign patent office is critical to protect the applicant's intellectual property there,

Figure 1. (Color online) R&D Expenditures and Patents Granted, United States vs. China



Note. R&D expenditures of both China and the United States are measured in billions of 2005 PPP dollars in panel (a). "Chinese patents" in panel (b) refer to invention patents granted at the CNIPA. "U.S. patents" in panel (b) refer to utility patents granted at the USPTO. The number of patents is expressed in thousands in panel (b). (a) R&D expenditures. (b) Patents granted.

domestic transfer because of trade barriers and limitations on talent mobility. The resulting decoupling does not directly speak to the relative competitiveness of the two nations. Vaccination against COVID-19 provides one example of technology decoupling. Sinovac of China developed its "inactivated vaccine" by exposing the body's immune system to deactivated viral particles. On the U.S. side, Moderna and Pfizer present "mRNA vaccines," tricking the body into making viral proteins that train and trigger the immune system. In comparison, the notion of "technology dependence" hinges critically on a country's one-sided reliance on foreign technology to advance its own. High dependence is thus associated with a weaker competitive situation in that particular area. For example, although China led in 5G technology in the 2010s, the key players, such as Huawei, relied on key chips made with U.S. technology. Prior and concurrent studies analyzing the U.S.–China technology relations have mostly focused on the dependence aspect, or relative competitiveness (e.g., Fang et al. 2021), instead of decoupling.

Despite the recent discussion of technology decoupling between the two nations, there has not been a well-defined metric to quantify the degree of decoupling, its variation across different sectors, and the impact of such attempts on the performance of firms in both countries. There could be a variety of notions of "decoupling" between the two economies. Because we focus on cross-country technology spillover and aim to quantify decoupling at both the aggregate and granular technology field level, we develop our measures based on the propensity of a domestic patent citing a foreign patent relative to citing a domestic one. Although patents constitute one segment of innovation and are known to have limitations (Moser 2013), they remain the most comprehensive and objective data source for technology spillover since the pioneering study of Jaffe et al. (1993). Patent-related metrics also form the basis for our measures of technology decoupling and dependence.

We start with a few notations to build up to the proposed measures. First, $P_{c,u,t}$ is the propensity for Chinese patents approved in year t to cite a U.S. patent relative to citing a Chinese one; analogously, $P_{u,c,t}$ is the propensity for a year-t U.S. patents to cite Chinese patents relative to citing U.S. patents. Algebraically,

$$P_{c,u,t} \equiv \frac{C_{c,u,t}/x_{u,t}}{C_{c,c,t}/x_{c,t}}, \quad P_{u,c,t} \equiv \frac{C_{u,c,t}/x_{c,t}}{C_{u,u,t}/x_{u,t}}. \qquad (1)$$

In the expressions, $C_{c,u,t}$ ($C_{c,c,t}$) is the number of citations Chinese patents make on U.S. patents (Chinese patents) in year t and $C_{u,c,t}$ ($C_{u,u,t}$) is analogously defined. Because a new patent builds on the full stock of existing knowledge, patents potentially available for citation grow over time. For this reason, we normalize the citation numbers by $x_{c,t}$ and $x_{u,t}$, which are the total numbers of patents granted at the national offices of the referencing patents up to year t. With the normalization, the time-series variation in the relative size of patent volume of the two countries, $\frac{x_{c,t}}{x_{u,t}}$, does not mechanically impact the measured propensity. Citations of foreign patents, $C_{c,u,t}$, are a product of "probability to cite" and "size of foreign patent production." Our purpose is for the measures to capture only the first part and be free from the direct impact of the second part. In the absence of scaling, the measures would have favored nations with a large stock of patents.[14]

With the expressions, we are able to provide a visualization of decoupling and dependence, presented in Figure 2. The horizontal and vertical axes measure $P_{u,c,t}$ and $P_{c,u,t}$, respectively. The state of "complete decoupling," or an absolute lack of integration, is associated with the origin and corresponds to the scenario where domestic patents in either country never cite any patents in the other. This is because presumably, each has its own ecosystem that is enclosed from the other. The opposite scenario is zero decoupling or complete integration corresponding to the point with (1, 1) coordinates (i.e., [illegible] 1). At this point, domestic patents cite a patent in the other country with the same probability as citing a domestic patent (i.e., an absence of any "home bias" in technology development).[15] Points interior of the box indicate a partial integration or imperfect decoupling.

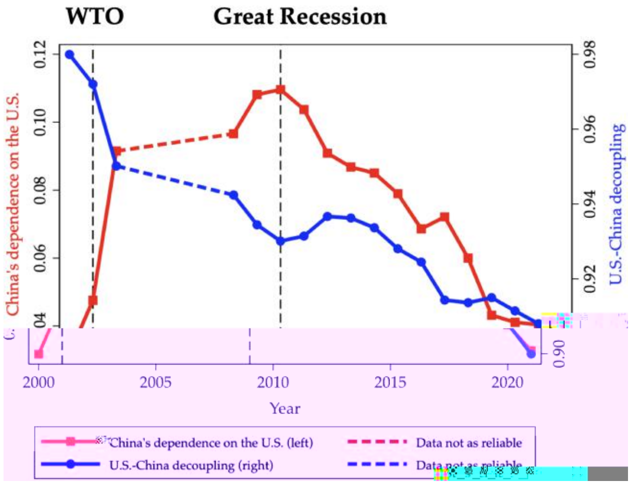
The 45° line in Figure 2 is the state of parity (i.e., [illegible]). Along this line, the propensity for Chinese patents to cite U.S. patents is exactly reciprocated, although the degree of integration / decoupling varies. In the triangular area above the 45° line, Chinese patents are more likely to build on U.S. patents than the other way around or [illegible] > [illegible]. We thus label this region as China's (relative) dependence on U.S. technol the same time period as a reference point for the relation between two mature economies.[17] For further external validation, we apply them to an out-of-sample setting of which we are informed about the truth so that we can have a "sanity check." Consider the following three representative academic journals: (AER; a leading economics journal), (JF; a leading finance journal), and (JBF; a leading journal in a subfield of finance). Applying the two citation-based measures, we find that the two finance journals are well integrated and that each is more decoupled from AER. Moreover, JBF depends more on JF, whereas the dependence between JF and AER is mutual. Finally, JF and AER became more decoupled during 2001–2010 but have since re-integrated. These findings mirror the evolution of finance academia, a vote of confidence in our measures.[18] We are happy to share the constructed measures and with interested academic researchers upon request.

2.3. U.S.–China Technology Decoupling in the Twenty-First Century

2.3.1. Dynamics of Technology Decoupling: 2000–2021

The measures developed in the previous section allow us to quantify the history and the current state of U.S.–China technology decoupling and dependence. Grouping all patents by country (the United States and China), we map the aggregate time series into three "screenshots" in Figure 3: 2000 (the year before China's entry to the WTO), 2009 (the end of the Great Recession), and 2021 (COVID-19 and the escalation of tension between the two nations). All three observations fall toward the lower left above the 45°

Figure 4. (Color online) U.S.–China Technology Decoupling and Dependence, 2000–2021



. This figure characterizes how U.S.–China technology decoupling and China's technological dependence on the United States evolved between 2000 and 2021. The right vertical axis in this figure is our measure of U.S.–China technology decoupling, and the left vertical axis is our measure of China's technological dependence on the United States. Both measures are defined in Section 2.2. The subperiod of 2003–2006 is skipped because of unreliable data specific to that time period.

information from other countries is difficult to access, we resort to another source of innovation: academic publications in science and engineering (S&E) based on information from the U.S. National Science Foundation. We retrieve data for the top five publishing nations: China, the United States, India, Germany, and the United Kingdom. At the beginning of the twenty-first century, the United Kingdom and Japan accounted for 13% and 10% of internationally coauthored S&E publications in the United States, respectively, whereas the shares of China and India are far lower. Although the share of the United Kingdom has remained stable over time, the share of Japan has declined to 5% in 2020. In contrast, the share of China has surged from 5% in 2000 to 26% in 2020. As a comparison, the share of India is still below 5% by 2020.[22] Therefore, the growing innovation integration between China and the United States cannot be explained by the global trend.

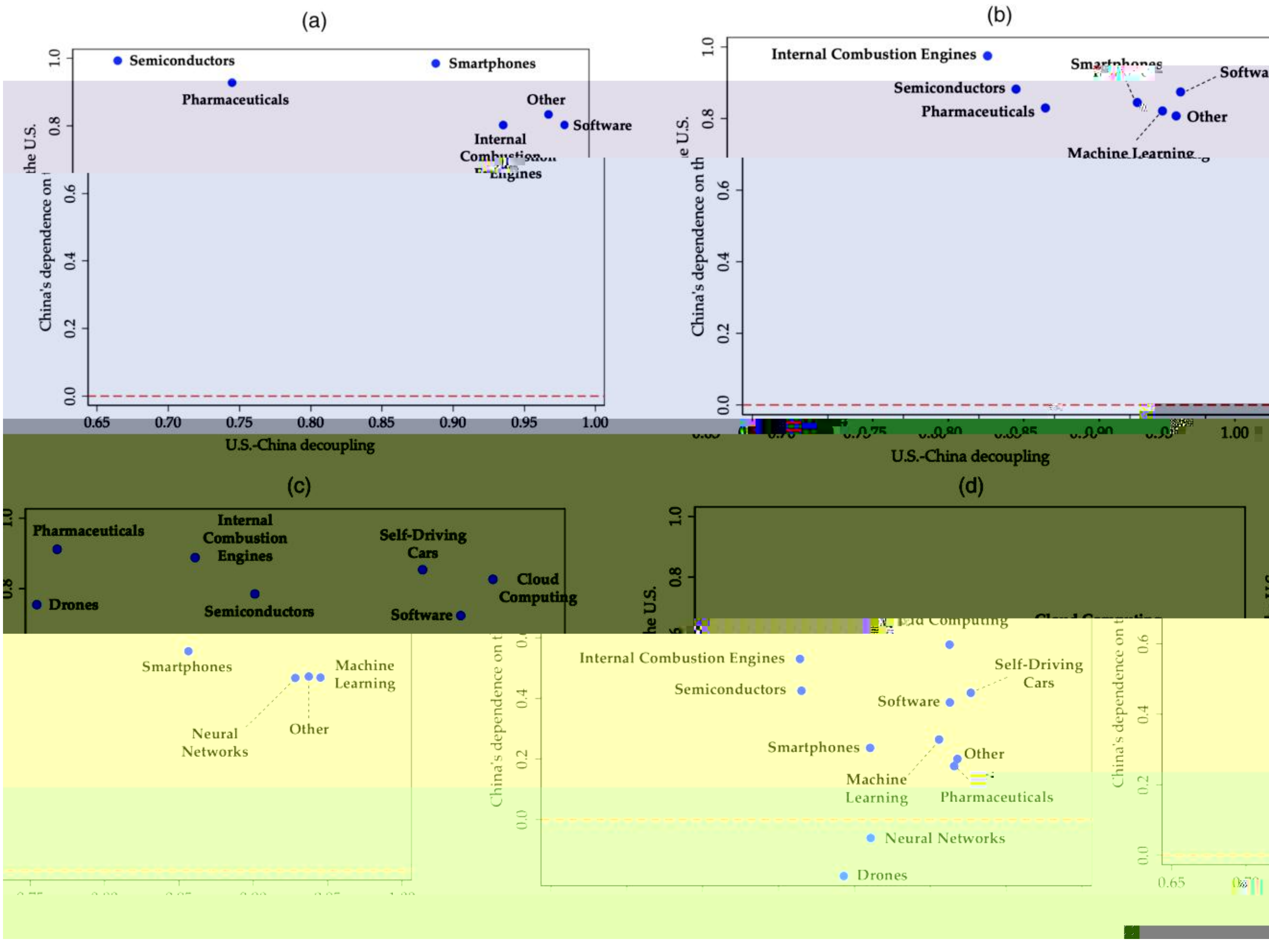
e C - 9 The 2020–2021 segment of the sample period allows us to shed light on the impact of COVID-19 on the technology decoupling between the United States and China, which is ambiguous because of two opposing forces. On the one hand, the development of virtual-based work environment could further de-emphasize the importance of colocation in facilitating scientific discovery and technological progress. On the other hand, the lockdown policies during the pandemic imposed severe restrictions on in-person exchanges (such as conferences and workshops). Our findings support the first hypothesis. The decoupling between the United States and China further dropped from 2020 to 2021. Both Bloom et al. (2021) and Cong et al. (2022) also document that the COVID-19 pandemic has spurred innovation toward technologies supporting video conferencing, telecommuting, remote interactivity, working from home, and those accelerating the digital transformation of small and medium firms. Such technologies have experienced swift global dissemination.

Perhaps a year or two more is required to assess the full impact of the COVID-19 shock. Our study nevertheless supports the view that remote work, which became the norm because of COVID-19, made the country boundaries less salient. Such a conclusion is further supported by coauthoring in academic publications in science and engineering based on information from the U.S. National Science Foundation. We find that the share of internationally coauthored S&E publications increased during the pandemic year 2020, despite the near impossibility of international personnel exchange. Moreover, despite the political tensions between the U.S. and Chinese governments during the COVID-19 years, the two countries were the top pair (among all nation pairings) in international collaboration on COVID-19-related S&E publications.[23]

2.3.2. Technology Class-Level Decoupling Dynamics. The aggregate states of decoupling and dependence shown thus far may have masked heterogeneity across different technology sectors. Established by the Strasbourg Agreement in 1971, the International Patent Classification (IPC) scheme provides a hierarchical system of language-independent symbols for the classification of patents. It is used by the national patent offices of more than 100 countries. We also examine the 10 high-tech fields defined by Webb et al. (2019), which include (by the order of the total number of patents) smartphones, semiconductors, software, pharmaceuticals, internal combustion engines, machine learning, neural networks, drones, cloud computing, and self-driving cars. For completeness, we group all other patents into the "other" field. Figure 5 plots the states of decoupling (corresponding to $\frac{Q}{\sqrt{2}}$ in Figure 2) and conditional dependence (corresponding to $=$ in Figure 2) for the technology sectors in the years 2000, 2009, 2015, and 2021.[24]

Among the 10 high-tech fields, China's dependence on the United States is the greatest in pharmaceuticals, semiconductors, software, and smartphones, but their dependence levels are decreasing over time. Except for software, most of the highly decoupled fields are also emerging technology sectors, such as neural networks, cloud computing, and self-driving cars, because of a variety of reasons from geopolitical sensitivities to

Figure 5. (Color online) Decoupling and Dependence, 10 High-Tech Fields



In this figure, we plot the states of decoupling and dependence (both measures are defined in Section 2.2) in the selected years of 2000, 2009, 2015, and 2021. The 10 high-tech fields are defined by Webb et al. (2019). All other patents are grouped into the "other" category. (a) Year: 2000. (b) Year: 2009. (c) Year: 2015. (d) Year: 2021.

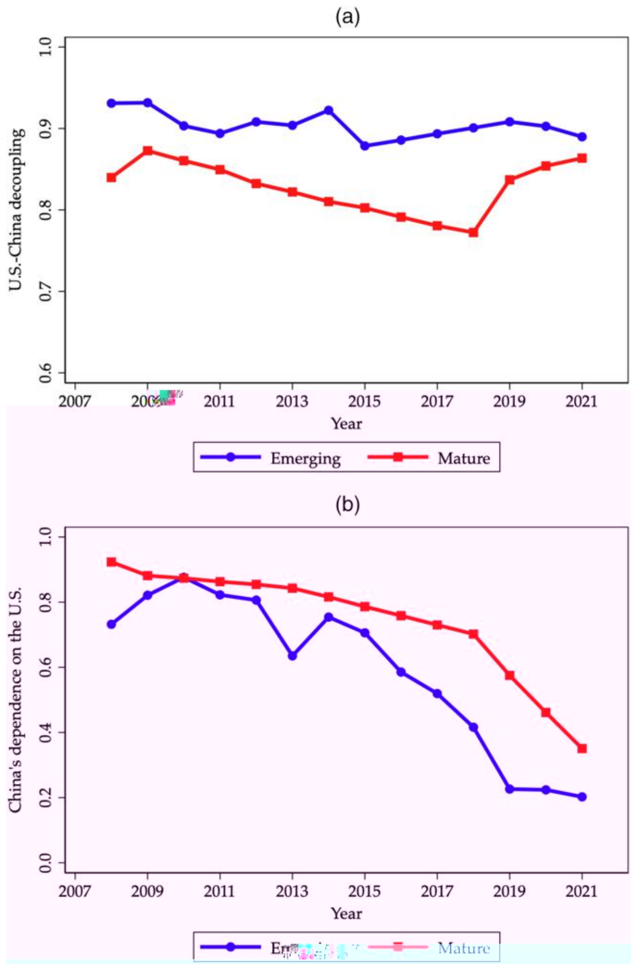
different legal infrastructures. For example, Google announced in 2020 that it scrapped its Cloud Initiative in China, citing, among other reasons, privacy and data sovereignty concerns. The grant year of the first patent in each field is a natural proxy for the maturity of the field. Although internal combustion engines, pharmaceuticals, semiconductors, smartphones, and software are preexisting technologies, machine learning, neural networks, drones, cloud computing, and self-driving cars are new entrants after 2008. Figure 6 compares the decoupling and dependence levels between mature and emerging technologies. It shows that the emerging technology fields exhibit both more decoupling and a steeper drop in China's dependence on the United States.

Our findings are mostly consistent with but formalize the anecdotal evidence on both the positive and negative sides regarding China's technological progress. First, China's hard work on reducing dependence in semiconductors seems to have paid off, as shown by the decreased dependence level from 0.55 in 2019 to 0.42 in 2021.[25] Second, China has continued the growth of its dominance in drones (with Da-Jiang Innovations, a Chinese firm, accounting for over 70% of the global drones market), and its meteoric rise to a leading position in neural networks (a key input for artificial intelligence technology) has also been noted and commented by practitioners.[26] The dependence measures for both sectors turned negative in 2021. Finally, the COVID-19 wave in China exposed the lack of integration and a deviation from the common standards with the West in vaccines and medicine. Compared with 2015, the decoupling measure for the pharmaceuticals sector has experienced an increase in 2021.[27]

2.3.3. Alternative Measures and Sensitivity Checks

Some citations might introduce noise to the process of knowledge inheritance and expansion. We discuss three major issues associated with patent citation metrics and their impact on our measures. First, patent trolling, mostly by nonpracticing entities and accelerated in the

Figure 6. (Color online) Decoupling and Dependence, Emerging vs. Mature Technologies



[illegible] In this figure, we compare the states of decoupling and dependence between emerging and mature technologies among the 10 high-tech fields defined by Webb et al. (2019). A technology is considered emerging if the grant year of its first patent is after 2008, which includes machine learning, neural networks, drones, cloud computing, and self-driving cars. Mature fields include internal combustion engines, pharmaceuticals, semiconductors, smartphones, and software. (a) U.S.–China decoupling. (b) China's dependence on the United States.

United States since 2011 (Cohen et al. 2016), may affect citation behavior and thus, measured decoupling during the second decade. Bian (2021) shows that trolling is not a major concern in China as 98.5% of the patent infringement lawsuits are brought out by individuals, research institutions, and operating companies, none of which are the usual suspects of trollers. Presumably, U.S. inventors have become cautious in citing prior art and engage in defensive publications in order to stay away from trolling, which could increase the propensity of U.S. patents to cite domestic patents. Such an evolution would, on its own, lead to an upward bias in [illegible]. Instead, we find that since 2011, [illegible] has been steadily decreasing. Hence, trolling, if having an impact, works against explaining our findings.

Second, citations mandated by patent examiners may also be a noisier proxy for the knowledge flows among patents. Unfortunately, it is infeasible to distinguish whether patent citations are made by the patent examiners in the Chinese patent data. However, the USPTO adopted new reporting procedures in 2001, separating examiner and applicant citations. Alcácer et al. (2009) show that examiners played a significant role in identifying prior art, especially from foreign patents. Therefore, we believe that applicant and examiner citations are potentially complementary. As a sensitivity check, we replicate Figure 4 but drop patent citations made by patent examiners. The general patterns are indistinguishable from the original figure.[28]

Finally, there is concern of "strategic citation" (that is, Chinese patent filers may strategically overcite Chinese patents or undercite U.S. patents, possibly in order to show that they are leading the race against the United States). Even if such behavior could have been overlooked (or even encouraged) by the examiner, we believe that it is inconsequential to our main finding. If the domestic citation bias by Chinese patents has been stable over time, it would not invalidate the time-series or cross-sectional relations because both yearly and technology class fixed effects are incorporated into all main regressions. Nevertheless, one may still wonder if such a domestic bias was ratcheting up over time, especially in light of China's rising technological ambitions in the recent decade. China's domestic citation bias would deflate [illegible], leading to [illegible] over time. (A rising domestic bias among U.S. patents would have a similar effect, but presumably, the same motive is unlikely among U.S. patent filers.) Because the decoupling measure is observed to trend [illegible] over time, strategic domestic citations do not seem to be of first-order importance in driving the time series.

[illegible] Although our study is unique in presenting an integrated analysis of technology decoupling and dependence, there has been a burgeoning literature studying the relative competitive positions of the United States versus China based on patent data. We thus compare and reconcile our analyses with those based on alternative measures. First, previous literature has shown that a substantial number of patents are of dubious scientific value in both nations (Liang 2012, Prud'homme and Zhang 2017, Cohen et al. 2019). The construction of our measures already mitigates the influence of uncited, presumably low-quality patents. We replicate Figure 4 while excluding low-quality patents in Figure A.1 and ensure robustness.[29] Second, we reconcile our method with related studies, notably Akcigit et al. (2020), that proxy the relative competitive position by a country's share of patents in a technology field among multiple countries. We verify that the two types of measures are significantly correlated in our sample; that is, China exhibits lower dependence on the United States in a technology sector for which the share of China-filed patents out of the U.S. and China total is higher. It is worth noting, however, that the relationship between our dependence measure and the share of Chinese patents became attenuated over time, as the number of Chinese patents soared.[30]

Two additional methods have been developed based on the content of the patents. Fang et al. (2021) resort to a new-word search in patent abstracts in defining innovation leadership. They find that China made steady progress in the share of patents with "frontier words" during the same sample period, although it is still much lower than the U.S. level. Such a pattern is consistent with our finding on dependence (e.g., in Figure 4). Alternatively, a few recent papers have resorted to " debt to total assets, both in book value. The detailed definitions of all variables are listed in Table A.1. Unless otherwise specified, all potentially unbounded variables are winsorized at the 1% extremes.

The summary statistics for the Chinese firms and the U.S. firms with at least one patent are provided in the appendix. Table A.2 shows that the average patent-filing Chinese firm in our sample is about 15 years old and has an asset of Renminbi (RMB) 10.8 billion (about U.S. $1.6 billion). The average Chinese firm files about four patents each year and is in a technology sector with a decoupling measure valued at 0.92. Capital expenditures amount to 5.8% of firm assets, and net value of property, plant, and equipment accounts for 23.0% of firm assets on average. The sample median is 1.6% for & and 7.7% for . Finally, the average firm features a leverage ratio of 40.8% and a Tobin's of 2.5. Analogously, Table A.3 shows that the average patent-filing U.S. firm in our sample is about 23 years old as a public company and has an asset of U.S. $9.9 billion. The average firm faces a technology decoupling measure of 0.92 and files about 32 patents each year. The sample median is 4.1% for & and 14.3% for . The average U.S. firm features a capex ratio of 3.8%, a PP&E ratio of 19.4%, a leverage ratio of 21.0%, and a Tobin's of 3.0.

3.2. Decoupling, Innovative Activities, and Firm Performance

3.2.1. Impact on Chinese Firms. The impact of U.S.–China technology decoupling on firm innovation and performance for both countries is ambiguous because of two opposing forces. On the one hand, global technology integration facilitates knowledge dissemination, allowing firms better access to foreign technology that is state of the art, and spurs domestic innovation. We term this negative relation between technology decoupling and domestic innovation the "complementarity effect." On the other hand, some domestic firms may strengthen their local dominance if sheltered from foreign competition and may innovate more by "reinventing the wheel." We define this positive relation between technology decoupling and domestic innovation as the "substitution effect."

We empirically investigate the relationship between technology decoupling and firm performance with the following firm-year-level regressions covering the period of 2007–2019 separately for U.S. and Chinese firms:

$$\ldots_{,1} \times \beta_1 + \ldots_{,2=3} \times \beta_2 + \delta' \ldots_{,1} + \gamma + \gamma + \ldots \qquad (2)$$

In Equation (2), the dependent variable indexed by firm , technology class , and year is one of the following performance metrics: (one plus the number of patents filings that were eventually approved, in logarithm), (the relative citation strength), (total factor productivity in logarithm), (return on invested capital), and (in logarithm). The key independent variables are at the technology class-year level and lagged by one year ($_{,1}$) for the short run and the average of lagged two to three years ($_{,2=3}$) for the intermediate-run effect. Because the dependent variable (performance) is at the firm level, whereas the key independent variable ( ) is at the technology class level, we match a firm to a unique IPC group that hosts the highest number of patents owned by the firm.[33] $_{,1}$ represents the vector of firm characteristic variables introduced in Section 3.1 and is set to lag the

Table 1.

expected to be associated with a 12.4% increase in Chinese firm patenting activity one year later but a decline in by 0.6 percentage points (7.6% of the sample mean), a 2.3% drop in firm , and a 3.0% decrease in in two to three years.

3.2.2. Mandatory or Voluntary Decoupling? From China's point of view, there can be two types of decoupling, "mandatory" and "voluntary," which may have different implications for the performance of Chinese firms. Mandatory decoupling is initiated by the United States to restrict technology transfers through policies, such as sanctions. In contrast, voluntary decoupling refers to China's own desire and effort in developing a separate technology system. Although it is difficult to distinguish between the two types of decoupling in the data, we conduct two tests to shed light on the difference. The first setting builds on U.S. sanctions against China, which are primary forces of mandatory decoupling (an issue that will be discussed in detail in Section 4.2). Sanctions have escalated since 2014 (the "escalation period"), allowing us to study the effect of heightened mandatory decoupling with an interaction term $\times$. Panel A of Table 2 shows improved innovation output during the escalation period, as well as significant declines in firm and . To summarize, mandatory decoupling is associated with higher innovation output but worse firm performance.

Because the United States was in a clear leading position in most technology fields during the sample period, we reason that decoupling is likely to be imposed on, instead of desired by, China. However, there are exceptions that allow us to study voluntary decoupling. Consider the following sectors (with IPC codes): A63 (sports, games, amusements), B60 (vehicles in general), B64 (aircraft, aviation, cosmonautics), and C07 (organic chemistry), which all experienced an increase in measured decoupling since 2016. Because these were unsanctioned sectors and the decoupling movement was trend defeating, we conjecture that such decoupling was most likely voluntary. Among firms in these sectors, panel B of Table 2 indicates that measured decoupling is positively associated with firm innovation output, the quality of innovation, firm , and . These findings constitute suggestive evidence that Chinese firms in "voluntarily" decoupled sectors enjoyed a boost in both innovation and productivity / profitability as they develop indigenous technology with protection from overseas competition.

3.2.3. Impact on U.S. Firms. The effects of technology decoupling on the U.S. firms, examined in Table 3, are less pronounced in comparison. There is no detectable relation between lagged decoupling and any performance measures for U.S. firms. This is presumably because U.S. firms, so far, are primarily at the world

Table 2. Mandatory vs. Voluntary Decoupling, Chinese Firms

	[illegible] (1)	[illegible] (2)	(3)	[illegible] (4)	[illegible] (5)
Panel A: Before vs. after escalations of U.S. sanctions					
[illegible]	1.456**	−0.218	0.186	−0.0874*	0.127
	(0.644)	(0.695)	(0.156)	(0.0449)	(0.223)
[illegible] × [illegible]	0.944**	1.490***	−0.270**	0.00639	−0.699***
	(0.472)	(0.571)	(0.118)	(0.0311)	(0.175)
Observations	14,739	14,739	14,739	14,739	14,739
Adjusted ^{2}	0.607	0.186	0.657	0.445	0.794
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes
Panel B: Voluntary decoupling sectors					
[illegible]	1.325**	1.306**	0.461***	0.0747*	−0.194
	(0.654)	(0.531)	(0.140)	(0.0436)	(0.235)
Observations	1,071	1,071	1,071	1,071	1,071
Adjusted ^{2}	0.691	0.231	0.651	0.482	0.795
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes

[illegible]. Based on firm-year-level regressions for the sample period of 2007–2019, we assess the roles of mandatory and voluntary technology decoupling in this table. U.S. sanctions against China have significantly escalated since 2014, and we interact the decoupling measure with the [illegible] indicator in panel A. This [illegible] indicator takes the value of one since 2014 and zero otherwise. In panel B, we conduct the analysis for firms in the following sectors (classified by three-digit IPC codes): A63 (sports, games, amusements), B60 (vehicles in general), B64 (aircraft, aviation, cosmonautics), and C07 (organic chemistry). Each of these technology classes experienced an increase in measured decoupling since 2016. Other variables are defined in Table A.1. All explanatory variables are lagged by one year, and year fixed effect and firm fixed effect are included. Robust standard errors are reported in the parentheses.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

Table 3. Technology Decoupling and Firm Performance, U.S. Firms

	[illegible] (1)	[illegible] (2)	(3)	[illegible] (4)	[illegible] (5)
[illegible] − 1	0.285	−0.741	−0.321	0.052	0.328
	(0.593)	(0.755)	(0.237)	(0.189)	(0.205)
[illegible] − 2=3	−0.085	−0.470	−0.141	−0.148	−0.179
	(0.344)	(0.504)	(0.124)	(0.095)	(0.121)
[illegible]	0.139***	−0.046	−0.046***	−0.011	−0.134***
	(0.019)	(0.028)	(0.015)	(0.011)	(0.010)
[illegible]	−0.024	−0.155**	0.019	−0.004	−0.133***
	(0.055)	(0.071)	(0.031)	(0.026)	(0.024)
[illegible]	0.463*	0.228	−0.055	0.097	0.288*
	(0.250)	(0.280)	(0.237)	(0.136)	(0.172)
&	0.151	−0.142	0.247**	−0.097	−0.308***
	(0.139)	(0.176)	(0.099)	(0.088)	(0.069)
[illegible]	−0.197***	−0.031	0.146***	0.101**	0.103***
	(0.047)	(0.070)	(0.042)	(0.045)	(0.029)
&	0.224***	−0.271*	−0.452***	−0.206**	0.163**
	(0.084)	(0.142)	(0.121)	(0.100)	(0.069)
Observations	13,884	13,884	13,884	13,884	13,884
Adjusted ^{2}	0.85	0.34	0.79	0.60	0.71
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes

[illegible]. Based on firm-year-level regressions for the sample period of 2007–2019, we examine the relationship between U.S.–China technology decoupling and the performance of U.S. firms. All variables are defined in Table A.1. In all regressions, the control variables are lagged by one year. All regressions include year fixed effect and firm fixed effect. Robust standard errors are reported in the parentheses.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

innovation frontier, and losing complementary technology from China inflicts little damage on their current productivity. Even for the few China-leading technology fields, China does not impose comparable sanctions that restrict technology flow to the United

Table 4. SEI Promotion Policy and Technology Decoupling

	[illegible] (1)	[illegible] (2)
[illegible] × [illegible]	−0.0105***	−0.0303***
	(0.00393)	(0.00808)
ln([illegible])	0.0195***	−0.0259***
	(0.00417)	(0.00905)
ln([illegible].)	−0.0184**	0.0820***
	(0.00849)	(0.0193)
Observations	1,343	1,343
Adjusted R^2	0.738	0.762
Technology class fixed effect	Yes	Yes
Year fixed effect	Yes	Yes

[illegible]. This table reports estimation results from the following difference-in-differences regression on the relationship between the SEI promotion policy and U.S.–China technology decoupling at the technology class ( )-year( ) level for the sample period of 2007–2019:

$$[illegible] = \beta \times [illegible] \times [illegible] + \delta' [illegible]_{-1} + \gamma + \gamma + [illegible]$$

The dependent variable features technology decoupling and dependence as defined in Table A.1. The dependence measure is residualized against the decoupling measure so that the two measures are orthogonalized concurrently by construction. The dummy variable [illegible] equals one if technology class [illegible] is promoted by the SEI and zero otherwise. The dummy variable [illegible] takes the value of one after 2012 and zero otherwise. In all regressions, the control variables are lagged by one year, and year fixed effect and technology class fixed effect are included. Robust standard errors are reported in the parentheses.

**Significance at the 5% level; ***significance at the 1% level.

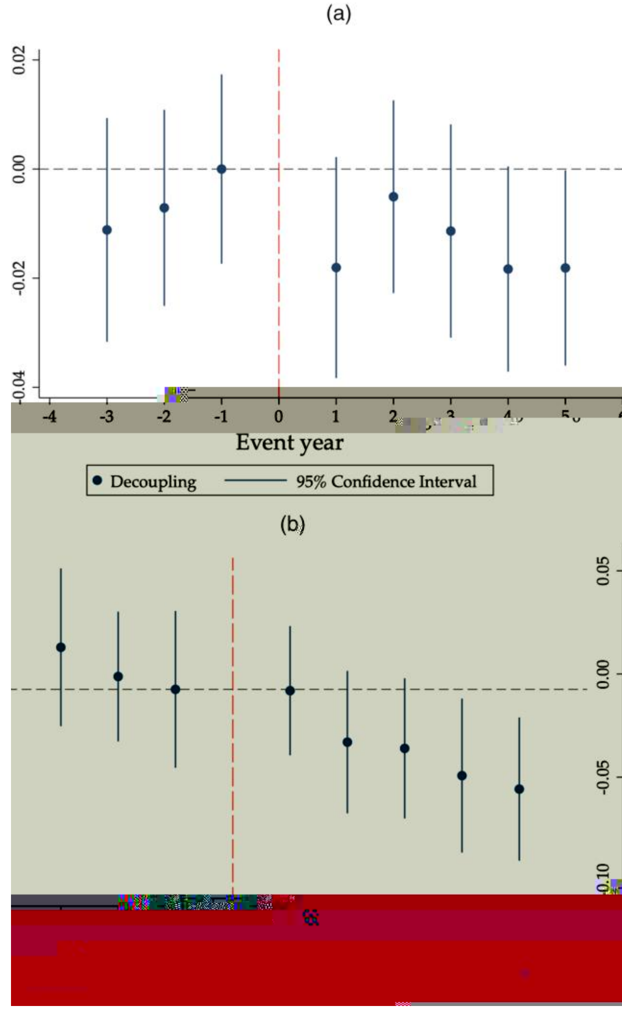
down after the event. Moreover, the decline of decoupling tends to occur faster than that of dependence.

Results teach us that China's SEI promotion policy was followed by technology [illegible] instead of decoupling with the United States. Such an outcome is more consistent with the stated objectives of the policy makers in China. As outlined by China's State Council (2010), China "will vigorously enhance integrated innovation and actively participate in the international division of labor" and "will strengthen the adoption, digestion, and absorption of foreign technologies, making full use of global innovation resources."[37]

Results also indicate that China's technological dependence on the United States drops in industries post-SEI coverage. This finding is consistent with the "self-sufficiency" narrative in U.S. policy circles regarding China's industrial policy. Although various industrial policies in China are designed to indigenize innovation and foster independence from Western technology, such a goal has actually been achieved by more integration with the global standards and more adoption of the global state of the art.[38]

Because both [illegible] and [illegible] are functions of [illegible] and [illegible] the relative propensity for a patent to cite foreign versus domestic patents (see Equation (1)), we can decompose the results in Table 4 by resorting to [illegible] and [illegible] as dependent variables in Equation (3). On the one hand, we find that U.S. patents are more likely to cite Chinese patents in technology sectors that are encouraged by the SEI policy. It suggests that China moved closer to the global frontier with the boost from government policies. On the other hand, we do not observe any decrease in the propensity of citations from China to the United States, consistent with China's State Council's stated goal, which aims to enhance the technological compatibility between the United States and China. Both findings are consistent with the inferences from the analyses that the SEI policy represented an endeavor by the government to promote both technology integration and self-sufficiency.[39]

Figure 7. (Color online) SEI Promotion Policy and Technology Decoupling, Dynamic Effects



[illegible]. This figure visualizes the dynamic effects of the SEI policy in the technology class-year-level regressions based on Equation (4). The dependent variable features technology decoupling and dependence as defined in Table A.1. The dependence measure is residualized against the decoupling measure so that the two measures are orthogonalized concurrently by construction. We plot the estimates of β_τ in Equation (4) for decoupling in panel (a) and for dependence in panel (b). (a) Decoupling. (b) Dependence.

4.1.2. SEI and Firm Performance. This section explores the SEI's impact on firm performance. Parallel to our analysis of SEI and technology decoupling in the previous section, we conduct the following DiD regressions at the firm( )-technology sector( )-year( ) level covering the period of 2007–2019:

$$ _{i,j,t} = \beta \times \quad \times \quad _{t} + \delta' \quad _{i,j,t-1} + \gamma_{i} + \gamma_{t} + \epsilon_{i,j,t} \quad (5)$$

$$ _{i,j,t} = \sum_{\tau} (\beta_{\tau} \times \quad \times \quad _{\tau}) + \delta' \quad _{i,j,t-1} + \gamma_{i} + \gamma_{t} + \epsilon_{i,j,t}. \quad (6)$$

We evaluate the relationship between the SEI promotion policy and firm performance in Equation (5) and the dynamic policy effects in Equation (6). In both equations, the sample construction, the dependent variables, the fixed effects, and the recurring variables are the same as those in Table 1. We report the estimation results for Equation (5) in Table 5 and plot the estimates of β_{τ} in Figure 8.

Column (1) of Table 5 reports that SEI promotion is associated with a 14.0% decline (significant at the 1% level) in firm innovation output. According to Figure 8(a), the drop in firm innovation output takes three to four years to materialize. Because the distribution of firm patenting output is count based and right skewed, we provide sensitivity checks based on the Poisson regression models to ensure robustness.[40] There is weak evidence of diminishing innovation quality; $\times$ [illegible] is negatively significant in Table 5, but the pattern is not salient in Figure 8(b). Notably, SEI promotion is not followed by any significant changes in firm [illegible] (see Figure 8(c) and column (3) of Table 5). Nevertheless, both Figure 8(d) and column (4) of Table 5 show a strong boost (significant at the 1% level) in firm profitability by 1.4 percentage points (17.7% of the sample mean). Rising profitability translates into bolstered firm valuation (Figure 8(e)). Column (5) of Table 5 shows that firm [illegible] has ratcheted up by 10.4% (significant at the 1% level). The combined evidence suggests that recipients of SEI benefited in cash flows and valuation but fail to register fundamental improvement in productivity under the policy.

We next provide tests to address alternative or mechanistic explanations. First, to alleviate the concern that the findings could be attributed to confounding policies, we control for the following three major innovation-related policies: (i) government subsidies for patents, (ii) tax cuts for new product development, and (iii) government support for small- and medium-sized high-tech enterprises. We exploit the regional variation of these policies and show that the findings regarding SEI survive these additional controls.[41]

Table 5. SEI Promotion Policy and Firm Performance

	[illegible] (1)	[illegible] (2)	(3)	[illegible] (4)	[illegible] (5)
$\times$ [illegible]	−0.140***	−0.126***	0.00984	0.0138***	0.104***
	(0.0332)	(0.0456)	(0.0103)	(0.00282)	(0.0150)
[illegible]	0.0918***	−0.0112	−0.00921*	−0.0158***	−0.293***
	(0.0174)	(0.0185)	(0.00553)	(0.00171)	(0.00793)
[illegible]	0.00745	0.0372	0.0283	−0.0141***	−0.0433*
	(0.0631)	(0.0645)	(0.0177)	(0.00498)	(0.0259)
[illegible]	−0.0569	0.266	−0.389***	−0.0138	−0.0434
	(0.151)	(0.197)	(0.0445)	(0.0114)	(0.0599)
[illegible]	−0.117	0.0567	0.117***	0.0426***	−0.109***
	(0.0801)	(0.0966)	(0.0251)	(0.00723)	(0.0357)
[illegible]	−0.0307	−0.134*	0.0227	0.00647	0.0864***
	(0.0578)	(0.0705)	(0.0200)	(0.00622)	(0.0270)
[illegible]	0.634	−1.285*	0.622***	0.182***	1.384***
	(0.611)	(0.670)	(0.150)	(0.0479)	(0.233)
Observations	16,247	16,247	16,247	16,247	16,247
Adjusted R^2	0.603	0.189	0.640	0.435	0.787
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes

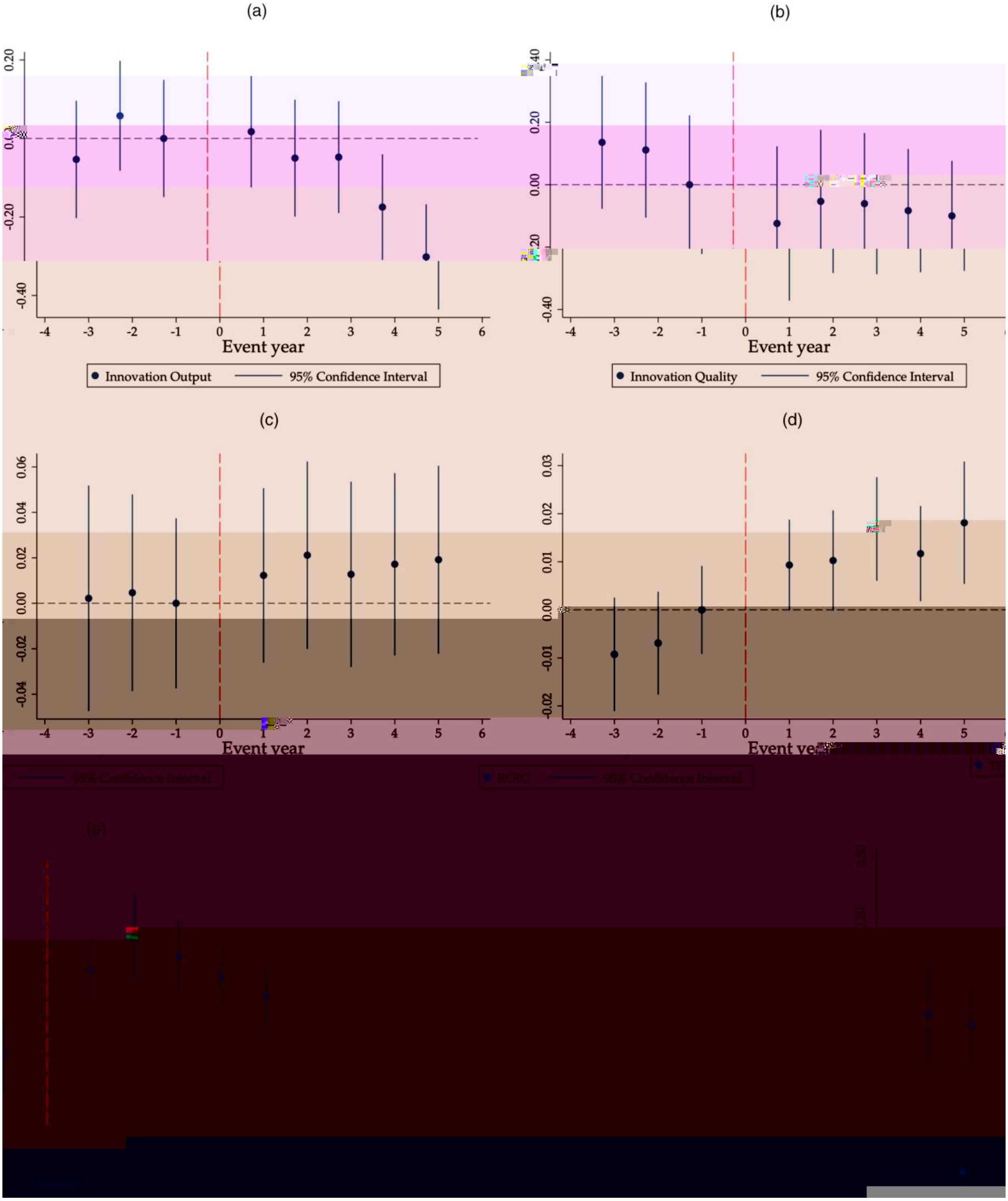
Notes. This table reports estimation results from the following regression relating the SEI policy and Chinese firm performance covering the period of 2007–2019:

$$ _{i,t} = \beta \times \quad \times \quad _{t} + \delta' \quad _{i,t-1} + \gamma_{i} + \gamma_{t} + \epsilon_{i,t}.$$

The regression is at the firm ( )-year( ) level, but each firm is also indexed by sector ( ). [illegible] equals one if sector [illegible] is promoted as an SEI and zero otherwise. [illegible] takes the value of one after 2012 and zero otherwise. All other variables are defined in Table A.1. In all regressions, the control variables are lagged by one year, and year fixed effect and firm fixed effect are included. Robust standard errors are reported in the parentheses.

*Significance at the 10% level; ***significance at the 1% level.

Figure 8. (Color online) SEI Promotion Policy and Firm Performance, Dynamic Effects



Notes. This figure examines the dynamics of

Second, we clarify whether the decline in innovation output post policies was because of falling innovation inputs (i.e., R&D-to-asset ratio) or R&D efficiency following Hirshleifer et al. (2013). *& f*, at the firm-year level, is constructed as the number of successful patent applications by a firm in a given year divided by the weighted average of its R&D expenditures in recent years. Table 6 demonstrates that the culprit of dwindling firm innovation output is waning innovative efficiency. Our findings are echoed in studies (e.g., Hu et al. 2019) documenting a drop in investment efficiency of Chinese firms upon receiving government support. Some government policies provide both incentives as well as financial resources for Chinese firms to import key technology of the most innovative parts instead of developing the technologies in house.[42] Post-SEI, *& f* of treated firms declined by 0.010 (34.3% of the sample mean). This echoes the earlier TFP results in Table 5 that SEI does not seem to have led to improvement in inherent efficiency.

We acknowledge that the simple quantitative measures in terms of the number of patents and their citations may not adequately capture innovation quality. We adopt the best practice in the literature by examining five established barometers of patenting performance in columns (3)–(7) of Table 6. Following Kerr (2010), we categorize a breakthrough patent as one that breaks into the top 5% in citations among the same cohort (i.e., same technology class and application year). Following patent strength measures proposed by Manso (2011) and developed in subsequent studies (e.g., Brav et al. 2018, Custódio et al. 2019), we categorize a patent to be exploitative if at least 80% of its citations are based on the firm's existing knowledge (i.e., its own patents or patents it cites in the past five years) and a patent to be explorative if at least 80% of its citations are based on new knowledge.

Chinese government. To the extent that China has yet to arrive at the world frontier in a great majority of the technology fields, technology integration will provide better access to the global frontier and enhance firm efficiency, but at the same time, it may also dampen the incentives for indigenous innovation in China. Conversely, United States-mandated technology decoupling, which we will analyze next, can force Chinese firms into indigenous innovation but at the cost of sacrificing firm efficiency associated with "reinventing the wheel."

4.2. U.S. Sanctions Against China and Decoupling

Amid rising political and economic tensions between the United States and China, the U.S. government has escalated its sanctions against some Chinese entities, aiming at technology decoupling or even a "deadly blow to the Chinese technology champion" as some media have forecasted.[44] The U.S. sanctions are part of the mandated U.S.–China technology decoupling in selected technology fields, which should hurt the performance of affected Chinese firms given our analyses in Section 3. Such policies may also spill over in light of the sheer depth and intensity of technological connections among sectors in the innovation network. This section provides an empirical investigation of these questions.

4.2.1. U.S. Entity List. We trace out the impact of U.S. sanctions based on the entity list issued by the Bureau of Industry and Security (BIS) of the U.S. Department of Commerce. According to the Export Administration Regulations of the United States, the entity list issued by the BIS is "a list of names of certain foreign persons—including businesses, research institutions, government and private organizations, individuals, and other types of legal persons—that are subject to specific license requirements for the export, re-export and/or transfer (in-country) of specified items." The entity list is a primary instrument for the U.S. government to impose sanctions against foreign entities, and we have gathered the list since 1997 (the first year when it was issued) from the BIS. After excluding the individual people sanctioned on the entity list, there are 297 unique Chinese entities, and they are primarily corporations, universities or research institutions, and government agencies in China. We are able to pinpoint the precise Chinese names for 292 (98.3%) of these sanctioned entities.

To assess how U.S. sanctions affect U.S.–China technology decoupling, we identify the primary technology class of each sanctioned Chinese entity by merging the entity list with the Chinese patent data using the algorithm delineated in Section 3.1. For all subsidiaries on the entity list, we use their parent companies or organizations in the merging process.[45]

By this algorithm, 74.3% of the Chinese entities on the list can be merged with the Chinese patent data and be classified into a primary technology class at the three-digit IPC level. Although U.S. sanctions were traditionally motivated by military concerns (e.g., nuclear technology, supercomputers, and aerospace and defense technology), they have increasingly covered civil and commercial technologies (e.g., communications technology, semiconductors, and artificial intelligence).

We consider a technology class to be exposed to U.S. sanctions in a given year if at least one entity associated with this technology class was sanctioned in that year. To illustrate how U.S. sanctions against China evolved in recent decades, we plot the number of sanctioned Chinese entities on the list and the number of technology classes exposed to U.S. sanctions in Figure 9. The first entity list was introduced by the Clinton administration in 1997, and only one Chinese entity (the Chinese Academy of Engineering Physics) was included in that list. After a moderate increase in the late 1990s, both the number of Chinese entities and technology classes exposed to U.S. sanctions remained virtually flat through the Bush administration and the first term of the Obama administration. The second term of the Obama administration, however, witnessed a structural break in U.S. sanction policies, and the surge continued into the Trump administration.

4.2.2. U.S. Sanctions and U.S.–China Technology Decoupling/Dependence. U.S. sanctions against Chinese entities explicitly aimed at decoupling in the affected technology areas. Have the attempts achieved the goal? Exploiting the staggered introductions of U.S. sanctions against China, we investigate this question with the following difference-in-differences setup at

Figure 9. (Color online) Number of Entities

Table 7. U.S. Sanctions and Technology Decoupling

	Decoupling (1)	*Dependence* (2)
Panel A: U.S. sanctions and technology decoupling		
Sanction	−0.0197***	−0.0276**
	(0.00355)	(0.0109)
Observations	1,343	1,343
Adjusted R^2	0.740	0.761
Technology class fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Control	Yes	Yes
Panel B: Network spillovers of U.S. sanctions		
Upstream_Sanction_Exposure	−0.183**	−0.0225
	(0.0734)	(0.180)
Downstream_Sanction_Exposure	0.128*	−0.00896
	(0.0696)	(0.170)
Observations	1,343	1,343
Adjusted R^2	0.741	0.760
Technology class fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Control	Yes	Yes

Note. Based on technology class-year-level regressions for the sample period of 2007–2019, this table reports the estimation results relating U.S. sanctions and technology decoupling/dependence. Panels A and B report the estimation results for Equations (3) and (8), respectively. In both panels, the dependent variable features technology decoupling and dependence, which are defined in Table A.1. The dependence measure is residualized against the decoupling measure so that the two measures are orthogonalized concurrently by construction. *Sanction* is equal to one for a technology class in a year if this technology class had been exposed to U.S. sanctions prior to that year and zero otherwise. As described in Table A.1, *Upstream* (*Downstream*) *Sanction_Exposure* is the weighted average of the sanction indicator of all upstream (downstream) technology classes of the focal technology class. In all regressions, the control variables are lagged by one year, and year fixed effect and technology class fixed effect are included. Robust standard errors are reported in the parentheses.

*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

the technology class(i)-year(t) level covering the period of 2007–2019:

$$Decoupling_{i,t} = \beta \times Sanction_{i,t} + \delta' X_{i,t-1} + \gamma_i + \gamma_t + \epsilon_{i,t}. \quad (7)$$

The empirical setup is analogous to our analysis of the SEI promotion policy in Section 4.1.1. The sample construction, the dependent variables, the fixed effects, and the recurring variables in this setup are the same as those in Equation (3) of the SEI analysis. The dummy variable $Sanction_{i,t}$ is equal to one if technology class i had been exposed to U.S. sanctions prior to year t and zero otherwise. The effects of the sanctions are captured by β. We report the estimation results for Equation (7) in panel A of Table 7. To trace out the dynamics of the sanction effects, we replace the sanction indicator in Table 7 with a set of dummies representing the years around the sanction events in Table 8, where year 0 is marked to the sanction year. $Sanction(-\tau)$ and $Sanction(\tau)$ refer to τ years before and after the sanction, respectively. $Sanction(3+)$ corresponds to three and more years after the sanction.

Perhaps contrary to intuition, the results in column (1) of panel A in Table 7 suggest that post sanctions, the exposed technology class experienced a significant (at the 1% level) *decline* in decoupling with the United States. Column (1) of Table 8 does not show any significant differences in the decoupling measure between sanctioned and non-sanctioned sectors before the event, but their differences emerge after the sanctions. Admittedly, the regression results are correlational and do not rule out the possibility that U.S. sanctions targeted sectors that would have seen far more integration in their absence. Nevertheless, the outcome indicates that U.S. interventions have not reversed the technology integration in recent decades as economic activities and technology exchanges run their own courses. Since China joined the WTO in 2001, U.S. international trade in goods with China has soared by 4.6 times by 2019.[46] Since China's opening up in 1978, 4.9 million Chinese students have completed their studies overseas, and 4.2 million returned to China.[47] Even during the 2019–2020 academic year amidst tension between the two nations, about 373,000 Chinese students (35% of all international students) studied in the United States, constituting the top source of international students on U.S. campuses.[48] Such strong economic ties and talent flows have fostered technology exchanges fluid at national boundaries and are difficult for the government to unwind short of draconian measures.

The effects of U.S. sanctions on China's technological dependence on the United States are ambiguous because of two opposing forces. By depriving Chinese firms of U.S. technologies, U.S. sanctions may weaken their technological capability, and in consequence, China may depend more on the United States down the road. On the other hand, losing access to U.S. technologies also forces and encourages Chinese firms to create their own innovations, reducing dependence on the United States. Column (2) in panel A of Table 7 suggests that the second force dominates; U.S. sanctions are negatively correlated with China's technological dependence on the United States. Importantly, no preexisting trends manifested themselves, as illustrated by column (2) of Table 8. Such a result is consistent with the narrative that the sanctions have encouraged or even forced China to become more technologically independent from the United States.[49]

Similar to the SEI policy analysis, we decompose the results in Table 7, panel A by using [illegible] and [illegible] (defined in Equation (1)) as separate dependent variables in Equation (7).[50] Post sanction, patents in the sanctioned technology classes in each nation are more likely to cite patents from the other. There could be two forces at work that deflated decoupling. First, after the U.S. sanctions, in the process of "reinventing the wheel," Chinese inventors reference U.S. patents more intensely to build up their own capacity. Second, Chinese firms, often with support from the government and collaboration among industry peers, enhanced their technological capabilities. As a result, their new invention and progress become more influential. Although sanctions could be effective in restricting export, re-export, and/or transfer (in country) of specified items (e.g., denying Huawei access to semiconductors produced by U.S. companies), it is far more difficult to block knowledge flows as well as mutual referencing of patents (e.g., there is intensive cross-licensing between Huawei and Qualcomm). As a result, sanctions seem to have had limited effectiveness in decoupling technologies.

4.2.3. Spillovers of Technology Decoupling from Sanctions. Knowledge and technology evolve in an organic network in which different sectors intertwine, giving rise to network spillover effects. As such, the impact of sanctions could extend beyond the focal sectors targeted, especially to upstream and downstream sectors. This section traces out such effects.

The first step is to formulate the innovation network. Following the literature (e.g., Acemoglu et al. 2016, Liu and Ma 2022), we build a patent citation-based IO table at the three-digit IPC level based on the U.S. patents granted between 1976 and 2019. Importantly, the innovation network is remarkably distinct from the production network and thus, captures intersector knowledge and technology linkages that do not overlap with production supply chains. Based on the IO table, we construct the indirect exposure to sanctions (of a non-sanctioned technology class) from the upstream and downstream as follows:

$$[illegible] \sum_{\neq} [illegible] \times [illegible]$$

$$[illegible] \sum_{\neq} [illegible] \times [illegible]$$

In the two equations, [illegible] refers to the share of citations made from technology class [illegible] to [illegible]. The sanction indicator [illegible] takes the value of one if technology class [illegible] is sanctioned in year [illegible] and zero otherwise. [illegible] evaluate the network spillovers of U.S. sanctions by the following setup:

$$
\begin{aligned}
&\beta_1 \times \quad x \\
&+ \beta_2 \times \quad x \\
&+ \delta \quad 1 + \gamma + \gamma + \qquad (8)
\end{aligned}
$$

Equation (8) is analogous to Equation (7), except that the sanction indicator in Equation (7) is replaced by upstream and downstream sanction exposures in Equation (8). Key coefficients of interest become β_1 and β_2, which reflect the network spillovers of U.S. sanctions. The results are reported in panel B of Table 7.

Empirical results reveal asymmetric network spillover effects. Column (1) shows that U.S. sanctions imposed on upstream sectors are associated with greater U.S.–China integration in the focal sector, but the reverse is true for sanctions imposed on downstream sectors. On the other hand, there are no significant sanction spillovers on the dependence measure (column (2)). Consider the following example, which hopefully facilitates illustration. Suppose semiconductors became the technology class that was sanctioned, and its supply in China was reduced as a result. Consumer electronics producers (with indirect sanction exposure from the upstream) in China now have to source such inputs from foreign suppliers, which forces them to tailor their product designs to fit into the global standard. Meanwhile, the semiconductors sector is denied their access to foreign technology and inputs, compelling them to switch to domestic sources. In consequence, the chip design sector (with indirect sanction exposure from the downstream) in China becomes more fenced off from foreign competitions and more decoupled from the world in a sheltered innovating environment.

4.2.4. Sanctions and Firm Performance. Sanctions, on their own or via spillovers, have implications for the performance of affected firms, which is the subject of this section. Parallel to the technology class-level investigations, we now conduct the following regression at the firm(

However, both the focal and downstream sectors beco
more integrated (i.e., less decoupled) with the Uni
States in their fight for survival, opposite to the object
of the sanction policies. Moreover, the upstream firms a
sectors in China (that are exposed to sanctions indire
from the downstream) generally thrive on the sanctio
Not only do these firms witness improved producti
and profitability, but also, they are investing more R&D
explorative research and making more breakthrough
technology. Such developments are expected to red
China's dependence on U.S. technologies.

5. Conclusion

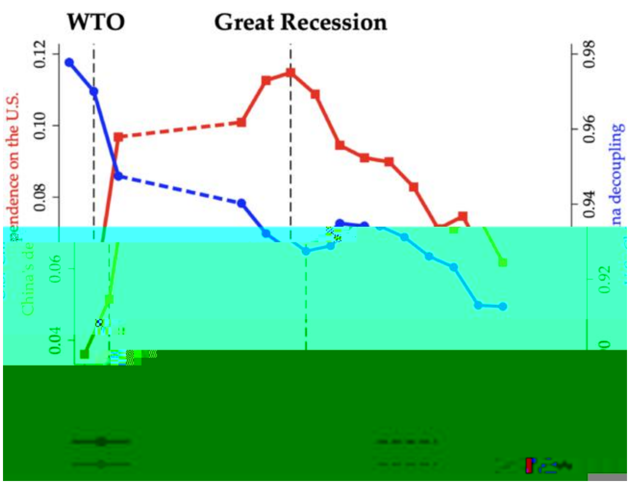
By integrating comprehensive patent data from
United States and China, we develop new measure
quantify the time-varying technology decoupling
dependence between the United States and China in
aggregate and in specific technology classes. The first
decades of the twenty-first century witnessed a ste
increase in technology integration (or less decoupli
but China's dependence on the United States increa
(decreased) during the first (second) decade. Analy
government policies in both nations, we find that Chi
innovation-promoting industrial policies are associ
with both more integration and less dependence d
the road, but the process has not registered improver
in either the productivity or the innovativeness of fi

On the other side, U.S. sanctions against China have
ot led to U.S.–China decoupling but have spurred more
ndependent and high-impact technological develop-
nent in China, especially in the upstream sectors of the
anctioned. Knowledge and technology form their own
etwork with complex spillovers across sectors, which
re fluid at national boundaries. Sanctions often instigate
roader, and often unintended, impact relative to what
was envisioned by the policy makers.[56] Our findings

University, and University of Illinois Urbana-Champaign and those of conferences at the Asian Meeting of the Econometric Society, Cavalcade, the China Economics Summer Institute, the China Financial Research Conference, the China International Conference in Finance, the China International Conference in Macroeconomics, the China Trade Research Group Conference, European Finance Association meeting, the National Bureau of Economic Research (NBER) Chinese economy working group meeting, and Northern Finance Association meeting for helpful comments and suggestions.

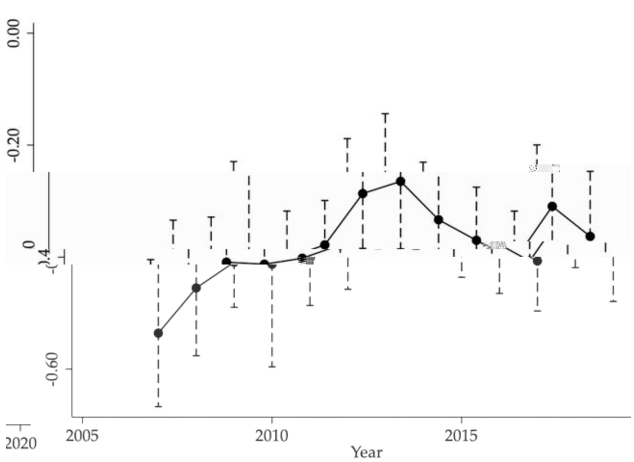
Appendix. Appendix Figures and Tables

Figure A.1. (Color online) U.S.–China Technology Decoupling Based on Renewed Patents



Note. This sensitivity analysis focuses on Chinese patents that have been renewed at least three times (to maintain patent validity, holders of Chinese patents must pay a maintenance fee to renew their patents annually).

Figure A.2. Technology Dependence and Chinese Patent Share



Note. This figure shows the relationship between our measure of technology dependence and the measure developed in Akcigit et al. (2020) (i.e., the number of Chinese patents divided by the sum of the number of Chinese patents and U.S. patents). We regress our measure of China's technological dependence on the United States against the share of Chinese patents each year at the technology class-year level and plot the estimates in each cross-sectional regression by year.

Table A.1. Variable Definition

Variable	Definition
[illegible]	A measure of technology decoupling between the United States and China, developed in Section 2.2
[illegible]	China's technological dependence on the United States, developed in Section 2.2
[illegible]	The natural logarithm of one plus the number of patent applications a firm files (and is eventually granted)
[illegible]	The number of citations a patent receives divided by the average number of citations received by patents in its cohort (i.e., patents applied in the same year and in the same technology class)
[illegible]	The natural logarithm of total factor productivity estimated by the method of Ackerberg et al. (2015)
[illegible]	EBITDA divided by the sum of the book value of debt and equity
[illegible]	The ratio of the sum of the market value of equity and the book value of debt to the sum of the book value of debt and equity
[illegible]	The natural logarithm of the book value of assets
[illegible]	The natural logarithm of one plus age since founding (initial public offering) for Chinese (U.S.) firms
[illegible]	R&D expenditures divided by assets; missing values are imputed zero
[illegible]	Capital expenditures divided by book value of assets
[illegible]	Net value of property, plant, and equipment divided by the book value of assets
[illegible]	Book value of total debt divided by book value of assets
[illegible]	Number of patent applications divided by the weighted average of R&D expenditures in recent years
[illegible]	The share of breakthrough patents filed by a firm each year; a breakthrough patent is defined to be the top 5% most cited patents in its cohort (i.e., patents in the same technology class and applied in the same year)
[illegible]	The share of explorative patents filed by a firm each year; a patent is categorized to be explorative if at least 80% of its citations are based on new knowledge (i.e., do not belong to the patents filed by the firm and the patents cited by the firm's patents filed in the past five years)
[illegible]	The share of exploitative patents filed by a firm each year; a patent is categorized to be exploitative if at least 80% of its citations are based on the firm's existing knowledge (i.e., belong to the patents filed by the firm or the patents cited by the firm's patents filed in the past five years)
[illegible]	Average originality scores of the patents filed by a firm each year; a patent's originality score is one minus the Herfindahl index of the number of citations made by a patent to each technology class
[illegible]	Average generality scores of the patents filed by a firm each year; a patent's generality score is one minus the Herfindahl index of the number of citations received by a patent from each technology class

Table A.1. Variable Definition

Variable	Definition
[illegible]	Weighted average of the sanction indicator of all upstream technology classes of the focal technology class; the weight is the share of citations made from the focal technology class to other upstream technology classes
[illegible]	Weighted average of the sanction indicator of all downstream technology classes of the focal technology class; the weight is the share of citations the focal technology class receives from other downstream technology classes

Table A.2. Descriptive Statistics, Chinese Companies

	Mean (1)	Standard deviation (2)	25th Percentile (3)	Median (4)	75th Percentile (5)	Observations (6)
[illegible] 1	0.920	0.0308	0.896	0.924	0.942	16,247
[illegible] (number of patents)	3.867	10.29	0	0	2.500	16,247
[illegible]	0.427	0.886	0	0	0.527	16,247
[illegible] (billion RMB)	10.75	28.25	1.400	2.861	7.016	16,247
[illegible] (number of years)	14.55	5.429	11	14	18	16,247
[illegible]	0.0189	0.0191	0.00139	0.0162	0.0273	16,247
[illegible]	0.0577	0.0494	0.0213	0.0435	0.0791	16,247
[illegible]	0.230	0.153	0.112	0.198	0.318	16,247
[illegible]	0.408	0.206	0.241	0.398	0.561	16,247
[illegible]	0.0791	0.0641	0.0504	0.0767	0.110	16,247
[illegible]	2.523	1.707	1.386	1.994	3.044	16,247
[illegible]	1.196	0.365	0.957	1.133	1.359	16,247

[illegible]. The sample includes all publicly listed Chinese companies that filed at least one patent between 2007 and 2019. The table reports the summary statistics of the main variables that are defined in Table A.1. To facilitate the economic interpretations of the following variables, we report the summary statistics of [illegible] in terms of the number of patents, [illegible] in terms of billions of RMB, and [illegible] in terms of the number of years. [illegible] in this table refers to the ratio of the sum of the market value of equity and the book value of debt to the sum of the book value of debt and equity. [illegible] in this table refers to the total factor productivity estimated by the method of Ackerberg et al. (2015). All potentially unbounded variables are winsorized at the 1st and 99th percentiles.

Table A.3. Descriptive Statistics, U.S. Companies

	Mean (1)	Standard deviation (2)	25th Percentile (3)	Median (4)	75th Percentile (5)	Observations (6)
[illegible]	0.916	0.030	0.895	0.919	0.937	14,839
[illegible] (number of patents)	31.898	109.588	0.000	1.000	10.000	14,839
[illegible]	0.546	1.183	0.000	0.000	0.618	14,839
[illegible] (billion RMB)	9.899	25.613	0.157	0.817	5.218	14,839
[illegible] (number of years)	23.002	19.730	9.000	17.000	31.000	14,839
[illegible]	0.101	0.159	0.006	0.041	0.123	14,839
[illegible]	0.038	0.042	0.013	0.026	0.050	14,839
[illegible]	0.194	0.191	0.057	0.126	0.265	14,839
[illegible]	0.210	0.232	0.004	0.163	0.315	14,839
[illegible]	0.030	0.453	0.021	0.143	0.221	14,839
[illegible]	3.020	2.964	1.361	2.052	3.400	14,839
[illegible]	2.258	1.188	1.655	2.242	2.683	14,839

[illegible]. The sample includes all publicly listed U.S. companies that filed at least one patent between 2007 and 2019. The table reports the summary statistics of the main variables that are defined in Table A.1. To facilitate the economic interpretations of the following variables, we report the summary statistics of [illegible] in terms of the number of patents, [illegible] in terms of billions of U.S. dollars, and [illegible] in terms of the number of years. [illegible] in this table refers to the ratio of the sum of the market value of equity and the book value of debt to the sum of the book value of debt and equity. [illegible] in this table refers to the total factor productivity estimated by the method of Ackerberg et al. (2015). All potentially unbounded variables are winsorized at the 1st and 99th percentiles.

Endnotes

[1] The source of data is the Educational, Scientific, and Cultural Organization of the United Nations.

[2] For instance, see the 2010 report of the U.S. Chamber of Commerce ("China's Drive for Indigenous Innovation—A Web of Industrial Policies") under the Obama administration and the 2017 report of the U.S. Chamber of Commerce ("Made in China 2025: Global Ambitions Built on Local Protections") under the Trump administration.

[3] A quote from China's State Council (2010) said that "we will vigorously enhance integrated innovation and actively participate in the international division of labor. We will strengthen the adoption, digestion, and absorption of foreign technologies, making full use of global innovation resources." See "Decision of the State Council on Accelerating the Cultivation and Development of Strategic Emerging Industries" published by the State Council. The source link to this reference is: https://www.gov.cn/zwgk/2010-10/18/content_1724848.htm.

[4] For example, Autor et al. (2013) and Pierce and Schott (2016) find that rising Chinese imports cause higher unemployment and lower wages in the United States. Amiti et al. (2019) provide suggestive evidence that U.S. tariffs imposed during the 2018 "trade war" were almost completely passed through to U.S. domestic prices. Cen et al. (2020) document that both high birth rates of Chinese firms and high Chinese subsidies predict same-industry firm exits and lower employment in the United States.

[5] Akcigit et al. (2020) find that foreign corporate investments in Silicon Valley contribute to knowledge spillovers to foreign investors. Bena and Simintzi (2021) find that U.S. firms operating in China decrease their process innovations following the 1999 U.S.–China bilateral agreement. Bian et al. (2021) find that bilateral investment treaties between countries contribute to the globalization of innovation.

[6] Fang et al. (2017) show that innovation increases after China's state-owned enterprises are privatized, and this increase is larger where protection for intellectual property rights is stronger. Wei et al. (2017) underscore the indispensable role of innovation in fueling future growth of the Chinese economy and discuss numerous challenges for China's transition toward an innovation-driven economy. Tian and Xu (2022) find that the national high-tech zones in China have contributed to local innovation and entrepreneurship. Cong and Howell (2021) find that the uncertainty associated with initial public offering suspension in China has discouraged corporate innovation. Exploiting staggered establishments of patent exchanges in China, Han et al. (2022) find that the market for technology promotes comparative advantage-based specialization.

[7] A paper that is close to ours is by Fang et al. (2021), which compares the quality of Chinese patents with that of U.S. patents and explores how learning contributes to patent quality convergence promotes

technology classes sorted by the measure of technology decoupling. Table IA3 in the online appendix shows the 10 technology classes in which China has the strongest and weakest dependence on the United States. Figure IA13 in the online appendix is the cross-sectional analog of Figure 2 at the three-digit IPC level.

[28] The figure is reported in Figure IA14 in the online appendix.

[29] As in previous studies, low-quality patents in this figure refer to patents that are not renewed by the patent holders.

[30] For more details, see Figure A.2.

[31] For details, see Figure IA15 in the online appendix for the annual time series of the correlations between decoupling / dependence and the textual similarity measures.

[32] This is the source link to the data updated to 2019: https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data.

[33] About 89.1% of patent-filing Chinese firms can be mapped to a unique IPC by the number of patents

Bian R (2021) Patent trolls in China: Some empirical data.