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

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Abstract

We develop measures for technology decoupling and dependence between the U.S. and China based on combined patent data. The first two decades of the century witnessed a steady increase in technology integration (or less decoupling), but Chinas dependence on the U.S. increased (decreased) during the first (second) decade. Firms covered by Chinas Strategic Emerging Industries policies became less decoupled with the U.S., gained cash flows and valuation but saw no improvement in either innovation output/quality or productivity. Post U.S. sanctions, firms in sanctioned sectors and their downstream suffer in performance but also became less decoupled with the U.S. However, firms in the upstream of the sanctioned sectors experienced significant improvements in productivity and produced more innovation of breaking-through and explorative quality.

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1 Introduction

During the first two decades of the twenty-first century, China emerged as a global economic power, building on its growth miracle fueled by investment and production since its "open-door" policy started in 1978. China became the top manufacturing nation in 2010, ending a 110-year U.S. lead. China became the largest trading nation in goods in 2013 and the largest economy by purchasing power parity (PPP) in 2014. While most of the time China was eager to learn from the West, it is natural for sustained economic growth to translate into technological ambitions. As the U.S. share of world research and development (R&D) has declined from 36.4% in 2000 to 25.6% in 2017, China's share has soared from 4.5% to 23.3% during this period (all in PPP terms).[1] The year 2019 marked another milestone: China filed the largest number of international patent applications at the World Intellectual Property Organization (WIPO).

China's technological progress benefited from its integration with the developed world, especially the United States. Science and technology are more fluid at national borders than goods or even people. Internet protocols, hardware design and manufacturing, software development and deployment, and IT services and standards have, to varying degrees, evolved in a global system. The last few years, however, have seen a rise in mutual distrust and actions to unwind the current level of technological interdependence. The process toward two ecosystems with an increasing degree of separation is now widely known as "decoupling." While there have been fierce debates among scholars and policymakers about the levels and consequences of decoupling, there has not been a comprehensive academic study mapping the current state and dynamics of competition and decoupling in technology between the two countries; nor has there been a study characterizing the motives and impact of recent policies that directly or indirectly aim at decoupling. Our study aims to fill the gap.

The first main mission of this paper is to map out technology decoupling (i.e., the opposite of integration) between the two nations over time, in the aggregate and across different technology classes, based on measures developed anew. We calibrate decoupling by the propensity for domestic patents in a technology area to cite foreign patents relative to citing their own. In simplified

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

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. While 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 for China's technological dependence on the U.S. (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 main theme in the twenty-first century. China's technological dependence on the U.S., on the other hand, is hump-shaped, having peaked 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 U.S.; while the next decade featured dependence-relaxing integration. Toward the last two years of our sample (since 2018), we observe signs of increasing decoupling, but the time period is yet too short to offer definitive inferences.

The second, and equally important, mission of this study is to assess the corporate finance implications from technology decoupling. The relation between decoupling and firm outcomes is *a priori* ambiguous due to two opposing forces. Global technology integration facilitates knowledge spillover, which complements and spurs domestic innovation (a "complementarity effect"). At the same time, technology decoupling forces domestic firms to create instead of merely follow, and provides a sheltered space for them to do so. Both factors provide stronger incentives for domestically oriented innovation (a "substitution effect"). Our empirical analyses indicate that heightened U.S.-China technology decoupling is followed by higher patenting outputs for Chinese firms, suggesting stronger substitution effect than complementarity effect. However, firm profitability, productivity, and valuation suffer in China, suggesting a cost for "reinventing the wheel" in a decoupling world. In contrast, The impact on U.S. firms is largely unnoticeable, presumably because the U.S. is still in the leading position in most fields.

We explore two sets of policies that aim at technology integration or decoupling from both countries so that we can probe the mechanism of decoupling in shaping innovation and firm performance. On the Chinese side, the "strategic emerging industries" (SEI) initiative launched in 2012 was among the most powerful technology-motivated industrial policies to this date. The leadership in the two countries do not completely agree on the central mission of the initiative. According to the narratives of both the Obama and Trump administrations, the major goal of China's innovation-promoting industrial policies was to achieve "self-sufficiency" by "domestic substitution of foreign technologies."[2] The Chinese government, however, indicated that its policies were attempting to achieve self-sufficiency *without* deviating from the global technical standards or advancing along a different technological trajectory.[3] Our empirical results lend more support to SEI being associated with more technology *integration* instead of decoupling between China and the United States, and China's technological *independence* from the U.S. We further document that firms in technology fields that are promoted by the SEI policy are, perhaps unsurprisingly, associated with lower patenting activities but higher profitability and market valuation. However, the policy has succeeded in neither nurturing breakthrough innovations nor fostering innovation originality.

Regarding policies on the U.S. side, we evaluate the impact of U.S. sanctions imposed via the entity list of the U.S. Department of Commerce, which had hovered at a low level but have escalated since 2014. Perhaps contrary to conventional wisdom, we find that U.S. sanctions against China, as of 2019, have not been followed by decoupling in the targeted technology area. It is often said that science and technology do not respect national boundaries, and U.S. government interventions, short of more draconian measures, have not been strong enough to reverse the fundamental forces driving global integration in recent decades. U.S. sanctions have compelled China to pursue more

[2] For instance, see the 2010 report of the United States Chamber of Commerce ("China's Drive for Indigenous Innovation–A Web of Industrial Policies") under the Obama administration, and the 2017 report of the United States 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. This is the source link to this reference.

independence-oriented technological development. While incurring moderate drops in innovation output, profitability, and productivity, Chinese firms exposed to sanctions started to produce more original innovations. Further, valuation of these firms exhibit resilience, possibly helped by support from the Chinese government and businesses as intensity of sanctions grew.

Technology, by its nature, is fluid at sectoral and national boundaries, with spillovers expected within the broad innovation network. Based on an innovation network built on patent-citation input-output table (Acemoglu et al. (2016), Liu and Ma (2022)), we find that U.S. sanctions imposed on a sector's upstream are associated with poorer performance of firms in the focal sector in terms of productivity, profitability, and valuation. The focal sector in China seeks more integration with the U.S. but still suffer in innovation output, efficiency, and impact. Exactly the opposite are true when sanctions are imposed on firms' downstream 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] While 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 the U.S.) experience, even in a cross-country setting such as building on shocks from foreign sources.[5] The literature on innovation in China has also been emerging.[6] As we

[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 U.S. 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 U.S.

[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.

[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

indicated earlier, this study is the first to quantify technology decoupling and the implications of government policies in both countries on 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 U.S. 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 U.S. and China

2.1 Overview: patenting in the U.S. 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 United States 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 covers inventions that function in a unique manner to produce a useful result and is 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,

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 (2021) find that the national high-tech zones in China has contributed to local innovation and entrepreneurship. Exploiting staggered establishments of patent exchanges in China, Han et al. (2022) find that patent trading 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 explore how learning contributes to patent quality convergence between the two countries.

[8] The other two lesser known categories are design patents and plant patents.

[9] The other two lesser known categories in the Chinese system are utility model patents and design patents. Compared to these two categories, invention patents in China are subject to more rigorous examination and enjoy a longer term of protection.

and neither of them discriminates based on the citizenship of applicants in regard to eligibility for patent applications. At the USPTO, all foreign nationals are eligible for patent applications, while CNIPA requires foreign nationals to have a residence or business office in China.[10] Filing patents at a foreign patent office is critical to protect the applicant's intellectual property there, because, according to the World Intellectual Property Organization (WIPO), "patents are territorial rights." That is, the exclusive rights are only applicable in the country or region in which a patent has been filed and granted.[11] At both patent offices, domestic and foreign applicants will go through three major phases: filing, examination, and the granting of patents.[12] Importantly, patent examiners in both countries are required to search for prior art in both domestic and foreign patents during the patent examination process.[13]

As an overview, Figures 1a and 1b plot the annual time-series of innovation inputs (R&D expenditures)[14] and outputs (patents) of the two countries. Apparent from both charts is that China has rapidly ascended to becoming a global R&D and patenting powerhouse in the two recent decades, challenging the U.S. leadership position at least in terms of these nominal metrics. While the U.S. R&D expenditures more than octupled China's level in 2000 and have been growing steadily, China had almost closed the gap by 2020 with a steady annual growth rate of 13.9%. Starting from fewer than one-thirteenth of the U.S. patenting volume at the beginning of the twenty-first century, China managed to surpass the U.S. in 2015 and has since remained in the

[10] According to China's patent law, even without any habitual residence or business offices in China, foreign nationals are still eligible to apply for patents at CNIPA as long as one of the following conditions is satisfied: (i) their home country has signed a bilateral agreement with China to provide patent protection to the nationals of each other; (ii) their home country and China have joined an international treaty to provide patent protection to the nationals of each other; (iii) the patent law in their home country provides patent protection to Chinese nationals.

[11] There are two options to file a patent application in a foreign patent office. The applicants can directly file an application at the national patent office of that country, or they can file an application via the Patent Cooperation Treaty (PCT) route. Applicants can simultaneously seek protection for an invention in over 150 countries if they follow the PCT route.

[12] Specific steps of each phase are illustrated in the flow chart of Figure IA1 in the Internet Appendix. These procedures are based on information from *IP5 Statistics Report,* 2018 Edition.

[13] According to this instruction manual of the USPTO, "a comprehensive prior art search would also include foreign patent publications and non-patent literature (newspapers, magazines, dissertations, conference proceedings, and websites)." More information about foreign patents can be found in the section "Search International Patent Offices" at the USPTO. In particular, USPTO provides a reference link to the Chinese patent office where machine translation of Chinese patents is available. At the Chinese patent office, both domestic and foreign prior art should be considered during the examination process for invention patents, according to the *Guidelines for Patent Examination* issued by CNIPA.

[14] R&D expenditures of both China and the United States are based on information from the Educational, Scientific, and Cultural Organization of the United Nations, and are measured in constant 2005 PPP dollars.

lead.[15] In addition to comparing the two nations as patent approval authorities, we also examine the patenting activities based on the nationalities of the assignees and the results are reported in the Internet Appendix.[16]

[Insert Figure 1 here.]

2.2 Technology decoupling and dependence explained

The previous section previewed the changing global landscape of innovation in recent decades, marked by China's relentless growth in innovation and a resulting shrinking gap vis-à-vis the U.S. The dynamics naturally invited the question of whether or to what extent the U.S. still dominates China in technology—overall and in specific sectors. Moreover, despite the recent attempts of technology decoupling by 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. Thus the first necessary step of our study is to develop a measurement framework which could quantify decoupling and dependence in technology between the two nations.

The desire to decouple requires pre-existing, one-sided or mutual dependence in technology; however, the two concepts are distinct and warrant separate measurement. Since technological standards can be different across countries (from issues as simple as the standard voltage), cross-border technology transfer could be limited by the incompatibility alone. Our measure for "technology decoupling" will capture the degree of incompatibility between different national technological systems because applying different technological standards is a form of decoupling. The level of 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 de-activated 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.

[15] China also became the top source of filing international patent applications at the World Intellectual Property Organization (WIPO), taking the crown from the U.S. in 2019.

[16] Please see Patenting activities by nationalities of patent assignees in the Internet Appendix. Figures IA2 – IA6 plot the analyses based on the nationalities of the patent assignees.

In comparison, the notion of "technology dependence" in this study hinges critically on a country's one-sided reliance on foreign technology to advance its own. High dependence is thus usually associated with a weaker competitive situation in that particular area. For example, though China led in the 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.

2.3 Measuring technology decoupling and dependence

This section develops measures of technology decoupling and dependence by mapping them to the propensity of a domestic patent citing a foreign patent relative to citing a domestic one. Pioneered by Jaffe et al. (1993), patent citations have been commonly adopted by researchers as an objective metric for the impact and knowledge spillover of patented inventions. Though patents consist of one segment of innovation and are known to have limitations (Moser (2013)), they remain the most comprehensive and objective data source for the innovation literature, and form the basis for our measures of technology decoupling and dependence.[17]

We start with a few notations to build up to the main measures. First, $p_{c,u}$ is the propensity for Chinese patents to cite a U.S. patent relative to citing a Chinese one; analogously, $p_{u,c}$ is the propensity for U.S. patents to cite Chinese patents relative to citing U.S. patents. More specifically,

$$p_{c,u} = \frac{n_{c,u}/x_u}{n_{c,c}/x_c},\ \ p_{u,c} = \frac{n_{u,c}/x_c}{n_{u,u}/x_u}.$$

In the expressions above, $n_{c,u}$ ($n_{c,c}$) is the number of citations Chinese patents make on U.S. patents (Chinese patents), $n_{u,c}$ ($n_{u,u}$) is analogously defined. Because the number of citations tends to increase as the patent stock grows, we normalize the citation numbers by x_c and x_u, which are the total number of patents granted at the national offices of the referenced patents.[18] The two

[17]Note there are different notions of "decoupling" between the two economies. We focus on knowledge-spillover-based decoupling which does not directly shed light on decoupling in other areas such as supply chains.

[18]In the absence of normalizing by total number of patents, $p_{c,u}$ will be mechanically deflated when x_c grows faster than x_u and it leads to an artifact of increasing "decoupling" between the two countries and decreasing "dependence" of China on the U.S.

propensity measures are both time-varying: $n_{i,j}$ ($i, j \in \{c, u\}$) are flow variables of patent citations in a given year, and x_i ($i \in \{c, u\}$) are stock variables of patent counts up to that year. The relative magnitude of $p_{c,u}$ and $p_{u,c}$ quantifies the propensity for a domestic patent to cite a foreign patent relative to its propensity to cite a domestic patent.

With the expressions, we are able to provide a visualization of decoupling and dependence, presented in Figure 2. The horizontal and vertical axes measure $p_{u,c}$ and $p_{c,u}$, 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 of "complete integration" corresponds to the point I with $(1, 1)$ coordinates (i.e., $p_{c,u} = p_{u,c} = 1$) where domestic patents cite a patent in the other country with the same probability as citing a domestic patent.[19] That is, technology embedded in patents in the other country is just as relevant (to the extent to justify a reference) to that produced domestically such that there is an absence of "home bias" for domestic technology. Any point interior of the box indicates a partial integration or imperfect decoupling.

[Insert Figure 2 here.]

The 45-degree line in Figure 2 is the state of parity. Any point on this diagonal line satisfies $p_{c,u} = p_{u,c}$, that is, the propensity for Chinese patents to cite the U.S. patents is exactly reciprocated, though the degree of integration/decoupling varies. In the triangular area above the 45-degree line, Chinese patents are more likely to build on U.S. patents than the other way around, or, $p_{c,u} > p_{u,c}$. We thus label this region as China's (relative) dependence on U.S. technology, or, "U.S. leading." By the same argument, the triangular area below the line is the "China leading" region. In the extreme, the corner $(0, 1)$ ($(1, 0)$) represents absolute "U.S. dominance" ("China dominance").

Any interior point in Figure 2 represents a unique combination of the extent of decoupling and that of dependence. We will use the point P (interior of the upper triangle) in the figure to

[19] Though "over-integration" (i.e., $p_{c,u}$ and $p_{u,c}$ exceeding 1) is theoretically possible, empirically it was never remotely the case. Hence, we focus on the practically relevant scenario where both $p_{c,u}$ and $p_{u,c}$ are bounded by 1 in the discussions about Figure 2.

illustrate how to quantify such a combination. As a first step, a projection of P onto the 45-degree parity line arrives at point Q. By construction, the vector $\overrightarrow{\mathrm{PQ}}$ is orthogonal to the 45-degree line.[20] The norm of $\overrightarrow{\mathrm{QI}}$ (i.e., the projection of $\overrightarrow{\mathrm{PI}}$ onto the par line) captures the degree of U.S.-China technology decoupling; while the norm of $\overrightarrow{\mathrm{PQ}}$ (i.e., the rejection of $\overrightarrow{\mathrm{PI}}$ from the par line) reflects China's technological dependence on the U.S.

Quantifying the norms of the vectors in Figure 2, and hence the resulting measures, now become relatively straightforward. The measure for decoupling simply becomes $\frac{||\overrightarrow{\mathrm{QI}}||}{\sqrt{2}}$.[21] A higher value of *Decoupling*(US & CN) stands for a higher degree of technology decoupling, or a lower degree of integration, between the two countries. The measure constructed this way is bounded between 0 (perfect integration) and 1 (perfect decoupling). Even though one country may have a stronger desire to decouple from the other, the outcome of decoupling is symmetric or mutual between the two countries. Next, the degree of China's technological dependence on the U.S., graphically becomes $\sqrt{2}||\overrightarrow{\mathrm{PQ}}||$ in the U.S.-leading region and $-\sqrt{2}||\overrightarrow{\mathrm{PQ}}||$ in the China-leading region in Figure 2. Dependence is asymmetric between the two countries. A positive sign of *Dependence*(CN on US) indicates that China depends more on U.S. technology than the other way around, or that the U.S. maintains a leading position. When *Dependence*(CN on US) $= 1$ (or -1), the U.S. (or China) is in absolute dominance. For the ease of notation, "dependence" refers to China's dependence on the U.S. unless otherwise specified for the rest of the paper.

We note that the degree of decoupling imposes ranges on the level of dependence. In the extreme of perfect decoupling, dependence becomes moot and is hence zero; and in the other extreme of perfect integration, the two countries must be on parity and hence dependence (which is on a relative scale) is also zero, the neutral value. Moving from the extreme points toward the middle of the 45-degree line in Figure 2, the range of permissible values of dependence increases. We thus also develop a conditional version of the dependence measure that is free from such a functional restriction. More specifically, let P' be the intersection point of the extension of the vector $\overrightarrow{QP}$ and the vertical axis. Then $||QP'||$ is the maximum level of dependence conditional

[20]In this setting, two vectors are said to be orthogonal if and only if their inner product is zero and at least one of them is a non-zero vector.

[21]Division by $\sqrt{2}$ normalizes the measure to be bounded between zero and unit.

on the level of decoupling. We thus define the level of dependence conditional on decoupling, or $Dependence|Decoupling$(CN on US), to be $\overrightarrow{QP}/||QP'||$, which is bounded between -1 and 1 and orthogonal to *Decoupling* (except when the measure is not defined in the two extreme states of perfect decoupling or integration).[22]

2.4 U.S.-China technology decoupling in the 21st century

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. If we group all patents by country (U.S. and China), we are able to 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 2019 (the end of our sample period, which coincides with open attempts of decoupling). All three observations fall toward the lower left above the 45-degree line, indicating that the two countries have mostly been running separate systems with China exhibiting more dependence on U.S. technology.[23] The change over time, however, is also informative. Since 2000, China moved first toward more integration with, and more dependence on U.S. technology during the first decade, and then reduced its dependence while furthering integration with the U.S. during the second decade.

[Insert Figure 3 here.]

Figure 4 offers a different presentation of the same history, and in more detail. In this chart, the horizontal axis is time in the calendar year, and the right (left) vertical axis marks the measure of decoupling (dependence). Between 2003 and 2006, backward citation information is missing

[22]For an external validity check, we apply the decoupling and dependence measures to three representative academic journals: American Economic Review (AER, a leading economics journal), Journal of Finance (JF, a leading finance journal), and Journal of Banking and Finance (JBF, a leading journal in a subfield of finance). The results are reported in Internet Appendix Figure IA7. Indeed, the two finance journals are well-integrated and each is more decoupled from AER. Moreover, JBF depends more on JF; while 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.

[23]The fact that English (but not Chinese) is a global language could contribute to a citation bias in favor of U.S. patents. Nevertheless, the USPTO puts much effort into facilitating U.S. patents to cite foreign ones (from China and other countries). First, the USPTO has access to almost all foreign patent documents through exchange agreements. Second, according to the instruction manual of the USPTO patent examiners, the examiners can request (human) translation of all patents that are cited in the reference or being considered for citation. Third, the translations are readily available for virtually all foreign languages (including Chinese) into English. Moreover, an English-language advantage, if it exists, would indeed be a real factor that favors English-speaking countries in general. Finally, the language issue should not impact cross-sectional nor time-series relations.

for the overwhelming majority of Chinese patents in our sample. These years are thus dropped in this figure. During the full sample period since 2000, technology decoupling has been falling steadily.[24] In other words, the general trend is for technologies in the two countries to become more integrated, conforming to the general theme of globalization.[25] China's technological dependence on the U.S., however, is hump-shaped over time, with the turning point being around the end of the Great Recession (2009). The combined evidence suggests that the first decade of the twenty-first century was characterized by dependence-*deepening* integration between the two countries, that is, technology in China became more dependent on U.S. technology during the integration process. During the second decade since 2010, the continued technology integration has been accompanied by China's declining dependence on the U.S.

Thus far we have been assigning the nationality of the patents based on the approving authorities. We thus provide a sensitivity check in which nationality also applies to the patent assignees. Appendix Figure A1 restricts the samples to Chinese patents granted to Chinese assignees and U.S. patents granted to U.S. assignees. An additional sensitivity analysis targets the concern that a substantial number of patents are of low quality, are not expected to generate impact, and could thus dilute citation-based measures. Such a concern is more pronounced for patents in China (e.g., Fang et al. (2021)). Accordingly, Appendix Figure A2 restricts the sample of Chinese patents to those that have been renewed at least three times.[26] Both Figures A1 and A2 exhibit similar patterns as those in Figure 4.

[Insert Figure 4 here.]

The aggregate states of decoupling and dependence shown thus far may have masked hetero-

[24] We examine further whether state owned enterprises (SOEs) and private firms have followed different dynamics. In Figure IA8 in the Internet Appendix, we separate patents by listed Chinese SOEs and those by private firms based on the actual controllers as disclosed in annual reports. The Figure shows little differences between the two groups, suggesting that the time trend transcends different types of firm ownership.

[25] To put U.S.-China decoupling in global perspective, we plot the time series of U.S.-EU decoupling in the Internet Appendix Figure IA9. Two features emerge. First, panel A of Figure IA9 suggests the U.S.-EU pair has been at a much higher level of integration with the average decoupling measure of 0.51, in comparison with 0.93 for the U.S.-China pair. Second, when we re-scale the decoupling levels of the two pairs to be on a similar footing in panel B, the two lines appear to be largely parallel, suggesting that the decoupling pattern in Figure 4 has not, up until 2019, deviated from the global trend though U.S.-China remains far more decoupled than U.S.-EU.

[26] To maintain patent validity, holders of Chinese patents must pay a maintenance fee to renew their patents annually.

geneity across different technology sectors. Therefore, we also examine ten high-tech fields defined by Webb et al. (2019), which include (by the order of the number of total 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 "non-high tech" field. Figure 5 plots the states of decoupling (corresponding to $\frac{||\overrightarrow{\mathrm{QI}}||}{\sqrt{2}}$ in Figure 2) and conditional dependence (corresponding to $\overrightarrow{QP}/||QP'||$ in Figure 2) for the technology sectors in years 2000, 2009, 2015, and 2019.[27]

[Insert Figure 5 here.]

Among the ten high-tech fields, China's dependence on the U.S. 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 relatively new technology sectors, such as neural networks, cloud computing, and self-driving cars, due to a variety of reasons from geopolitical sensitivities to different legal infrastructure.[28] The grant year of the first patent in each field marks a natural division between old and new technologies: While internal combustion engines, pharmaceuticals, semiconductors, smartphones, and software are pre-existing 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 old and new technologies.[29] It shows that the new technology fields exhibit both more decoupling and a steeper drop in China's dependence on the U.S. Particularly worth noting is the "drones" sector, whose dependence measure turned negative—i.e., China took the leadership—in 2019.[30]

[Insert Figure 6 here.]

We can further apply the methodology to more granular levels, such as at the three-digit International Patent Classification (IPC) code level. While the U.S. was in strict dominance in

[27]Some sectors with new technologies (e.g., neural network) are missing in the top panels because there are no patent grants in these fields in the earlier years.

[28]Google announced that it scrapped its Cloud Initiative in China, citing, among other reasons, the privacy and data sovereignty concerns.

[29]The comparison starts from 2007 because of the missing citations for the Chinese patents between 2003 and 2006.

[30]One Chinese firm, Da-Jiang Innovations (DJI), accounts for over 70% of the global drones market.

virtually all tech sectors in 2000, about 42.9% of the tech classes have evolved into China-leading by 2019. The tech fields in which the U.S. retains leadership include information storage, electronic circuitry, and combustion engines, where the dependence measures range from 0.24 to 0.38. Tech sectors in which China has the greatest lead include pelts and leather, the metallurgy of iron, and treatment of alloys and non-ferrous metals, where the dependence measures range from -0.95 to -0.19. The most decoupled tech fields include building; agriculture, forestry, and husbandry; and construction of roads, railways, and bridges, where the measures of decoupling range from 0.96 to 0.97. Finally, the most integrated technology classes are pelts and leather; information storage; and metallurgy of iron, where the measures of decoupling range from 0.47 to 0.81.[31]

Though our study is unique in presenting an integrated analysis of technology decoupling and dependence, there have been a burgeoning literature studying the relatively competitive positions of U.S. vs. China based on patent data. We thus compare and reconcile our analyses with those based on alternative measures. First, one common challenge facing all patent-based research is that patents, especially the quantities, are inaccurate measures of innovation. Our measures of decoupling and dependence are both citation based and therefore extract quality instead of relying on the sheer quantity of patent approvals.[32] We also reconcile our method with related literature, e.g., Akcigit et al. (2020), that resorts to the stock of knowledge proxied by a country's share of patents in a technology field among multiple countries. We verify that these two types of measures are significantly correlated in our sample, that is, China exhibits lower dependence on the U.S. in a technology sector for which the share of China-filed patents out of U.S.-and-China total is higher.[33] 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.

Two alternative methods have been developed in the literature that are based on the content

[31] For more detail, please see Technology decoupling at the technology class level in the Internet Appendix. Table IA2 reports the top and bottom ten technology classes sorted by the measure of technology decoupling between 2017 and 2019. Table IA3 shows the ten tech classes in which China has the strongest and the weakest dependence on the U.S. Figure IA10 is the cross-sectional analog of Figure 2 at the three-digit IPC level for years 2000, 2009, and 2019.

[32] A large literature has shown that a substantial number of patents are of dubious scientific value in both nations (Cohen et al. (2019), Liang (2012), Prud'homme and Zhang (2017)). The construction of our measures thus mitigates the influence of uncited, presumably low-quality patents. As delineated in previous discussions, we have also conducted a robustness check by excluding low-quality patents in Appendix Figure A2.

[33] For more details, see Appendix Figure A3.

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, though 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 "textual similarity" of patents as a proxy for technology similarity or compatibility (Younge and Kuhn (2016), Kelly et al. (2021)). We apply the method on U.S. and China patents and discover that the textual similarity between patents filed in the two nations has a cross-sectional correlation (at the technology class-year level) of -0.12 with our decoupling measure (significant at the 1% level), but bears no significant correlation with our dependence measure.[34] Our method could be complementary to the textual-based methods, and, more importantly, our method allows an integrated analysis of both decoupling and dependence.

3 Decoupling and firm performance: Diagnostics

This section provides diagnostic analyses of the relationship between technology decoupling and innovation and general performance of firms in both countries, paving the way for event studies in the next section.

3.1 Overview of sample U.S. and Chinese firms

A priori, neither the direction of the impact of technology decoupling, nor its symmetry (or the lack thereof) between the two nations, is clear. To answer these questions, we assemble panels of firms in the U.S. and China. Restricted by information availability, the sample is limited to publicly traded companies that file at least one patent between 2007 and 2019.[35] On the China side, financial statements and trading information of firms come from the China Stock Market and Accounting Research (CSMAR) database. We then merged the CSMAR data with the Chinese patent database by matching company names, accounting for the unique features of the Chinese language during

[34] For details, see Internet Appendix Figure IA11 for the annual time series of the correlations between decoupling/dependence and the textual similarity measures.

[35] Following Fang et al. (2018), our sample period starts from 2007 because publicly listed firms in China were not required to disclose certain important accounting information (e.g., R&D expenditures) prior to 2007.

the merging process. On the U.S. side, we merged the U.S. patent database to Compustat using the procedure developed in Kogan et al. (2017).[36] Firm information for both countries is accessed via Wharton Research Data Services (WRDS). We exclude firms in the financial industry following the common practice.

Following the literature in corporate finance and innovation, we resort to the following measures as dependent variables capturing firm performance. For innovation-specific metrics, the first is *Innovation Output*, measured as the natural logarithm of one plus the number of patent applications a firm files (and eventually granted) in that year. The second measure, *Innovation Quality*, is the relative citation strength of the patents, defined as the number of citations the patents (a firm owns) has received by 2019, divided by the average number of citations received by patents in its cohort (i.e., patents applied in the same year and the same technology class). Such an adjustment makes the quality comparable for patents from different time vintages and technology classes. The firm-year level measure is the relative citation strength averaged over all the patents applied by the firm in a given year.

As for general performance, we resort to the natural logarithm of a firm's total factor productivity, TFP, following the method developed in Ackerberg et al. (2015).[37] The TFP estimation is based on a Cobb–Douglas production function where output is proxied by a firm's total revenue. Inputs include capital and labor, approximated by total assets and total number of employees. Following the standard practice in the literature, intermediate inputs are approximated by cash payments for raw materials and service for Chinese firms, and by total expense minus labor expense for U.S. firms.[38] The next measure of firm profitability is *ROIC*, defined as operating income (earnings before interest, taxes, depreciation, and amortization, or EBITDA) divided by invested capital, i.e., the sum of the book value of debt and equity. Finally, firm valuation is proxied by *Tobin's Q*, approximated by the ratio of the sum of the market value of equity and the book value

[36] This is the source link to the data updated to 2019.

[37] The estimation method proposed in Ackerberg et al. (2015) addresses the functional dependence problem in previous studies.

[38] The proxy variables used in TFP estimation for the sample of Chinese firms follow the practice developed by Giannetti et al. (2015). For the sample of U.S. firms, total expense is revenue minus operating income before depreciation and amortization. When a firm's labor expense is missing in Compustat, we multiply the average wage per employee within its industry by the number of its employees, following the practice of Bennett et al. (2020).

of debt to the sum of the book value of debt and equity.

Standard firm characteristics variables included in the regression are defined as follows. *Assets* is a firm's book value of assets (in natural logarithm). *Age* is the natural logarithm of one plus number of years since a Chinese firm is founded[39] or a U.S. firm's first appearance in the public company databases. *R&D* is defined as a firm's R&D expenditures scaled by assets (with missing values imputed as zero). *Capex* is the ratio of firm capital expenditures to the book value of assets. *PP&E* is the ratio of property, plant, and equipment to book value of assets, a measure for asset tangibility. *Leverage* is the ratio of total debt to total assets, both in book value. The detailed definitions of all variables are listed in Table A1 in the Appendix. Unless otherwise specified, all potentially unbounded variables are winsorized at the 1% extremes.

The summary statistics for the Chinese firms and U.S. firms with at least one patent are provided in the Appendix. Table A2 shows that the average patent-filing Chinese firm in our sample is about 15 years old since birth and has an asset of RMB 10.8 billion (about US$1.6 billion). The average Chinese firm in the sample 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 *R&D* and 7.7% for *ROIC*. Finally, the average firm features a leverage ratio of 40.8% and a Tobin's Q of 2.5. Analogously, Table A3 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 US$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 *R&D* and 14.3% for *ROIC*. 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 Q of 3.0.

3.2 Decoupling, innovative activities, and firm performance

The impact of U.S.-China technology decoupling on firm innovation and performance for both countries is, a priori, ambiguous due to two opposing forces. On the one hand, global technology integration facilitates knowledge dissemination, allowing firms better access to foreign technology

[39] Such information is disclosed in China.

that is state-of-art, and complements and spurs domestic innovation. We term this negative relation between technology decoupling and domestic innovation as 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 panel regressions covering the period of 2007–2019, separately for U.S. and Chinese firms:

$$y_{i,j,t} = \text{Decoupling}_{j,t-1} \times \beta_1 + \text{Decoupling}_{j,t-2/3} \times \beta_2 + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \tag{1}$$

In equation (1), the dependent variable $y_{i,j,t}$, indexed by firm i, technology class j, and year t, is one of the following performance metrics: *Innovation Output* (the logarithm of one plus the number of patents filings that were eventually approved), *Innovation Quality* (the relative citation strength), TFP (the logarithm of total factor productivity), *ROIC* (return on invested capital) and *Tobin's Q* (in logarithm). The key independent variables are *Decoupling*, our measure of U.S.-China technology decoupling, measured at the technology class-year level. $\text{Decoupling}_{j,t-1}$ (our decoupling measure lagged by one year) is included to evaluate the short-run effects of decoupling, and $\text{Decoupling}_{j,t-2/3}$ (the average decoupling measure in lagged two and three years) is incorporated to assess the effects in the intermediate run. Because the dependent variable (performance) is at the firm level while the key independent variable (*Decoupling*) 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.[40] X represents the vector of firm characteristic variables introduced in Section 3.1, and are set to lag the dependent variable by one year. γ_t refers to country-specific year fixed effect that absorbs shocks to the aggregate economy, and γ_i refers to firm fixed effect which absorbs unobserved and time-invariant firm heterogeneity. $\epsilon_{i,j,t}$ is the error term. The estimation is conducted separately

[40] About 89.1% of patent-filing Chinese firms can be mapped to a unique IPC by the number of patents they have filed. For firms that could be mapped into multiple IPC classes due to ties in the number of patents, we further sort by (i) number of citations received, (ii) number of claims, and (iii) number of citations made, in that order. A patent is attributed pro-rata if there are multiple assignees. When there are N assignees for a patent, we assume each assignee owns $\frac{1}{N}$ share of the patent.

for Chinese firms and U.S. firms, respectively.

Start with Chinese firms reported in Table 1. Column (1) of Table 1 uncovers that increasing technology decoupling in a technology field is associated with significantly (at the 1% level) higher domestic patenting outputs in the same field a year later, and the effect mostly dies out two years down the road. Quantity aside, the patent quality, as measured by the relative citation strength, does not exhibit a significant change; but if anything, the coefficients (in column (2)) are positive on lagged *Decoupling*. Hence, the boom in innovation outputs does not come at the cost of quality. This positive correlation between technology decoupling and firm innovation output could be suggestive evidence that the substitution effect of decoupling is stronger than its complementarity effect for the Chinese firms in the short term (one-year horizon). Columns (4) and (5), however, could reveal the dark side of technology decoupling, in lowered firm *ROIC* and *Tobin's Q*. "Reinventing the wheel" may crowd out firm resources in other productive activities, erodes firm profitability, and dampens firm valuation. Consistent with this interpretation, column (3) of Table 1 indicates that intensified decoupling is indeed associated with deteriorating firm productivity over a horizon of two to three years. To put the estimates into context, consider a hypothetical increase in U.S.-China technology decoupling of 0.0685 or 7.4% of the sample mean, a number picked to mimic the reverse of the aggregate change in the level of decoupling from 2000 to 2019. Such a change would be associated with a 12.4% increase in Chinese firm patenting activity instantly (one year later), but a decline in ROIC by 0.6 percentage points (7.6% of the sample mean), a 2.3% drop in firm TFP, and a 3.0% decrease in Tobin's Q in the intermediate run (in two to three years).

[Insert Table 1 here.]

The effects of technology decoupling on the U.S. firms, examined in Table 2, are less pronounced in comparison. There is no detectable relation between lagged decoupling and any performance measures for U.S. firms. Table 2 provides suggestive evidence that the U.S. firms do not suffer any productivity losses for having to do more "reinventing the wheel." This is presumably because U.S. firms, so far, are primarily at the world innovation frontier and losing complementary technology from China inflicts little damage on their current productivity. Finally, it is worth noting that

U.S.-China decoupling is, for China, a likely proxy (though to a lesser extent) for its decoupling with the rest of the Western world; while bilateral decoupling has no bearing on the tendency for the U.S. to decouple with other tech-important nations.

[Insert Table 2 here.]

4 Government policies and decoupling

As rising income, and hence labor costs, gradually erode China's advantage as the "world's factory," the Chinese government has introduced major industrial policies to foster "indigenous innovation" in China to enhance technology leadership and firm competitiveness. Meanwhile, the perception of China as a competitive threat also prompted U.S. sanctions against China. This section conducts the first large-sample empirical test on whether China's industrial policies accomplished goals, as stated by China or perceived by the U.S.; and whether the U.S. sanction succeeded in decoupling as intended. The two tests are motivated by and shed light on the asymmetric relation, documented in the previous section, between decoupling and firm performance in the two nations.

4.1 Have China's industrial policies encouraged decoupling?

4.1.1 The strategic emerging industries (SEI) initiative and decoupling

No other centralized industrial policy better showcases China's ambition in technology than the "Strategic Emerging Industries (SEI)" initiative launched in 2012. In this initiative, the Chinese government identified seven high-tech sectors as "strategic emerging industries:" energy-efficient and environmental technologies, next-generation information technology, biotechnology, high-end equipment manufacturing, new energy, new materials, and new-energy vehicles. Such industries were put in the front row to receive government support from R&D grants to matching benefits in top talent recruiting. These SEI-related industries have since come to the center stage of the ongoing debate on the causes and consequences of U.S.-China technology decoupling. As underscored by the State Council of China, "enhancing the ability of indigenous and independent innovation is key to the SEI-promotion policies."[41] According to the commentaries from both the Obama and the Trump Administrations, the major goal of China's innovation-promoting industrial policies is perceived to be achieving "self-sufficiency" by "domestic substitution of foreign technologies."[42]

As a first step, we identify whether a technology class is SEI-related by cross-checking with the SEI list obtained from China's National Bureau of Statistics (NBS). China's NBS published an SEI list of industries based on the Chinese Industrial Classification (CIC) system in 2012. We map each CIC-based industry to the three-digit IPC code using the CIC-IPC concordance table obtained from CNIPA. Then we apply the following difference-in-differences (DiD) setup to quantify the relationship between the SEI-promotion policy and U.S.-China technology decoupling at the technology class(i)-year(t) level for the sample period of 2007–2019:

$$y_{i,t} = \beta \times SEI_i \times Post_t + \delta' X_{i,t-1} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{2}$$

In equation (2), the dependent variable $y_{i,t}$ features technology decoupling and dependence at the technology class-year level. Because the two variables are correlated in our sample (with the full sample concurrent correlation coefficient of -0.13), the dependence measure is residualized against the decoupling measure so that the two measures are orthogonalized concurrently by construction. Fixed effects for both technology class and year are included. The dummy variable SEI_i equals one if technology class i is promoted by the SEI and zero otherwise. The dummy variable $Post_t$ takes the value of one after 2012 and zero otherwise. X is a vector of control variables including the number of patents granted at CNIPA and USPTO (both in natural logarithms) in each field and each year, and lags the dependent variable by one year. Technology class and year fixed effects absorb SEI_i and $Post_t$ on their own. The coefficient β is of key interest as it captures the changes in technology decoupling and dependence after the policy shock of the sectors exposed to the SEI policy, relative to the unexposed. Results are reported in Table 3.

[41] See *"Decision of the State Council On Accelerating the Cultivation and Development of Strategic Emerging Industries,"* published by the State Council. This is the source link to this reference.

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

[Insert Table 3 here.]

Columns (1) and (2) of Table 3 show that the SEI-exposed sectors experienced significantly (at the 1% level) more decline in both decoupling and dependence. In both regressions, variables corresponding to the number of patents granted at CNIPA and USPTO have opposite signs. High patent output in China is followed by more decoupling and less dependence in the following year, but the effect of patent activities in the U.S. runs in the opposite direction.

To trace out the dynamics of the SEI-promotion policy, we expand equation (2) to the following setup with key terms interaction with year dummies around SEI:

$$y_{i,t} = \sum_{\tau}(\beta_\tau \times SEI_i \times T_\tau) + \delta' X_{i,t-1} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{3}$$

That is, we interact SEI_i with a full set of year dummies (i.e., T_τ). To visualize the dynamic effects of the SEI-promotion policy, we plot the estimates of β_τ for decoupling and dependence in Figure 7. Year 0 corresponds to 2012, the event year of the SEI-promotion policy. Despite potential selection concerns, no pre-existing trends are visible but both decoupling and dependence trend down after the event. Moreover, the decline of decoupling tends to occur faster than that of dependence.

[Insert Figure 7 here.]

Results teach us that China's SEI-promotion policy was followed by technology *integration* instead of decoupling with the United States. Such an outcome is more consistent with the stated objectives of the policymakers 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."[43] Though various industrial policies in China are designed to indigenize innovation, such a goal is to be achieved by more integration with the global standards and more adoption of the global state of the art. For instance, the State Council endorses various measures to foster global scientific and technological cooperation.[44]

[43]See *"Decision of the State Council On Accelerating the Cultivation and Development of Strategic Emerging Industries"* published by the State Council. This is the source link to this reference.

[44]To be specific, the State Council encourages foreign enterprises and research institutions to (i) set up R&D

Perhaps more importantly, results also indicate that China's technological dependence on the U.S. drops in industries post SEI coverage. That is, strong industrial policy, implemented via integration with the U.S. (and the rest of the developed world), was associated with remarkable reduction in China's technological dependence on the U.S. This finding is consistent with the U.S. "self-sufficiency" narrative for China's industrial policy, but such self-sufficiency is achieved by China's technology integration with the U.S. instead of decoupling.[45]

4.1.2 SEI and firm performance

In light of the impact of the SEI-promotion policy on U.S.-China technology decoupling and China's technological dependence on the U.S., we next explore 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(i)-sector(j)-year(t) level covering the period of 2007–2019:

$$y_{i,j,t} = \beta \times SEI_j \times Post_t + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \tag{4}$$

$$y_{i,j,t} = \sum_{\tau} (\beta_\tau \times SEI_j \times T_\tau) + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \tag{5}$$

We evaluate the relationship between the SEI-promotion policy and firm performance in equation (4) and we assess the dynamic policy effects in equation (5). In both equations, the sample construction, the dependent variable, the fixed effects, and the recurring variables are the same as in Table 1. Coefficient β in equation (4) captures the effects of the SEI-promotion policy; coefficients β_τ in equation (5) track the dynamics of the policy effects. We report the estimation results for equation (4) in Table 4 and we plot the estimates of β_τ in Figure 8.

[Insert Table 4 here.]

[Insert Figure 8 here.]

facilities in China, (ii) participate in technology demonstration projects in China, (iii) jointly apply for Chinese research grants with Chinese partners, and (iv) jointly establish global technology standards with Chinese partners. The State Council also supports Chinese enterprises and research institutions to (i) provide outsourcing R&D services to foreign enterprises, (ii) set up R&D facilities overseas, (iii) apply for foreign patents, and (iv) participate in establishing global technology standards.

[45]Echoing our findings, a recent article in *The Economist* argues that "China is pursuing a strategy of asymmetric decoupling: reducing its dependence on the West even as it seeks to increase the Wests dependence on China." See *The Economist* report, "China courts global capital, on its own terms," December 11, 2021.

Column (1) of Table 4 suggests that SEI-promotion is associated with a 14.0% decline (significant at the 1% level) in firm innovation output. According to Figure 8a, the drop in firm innovation output takes 3-4 years. Since the distribution of firm patenting output is right-skewed, we provide sensitivity checks based on the Poisson regression models. Results are robust.[46] There is also weak evidence of diminishing innovation quality: $SEI \times Post$ is negatively significant in Table 4, but the pattern is not salient in Figure 8b as we break down the dynamics into yearly frequency. Notably, SEI-promotion is not followed by any significant changes in firm TFP (see column (3) of the Table 4 and Figure 8c). Nevertheless, both column (4) of Table 4 and Figure 8d also show a strong boost (significant at the 1% level) in firm profitability by 1.4 percentage points (17.7% of the sample mean). Rising firm profitability translates into bolstered firm valuation (Figure 8e). Column (5) of Table 4 suggests that firm Tobin's Q has ratcheted up by 10.4% (significant at the 1% level). The combined evidence suggest that recipients of SEI benefited in cash flows and valuation, but fail to register fundamental improvement under the policy.

We next run tests aiming to address alternative or mechanistic explanations. First, there is always the concern that the findings could be attributed to confounding policies. To alleviate this concern, 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 results regarding SEI survive these additional controls.[47] Second, we further explore whether the decline in innovation output post policies was due to falling innovation inputs (i.e., R&D-to-asset ratio) or efficiency (following Hirshleifer et al. (2013)[48]). Table 5 demonstrates that the culprit of dwindling firm innovation output is waning innovative efficiency. Post SEI, *R&D Efficiency* of treated firms declined by 0.010 (34.3% of the sample mean). This echoes the earlier TFP results in Table 4 that SEI does not seem to have led to improvement in inherent efficiency.

[Insert Table 5 here.]

[46] For details, see Internet Appendix Table IA7.

[47] For details, please see Internet Appendix Table IA4.

[48] *R&D Efficiency*, at the firm-year level, in Hirshleifer et al. (2013) is constructed as the number of successful patent applications by a firm in a given year by the weighted average of its R&D expenditures in recent years.

We acknowledge that the simple quantitative measures in terms of 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 column (3)–(7) of Table 5. Following Kerr (2010), we categorize a breakthrough patent as one that breaks into the top five percent in citations among the same cohort (i.e., same technology class and application year). Following the measures of exploitative patents 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);[49] a patent to be explorative if at least 80% of its citations are based on new knowledge. Exploitative patents are signs of core competence while explorative patents signals new knowledge creation. Following Hall et al. (2001), we define the patent originality score as one minus the Herfindahl index of the number of citations made by a patent to each technology class.[50] Finally, we define the patent generality score as one minus the Herfindahl index of the number of citations received by a patent from each technology class. Originality measures the diversity of knowledge a patent builds on; while generality measures the radius of a patent's influences over subsequent innovations. According to the results in Table 5, the SEI has not measurably enhanced the innovation qualtiy along these dimensions, except that firm innovation does become significantly more general (significant at the 1% level) after the policy treatment.

Our findings speak to an intrinsic non-congruence between the two major policy objectives (i.e., indigenous innovation versus firm competitiveness) of the Chinese government. To the extent that China has yet to arrive at the world technology frontier, 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, U.S.-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."

[49] To be more specific, a firm's existing knowledge refers to the patents filed by the firm and the patents cited by the firm's patents filed in the past five years.

[50] In the calculation of the originality and generality scores, the technological classification is based on three-digit IPC.

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.[51] A priori, 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 spillover 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 (EAR) 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. The list for this study spans between 1997 (the first year when it was issued) and 2019. After excluding the individual people sanctioned on the entity list, there are 163 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 158 (96.9%) 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.[52] By this algorithm, 75.4%

[51] See CNN report, "New sanctions deal 'lethal blow' to Huawei," August 18, 2020.

[52] For instance, both "Shanghai Huawei Technologies Co., Ltd." and "Beijing Huawei Digital Technologies Co., Ltd." are coded as "Huawei Technologies Co., Ltd." in the merging process.

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

We define 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 (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.

[Insert Figure 9 here.]

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

$$y_{i,t} = \beta \times Post\ Sanction_{i,t} + \delta' X_{i,t-1} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{6}$$

The empirical setup above is analogous to our analysis of the SEI-promotion policy in Section (4.1.1). The sample construction, dependent variables, the fixed effects, and the recurring variables in this setup are the same as that in equation (2) of the SEI analysis. The dummy variable

Post 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, the coefficient of key interest in equation (6). We report the estimation results for equation (6) in Panel A of Table 6. To trace out the dynamics of the sanction effects, we replace the sanction indicator in Table 6 with a set of dummies representing the years around the sanction events in Table 7, where year 0 is marked to to the sanction year. $Sanction(-\tau)$ and $Sanction(\tau)$ refer to τ years before and after the sanction, respectively. $Sanction(3+)$ correspond to three and more years after the sanction.

[Insert Table 6 here.]

[Insert Table 7 here.]

Perhaps contrary to intuition, the results in column (1) of Panel A in Table 6 suggest that U.S. sanctions in a technology class were associated with a significant (at the 1% level) *decrease* in the decoupling measure in that technology class. Column (1) of Table 7 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 which 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 up to 2019 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.[53] During the 2019-2020 academic year, about 373,000 Chinese students (35% of all international students) studied in the United States, constituting the top source of international students in U.S. campuses.[54] A significant share of Chinese students returned home post-graduation. Since China's opening-up in 1978, 4.9 million Chinese students have completed their studies overseas and 4.2 million returned to China.[55] 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.

[53]Source: The U.S. Census Bureau.

[54]Source: The Institute of International Education.

[55]Source: The Ministry of Education of China.

The effects of U.S. sanctions on China's technological dependence on the U.S. are, on the other hand, ambiguous due to two opposing forces. By depriving Chinese firms of U.S. technologies and components, U.S. sanctions may weaken their technological capability and in consequence, China may depend more on the U.S. 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 U.S. Column (2) in Panel A of Table 6 suggest the second force dominates: U.S. sanctions are negatively correlated with China's technological dependence on the U.S. Importantly, no pre-existing trends manifested themselves, as illustrated by column (2) of Table 7. Such a result is consistent with the narrative that the sanctions have encouraged or even forced China to become more technologically independent from the U.S.[56]

Comparing the effects of China's SEI-promotion policy in Table 3 with the effects of U.S. sanctions against China in Table 6, we learn that integration-oriented government intervention (i.e., China's SEI-promotion policy) can accelerate the momentum of U.S.-China integration, whereas decoupling-oriented government intervention (i.e., U.S. sanctions against China) has yet to reverse the fundamental forces driving U.S.-China integration. Both speak to a desire on China's side to be an integral part of global technology development and application. Due to the recency of most sanctions, our sample has limited power for longer-term inferences. We look forward to extending the analyses as more years of data become available.

4.2.3 Spillovers of technology decoupling from sanctions

Knowledge and technology naturally 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 common practice in the literature (e.g., Acemoglu et al. (2016), Liu and Ma (2022)), we build an innovation network by

[56] See Wire China's interview with Willy C. Shih (a professor of management practice at Harvard Business School), "Willy Shih on Why the U.S. Needs to Run Faster," April 19, 2020. Also see the Bloomberg report, "New U.S. Restrictions Will Help Make China Great Again," December 18, 2020, and *The Economist* report, "China courts global capital, on its own terms," December 11, 2021.

patent-citation-based input-output (IO) table at the three-digit IPC level based on the U.S. patents granted between 1976 and 2019.[57] Importantly, the innovation network is remarkably distinct from the production network, and, thus, captures inter-sector 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:

$$\begin{aligned}
\textit{Upstream Sanction Exposure}_{i,t} &= \sum_{j \neq i} w(i,j) \times \textit{Sanction}_{j,t} \\
\textit{Downstream Sanction Exposure}_{i,t} &= \sum_{k \neq i} w(k,i) \times \textit{Sanction}_{k,t}
\end{aligned}$$

In the two equations above, $w(m,n)$ refers to the share of citations made from technology class m to n. The sanction indicator $\textit{Sanction}_{m,t}$ takes the value of one if technology class m is sanctioned in year t and zero otherwise. $\textit{Upstream Sanction Exposure}_{i,t}$ is the weighted average sanction indicators of all upstream technology classes of class i in year t, where the weights are the shares of citations made from i to its upstream technology classes. Analogously, $\textit{Downstream Sanction Exposure}_{i,t}$ is the weighted average sanction indicators of all downstream technology classes of class i in year t, and the weights are the shares of citations that i receives from its downstream technology classes. $\textit{Upstream Sanction Exposure}_{i,t}$ and $\textit{Downstream Sanction Exposure}_{i,t}$ capture the exposure of technology class i to sanctions via the network spillovers from its upstream and downstream sectors, respectively.

With the constructed measures of upstream and downstream sanction exposures, we are able to evaluate the network spillovers of U.S. sanctions by the following setup:

$$\begin{aligned}
y_{i,t} = \; &\beta_1 \times \textit{Upstream Sanction Exposure}_{i,t} + \beta_2 \times \textit{Downstream Sanction Exposure}_{i,t} \\
&+ \delta' X_{i,t-1} + \gamma_i + \gamma_t + \epsilon_{i,t}
\end{aligned} \tag{7}$$

[57] Liu and Ma (2022) show that the innovation network is highly persistent over time and highly correlated across countries, and that the innovation network constructed by aggregating patents from all countries is close to perfectly correlated with that based on U.S. data alone.

The setup of equation (7) is analogous to equation (6), except that the sanction indicator in equation (6) is replaced by upstream and downstream sanction exposures in equation (7). 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 6.

Empirical results reveal network spillovers effects from sanctions that are asymmetric. 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)). Here is an example which hopefully facilitates illustration. Suppose semiconductors became the technology class that was sanctioned and its capacity reduced as a result. Consumer electronics producers (with a high 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. On the other hand, the semiconductors sector is denied of their access to foreign technology and inputs, compelling them to switch to domestic sources. In consequence, the chip design sector (with a high indirect sanction exposure from the downstream) in China become more fenced off from foreign competitions, and more decoupled from the world in a sheltered innovating environment.

4.2.4 Sanctions and firm performance

The spillovers at the technology class level documented in the previous section should have natural 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(i)-sector(j)-year(t) level covering 2007–2019:

$$y_{i,j,t} = \beta \times \textit{Post Sanction}_{j,t} + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \tag{8}$$

$$\begin{aligned} y_{i,j,t} = {} & \beta_1 \times \textit{Upstream Sanction Exposure}_{j,t} + \beta_2 \times \textit{Downstream Sanction Exposure}_{j,t} \\ & + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \end{aligned} \tag{9}$$

The setups of equation (8) and (9) are analogous to equations (6) and (7), respectively. Similar to Section 4.1.2, we report the estimation results for the five firm outcome variables in Table 8.

[Insert Table 8 here.]

Column (1) in Panel A of Table 8 shows that U.S. sanctions are associated with a 12.4% decline (significant at the 1% level) in innovation output for Chinese firms in the sanctioned sectors. Breaking it down, we further discover that the decline can primarily be attributed to falling innovation efficiency instead of innovation input. The drop in firm innovation efficiency amounts to 55.1% of the sample mean (significant at the 1% level), signifying China's reliance on U.S. inputs (including human capital) in converting R&D into patentable technology.[58] Innovation quality exhibits no noticeable change (column (2)). Columns (3) and (4) report that U.S. sanctions are associated with a 2.3% decline in firm TFP (significant at the 5% level) and a drop in ROIC of 0.99 percentage points (12.5% of the sample mean; significant at the 1% level). Despite suffering in productivity and profitability, affected firms do not experience a significant drop in firm valuation (column (5)). Such valuation resiliency might has benefited from adaptive responses from the Chinese government and businesses as sanctions became more aggressive and widespread.[59] Another bright spot is that innovation by affected firms in China has become more original, a suggestive evidence that Chinese firms may have to conduct more discovery-based research after being deprived of access to U.S. technologies.[60]

For sensitivity checks, we control for three general innovation policies described in Section 4.1.2.[61] We also conduct a robustness check based on Poisson regressions to accommodate skewness in patent data.[62] All our findings are robust in these tests.

[58]For detailed results, please see Internet Appendix Table IA5.

[59]As U.S. sanctions expanded from specialized military technologies to more civil and commercially oriented technologies, the affected businesses tend to be more nimble in market places and the Chinese government also started to counter-intervene by bolstering firms targeted by U.S. sanctions. For example, China's Anti-Foreign Sanctions Law passed in June 2021 establishes a legal ground to retaliate against foreign sanctions. Firms sanctioned by the U.S. in some cases sought "national symbol" status in an ideologized sentiment. In unreported (due to space limit) results, we find that U.S. sanctions are associated with increasing government subsidies received by firms in the sanctioned sectors.

[60]For detailed results, please see Panel A of Internet Appendix Table IA5.

[61]Results are reported in Internet Appendix Table IA6

[62]Results are reported in Internet Appendix Table IA7.

4.2.5 Sanction spillovers on firm performance

Following the structure of Section 4.2.3, we analyze the spillover effect of sanctions on firm performance and report the results in Panel B of Table 8. Sanctioning upstream sectors is associated with a decline in innovation output, productivity, profitability, and valuation of the focal firm (all significant at the 1% level). As a stark contrast, sanctioning downstream sectors features exactly the opposite effects. The example in the previous section, modified to fit into firms/industries, can put this asymmetry into context. Suppose the semiconductor makers are the focal sector who was the direct target of sanction. Chinese consumer electronics producers (who face indirect sanction exposure from the upstream) are also battered because their domestic suppliers have been compromised, forcing them to resort to foreign suppliers who gain more market power. Chinese chip designers (who face indirect sanction exposure from the downstream), on the other hand, could be better off as they enjoy a captured customer base.[63]

The quality of firm innovation following the sanctions also follows similarly asymmetric paths for firms when the sanction shocks propagate from the upstream or downstream. After an upstream sector is sanctioned, firms in the focal sector tend to experience significant decrease in R&D as well as R&D efficiency, significant fewer chances in breakthrough innovation, and overall decline in the metrics for patent quality. The reverse is the case for firms that face indirect sanction exposure from the downstream: They significantly increase R&D, produce significantly more high-impact, explorative, and high-generality patents.[64]

To the extent that U.S. sanctions aims at decoupling China from the West and containing the rise of Chinese firms, our findings uncover some perhaps unintended consequences of the sanctions, due to network spillovers. When the U.S. sanctions a particular technology sector in China, innovation output as well as firm performance of the targeted sector suffer, and so do the downstream sectors and firms in China (who are exposed to sanctions indirectly from the upstream). However, both the focal and downstream sectors become more integrated (i.e., less decoupled) with the U.S. in their fight for survival, opposite to the objective of the sanction policies. Moreover, the upstream firms and sectors in China (who are exposed to sanctions indirectly from the downstream) generally

[63] By anecdotal evidence, these Chinese firms may also gain more support from the Chinese government.
[64] For detailed results, see please see Panel B of Internet Appendix Table IA5.

thrive on the sanctions. Not only do these firms witness improved productivity and profitability but also they are investing more R&D in explorative research and making more breakthroughs in technology. Such developments are expected to reduce China's dependence on U.S. technologies.

5 Conclusion

By integrating comprehensive patent data from the U.S. and China, we develop new measures to quantify the time-varying technology decoupling and dependence between the U.S. and China, in the aggregate and in specific technology classes. The first two decades of the 21st century witnessed a steady increase in technology integration (or less decoupling), but China's dependence on the U.S. increased (decreased) during the first (second) decade. Analyzing government policies in both nations, we find that China's innovation-promoting industrial policies are associated with both more integration and less dependence down the road, but the process has not registered improvement in either productivity or innovativeness of firms. On the other side, U.S. sanctions against China have not led to U.S.-China decoupling by 2019 but have spurred more independent and high-impact technological development in China, especially in the upstream sectors of the sanctioned. Knowledge and technology form their own network with complex spillovers across sectors which are fluid at national boundaries. Sanctions often instigate broader, and often unintended, impact relative to what were envisioned by the policymakers.[65] Our findings provide micro-level evidence for the direct as well as the spillover effects that could contribute to the policy debate.

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[65] This sentiment is echoed by some industry practitioners and think tanks. According to the report of the Carnegie Endowment for International Peace, "technology restrictions can be costly (harming U.S. industries and innovators), imprecise (chilling more activity than intended), and even futile (failing to remedy the relevant Chinese tech threats)." See more details in the report of Carnegie Endowment for International Peace, "U.S.-China Technological Decoupling: A Strategy and Policy Framework," April 25, 2022.

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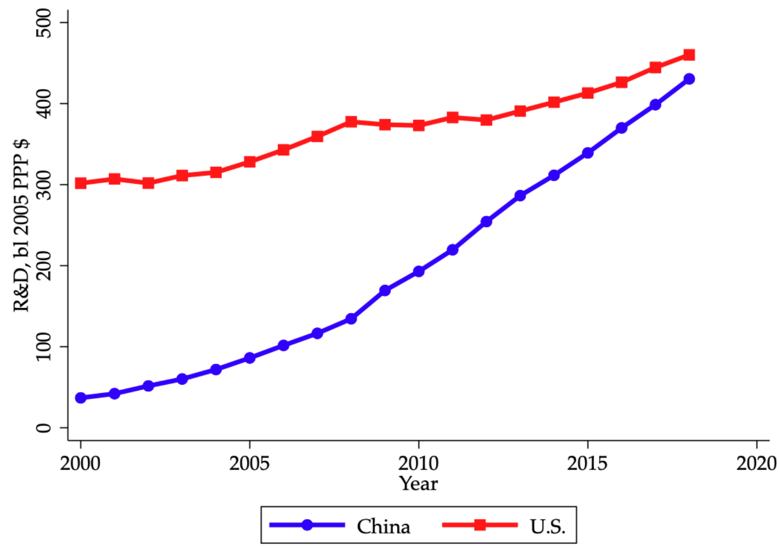
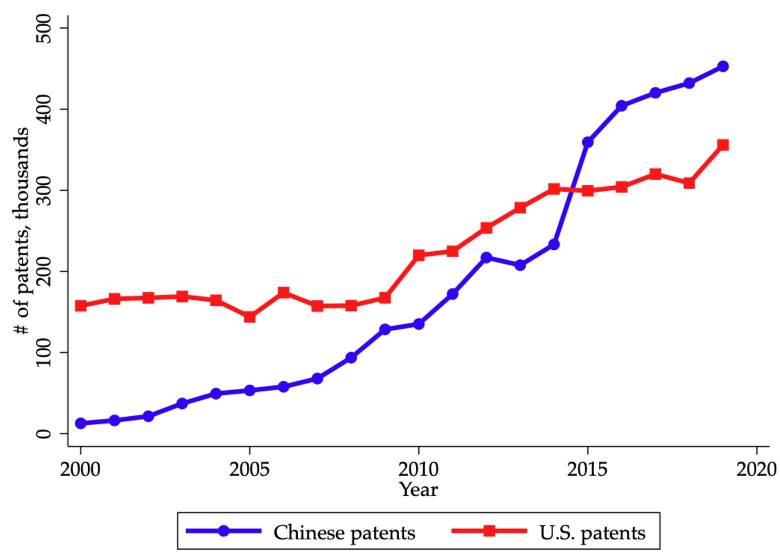
Figure 1: **R&D expenditures and patents granted, U.S. vs China**

R&D expenditures of both China and the United States are measured in billion 2005 PPP dollars in figure 1a. "Chinese patents" in figure 1b refer to invention patents granted at the Chinese National Intellectual Property Administration (CNIPA). "U.S. patents" in figure 1b refer to utility patents granted at the United States Patent and Trademark Office (USPTO). The number of patents is expressed in thousands in figure 1b.



(a) R&D Expenditures



(b) Patents Granted

Figure 2: **Measures of technology decoupling and dependence**

This diagram visualizes how we construct our measures of U.S.-China technology decoupling and China's dependence on the U.S. The vertical axis ($p_{c,u}$) is a proxy of the propensity for Chinese patents to cite a U.S. patent relative to citing a Chinese one. The horizontal axis ($p_{u,c}$) is a proxy of the propensity for U.S. patents to cite a Chinese patent relative to citing a U.S. one. Reflecting the state of parity, the 45-degree line is defined as the "par line." The triangular area above (below) the 45-degree line is defined as "U.S.-leading" ("China-leading") region. Projecting point P onto the 45-degree line, we decompose the vector $\overrightarrow{\mathrm{PI}}$ into two orthogonal vectors $\overrightarrow{\mathrm{PQ}}$ and $\overrightarrow{\mathrm{QI}}$. The vector $\overrightarrow{\mathrm{QI}}$ (i.e., the projection of $\overrightarrow{\mathrm{PI}}$ on the par line) captures the degree of U.S.-China technology decoupling. The vector $\overrightarrow{\mathrm{PQ}}$ (i.e., the rejection of $\overrightarrow{\mathrm{PI}}$ from the par line) reflects China's technological dependence on the U.S.

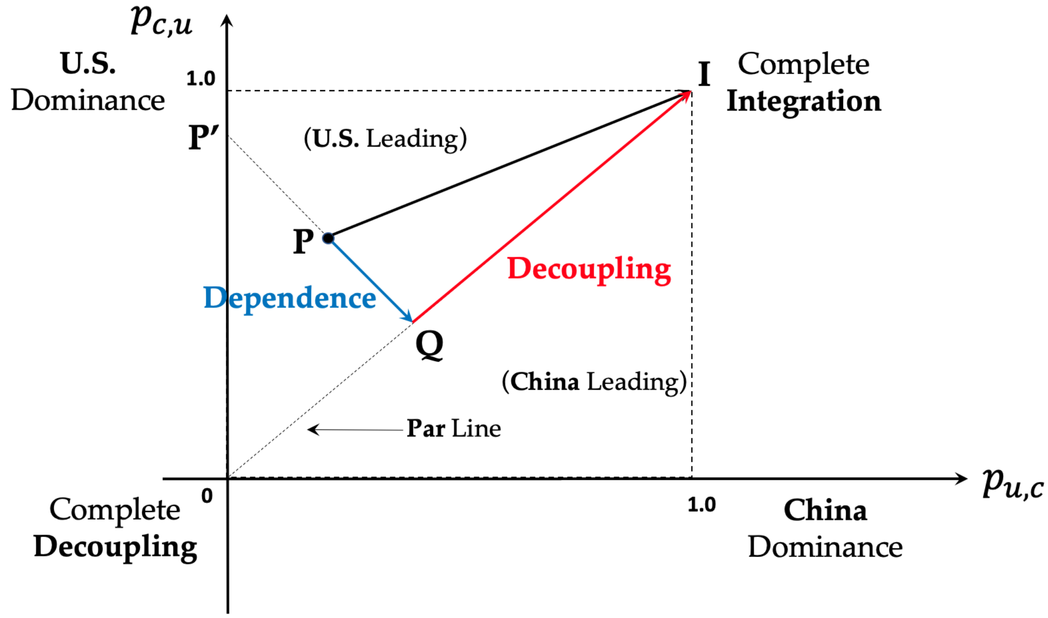


Figure 3: **U.S.-China technology decoupling and dependence, 2000, 2009, and 2019**

This figure is the empirical analog of Figure 2. The vertical axis ($p_{c,u}$) is a proxy of the propensity for Chinese patents to cite a U.S. patent relative to citing a Chinese one. The horizontal axis ($p_{u,c}$) is a proxy of the propensity for U.S. patents to cite a Chinese patent relative to citing a U.S. one. To highlight critical turning points of the transition, we zoom in on three crucial years: 2000 (the year before China joined the World Trade Organization), 2009 (the end of the Great Recession), and 2019 (the end of our sample period).

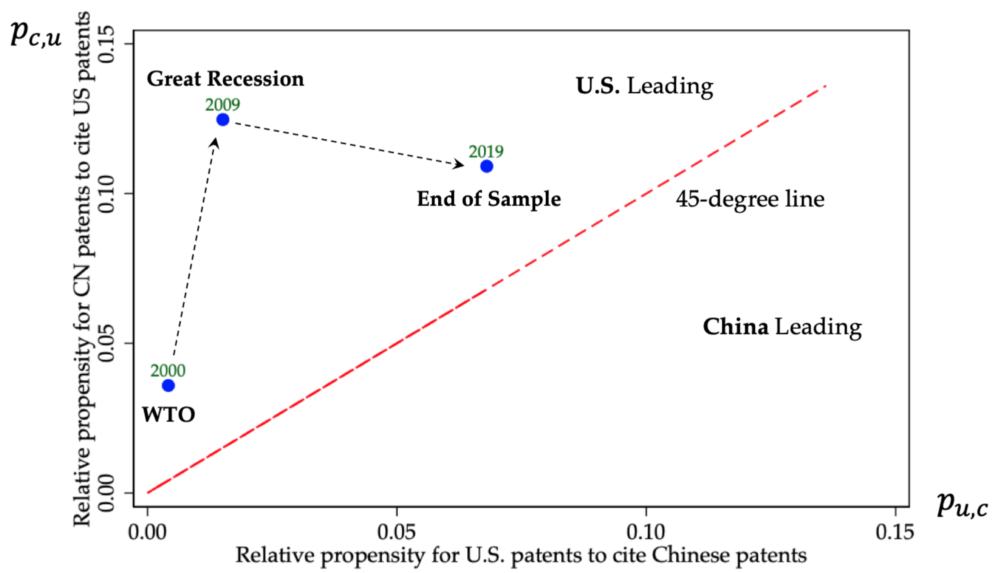


FIGURE 4: **U.S.-China technology decoupling and dependence, 2000–2019**

This figure characterizes how U.S.-China technology decoupling and China's technological dependence on the U.S. evolved between 2000 and 2019. 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 U.S. Both measures are defined in Section 2.3. The subperiod of 2003-2006 was skipped due to unreliable data specific to this time period.

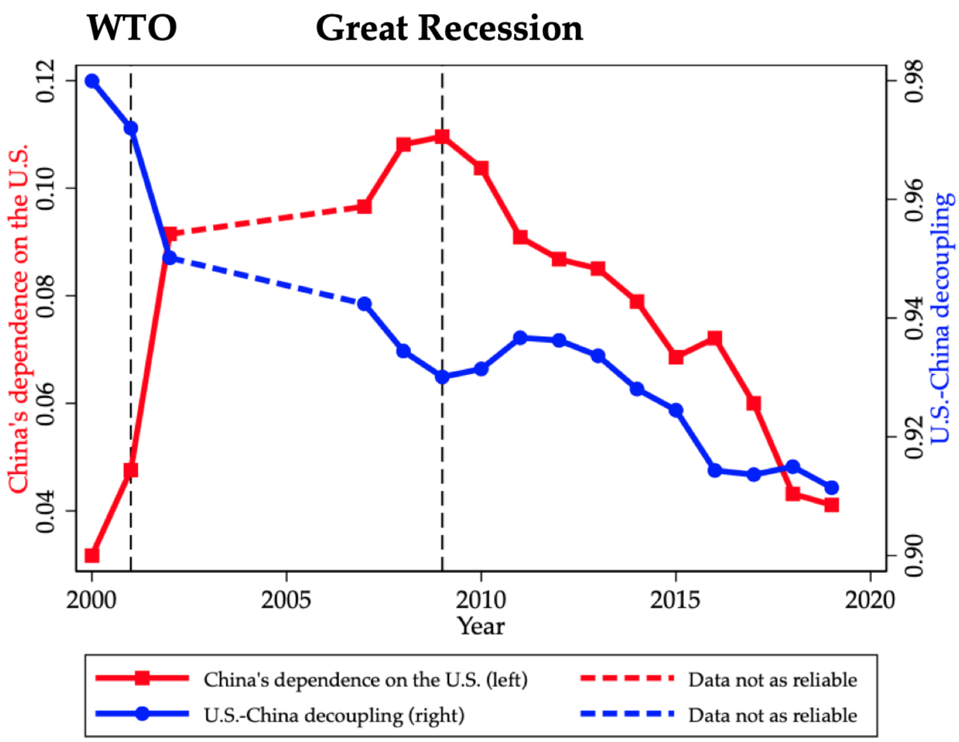
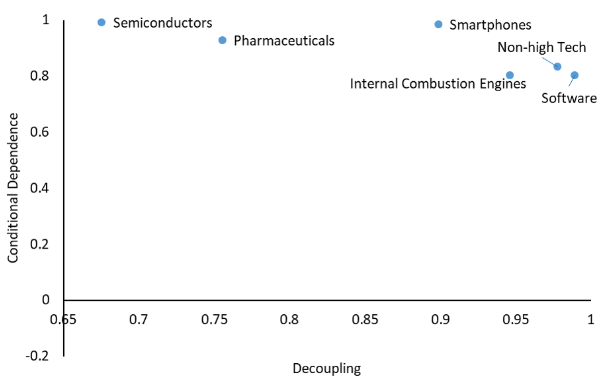
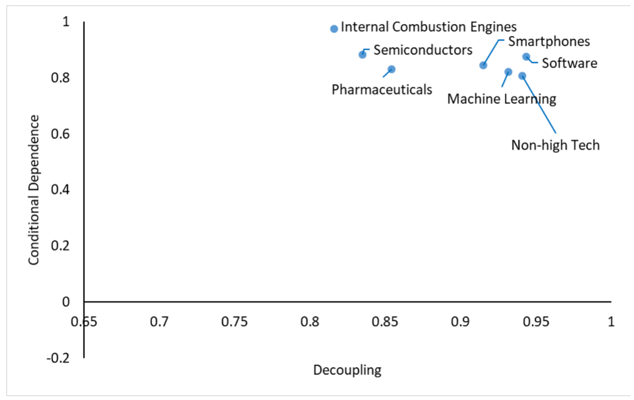


Figure 5: **Decoupling and dependence, ten high-tech fields**

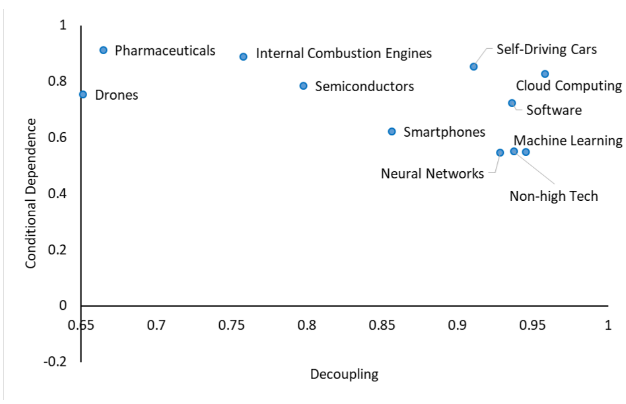
In this figure, we plot the states of decoupling and conditional dependence (both measures are defined in Section 2.3) in selected years of 2000, 2009, 2015, and 2019. The ten high-tech fields are defined by Webb et al. (2019). All other patents are grouped into the “non-high tech” field.



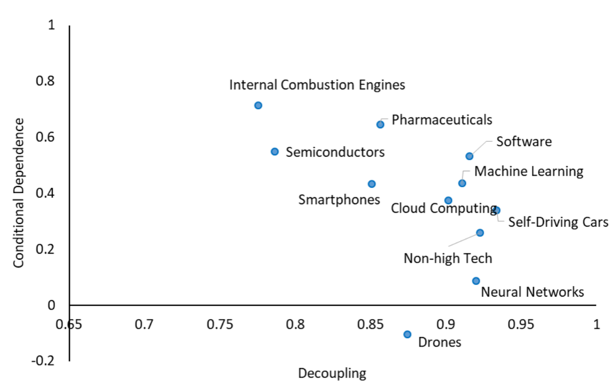
(a) Year: 2000



(b) Year: 2009



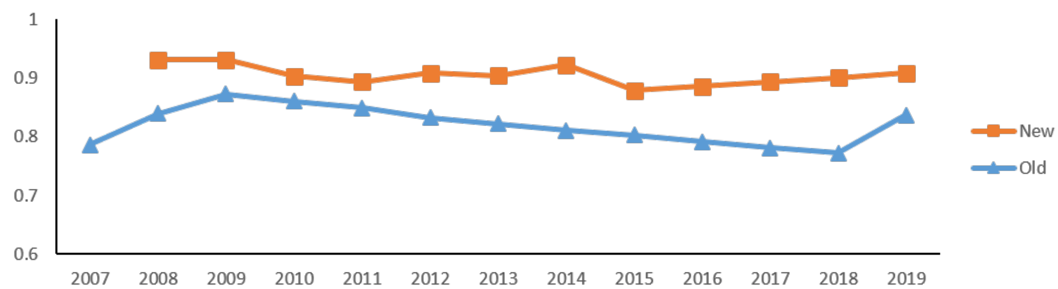
(c) Year: 2015



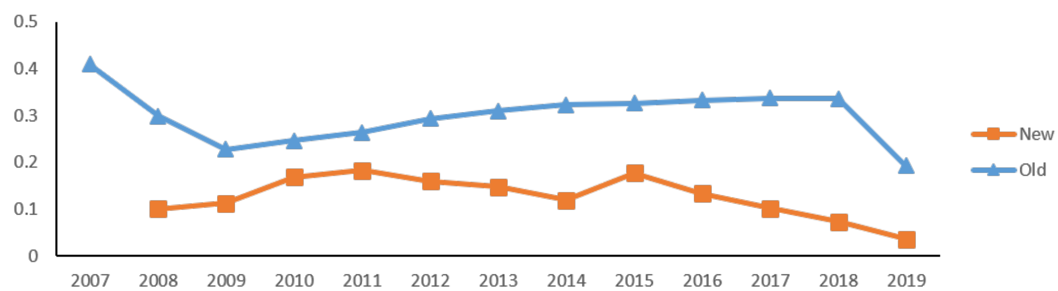
(d) Year: 2019

Figure 6: **Decoupling and dependence, new vs. old technologies**

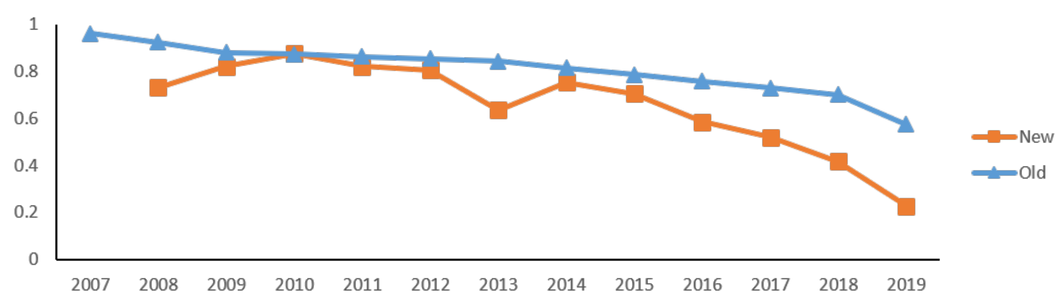
In this figure, we compare the states of decoupling, dependence, and conditional dependence between new and old technologies among the ten high-tech fields. The ten high-tech fields are defined by Webb et al. (2019). A technology is considered new if the grant year of its first patent is after 2008, which include machine learning, neural networks, drones, cloud computing, and self-driving cars. Old fields include internal combustion engines, pharmaceuticals, semiconductors, smartphones, and software.



(a) Decoupling



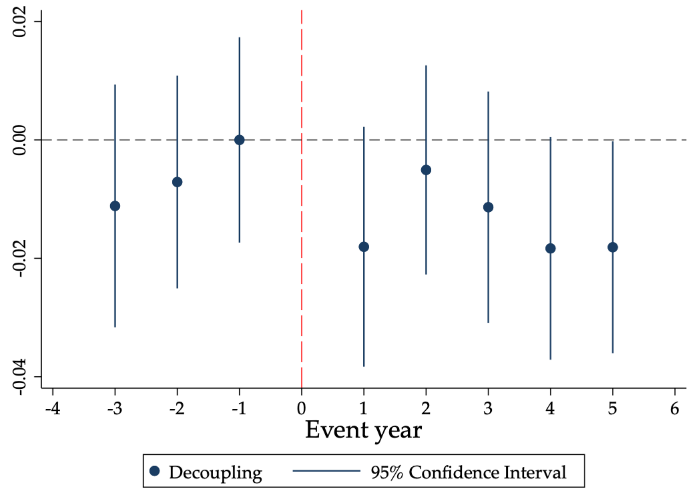
(b) Dependence



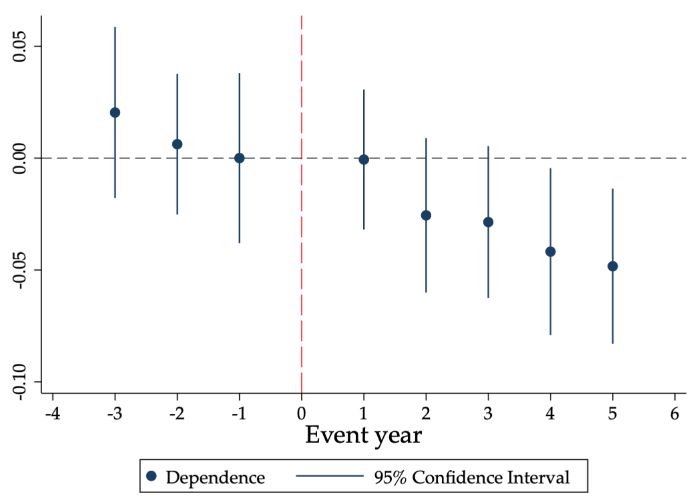
(c) Conditional Dependence

Figure 7: **SEI-promotion policy and technology decoupling, dynamic effects**

This figure visualizes the dynamic effects of the SEI policy in the technology-class-year-level regressions based on equation (3). The dependent variable features technology decoupling and dependence as defined in Table A1. 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 (3) for decoupling in Figure 7a and for dependence in Figure 7b.



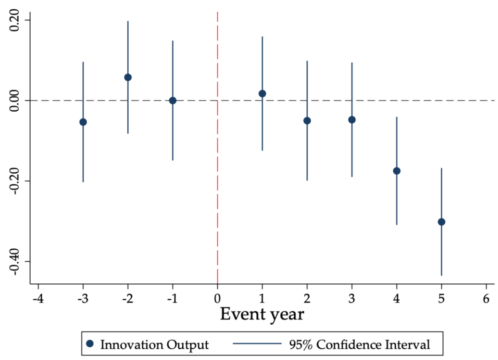
(a) Decoupling



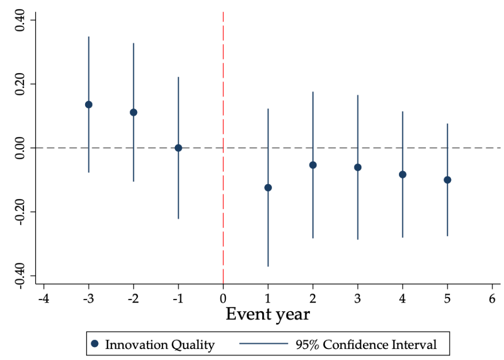
(b) Dependence

FIGURE 8: **SEI-promotion policy and firm performance, dynamic effects**

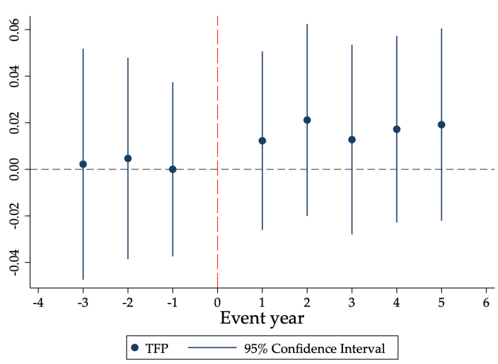
This figure examines the dynamics of the SEI policy in the firm-year-level regressions based on equation (5). We plot the estimates of β_τ in equation (5) for the following dependent variables: *Innovation Output* in Figure 8a, *Innovation Quality* in Figure 8b, *TFP* in Figure 8c, *ROIC* in Figure 8d, and *Tobin's Q* in Figure 8e. All variables are defined in Table A1.



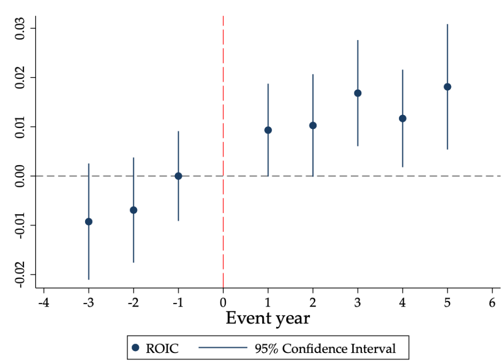
(A) INNOVATION OUTPUT



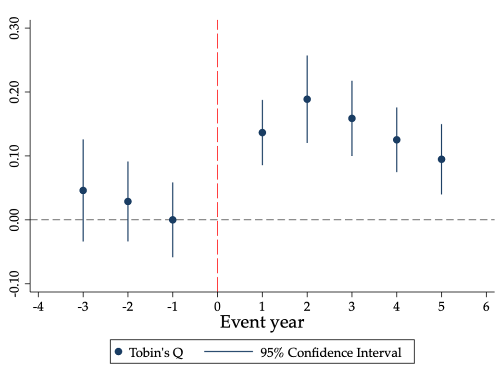
(B) INNOVATION QUALITY



(C) FIRM TFP



(D) ROIC



(E) TOBIN'S Q

FIGURE 9: **Number of entities and tech classes exposed to U.S. sanctions**

This figure plots the number of sanctioned Chinese entities on the U.S. entity list and the number of technology classes involved in U.S. sanctions each year from 1997 to 2019. We identify the primary technology class of each sanctioned Chinese entity by the patents they file. A technology class is considered being involved in sanction in a given year if at least one sanctioned entity is associated with this technology class.

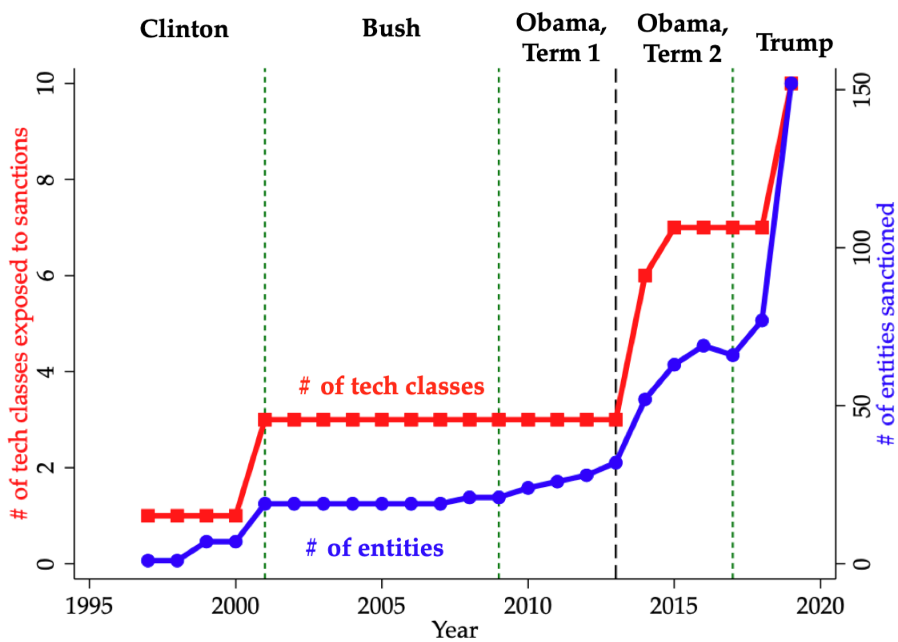


Table 1: Technology Decoupling and Firm Performance, Chinese Firms

The regressions in this table examine the relationship between U.S.-China technology decoupling and the performance of Chinese firms. All variables are defined in Table A1. 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. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Innovation Output	*Innovation Quality*	*TFP*	*ROIC*	*Tobin's Q*
	(1)	(2)	(3)	(4)	(5)
Decoupling, $t-1$	1.815***	0.568	0.122	-0.0804*	-0.439**
	(0.586)	(0.679)	(0.141)	(0.0429)	(0.207)
Decoupling, $t-2/3$	0.811	0.733	-0.330*	-0.00601	0.150
	(0.726)	(0.799)	(0.188)	(0.0541)	(0.280)
Assets	0.0594***	-0.0270	-0.00697	-0.0157***	-0.290***
	(0.0197)	(0.0211)	(0.00601)	(0.00186)	(0.00902)
Age	-0.0353	0.0971	0.0592***	-0.00449	-0.00294
	(0.0758)	(0.0739)	(0.0204)	(0.00559)	(0.0298)
Capex	-0.0305	0.177	-0.398***	-0.0281**	-0.106
	(0.166)	(0.218)	(0.0456)	(0.0124)	(0.0655)
PP&E	-0.173*	0.0308	0.126***	0.0444***	-0.0684*
	(0.0894)	(0.109)	(0.0268)	(0.00813)	(0.0395)
Leverage	0.00999	-0.177**	0.0277	0.00535	0.0742**
	(0.0645)	(0.0781)	(0.0210)	(0.00663)	(0.0291)
R&D	-0.168	-0.869	0.642***	0.220***	1.190***
	(0.644)	(0.716)	(0.164)	(0.0521)	(0.253)
Observations	14,739	14,739	14,739	14,739	14,739
Adjusted R-squared	0.607	0.186	0.657	0.445	0.793
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes

Table 2: Technology Decoupling and Firm Performance, U.S. Firms

The regressions in this table examine the relationship between U.S.-China technology decoupling and the performance of U.S. firms. All variables are defined in Table A1. 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. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Innovation Output	*Innovation Quality*	*TFP*	*ROIC*	*Tobin's Q*
Decoupling, $t-1$	0.285	-0.741	-0.321	0.052	0.328
	(0.593)	(0.755)	(0.237)	(0.189)	(0.205)
Decoupling, $t-2/3$	-0.085	-0.470	-0.141	-0.148	-0.179
	(0.344)	(0.504)	(0.124)	(0.095)	(0.121)
Assets	0.139***	-0.046	-0.046***	-0.011	-0.134***
	(0.019)	(0.028)	(0.015)	(0.011)	(0.010)
Age	-0.024	-0.155**	0.019	-0.004	-0.133***
	(0.055)	(0.071)	(0.031)	(0.026)	(0.024)
Capex	0.463*	0.228	-0.055	0.097	0.288*
	(0.250)	(0.280)	(0.237)	(0.136)	(0.172)
PP&E	0.151	-0.142	0.247**	-0.097	-0.308***
	(0.139)	(0.176)	(0.099)	(0.088)	(0.069)
Leverage	-0.197***	-0.031	0.146***	0.101**	0.103***
	(0.047)	(0.070)	(0.042)	(0.045)	(0.029)
R&D	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 R-squared	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

Table 3: SEI-Promotion Policy and Technology Decoupling

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 (i)-year(t) level for the sample period of 2007–2019:

$$y_{i,t} = \beta_1 \times SEI_i \times Post_t + \delta' X_{i,t-1} + \gamma_i + \gamma_t + \epsilon_{i,t}$$

The dependent variable features technology decoupling and dependence as defined in Table A1. The dependence measure is residualized against the decoupling measure so that the two measures are orthogonalized concurrently by construction. The dummy variable SEI_i equals one if technology class i is promoted by the SEI and zero otherwise. The dummy variable $Post_t$ 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. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Decoupling	*Dependence*
	(1)	(2)
SEI × Post	-0.0105***	-0.0303***
	(0.00393)	(0.00808)
ln(Patents granted in China)	0.0195***	-0.0259***
	(0.00417)	(0.00905)
ln(Patents granted in the U.S.)	-0.0184**	0.0820***
	(0.00849)	(0.0193)
Observations	1,343	1,343
Adjusted R-squared	0.738	0.762
Technology class fixed effect	Yes	Yes
Year fixed effect	Yes	Yes

Table 4: SEI-Promotion Policy and Firm Performance

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

$$y_{i,j,t} = \beta_1 \times SEI_j \times Post_t + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t}$$

The regression is at the firm (i)-year(t) level but each firm is also indexed by sector (j). SEI_j equals one if sector j is promoted as an SEI and zero otherwise. $Post_t$ takes the value of one after 2012 and zero otherwise. All other variables are defined in Table A1. 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. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Innovation Output	*Innovation Quality*	*TFP*	*ROIC*	*Tobin's Q*
	(1)	(2)	(3)	(4)	(5)
SEI × *Post*	-0.140***	-0.126***	0.00984	0.0138***	0.104***
	(0.0332)	(0.0456)	(0.0103)	(0.00282)	(0.0150)
Assets	0.0918***	-0.0112	-0.00921*	-0.0158***	-0.293***
	(0.0174)	(0.0185)	(0.00553)	(0.00171)	(0.00793)
Age	0.00745	0.0372	0.0283	-0.0141***	-0.0433*
	(0.0631)	(0.0645)	(0.0177)	(0.00498)	(0.0259)
Capex	-0.0569	0.266	-0.389***	-0.0138	-0.0434
	(0.151)	(0.197)	(0.0445)	(0.0114)	(0.0599)
PP&E	-0.117	0.0567	0.117***	0.0426***	-0.109***
	(0.0801)	(0.0966)	(0.0251)	(0.00723)	(0.0357)
Leverage	-0.0307	-0.134*	0.0227	0.00647	0.0864***
	(0.0578)	(0.0705)	(0.0200)	(0.00622)	(0.0270)
R&D	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-squared	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

Table 5: SEI-promotion policy and further evidence on firm innovation

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

$$y_{i,j,t} = \beta_1 \times SEI_j \times Post_t + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t}$$

The regression is at the firm (i)-year(t) level but each firm is also indexed by sector (j). SEI_j equals one if sector j is promoted as an SEI and zero otherwise. $Post_t$ takes the value of one after 2012 and zero otherwise. All other variables are defined in Table A1. 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. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	R&D	*R&D Efficiency*	*Breakthrough Innovation*	*Explorative*	*Exploitative*	*Originality*	*Generality*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SEI × Post	0.00554***	-0.0101*	0.0226	0.0388	-0.00148	-0.000897	0.0490***
	(0.000418)	(0.00612)	(0.0228)	(0.0254)	(0.00728)	(0.0188)	(0.0178)
Assets	-0.000410	-0.00252	-0.0147	0.0131	-0.00388	-0.0103	-0.00373
	(0.000284)	(0.00222)	(0.0109)	(0.0122)	(0.00360)	(0.00879)	(0.00905)
Age	-0.00944***	0.0513***	0.0583*	-0.0199	0.0201	-0.0863***	0.0174
	(0.00103)	(0.0106)	(0.0330)	(0.0427)	(0.0133)	(0.0290)	(0.0243)
Capex	0.00839***	-0.00895	-0.0357	0.105	0.00961	0.0193	0.0785
	(0.00230)	(0.0198)	(0.0836)	(0.0923)	(0.0317)	(0.0616)	(0.0638)
PP&E	0.00134	-0.0240**	-0.0770	-0.0380	-0.00730	-0.0246	0.0746**
	(0.00119)	(0.0111)	(0.0528)	(0.0572)	(0.0181)	(0.0387)	(0.0380)
Leverage	-0.00396***	0.0141*	-0.0877**	0.0711*	-0.0168	-0.00176	0.0283
	(0.00108)	(0.00826)	(0.0370)	(0.0431)	(0.0137)	(0.0290)	(0.0267)
Observations	16,247	12,630	6,478	6,478	6,478	6,478	4,271
Adjusted R-squared	0.733	0.386	0.463	0.336	0.199	0.209	0.222
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: U.S. Sanctions and Technology Decoupling

This table reports estimation results relating U.S. sanctions and technology decoupling/dependence. Panel A and B report the estimation results for equation (2) and (7), respectively. In both panels, the dependent variable features technology decoupling and dependence that are defined in Table A1. The dependence measure is residualized against the decoupling measure so that the two measures are orthogonalized concurrently by construction. *Post 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 A1, *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. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Panel A. U.S. sanctions and technology decoupling		
	Decoupling	*Dependence*
	(1)	(2)
Post Sanction	-0.0197***	-0.0276**
	(0.00355)	(0.0109)
Observations	1,343	1,343
Adjusted R-squared	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		
	Decoupling	*Dependence*
	(1)	(2)
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-squared	0.741	0.760
Technology class fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Control	Yes	Yes

Table 7: U.S. sanctions and technology decoupling, dynamic effects

This table traces out the dynamic impact of the U.S. sanctions at the technology-class-year-level. The dependent variable features technology decoupling and dependence that are defined in Table A1. The dependence measure is residualized against the decoupling measure so that they are orthogonalized concurrently by construction. $Sanction(-\tau)$ and $Sanction(\tau)$ refer to τ years before and after the sanction. $Sanction(3+)$ correspond to three and more years after the sanction. 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. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Decoupling	*Dependence*
	(1)	(2)
$Sanction(-5)$	-0.00294	-0.0122
	(0.00982)	(0.0207)
$Sanction(-4)$	-0.00445	-0.0142
	(0.00987)	(0.0208)
$Sanction(-3)$	-0.00525	-0.0230
	(0.00988)	(0.0208)
$Sanction(-2)$	-0.0105	-0.0294
	(0.00989)	(0.0208)
$Sanction(-1)$	-0.0104	-0.0333
	(0.00990)	(0.0208)
$Sanction(0)$	-0.0198**	-0.0360*
	(0.00993)	(0.0209)
$Sanction(1)$	-0.0205**	-0.0457**
	(0.00995)	(0.0209)
$Sanction(2)$	-0.0171*	-0.0355*
	(0.00997)	(0.0210)
$Sanction(3+)$	-0.0150*	-0.0396**
	(0.00876)	(0.0184)
Observations	1,343	1,343
Adjusted R-squared	0.737	0.760
Technology class fixed effect	Yes	Yes
Year fixed effect	Yes	Yes
Control	Yes	Yes

Table 8: U.S. sanctions and performance of Chinese firms

This table reports estimation results relating U.S. sanctions and the performance of Chinese firms. Panel A and B report the estimation results for equation (8) and (9), respectively. *Post Sanction* is equal to one for a firm in a year if this firm's sector had been exposed to U.S. sanctions prior to that year and zero otherwise. As delineated in Table A1, *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 firm fixed effect are included. Robust standard errors are reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Panel A. U.S. sanctions and firm performance					
	Innovation Output	*Innovation Quality*	*TFP*	*ROIC*	*Tobin's Q*
	(1)	(2)	(3)	(4)	(5)
Post Sanction	-0.124***	-0.0235	-0.0229**	-0.00989***	0.0169
	(0.0413)	(0.0477)	(0.0116)	(0.00327)	(0.0160)
Observations	16,247	16,247	16,247	16,247	16,247
Adjusted R-squared	0.603	0.188	0.621	0.435	0.786
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes

Panel B. Network spillovers of U.S. sanctions					
	Innovation Output	*Innovation Quality*	*TFP*	*ROIC*	*Tobin's Q*
	(1)	(2)	(3)	(4)	(5)
Upstream Sanction Exposure	-1.463***	0.230	-0.551***	-0.129***	-1.403***
	(0.511)	(0.667)	(0.136)	(0.0379)	(0.207)
Downstream Sanction Exposure	0.934**	-0.390	0.489***	0.118***	1.319***
	(0.461)	(0.597)	(0.123)	(0.0337)	(0.185)
Observations	16,247	16,247	16,247	16,247	16,247
Adjusted R-squared	0.604	0.188	0.622	0.435	0.787
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes

Appendix

FIGURE A1: **U.S.-China technology decoupling, classification by assignee nationality**

In this figure, we provide a sensitivity check in which nationality also applies to the patent assignees (i.e., we restrict the samples to Chinese patents granted to Chinese assignees and U.S. patents granted to U.S. assignees).

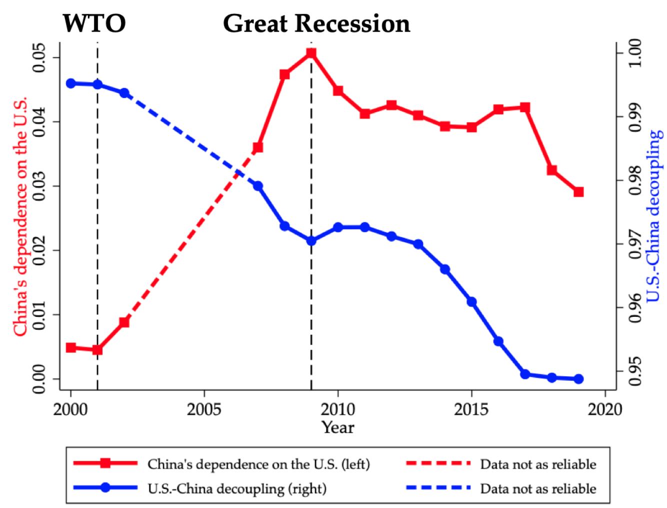


FIGURE A2: **U.S.-China technology decoupling based on renewed patents**

This sensitivity analysis restricts the sample of Chinese patents to those 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).

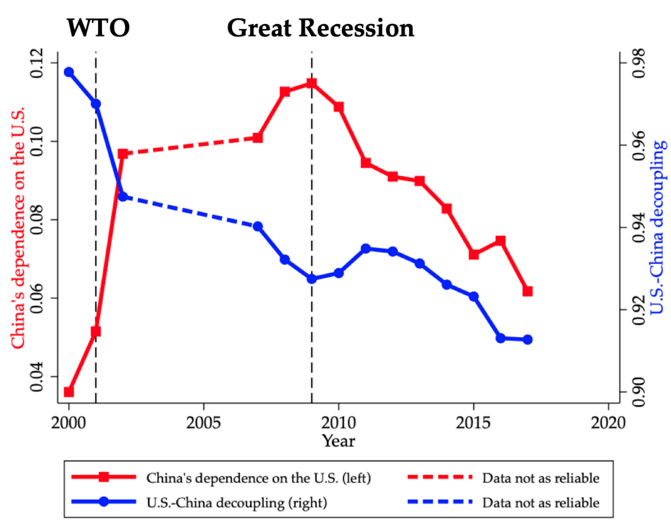


Figure A3: **Technology dependence and Chinese patent share**

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 the U.S. patents). We regress our measure of Chinas technological dependence on the U.S. against the share of Chinese patents each year at the technology class-year level, and plot the estimates of each cross-sectional regression by year in this figure.

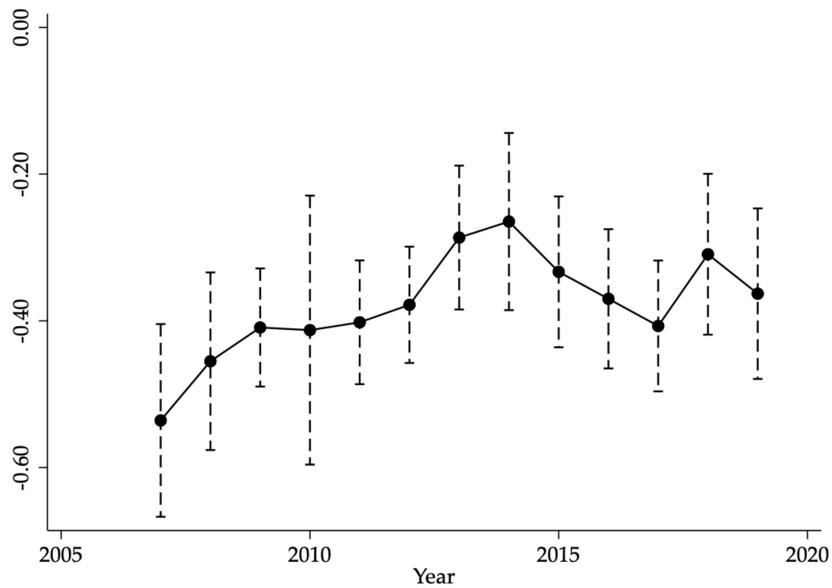


Table A1: Variable Definition

Variable	Definition
Decoupling	A measure of technology decoupling between the U.S. and China, developed in Section 2.3
Dependence	China's technological dependence on the U.S., developed in Section 2.3
Innovation Output	The natural logarithm of one plus the number of patent applications a firm files (and is eventually granted)
Innovation Quality	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)
TFP	The natural logarithm of total factor productivity estimated by the method of Ackerberg et al. (2015)
ROIC	EBITDA divided by the sum of the book value of debt and equity
Tobin's Q	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
Assets	The natural logarithm of the book value of assets
Age	The natural logarithm of one plus age since founding (IPO) for Chinese (U.S.) firms
R&D	R&D expenditures divided by assets; missing values are imputed zero
Capex	Capital expenditures divided by book value of assets
PP&E	Net value of property, plant, and equipment divided by the book value of assets
Leverage	Book value of total debt divided by book value of assets
R&D Efficiency	Number of patent applications divided by the weighted average of R&D expenditures in recent years
Breakthrough Innovation	The share of breakthrough patents filed by a firm each year. A breakthrough patent is defined to be the top five percent most cited patents in its cohort (i.e., patents in the same technology class and applied in the same year)
Explorative	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).
Exploitative	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 firms existing knowledge (i.e., belong to the patents filed by the firm or the patents cited by the firm's patents filed in the past five years).
Originality	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
Generality	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
Upstream Sanction Exposure	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
Downstream Sanction Exposure	Weighted average of the sanction indicator of all downstream tech classes of the focal technology class. The weight is the share of citations the focal technology class receives from other downstream technology classes

Table A2: Descriptive Statistics, Chinese Companies

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 main variables that are defined in Table A1. To facilitate the economic interpretations of the following variables, we report the summary statistics of *Innovation Output* in terms of the number of patents, *Assets* in terms of billions of RMB, and *Age* in terms of the number of years. *Tobin's Q* in this table refers to the ratio of the market value of equity plus the book value of debt to the book value of equity plus the book value of debt. *TFP* 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 1^{st} and 99^{th} percentiles.

	Mean	Standard Deviation	p25	Median	p75	Observations
	(1)	(2)	(3)	(4)	(5)	(6)
Decoupling	0.920	0.0308	0.896	0.924	0.942	16,247
Innovation Output (number of patents)	3.867	10.29	0	0	2.500	16,247
Innovation Quality	0.427	0.886	0	0	0.527	16,247
Assets (billion RMB)	10.75	28.25	1.400	2.861	7.016	16,247
Age (number of years)	14.55	5.429	11	14	18	16,247
R&D	0.0189	0.0191	0.00139	0.0162	0.0273	16,247
Capex	0.0577	0.0494	0.0213	0.0435	0.0791	16,247
PP&E	0.230	0.153	0.112	0.198	0.318	16,247
Leverage	0.408	0.206	0.241	0.398	0.561	16,247
ROIC	0.0791	0.0641	0.0504	0.0767	0.110	16,247
Tobin's Q	2.523	1.707	1.386	1.994	3.044	16,247
TFP	1.196	0.365	0.957	1.133	1.359	16,247

Table A3: Descriptive Statistics, U.S. Companies

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 main variables that are defined in Table A1. To facilitate the economic interpretations of the following variables, we report the summary statistics of *Innovation Output* in terms of the number of patents, *Assets* in terms of billions of U.S. dollars, and *Age* in terms of the number of years. *Tobin's Q* in this table refers to the ratio of the market value of equity plus the book value of debt to the book value of equity plus the book value of debt. *TFP* 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 1^{st} and 99^{th} percentiles.

	Mean	Standard Deviation	p25	Median	p75	Observations
Decoupling	0.916	0.030	0.895	0.919	0.937	14,839
Innovation Output (number of patents)	31.898	109.588	0.000	1.000	10.000	14,839
Innovation Quality	0.546	1.183	0.000	0.000	0.618	14,839
Assets (billion RMB)	9.899	25.613	0.157	0.817	5.218	14,839
Age (number of years)	23.002	19.730	9.000	17.000	31.000	14,839
R&D	0.101	0.159	0.006	0.041	0.123	14,839
Capex	0.038	0.042	0.013	0.026	0.050	14,839
PP&E	0.194	0.191	0.057	0.126	0.265	14,839
Leverage	0.210	0.232	0.004	0.163	0.315	14,839
ROIC	0.030	0.453	0.021	0.143	0.221	14,839
Tobin's Q	3.020	2.964	1.361	2.052	3.400	14,839
TFP	2.258	1.188	1.655	2.242	2.683	14,839

Internet appendix

Internet appendix for "Mapping U.S.-China Technology Decoupling, Innovation, and Firm Performance"

Patent examination procedures, U.S. vs China

Figure IA1 shows a comparison of the patent examination procedures at the United States Patent and Trademark Office (USPTO) and the Chinese National Intellectual Property Administration (CNIPA). Despite subtle differences in implementation, the patent examination procedures at USPTO and CNIPA are comparable to each other. At both patent offices, both domestic applicants and foreign applicants will go through three major phases: Filing, examination, and the granting of patents. At both USPTO and CNIPA, patent examiners are required to search for prior art in both domestic and foreign patents during the patent examination process.

[Insert Figure IA1 here.]

Patenting activities by nationalities of patent assignees

After comparing nations as patent approval authorities, we compare patenting activities in the two countries further based on the nationalities of the assignees as shown in Figure IA2. Panel A compares the number of Chinese patents granted to assignees with the U.S. and Chinese nationalities. Panel B presents the mirror image for the U.S. patents. The two figures demonstrate a common and familiar home bias, but also reveal different dynamics. Panel A shows that there were no significant differences in the number of Chinese patents granted to Chinese and U.S. assignees in the early 2000s, but Chinese assignees outpaced U.S. assignees since 2010 and have dominated as the recipients of Chinese-approved patents in recent years. Panel B shows that although patenting activities by Chinese assignees have been in the strict minority in the U.S., their representation in the total number of U.S. patents has risen from 0.03% in 2000 to 4.7% in 2019.

[Insert Figure IA2 here.]

After providing the aggregate evidence, we resort to a regression framework to gauge the relative level of patenting activities in both systems and by both nationals from micro data. More specifically, we estimate the following stacked panel regression at the technology class (i), the nationality of the assignees (a), the nationality of the patent office (p), and year (t) level:

$$\begin{aligned} y_{i,a,p,t} = \beta_0 &+ \beta_1 \times 1\{\text{US Assignees}\} + \beta_2 \times 1\{\text{US Patents}\} \\ &+ \beta_3 \times 1\{\text{US Assignees}\} \times 1\{\text{US Patents}\} + \gamma_i + \gamma_t + \gamma_{i,t} + \epsilon_{i,a,p,t} \end{aligned} \tag{IA1}$$

The sample for the regression above includes all patents granted at CNIPA and USPTO, stacked into one panel spanning the time period of 2000-2019. The dependent variable $y_{i,a,p,t}$ is the natural logarithm of one plus the number of patents granted at patent office p in technology class i to assignees with nationality a in year t. The classification of technology classes is based on the three-digit codes of the International Patent Classification (IPC) system. γ_t represents the year fixed effect to absorb the aggregate time trend. γ_i, the technology class fixed effect, is included to control for all time-invariant, unobserved heterogeneity at the technology class level. Finally, to account for potential time-varying heterogeneity, we also add the technology class-year fixed effect, $\gamma_{i,t}$. The patents office index $p \in \{\text{US Patents}, \text{Chinese Patents}\}$ and the assignee index $a \in \{\text{US Assignees}, \text{Chinese Assignees}\}$. The dummy variables $1\{\text{US Assignees}\}$ and $1\{\text{US Patents}\}$ are defined accordingly.

In equation IA1, coefficient β_1 captures the technological advantage of U.S. assignees, in terms of their total patenting activities in China, over Chinese assignees. That is, a negative estimate of β_1 implies that the Chinese assignees lead the U.S. ones in the Chinese patenting system. The technological advantage of U.S. assignees over their Chinese counterparts in filing U.S. patents is, instead, captured by $\beta_1 + \beta_3$, where a positive estimate suggests that the U.S. assignees are the leading force in filing U.S. patents. As a difference-in-differences estimate, β_3 corresponds to the advantage that the U.S. assignees enjoy in filing U.S. patents relative to their advantage in filing Chinese patents.

Table IA1 reports the regression results for the full sample in column (1), and in four-year subperiods in columns (2) to (6). It shows that patenting by Chinese assignees over the full sample period is 1.75 times higher than that of their U.S. counterparts in terms of Chinese patents, whereas patenting of U.S. assignees is 3.42 times higher than that of their Chinese counterparts in terms of U.S. patents. The subsample analyses show that the relative advantage changes over time. U.S. assignees steadily lag further behind their Chinese counterparts in the China system over time; at the same time, their lead in the U.S. system also wanes over time at about the same rate. The time trend is visualized in Figure IA3. Overall, Chinese assignees grow their share in both patent systems at about the same rate, though assignees of each nationality have maintained their lead in the patent system of the respective country.

[Insert Table IA1 here.]

[Insert Figure IA3 here.]

We next explore potential heterogeneity across different technology fields and focus specifically on ten crucial high-tech sectors outlined in Webb et al. (2019): Smartphones, semiconductors, software, pharmaceuticals, internal combustion engines, machine learning, neural networks, drones, cloud computing, self-driving cars. To uncover heterogeneities across technology classes, we estimate the U.S. patenting advantage in each high-tech field between 2000 and 2019 and the results are visualized in Figure IA4.[66] Applying the same methodology as those in Figure IA3, we estimate the U.S. patenting advantage in each technology class and in each sub-period in Figure IA5 and IA6.

[Insert Figure IA5 here.]

[Insert Figure IA6 here.]

If we attribute national advantage to the nationality of the assignees, we observe that the U.S. advantage remains strong in pharmaceutical, internal combustion engines, semiconductors, and smartphones. While the advantage is dwindling in semiconductors, it has been strengthened

[66] In such technology class-level regressions, there are only year fixed effects but no technology class fixed effects and technology class-specific year fixed effects.

in internal combustion engines. In several "neck-and-neck" technologies, patent assignees in each country enjoy an advantage in filing patents in their home countries, but their gap is fairly small. Such neck-and-neck technologies include several cutting-edge fields, such as AI-algorithm-related technologies (e.g., machine learning and neural networks), AI-application-related technologies (e.g., self-driving cars and drones), and cloud computing. In software patenting, both Chinese assignees and U.S. assignees are characterized by a huge advantage in their home countries. Moreover, the home-country advantages have been growing over time, which is suggestive evidence that each country increasingly advances along its own technological trajectory, and, thus, may lead to two distinct or parallel technological paradigms.

Technology decoupling at the technology class level

In this section, we report the cross-sectional evidence of technology decoupling and dependence at the technology class level. Table IA2 reports the top and bottom ten technology classes sorted by the measure of technology decoupling between 2017 and 2019. Table IA3 shows the ten tech classes in which China has the strongest (weakest) dependence on the U.S.

We apply the measures to each of the technology classes at the three-digit International Patent Classification (IPC) codes in Figure IA10. That is to say, we plot $p_{c,u}$ against $p_{u,c}$ for each technology class (at three-digit IPC codes) and highlight the industry profiles in each of the three critical years (i.e., 2000, 2009, 2019). Echoing the anti-decoupling trend in the aggregate data, all featured technology classes in Figure IA10 tend to move toward the complete integration point over time. Almost all technology classes started near the origin (low integration and low dependence). Most of them rose further above the 45-degree line in 2009, suggesting stronger U.S. technology leadership. By 2019, however, these technology classes became more evenly distributed on both sides of the 45-degree line, indicating a more balanced mutual dependence between the two nations.

[Insert Table IA2 here.]

[Insert Table IA3 here.]

[Insert Figure IA10 here.]

Figure IA1: **Patent examination procedures, U.S. vs China**

This flow chart is a comparison of the patent examination procedures at the United States Patent and Trademark Office (USPTO) and the Chinese National Intellectual Property Administration (CNIPA). The source of this flow chart is *IP5 Statistics Report,* 2018 Edition.

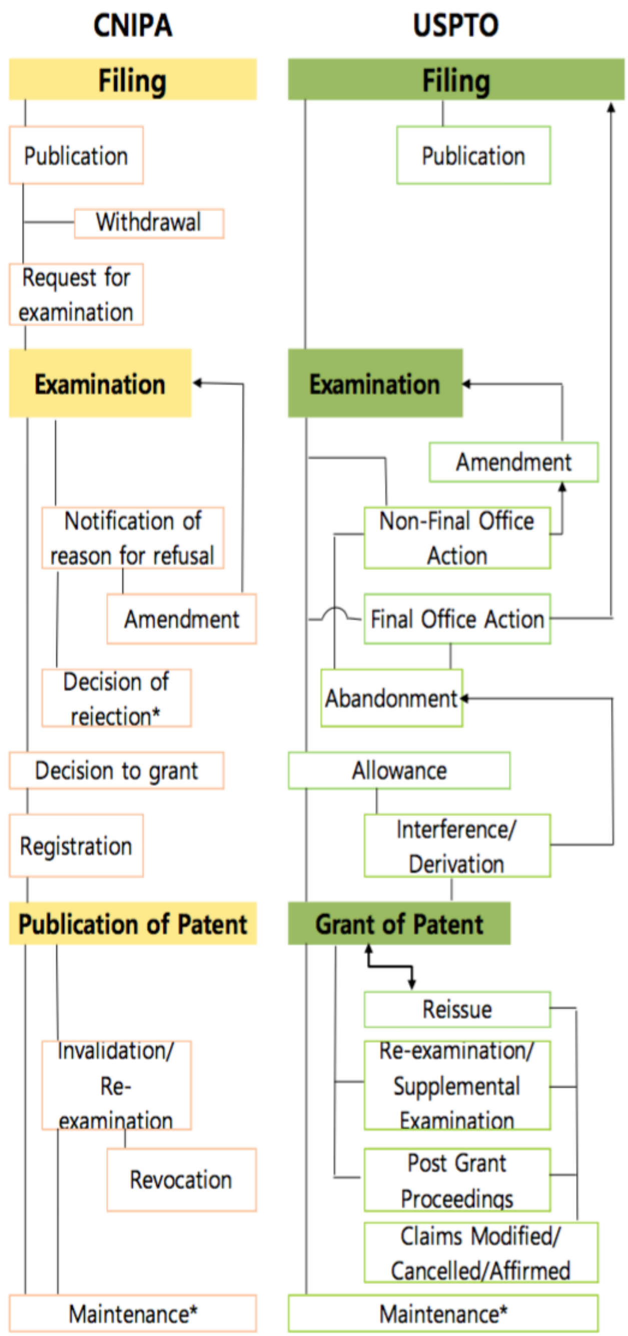
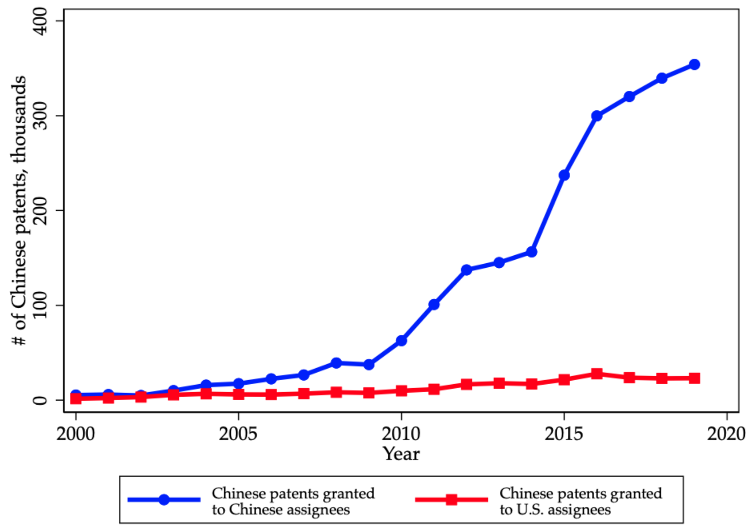
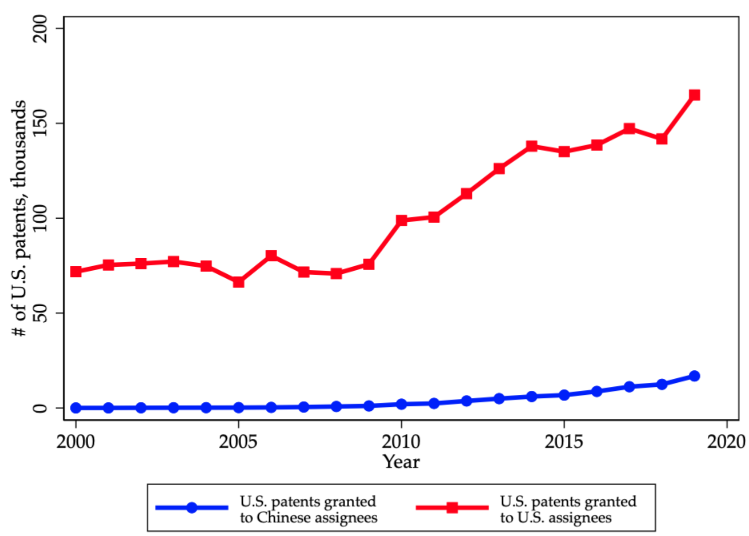


FIGURE IA2: **Patents granted, Chinese vs U.S. assignees**

We compare the number of Chinese patents (panel A) and U.S. patents (panel B) granted to Chinese assignees and U.S. assignees. "Chinese patents" in this figure refers to invention patents granted at the Chinese National Intellectual Property Administration (CNIPA). "U.S. patents" in this figure refers to utility patents granted at the United States Patent and Trademark Office (USPTO). The number of patents is expressed in thousands in both figures.



(A) CHINESE PATENTS GRANTED



(B) U.S. PATENTS GRANTED

FIGURE IA3: **U.S. advantage in patenting, dynamics**

We estimate the following "stacked" panel regressions to gauge the U.S. advantage in patenting:

$$
\begin{aligned}
y_{i,a,p,t} = \beta_0 &+ \beta_1 \times 1\{\text{U.S. Assignees}\} + \beta_2 \times 1\{\text{U.S. Patents}\} \\
&+ \beta_3 \times 1\{\text{U.S. Assignees}\} \times 1\{\text{U.S. Patents}\} + \gamma_i + \gamma_t + \gamma_{i,t} + \epsilon_{i,a,p,t}
\end{aligned}
$$

In this regression, we stack two samples of patents granted at CNIPA and USPTO into a balanced panel. The subscript i indexes for a technology class, a indexes for the nationality of the patent assignees, p indexes for the patent office, and t indexes for year. The dependent variable $y_{i,a,p,t}$ is the natural logarithm of one plus the number of patents granted at patent office p in technology class i to assignees with nationality a in year t. We focus on patents granted at two patent offices and granted to assignees in two countries, so $p \in \{\text{U.S. Patents}, \text{Chinese Patents}\}$ and $a \in \{\text{U.S. Assignees}, \text{Chinese Assignees}\}$. $1\{\text{U.S. Assignees}\}$ takes the value of one (zero) for the U.S (Chines) patent assignees. $1\{\text{U.S. Patents}\}$ equals one (zero) for patents granted at the U.S. (Chinese) patent office. The patenting advantage of U.S. assignees over their Chinese counterparts in filing Chinese (U.S.) patents is captured by β_1 ($\beta_1+\beta_3$). A positive estimate of the U.S. patenting advantage indicates that the U.S. assignees have an advantage over their Chinese counterparts in filing patents. A negative estimate of the U.S. patenting advantage implies that the Chinese assignees are taking a leading position in filing patents.

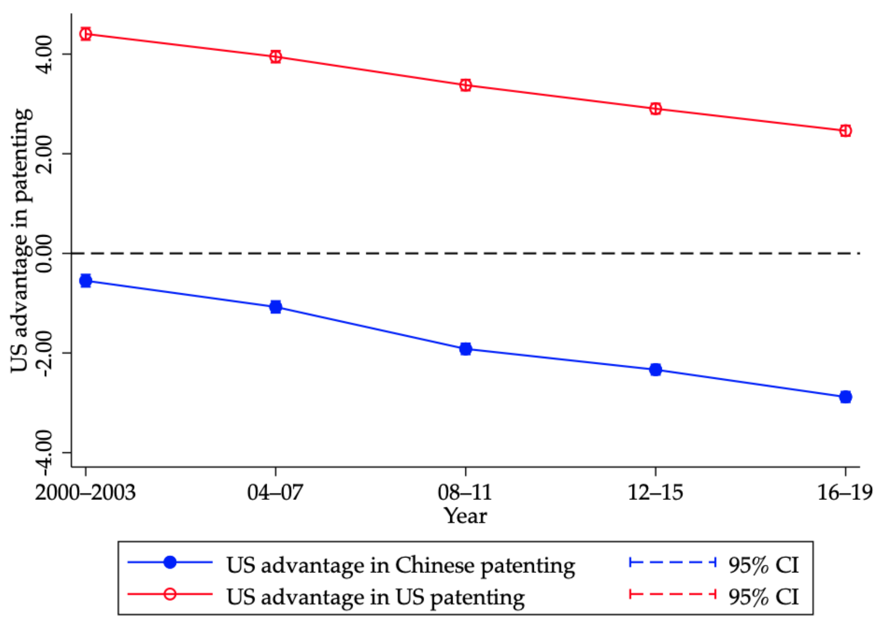


FIGURE IA4: **U.S. advantage in patenting, tech class heterogeneity**

We estimate the U.S. patenting advantage in ten high-technology fields between 2000 and 2019, and the results are visualized in this figure. Following Webb et al. (2019), we identify patents in these technological fields by their CPC codes, patent titles, and abstracts. For completeness, we group all other patents into the "non-high tech field. A positive estimate of the U.S. patenting advantage indicates that the U.S. assignees have an advantage over their Chinese counterparts in filing patents. A negative estimate of the U.S. patenting advantage implies that the Chinese assignees are taking a leading position in filing patents. "Chinese patents" in this figure refers to invention patents granted at the Chinese National Intellectual Property Administration (CNIPA). "U.S. patents" in this figure refers to utility patents granted at the United States Patent and Trademark Office (USPTO).

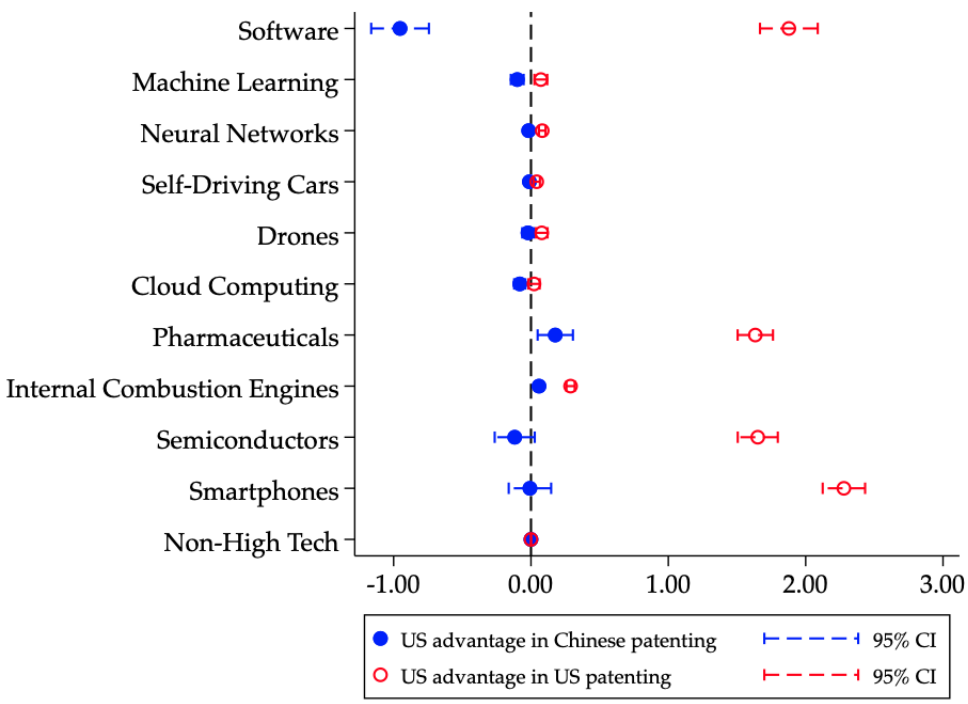
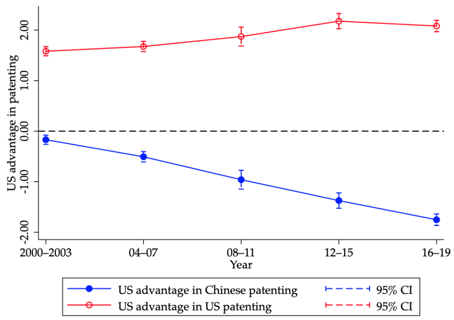
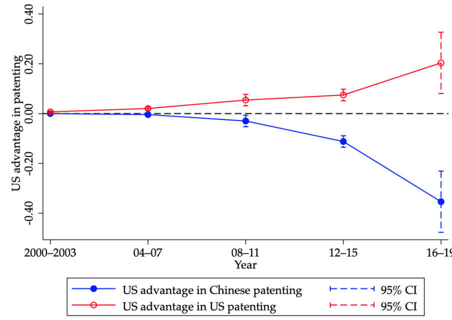


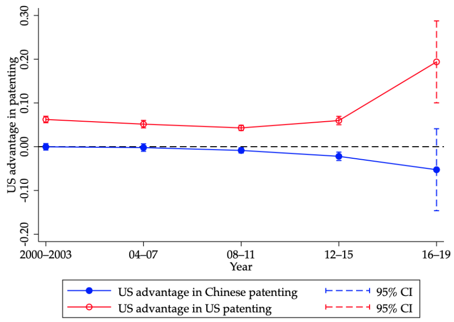
Figure IA5: **U.S. patenting advantage**



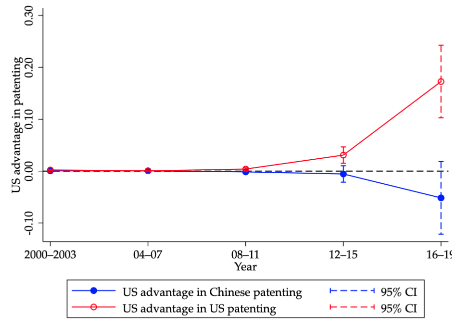
(a) Software



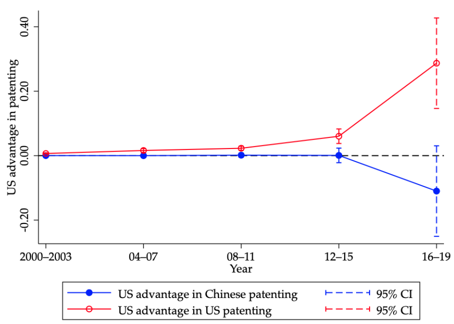
(b) Machine learning



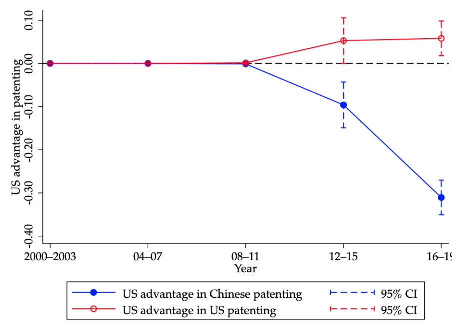
(c) Neural networks



(d) Self-driving cars

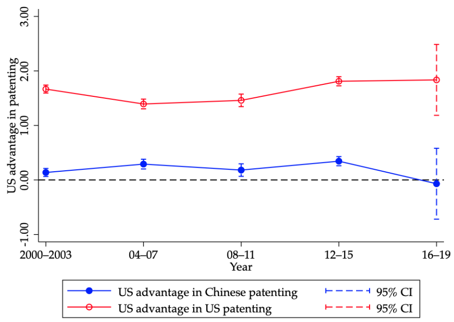


(e) Drones

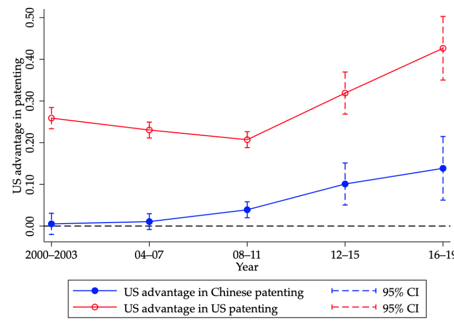


(f) Cloud computing

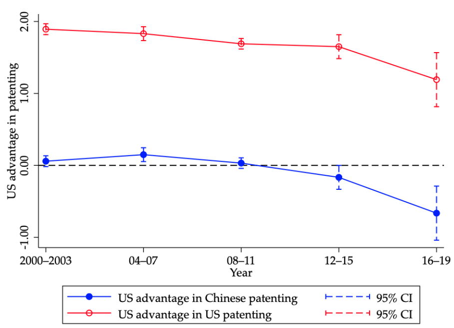
Figure IA6: **U.S. patenting advantage**



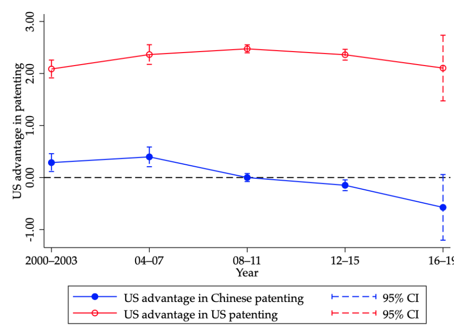
(a) Pharmaceuticals



(b) Internal combustion engines



(c) Semiconductors



(d) Smartphones

Figure IA7: **External validity checks with academic journals**

For an external validity check, we apply the decoupling and dependence measures to three representative academic journals: American Economic Review (AER, a leading economics journal), Journal of Finance (JF, a leading finance journal), and Journal of Banking and Finance (JBF, a leading journal in a subfield of finance). We report the results between 1971 and 2020 in this figure.

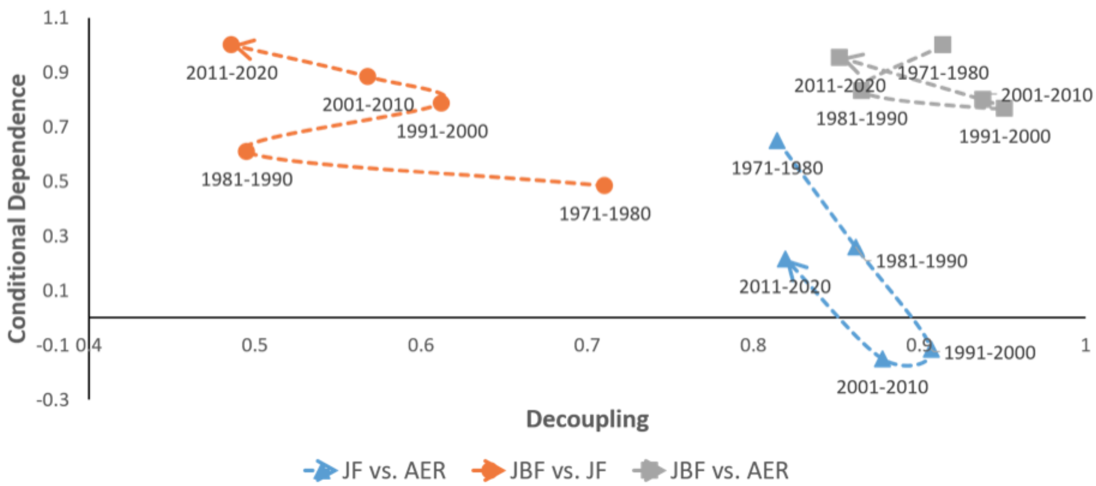


Figure IA8: **U.S.-China technology decoupling, SOEs vs private firms**

We examine further whether state owned enterprises (SOEs) and private firms have followed different dynamics. In this figure, we separate patents by listed Chinese SOEs and those by private firms based on the actual controllers as disclosed in annual reports. The decoupling measure is missing in the early sample period because listed firms in China were not required to report their actual controllers around that time.

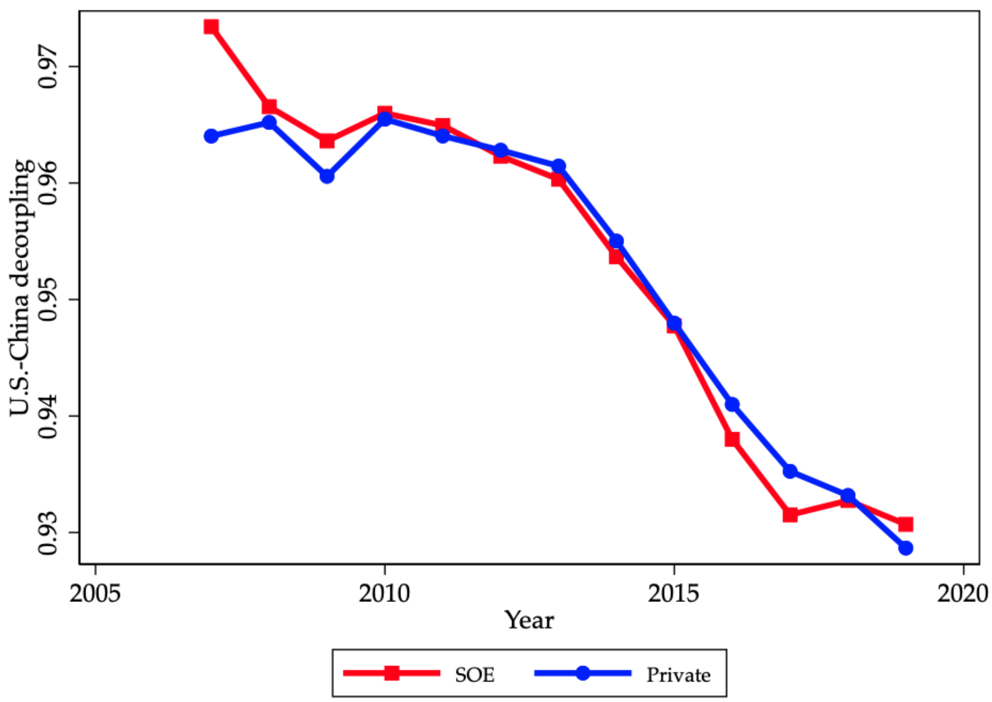
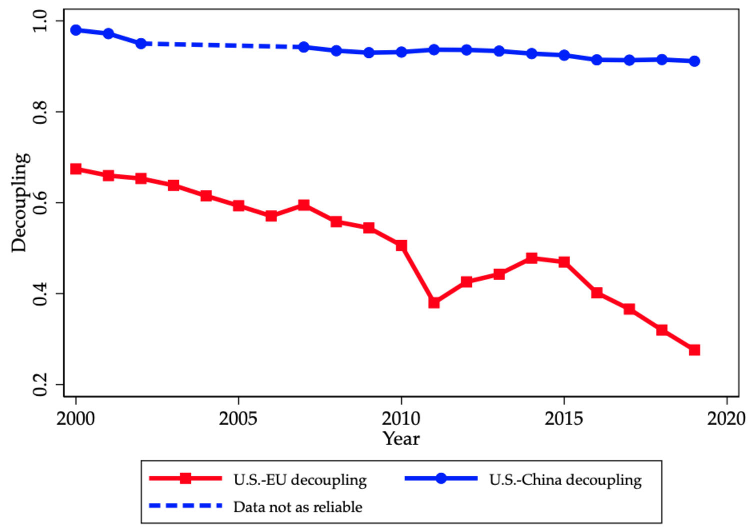
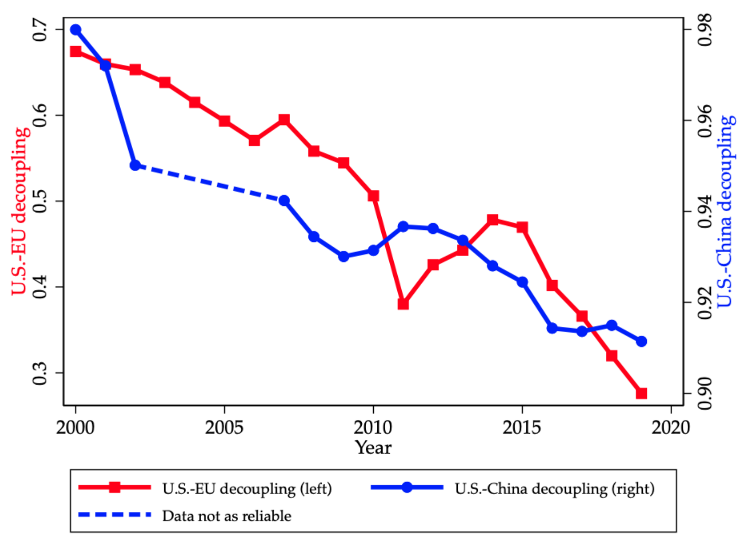


FIGURE IA9: **Technology decoupling, U.S.-China vs U.S.-EU**

We compare U.S.-China decoupling with U.S.-EU decoupling in this figure. The technology decoupling measures are plotted on one common axis in panel IA9a and they are plotted on two separate axes in panel IA9b.



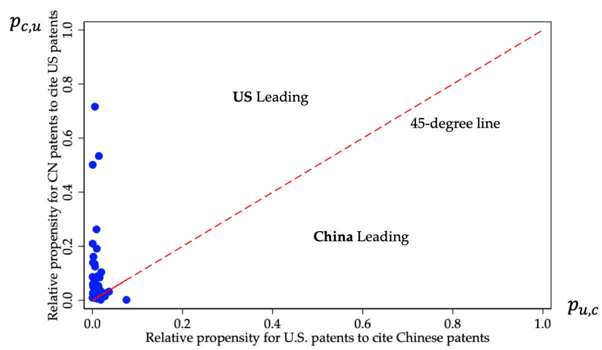
(A) DECOUPLING COMPARISON ON ONE COMMON AXIS



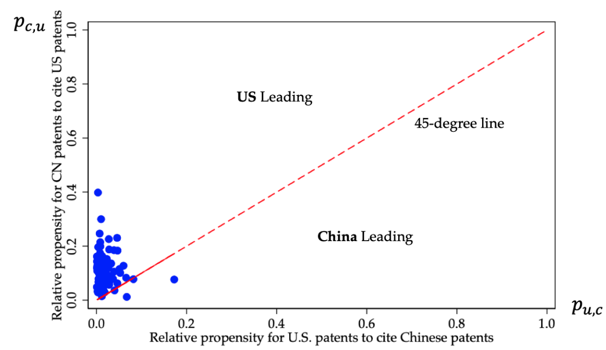
(B) DECOUPLING COMPARISON ON TWO SEPARATE AXES

FIGURE IA10: **Propensity to cite foreign patents relative to citing domestic patents**

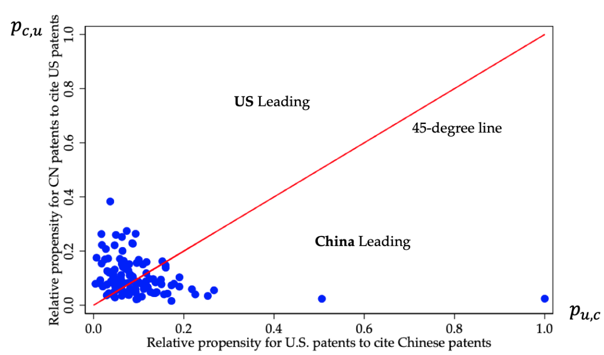
In this figure, we plot $p_{c,u}$ against $p_{u,c}$ for each technology class at three-digit IPC codes. In each figure, the vertical axis ($p_{c,u}$) is a proxy of the propensity for Chinese patents to cite a U.S. patent relative to citing a Chinese one. The horizontal axis ($p_{u,c}$) is a proxy of the propensity for U.S. patents to cite a Chinese patent relative to citing a U.S. one. To highlight critical turning points of the transition, we zoom in on three crucial years: 2000 (the year before China joined WTO), 2009 (the end of the Great Recession), and 2019 (the end of our sample period). The outlier with an exceptionally large value of $p_{u,c}$ in 2019 is technology class C14 (skins; hides; pelts or leather).



(A) 2000



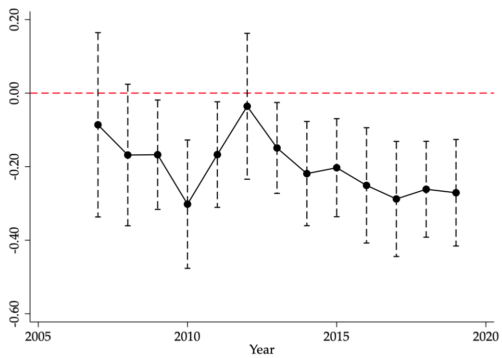
(B) 2009



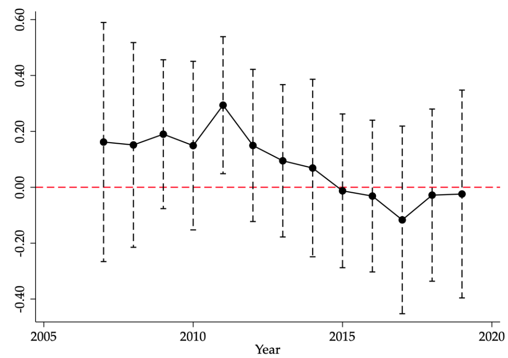
(C) 2019

FIGURE IA11: **Decoupling and dependence measures vs textual similarity**

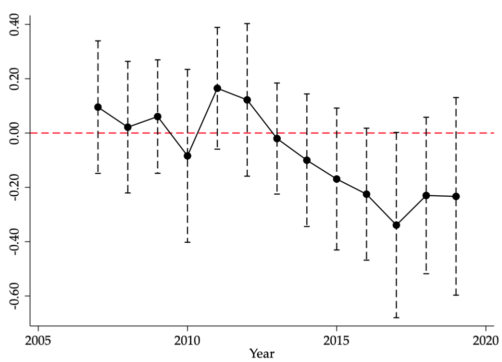
This figure shows the relationship between our measures of technology decoupling and dependence and a measure of the textual similarity between U.S. patents and Chinese patents. In Figure IA11a, we regress our technological decoupling measure against the textual similarity measure each year at the technology class-year level, and plot the estimates of each cross-sectional regression by year. Analogously, the dependent variable in the regression is our measure of China's technological dependence on the U.S. in Figure IA11b and the residualized dependence measure in Figure IA11c.



(A) DECOUPLING VS SIMILARITY



(B) DEPENDENCE VS SIMILARITY



(C) RESIDUALIZED DEPENDENCE VS SIMILARITY

Table IA1: U.S. Advantage In Patenting, Dynamics

We estimate the following "stacked" panel regressions to gauge the U.S. advantage in patenting:

$$\begin{aligned} \textit{Innovation Output}_{i,a,p,t} = & \ \beta_0 + \beta_1 \times 1\{\text{US Assignees}\} + \beta_2 \times 1\{\text{US Patents}\} \\ & + \beta_3 \times 1\{\text{US Assignees}\} \times 1\{\text{US Patents}\} + \gamma_i + \gamma_t + \gamma_{i,t} + \epsilon_{i,a,p,t} \end{aligned}$$

In this regression, we stack two samples of patents granted at CNIPA and USPTO into a balanced panel. The subscript i indexes for a technology class, a indexes for the nationality of the patent assignees, p indexes for the patent office, and t indexes for year. The dependent variable $\textit{Innovation Output}_{i,a,p,t}$ is the natural logarithm of one plus the number of patents granted at patent office p in technology class i to assignees with nationality a in year t. The patenting advantage of U.S. assignees over their Chinese counterparts in filing Chinese (U.S.) patents is captured by β_1 $(\beta_1 + \beta_3)$. A positive estimate of the U.S. patenting advantage indicates that the U.S. assignees have an advantage over their Chinese counterparts in filing patents. A negative estimate of the U.S. patenting advantage implies that the Chinese assignees are taking a leading position in filing patents. Standard errors are reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Innovation Output					
	Full Sample	2000–2003	2004–2007	2008–2011	2012–2015	2016–2019
	(1)	(2)	(3)	(4)	(5)	(6)
1{US Assignees}	-1.751***	-0.549***	-1.075***	-1.918***	-2.334***	-2.882***
	(0.0293)	(0.0619)	(0.0592)	(0.0552)	(0.0523)	(0.0529)
1{US Patents}	-3.225***	-2.224***	-2.899***	-3.387***	-3.691***	-3.922***
	(0.0293)	(0.0619)	(0.0592)	(0.0552)	(0.0523)	(0.0529)
1{US Assignees} × 1{US Patents}	5.171***	4.955***	5.023***	5.296***	5.239***	5.344***
	(0.0415)	(0.0875)	(0.0838)	(0.0780)	(0.0739)	(0.0749)
Observations	10,480	2,096	2,096	2,096	2,096	2,096
R-squared	0.862	0.848	0.864	0.892	0.912	0.916
Tech class fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Tech class × year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Table IA2: Most Decoupled vs Most Integrated Tech Classes, Top Ten

Panel A reports the top ten most decoupled technology classes at three-digit International Patent Classification (IPC) codes during the last three years of our sample (i.e., 2017–2019). Panel B reports the top ten most integrated technology classes. 'Tech decoupling" refers to the measure of technology decoupling between the United States and China.

IPC	Technological Fields	Tech Decoupling
	Panel A. Most Decoupled Tech Classes, Top Ten	
E04	building	0.969
A01	agriculture; forestry; animal husbandry; hunting; trapping; fishing	0.964
E01	construction of roads, railways, or bridges	0.963
B09	disposal of solid waste; reclamation of contaminated soil	0.961
B44	decorative arts	0.960
E02	hydraulic engineering; foundations; soil-shifting	0.960
F42	ammunition; blasting	0.957
B07	separating solids from solids; sorting	0.956
B02	crushing, pulverising, or disintegrating; preparatory treatment of grain for milling	0.952
G07	checking-devices	0.952
	Panel B. Most Integrated Tech Classes, Top Ten	
C14	skins; hides; pelts or leather	0.474
G11	information storage	0.783
C21	metallurgy of iron	0.806
B81	microstructural technology	0.807
G03	photography; cinematography; analogous techniques using waves other than optical waves; electrography; holography	0.808
H03	basic electronic circuitry	0.831
F01	machines or engines in general; engine plants in general; steam engines	0.843
F02	combustion engines; hot-gas or combustion-product engine plants	0.845
B06	generating or transmitting mechanical vibrations in general	0.848
G02	optics	0.856

TABLE IA3: U.S.-LEADING VS CHINA-LEADING TECH CLASSES, TOP TEN

Panel A reports the top ten U.S.-leading technology classes at three-digit International Patent Classification (IPC) codes during the last three years of our sample (i.e., 2017–2019). Panel B reports the top ten China-leading technology classes. "Tech dependence" refers to China's technological dependence on the United States.

IPC	Technological Fields	Tech Dependence
	Panel A. U.S.-Leading Tech Classes, Top Ten	
G11	information storage	0.38
H03	basic electronic circuitry	0.24
A42	headwear	0.24
F02	combustion engines; hot-gas or combustion-product engine plants	0.24
F01	machines or engines in general; engine plants in general; steam engines	0.21
C40	combinatorial technology	0.20
A61	medical or veterinary science; hygiene	0.19
G03	photography; cinematography; analogous techniques using waves other than optical waves; electrography; holography	0.18
A43	footwear	0.17
F41	weapons	0.15
	Panel B. China-Leading Tech Classes, Top Ten	
C14	skins; hides; pelts or leather	-0.95
C21	metallurgy of iron	-0.34
C22	metallurgy; ferrous or non-ferrous alloys; treatment of alloys or non-ferrous metals	-0.19
D06	treatment of textiles or the like; laundering; flexible materials not otherwise provided for	-0.16
C05	fertilisers; manufacture thereof	-0.15
C30	crystal growth	-0.13
C01	inorganic chemistry	-0.11
C04	cements; concrete; artificial stone; ceramics; refractories	-0.09
F22	steam generation	-0.09
C13	sugar industry	-0.06

Table IA4: SEI-Promotion Policy and Firm Performance, Controlling for other innovation policies

In this table, we conduct a robustness check by controlling for three major innovation policies. The empirical setup is based on equation (4). *Patent Subsidy* takes the value of one for a firm in a year if there are government subsidies for patents (either patent applications or grants) in the province where this firm is located in that year, and zero otherwise. Analogously, *Tax Cut* is a dummy variable for tax cuts for new product development, and *Tech SMEs* is a dummy variable for supporting policies for technology small and medium-sized enterprises. All other variables are defined in Table A1. 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. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Innovation Output	*Innovation Quality*	*TFP*	*ROIC*	*Tobin's Q*
	(1)	(2)	(3)	(4)	(5)
SEI × Post	-0.142***	-0.126***	0.00940	0.0138***	0.104***
	(0.0333)	(0.0456)	(0.0103)	(0.00282)	(0.0150)
Assets	0.0908***	-0.0115	-0.00945*	-0.0159***	-0.293***
	(0.0174)	(0.0185)	(0.00553)	(0.00171)	(0.00793)
Age	0.00560	0.0353	0.0274	-0.0143***	-0.0430*
	(0.0633)	(0.0646)	(0.0176)	(0.00498)	(0.0259)
Capex	-0.0628	0.259	-0.390***	-0.0137	-0.0405
	(0.151)	(0.197)	(0.0445)	(0.0114)	(0.0599)
PP&E	-0.123	0.0544	0.116***	0.0427***	-0.109***
	(0.0802)	(0.0966)	(0.0251)	(0.00723)	(0.0357)
Leverage	-0.0264	-0.133*	0.0227	0.00635	0.0863***
	(0.0579)	(0.0705)	(0.0199)	(0.00621)	(0.0270)
R&D	0.647	-1.280*	0.618***	0.181***	1.381***
	(0.609)	(0.670)	(0.150)	(0.0479)	(0.233)
Patent Subsidy	-0.00695	-0.0138	-0.0177	-0.00356	-0.00263
	(0.0410)	(0.0391)	(0.0116)	(0.00337)	(0.0161)
Tax Cut	0.0305	0.0474	-0.00853	-0.00182	-0.0278***
	(0.0257)	(0.0313)	(0.00749)	(0.00202)	(0.0104)
Tech SMEs	0.0883**	0.0106	0.0108	-0.000735	0.0162
	(0.0365)	(0.0421)	(0.0107)	(0.00267)	(0.0147)
Observations	16,247	16,247	16,247	16,247	16,247
Adjusted R-squared	0.604	0.189	0.640	0.435	0.787
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes

Table IA5: U.S. sanctions and further evidence on firm innovation

This table reports estimation results relating U.S. sanctions and the performance of Chinese firms. Panel A and B report the estimation results for equation (8) and (9), respectively. *Post Sanction* is equal to one for a firm in a year if this firm's sector had been exposed to U.S. sanctions prior to that year and zero otherwise. As delineated in Table A1, *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 firm fixed effect are included. Robust standard errors are reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

Panel A. U.S. sanctions and further evidence on firm innovation							
	R&D	*R&D Efficiency*	*Breakthrough Innovation*	*Explorative*	*Exploitative*	*Originality*	*Generality*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post Sanction	0.000288	-0.0162***	-0.00183	0.0269	-0.00119	0.0230*	0.00351
	(0.000703)	(0.00431)	(0.0188)	(0.0179)	(0.00418)	(0.0123)	(0.0100)
Observations	16,247	12,630	6,478	6,478	6,478	6,478	4,271
Adjusted R-squared	0.731	0.387	0.463	0.336	0.199	0.209	0.220
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Network spillovers of U.S. sanctions							
	R&D	*R&D Efficiency*	*Breakthrough Innovation*	*Explorative*	*Exploitative*	*Originality*	*Generality*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Upstream Sanction Exposure	-0.0123*	-0.0860*	-1.314***	-0.589**	-0.00725	0.0793	-0.459***
	(0.00705)	(0.0483)	(0.243)	(0.258)	(0.0670)	(0.208)	(0.173)
Downstream Sanction Exposure	0.0248***	0.0524	0.880***	0.500**	-0.00944	-0.129	0.414***
	(0.00679)	(0.0445)	(0.214)	(0.228)	(0.0601)	(0.185)	(0.156)
Observations	16,247	12,630	6,478	6,478	6,478	6,478	4,271
Adjusted R-squared	0.733	0.386	0.468	0.336	0.199	0.209	0.221
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA6: U.S. sanctions and performance of Chinese firms, Controlling for other innovation policies

In this table, we conduct a robustness check by controlling for three major innovation policies. The empirical setup is based on equation (8). *Patent Subsidy* takes the value of one for a firm in a year if there are government subsidies for patents (either patent applications or grants) in the province where this firm is located in that year, and zero otherwise. Analogously, *Tax Cut* is a dummy variable for tax cuts for new product development, and *Tech SMEs* is a dummy variable for supporting policies for technology small and medium-sized enterprises. All other variables are defined in Table A1. 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. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Innovation Output	*Innovation Quality*	*TFP*	*ROIC*	*Tobin's Q*
	(1)	(2)	(3)	(4)	(5)
Post Sanction	-0.121***	-0.0214	-0.0231**	-0.0100***	0.0160
	(0.0414)	(0.0477)	(0.0116)	(0.00327)	(0.0161)
Assets	0.0880***	-0.0140	-0.00261	-0.0156***	-0.291***
	(0.0174)	(0.0185)	(0.00634)	(0.00171)	(0.00794)
Age	0.00567	0.0357	0.0148	-0.0144***	-0.0433*
	(0.0635)	(0.0647)	(0.0191)	(0.00500)	(0.0259)
Capex	-0.0686	0.250	-0.433***	-0.0121	-0.0328
	(0.151)	(0.197)	(0.0515)	(0.0114)	(0.0601)
PP&E	-0.141*	0.0393	0.153***	0.0442***	-0.0962***
	(0.0800)	(0.0966)	(0.0313)	(0.00724)	(0.0357)
Leverage	-0.0159	-0.127*	-0.00152	0.00610	0.0812***
	(0.0579)	(0.0705)	(0.0227)	(0.00621)	(0.0270)
R&D	0.470	-1.450**	0.752***	0.201***	1.521***
	(0.606)	(0.668)	(0.166)	(0.0478)	(0.233)
Patent Subsidy	-0.00688	-0.0131	-0.0159	-0.00372	-0.00322
	(0.0410)	(0.0391)	(0.0125)	(0.00339)	(0.0161)
Tax Cut	0.0290	0.0477	-0.00857	-0.00210	-0.0281***
	(0.0256)	(0.0313)	(0.00811)	(0.00204)	(0.0105)
Tech SMEs	0.0834**	0.00744	0.0119	-0.000558	0.0188
	(0.0365)	(0.0420)	(0.0116)	(0.00267)	(0.0148)
Observations	16,247	16,247	16,247	16,247	16,247
Adjusted R-squared	0.603	0.188	0.621	0.435	0.786
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes

Table IA7: Poisson regressions

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

	Innovation Output	
SEI × Post	-0.200**	
	(0.100)	
Post Sanction		-0.199*
		(0.108)
Assets	0.418***	0.406***
	(0.0668)	(0.0656)
Age	0.104	0.112
	(0.260)	(0.250)
Capex	0.962**	0.947**
	(0.437)	(0.435)
PP&E	0.144	0.0790
	(0.263)	(0.263)
Leverage	-0.448*	-0.405*
	(0.244)	(0.243)
R&D	4.958***	4.946***
	(1.596)	(1.521)
Observations	16,231	16,231
Firm fixed effect	Yes	Yes
Year fixed effect	Yes	Yes