Mapping U.S.-China Technology Decoupling, 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 China's dependence on the U.S. increased (decreased) during the first (second) decade. Decoupling in a technology field predicts China's growing dependence on U.S. technology, which, in turn, predicts less decoupling further down the road. Decoupling is associated with more patent outputs in China, but lower firm productivity and valuation. China's innovation-oriented industrial policies trade off the inherent conflict between indigenous innovation and firm competitiveness.

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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.

Achieving technological independence from the West, especially the U.S., has been a stated goal of the Chinese government and reaffirmed by the current leader.[2] Can China achieve independence via decoupling? A panel vector autoregressive (panel VAR) analysis at the technology field-year level uncovers a nuanced empirical relation. On the one hand, a lower level of China's dependence on the U.S. in a given technology class (by the three-digit codes of the International Patent Classification (IPC) system) predicts a higher level of decoupling in the coming year. On the other hand, a higher level of decoupling predicts a higher level of dependence two years down the road. Such a feedback loop suggests that overall, China has not been able to continue to reduce dependence for an extended period of time without learning from and engaging with U.S. technology, even if China had the desire to decouple after some success in reducing dependence.

[2]See Bloomberg report, "Xi Mobilizes China for Tech Revolution to Cut Dependence on West," March 2, 2021.

Such an interactive process echoes a technology-adoption-driven narrative. China's technological advancement in recent decades relied heavily on adopting the cutting-edge technologies developed at the global frontier, particularly the United States. Opening and integrating with the world accelerated learning and innovation, followed by a declining dependence on U.S. technology after the initial adoption. Afterward, China's stronger domestic capability enabled a higher level of technology decoupling from the U.S. This process is consistent with the first finding. However, technology decoupling creates a barrier for Chinese companies to further learn from their foreign counterparts and to acquire knowledge at the same or a faster pace as the outside world. In due time, Chinese companies could lag behind again when a new wave of technologies emerges at the global frontier. In order to remain competitive, Chinese companies need to import foreign technology, which raises the level of dependence. This process is consistent with the second finding.

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 efficiency and valuation suffer in China, suggesting a cost for "reinventing the wheel" in a decoupling world. In contrast, the impact of decoupling on U.S. firms has been much less pronounced, presumably because the U.S. is still in the leading position in most fields.

Given the asymmetric effects of decoupling on firms in China and the U.S., we explore the motives and consequences of policies that aim at technology integration or decoupling from both countries. 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."[3] 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.[4] 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 and receive government subsidies are associated with lower patenting activities but higher productivity and market valuation. The combined results reveal an inherent trade-off between fostering "indigenous innovation" in China and enhancing firm efficiency.

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. Since the "escalation period" of U.S. sanctions (post 2013), China has been pursuing more independence-oriented technological development. While incurring moderate drops in patenting outputs and firm efficiency, Chinese firms in the sanctioned sectors have also exhibited a boost in firm valuation, presumably because the Chinese government has counteracted by buttressing the affected firms since 2014, making them symbols of national resilience.

[3]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.

[4]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.

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.[5] 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.[6] Finally, Bian et al. (2021) find that bilateral investment treaties between countries contribute to the globalization of innovation. The literature on innovation in China has also been emerging.[7] As we indicated earlier, this study is the first to quantify technology decoupling and to analyze how decoupling predicts future technology dependence, as well as the operating and innovative performance of firms in both countries.[8]

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.

[5]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.

[6]Hombert and Matray (2018) find that import competition from China leads to slower sales growth and lower profitability of U.S. firms, though firms with larger R&D stock can alleviate such negative effects via product differentiation. 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.

[7]Fang et al. (2017) show that innovation increases after China's state-owned enterprises are privatized, and this increase is larger where protection for intellectual property rights is stronger. Wei et al. (2017) underscore the indispensable role of innovation in fueling future growth of the Chinese economy and discuss numerous challenges for China's transition toward an innovation-driven economy. Exploiting staggered establishments of patent exchanges in China, Han et al. (2020) find that patent trading promotes comparative-advantage-based specialization and enhances firm performance.

[8]A paper in early stage (at this moment) 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.

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.[9] The counterparts in the CNIPA system are "invention patents" ("Chinese patents" hereafter).[10]

Despite differences in many details, the patent examination procedures at USPTO and CNIPA are mostly comparable. USPTO and CNIPA grant patents to both domestic and foreign assignees, and neither of them 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.[11] 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.[12] At both patent offices, domestic and foreign applicants will go through three major phases: filing, examination, and the granting of patents.[13] Importantly, patent examiners in

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

[10]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.

[11]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.

[12]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.

[13]Specific steps of each phase are illustrated in the flow chart of Figure IA1 in the Internet Appendix. These

both countries are required to search for prior art in both domestic and foreign patents during the patent examination process.[14]

As an overview, Figures 1a and 1b plot the annual time-series of innovation inputs (R&D expenditures)[15] 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 lead.[16] 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.[17]

[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

procedures are based on information from *IP5 Statistics Report,* 2018 Edition.

[14] 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.

[15] 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.

[16] 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.

[17] Please see Patenting activities by nationalities of patent assignees in the Internet Appendix. Figures IA2 – IA14 plot the analyses based on the nationalities of the patent assignees.

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. Generally, we hope that a measure for "technology decoupling" will capture the extent to which countries apply different technological standards and, relatedly, advance along different technological trajectories with little need to build on each other's work. 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.

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.[18]

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. The two 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. 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.

[18]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.

[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 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.[19] 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 $\frac{||\overrightarrow{\mathrm{QI}}||}{\sqrt{2}}$, which, based on the geometric relations, could be simplified to $Decoupling(\text{US \& CN}) = 1 - (p_{c,u} + p_{u,c})/2$. Division by $\sqrt{2}$ normalizes the measure to be bounded between zero and unit. 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 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. Again, the geometric characterization amounts to a simple and intuitive algebraic expression of $Dependence(\text{CN on US}) =$

[19] 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.

$p_{c,u} - p_{u,c}$. The normalization by $\sqrt{2}$ ensures that the dependence measure is bounded between -1 and 1. 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 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).[20]

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

[20]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 IA15. 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.

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.[21] 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 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.[22] In other words, the general trend is for technologies in the two countries to become more integrated, conforming to the general theme of globalization.[23] 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.

[21]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.

[22]We examine further whether state owned enterprises (SOEs) and private firms have followed different dynamics. In Figure IA16 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.

[23]To put U.S.-China decoupling in global perspective, we plot the time series of U.S.-EU decoupling in the Internet Appendix Figure IA17. Two features emerge. First, panel A of Figure IA17 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.

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.[24] 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 heterogeneity 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.[25]

[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

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

[25]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.

sectors, such as neural networks, cloud computing, and self-driving cars, due to a variety of reasons from geopolitical sensitivities to different legal infrastructure.[26] 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.[27] 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.[28]

[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 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.[29]

One common challenge facing all patent-based research, as well as a consensus, is that patents are inaccurate measures but remain the most reliable barometer of innovation, especially at the

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

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

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

[29] 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 IA18 is the cross-sectional analog of Figure 2 at the three-digit IPC level for years 2000, 2009, and 2019.

aggregate level. Our measures of decoupling and dependence capture the connectedness and relative competitiveness of innovation of the two nations by the extent of any asymmetry in mutual citations. The measures therefore extract quality instead of relying on the sheer quantity of patent approvals.[30] We 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.[31] 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. The pattern uncovered in our study (e.g., in Figure 4) is also consistent with the findings by Fang et al. (2021), based on new-word search in patent abstracts, that China came forward in the share of patents with "frontier words" during the same sample period, though it is still much lower than the U.S. level. The two methods are complementary, and our method allows an integrated analysis of both decoupling and dependence.

2.5 Relation between decoupling and dependence: technology class–year level

Based on the construction and overview of the decoupling and dependence measures, this section examines the relation between decoupling and dependence in more detail as they capture distinct aspects of the relation between the two nations in the technology space. More specifically, we resort to the following panel vector autoregressive (VAR) model to assess the inter-temporal and mutual relations:[32]

$$y_{i,t} = y_{i,t-1}B_1 + y_{i,t-2}B_2 + \cdots + y_{i,t-p}B_p + \gamma_i + \epsilon_{i,t},$$

[30] 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 an alternative approach to gauge patent quality, Kelly et al. (2021) assess the importance of a patent based on its textual similarity to previous and subsequent inventions.

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

[32] We also report a reduced-form OLS regression as a diagnostic test of their dynamic relationship in Table IA4 in the Internet Appendix.

where $y_{i,t}$ is a (1×2) vector of the dependent variables (i.e., technology decoupling and dependence). γ_i is a vector of technology-class-specific fixed effect and $\epsilon_{i,t}$ is a vector of the error disturbances. The coefficients, $B_1, B_2, \cdots, B_p$, are (2×2) matrices to be estimated. In order to have a well-identified system, we make the following assumptions about the innovations in the residual terms that are common in the literature applying the VAR model: $\mathbb{E}(\epsilon_{i,t}) = \mathbf{0}$, $\mathbb{E}(\epsilon'_{i,t}\epsilon_{i,t}) = \Sigma$, and $\mathbb{E}(\epsilon'_{i,t}\epsilon_{i,s}) = \mathbf{0}$ for all $t > s$. Last, the panel fixed effects are removed by forward orthogonal deviation transformation proposed by Arellano and Bover (1995). Results are reported in Table 1.

[Insert Table 1 here.]

In Table 1, the dependent variables are U.S.-China decoupling in odd-numbered regressions and China's technological dependence on the U.S. in even-numbered regressions. Each pair of regressions is simultaneously estimated. Lagged variables of both measures, up to two lags, appear in all regressions. In regressions (1) and (2), both the decoupling and dependence measures are in their original scale. Because the two variables are correlated in our sample (with the full sample concurrent correlation coefficient of -0.12), columns (3) and (4) explore a specification in which the dependence measure is residualized against the decoupling measure so that the two measures are orthogonalized concurrently by construction. Both specifications in Table 1 yield qualitatively similar results.

While the persistence of each dependent variable is expected, the cross effects turn out to be quite intriguing. A lower level of dependence predicts a higher level of decoupling in the next year; but a higher level of decoupling predicts a higher level of dependence two years later. Both relations pass the Granger causality test at the 5% level. In other words, a technology field for which China does not strongly depend on the U.S. is more likely to face decoupling; but then the decoupling results in heightened dependence further down the road, reverting the tendency for decoupling.[33] The dynamics echo a technology-adoption-driven narrative of China's recent technological progress. The nation's technological advancement had relied heavily on adopting the

[33]The impulse-response functions (IRF) from the VAR model using the Cholesky decomposition, plotted in Figure IA19 in the Internet Appendix, allow us to evaluate the response to shocks in decoupling and dependence where the shocks could originate in either series. The inferences are consistent whether the exogenous shock is assumed to originate from decoupling (Panels A and B), or assumed to come from dependence (Panels C and D).

cutting-edge technologies developed at the global frontier, particularly in the United States. After a wave of learning and adoption, China's technological dependence on the U.S. declined; and a stronger domestic technological capability enables a higher level of technology decoupling with the U.S. On the other hand, technology decoupling can create a barrier for Chinese companies to learn from their foreign counterparts which hinders further progress; making China lag again when a new wave of more advanced technologies arrived. Such a zigzag process suggests a tension between China's desire and its inability to progress independently, and also explains its growing integration with the rest of the world, including the U.S., over time despite the mutual distrust.

The high-speed railway (HSR) development in China could showcase such a dynamic relationship between decoupling and dependence. Between 2004 and 2006, the Ministry of Railway in China purchased a series of high-speed trains from leading foreign HSR manufacturers, under the condition that their HSR technologies were also transferred as part of the deals.[34] Under such a technology transfer agreement, each high-speed train was required to be built by a joint venture between a foreign train producer and a Chinese local partner. After cooperating with foreign producers, Chinese producers swiftly gained the capability to build their own high-speed trains, and afterward, built a more decoupled transit system from the original exporting countries.

3 Decoupling and firm performance

3.1 Overview of sample U.S. and Chinese firms

In this section, we turn our focus onto the impact of technology decoupling on the innovation and general performance of firms in both countries. A priori, neither the direction of the impact, 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

[34] The main foreign HSR manufacturers in these deals are Siemens, Alstom, Bombardier Inc., and Kawasaki Heavy Industries.

[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.

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 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 general and innovation-specific performance. The first measure 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. The third measure is 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] Finally, firm valuation is proxied by the inverse of Tobin's Q, or $1/Q$, approximated by the ratio of the sum of the book value of debt and equity to the sum of the market value of equity and book value of debt.[39]

[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).

[39]We adopt the inverse, rather than the original scale of, Q because equity book values may get arbitrarily small

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[40] 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 sales (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. For the sample of Chinese firms, *Subsidy* is the amount of subsidies (scaled by sales) that a firm receives from the government.[41] 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 10.74 billion (about US$ 1.66 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. R&D expenditures amount to 3.7% of firm sales, capital expenditures amount to 5.8% of firm assets, subsidies amount to 2.7% of firm sales, and net value of property, plant, and equipment accounts for 23.0% of firm assets, on average. Finally, the average firm features a leverage ratio of 40.8% and an inverse of Tobin's Q of 0.54. Analogously, Table A3 shows that the average patent-filing U.S. firm in our sample is about 22 years old as a public company and has an asset of US$ 9.21 billion. The average firm also faces a technology decoupling measure of 0.92 and files about 30 patents each year. The average U.S. firm features a capex ratio of 3.8%, a PP&E ratio of 19.2%, a leverage ratio of 21.1%, and an inverse of Tobin's Q of 0.56.

3.2 Decoupling, innovative activities, and firm performance

The impact of U.S.-China technology decoupling on firm innovation and performance is, a priori, ambiguous due to two opposing forces. On the one hand, global technology integration facilitates

or even negative, resulting in erratic Q values.

[40]Such information is disclosed in China.

[41]Such information is disclosed by Chinese firms but not available for U.S. firms. Moreover, subsidy received by U.S. firms is not a focus of this study.

knowledge dissemination, allowing firms better access to foreign technology 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 effect of technology decoupling with the following firm-year level panel regressions, 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 total number of patents filed that were eventually approved), *Innovation Quality* (the relative citation strength), TFP (the logarithm of total factor productivity), and $1/Q$, the inverse of Tobin's Q. 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.[42] 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.[43] 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.

[42]Results are qualitatively similar if we consider the lagged two to five years as the intermediate term.

[43]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.

$\epsilon_{i,j,t}$ is the error term. The estimation is conducted separately for Chinese firms and U.S. firms, respectively.

Start with Chinese firms reported in Table 2. Column (1) of Table 2 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. These results indicate that the substitution effect of technology decoupling is stronger than its complementarity effect for the Chinese firms in the short term (one-year horizon). The last two columns of Table 2, however, reveal the dark side of decoupling in the longer term. Although "reinventing the wheel" appears to boost domestic firm innovation output, a heightened decoupling is associated with lower firm productivity and valuation (significant at the 1% level) 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 13.1% increase in Chinese firm patenting activity one year later, but a 2.1% drop in firm TFP and an increase of inverse Tobin's Q by 0.028 (or 5.2% of the sample average) over a horizon of two to three years.

[Insert Table 2 here.]

The effects of technology decoupling on the U.S. firms, examined in Table 3, are less pronounced in comparison. There is no detectable relation between lagged decoupling and innovation output, innovation quality, or productivity. Further, 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. However, U.S. firms also experienced a drop in valuation, with about half the magnitude of the effect incurred by Chinese firms. Therefore, the stock market, being forward-looking, believes that decoupling does not benefit U.S. firms in the long run: They are losing part of the product market as a result of decoupling, in addition to the loss due to reduced technology and talent exchanges. 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. Such an asymmetry contributes to the more one-sided effect of decoupling on firm productivity and valuation in the two countries.

[Insert Table 3 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.

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."[44] 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."[45]

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 359 industries at four-digit codes based on the Chinese Industrial Classification (CIC) system in 2012. We map each four-digit-CIC industry to the three-digit IPC code using the CIC-IPC concordance table obtained from CNIPA. Then we apply the following difference-in-differences 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:

$$y_{i,t} = \beta_1 \times SEI_i \times Post_t + \delta' X_{i,t-1} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{2}$$

In equation (2), the dependent variable $y_{i,t}$ features technology decoupling and dependence at the technology class-year level. 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_1 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 4.

[Insert Table 4 here.]

Columns (1) and (2) of Table 4 show that the SEI-exposed sectors experienced significantly (at

[44] 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.

[45] 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.

the 5%) more decline in both decoupling and dependence. The extra decline in decoupling amounts to 0.013, or 1.4% of the sample mean; and that in dependence is 0.019, or 30.1% of the sample mean. 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. Three out of the four coefficients are significant at the 1% level. The last column of the table presents residualized *Dependence* (see explanations in Section 2.5) as a dependent variable as a sensitivity check. Results are similar and even stronger, suggesting that the impact on dependence is not driven by the concurrent correlation with decoupling.

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."[46] 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.[47]

Perhaps more importantly, results also indicate that China's technological dependence on the U.S. drops precipitously (by an average of 30.1%) in industries post SEI coverage, by a magnitude far exceeding the change in decoupling. 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

[46] 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.

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

technology integration with the U.S. instead of decoupling.[48]

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. For this purpose, we collect additional information on government subsidies at the firm-year level from firms' financial statements.[49] We then conduct the following triple-difference regression at the firm (i)-technology class(j)-year(t) level covering the period of 2007–2019:

$$\begin{aligned} y_{i,j,t} = \beta_1 \times SEI_j \times Post_t \times High\ Subsidy_{i,j} + \beta_2 \times SEI_j \times Post_t \\ + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \end{aligned} \tag{3}$$

In equation 3, the sample construction, the dependent variable, the fixed effects, and the recurring variables are the same as in Table 2. What is new is that among firms within the SEI-promoted technology sectors, we classify "high subsidy" firms as those with government subsidies (scaled by firm sales) during 2007–2011 (pre-SEI) above the sample median. A dummy variable $High\ Subsidy_{i,j}$ is coded accordingly, which is a firm-specific and time-invariant indicator. Because $High\ Subsidy_{i,j}$ is a subset of SEI_j, the double term $High\ Subsidy_{i,j} \times Post_t$ is subsumed. The coefficient of key interest is that of the triple interaction term $SEI_j \times Post_t \times High\ Subsidy_{i,j}$. Table 5 reports the results.

[Insert Table 5 here.]

The coefficient (except the one in column (3)) on $SEI_j \times Post_t$ turn out to be statistically insignificant with or without the additional triple term. That is, merely operating in technology sectors that are covered by the SEI does not induce significant positive changes in the innovation

[48] 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.

[49] After Accounting Rules of China's Enterprises (2006), all listed firms in China must disclose the government subsidy they receive in the footnotes of their financial statements.

and general performance of the firms. However, the coefficients associated with the triple interaction terms $SEI_j \times Post_t \times High\ Subsidy_{i,j}$ (reported in the even-numbered regressions of Table 5) demonstrate that the SEI-promotion policy is indeed associated with significant (at the 1% level) changes in performance (except for innovation quality) among firms that received a high level of direct government support. Compared with their low-subsidy counterparts, the highly subsidized firms operating in SEI-promoted technology sectors end up filing 11.7% *fewer* patents, but their productivity increases by 5.2% and inverse Q decreases by 0.0303 (or 5.6% of the sample average). Such a combination suggests that firms supported by the government in fact allocate fewer resources into original research but achieve better production efficiency.

To trace out the dynamics of the SEI policy, we expand equation (3) to the following setup with key terms interaction with year dummies around SEI:

$$y_{i,j,t} = \sum_{\tau}(\beta_{1,\tau} \times SEI_j \times High\ Subsidy_{i,j} \times T_\tau) + \sum_{\tau}(\beta_{2,\tau} \times SEI_j \times T_\tau) + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \quad (4)$$

That is, we interact both SEI_j and $SEI_j \times High\ Subsidy_{i,j}$ with a full set of year dummies (i.e., T_τ).We then plot the estimates for $\beta_{1,\tau}$ for each of the dependent variables in Figure 7. Year 0 corresponds to 2012, the event year of the SEI-promotion policy.

[Insert Figure 7 here.]

Figure 7 displays any pre-existing trends before the SEI. It seems that patenting activities were already declining and firm TFP were already rising in the highly subsidized SEI targeted sectors, but the changes in the continuing direction become statistically significant post SEI. In the other two variables, there were no discernable pre-trends. Patent quality does not see significant improvement afterward. Firm valuation experiences a significant uptick (or inverse Q decreases) right after the policy shock. If the stock market is fairly efficient and incorporates all forward-looking information, then the result suggests that investors expect value improvement for the policy-treated firms.

The smartphone industry in China in the past decade could serve as a poster-child of the patterns uncovered from the regressions. Rising from humble backgrounds, numerous Chinese smartphone makers (e.g., Huawei, Xiaomi, and Vivo) have swiftly ascended to become world industry leaders. Surpassing Apple in 2018, Huawei became the second-largest smartphone maker in the world. The success of Chinese smartphone makers is in part attributed to their seamless integration into the global supply chain. Instead of decoupling from the world and creating a different "Chinese standard," they adapted to the global technology standard and strove to participate in the standard-setting process. And by doing so these Chinese enterprises enjoyed easy access to cutting-edge foreign technologies and key inputs (particularly semiconductors) from foreign suppliers. The globally integrated supply chain of semiconductors contributes to accelerating the rise of Chinese smartphone makers, but is also responsible for disincentivizing them to develop the domestic semiconductor industry, leading to Huawei's plight after it was denied access to foreign suppliers in 2020.

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."

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.[50] This section studies whether U.S. sanctions are followed by U.S.-China technology decoupling and deteriorating performance of the affected Chinese firms, where we trace out sanctions based on the entity list issued by the Bureau of Industry and Security (BIS) of the U.S. Department of Commerce.

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

4.2.1 U.S. entity list

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.[51] 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). By this algorithm, 75.4% 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.

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 8. 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.

[51] 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.

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. Therefore, we refer to the period post 2013 as the sanction "escalation period" in our subsequent analyses.

[Insert Figure 8 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 (j)-year(t) level covering the period of 2007–2019:

$$
\begin{aligned}
y_{j,t} = \beta_1 \times \textit{Post Sanction}_{j,t} + \beta_2 \times \textit{Post Sanction}_{j,t} \times \textit{Escalation Period}_t \\
+ \delta' X_{j,t-1} + \gamma_j + \gamma_t + \epsilon_{j,t} \qquad (5)
\end{aligned}
$$

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 $\textit{Post Sanction}_{j,t}$ is equal to one if at least one Chinese entity associated with this technology class had been sanctioned before that year. In light of the structural break of U.S. sanction policies against China demonstrated in Figure 8, we introduce a dummy variable $\textit{Escalation Period}_t$ (which takes the value of one if t is after 2013) in equation (5) to detect whether the effects of U.S. sanctions have changed over time. Results are reported in Table 6 in which the odd-numbered columns omit $\textit{Post Sanction}_{j,t} \times \textit{Escalation Period}_t$ while the even-numbered columns report the full regression.

[Insert Table 6 here.]

Perhaps contrary to intuition, the results in column (1) suggest that U.S. sanctions in a technology class were associated with a significant (at the 1% level) *decrease* in the decoupling measure by 0.0156 (or 1.7% of sample mean) in that technology class. Results in column (2) further confirm that this negative relationship between U.S. sanctions and technology decoupling has not significantly changed even after the sanctions escalated after 2013. 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.[52] 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.[53] 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.[54] Such strong economic ties and talent flows have fostered technology exchanges fluid at national boundaries and are difficult for the government to unwind short of draconian measures.

The effects of U.S. sanctions on China's technological dependence on the 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 (3)–(6) of Table 6 suggest the second force dominates: U.S. sanctions are negatively correlated with China's technological dependence on the U.S. and this negative relationship is particularly driven by the "escalation period." 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.[55]

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

[53]Source: The Institute of International Education.

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

[55]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.

Comparing the effects of China's SEI-promotion policy in Table 4 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. 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 U.S. sanctions and firm performance

Next we analyze to what extent sanctions impact the performance of affected firms. The following regression at the firm (i)-year(t) level covering 2007–2019 hopes to shed light on the question:

$$y_{i,j,t} = \beta_1 \times \textit{Post Sanction}_{j,t} + \beta_2 \times \textit{Post Sanction}_{j,t} \times \textit{Escalation Period}_t \\ + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \tag{6}$$

Though the panel is at the firm-year level, each firm is triple-indexed by firm (i)-technology class (j)-year(t) so that the firm could be matched to its primary technology class using the same algorithm as in Section 3.2. The sample construction, dependent variables, the fixed effects, and the recurring variables in this setup mirror our firm-level SEI analysis in equation (3), while variable $\textit{Post Sanction}_{j,t}$ and $\textit{Escalation Period}_t$ are the same as in equation (5). Results are reported in Table 7.

[Insert Table 7 here.]

Column (1) and (5) of Table 7 shows that U.S. sanctions in a technology class were associated with an 8.7% drop in patenting output and a 1.8% decline in TFP of firms in that technology class. Moreover, column (2) and (6) suggest that this negative relationship was not unique to the "escalation period." In other words, it is not a recent phenomenon that Chinese firms suffered from a decline in innovation output and firm productivity after they were denied access to U.S. technologies and inputs. There has not been a significant change in innovation quality post sanction (columns (3) and (4)). Though column (7) shows no significant relation between sanctions and firm valuation, column (8) unveils the opposing effects of sanctions before 2014 and since then: While valuation of Chinese firms in the sanctioned sectors suffered during the first period, the valuation of similar firms has enjoyed a boost in the second period. In both periods, the relations are significant at the 5% level or less.

One explanation for the changing firm outcomes post sanction could be attributed to adaptive responses from the Chinese government and businesses to U.S. sanctions as sanctions became more aggressive and widespread. Prior to 2014, U.S. sanctions were sporadic but inflicted damages on the entities in the sanctioned sectors. 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.[56] Firms sanctioned by the U.S. in some cases sought "national symbol" status in an ideologized sentiment. In the end, up to 2019 the sanctions have not crippled the targeted firms relative to other firms. We look forward to extending the analysis when more data post 2019 become available.

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 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. In the cross-section, a higher level of decoupling in a given technology field predicts more patent outputs in the same sector in China, but lower firm productivity and valuation in the longer term. In contrast, the impact of decoupling on U.S. firms is less noticeable. Analyzing government policies in both nations, we find that China's innovation-promoting industrial policies are associated with both more integration and

[56] For example, China's Anti-Foreign Sanctions Law passed in June 2021 establishes a legal ground to retaliate against foreign sanctions.

less dependence down the road, but the process is embedded with an intrinsic trade-off between the two major policy objectives (i.e., indigenous innovation versus firm competitiveness) of the Chinese government. On the other side, U.S. sanctions against China have not led to U.S.-China decoupling but have spurred more independent technological development in China. The findings suggest that policies can leverage the momentum, but are hard to reverse the trend, of global technology integration.

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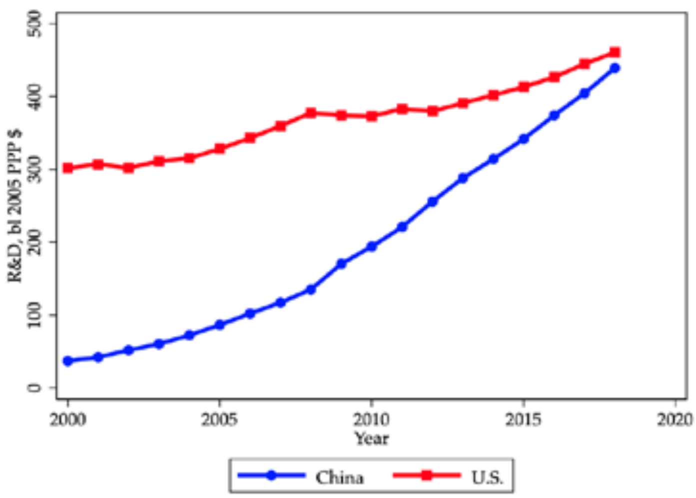
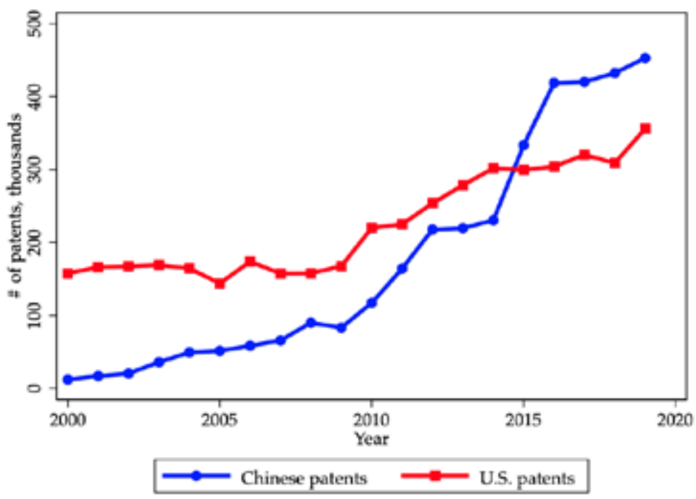
Figure 1: **R&D expenditures and patents granted, U.S. vs China**

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.

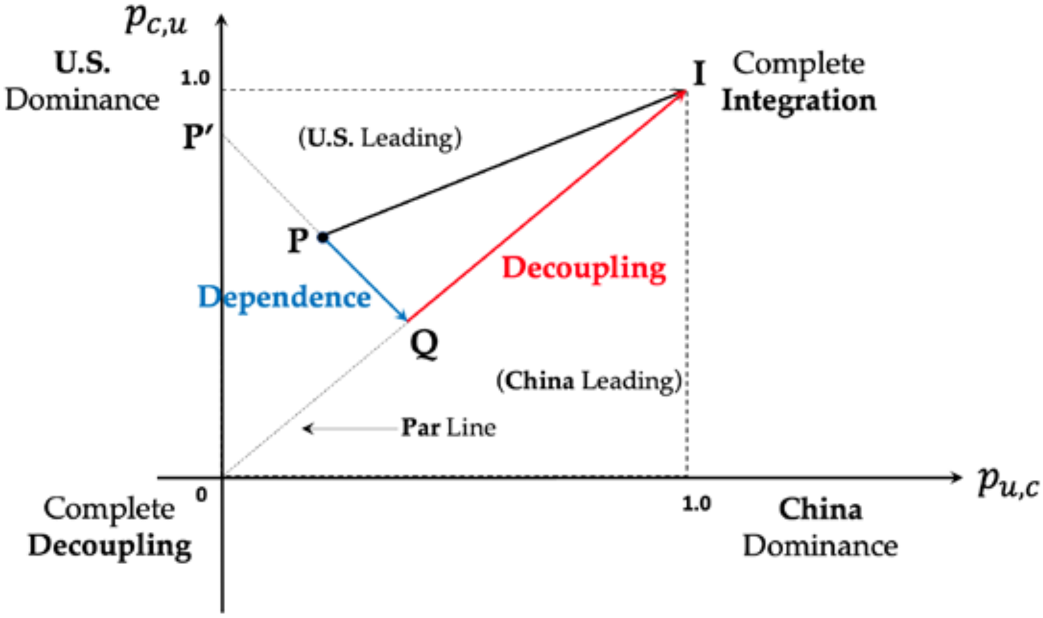


FIGURE 3: **U.S.-China technology decoupling and dependence, 2000, 2009, and 2019**

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).

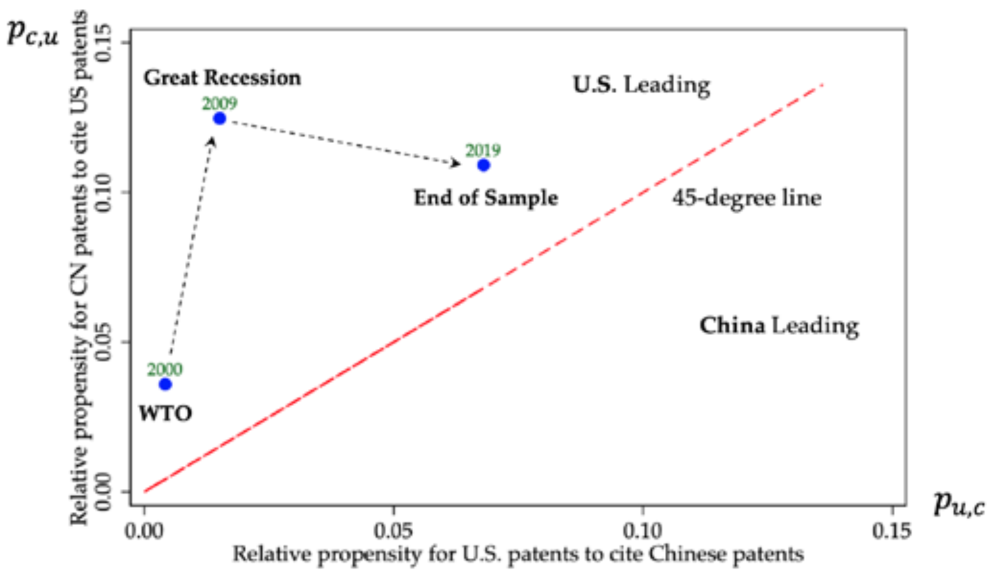


FIGURE 4: **U.S.-China technology decoupling and dependence, 2000–2019**

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.

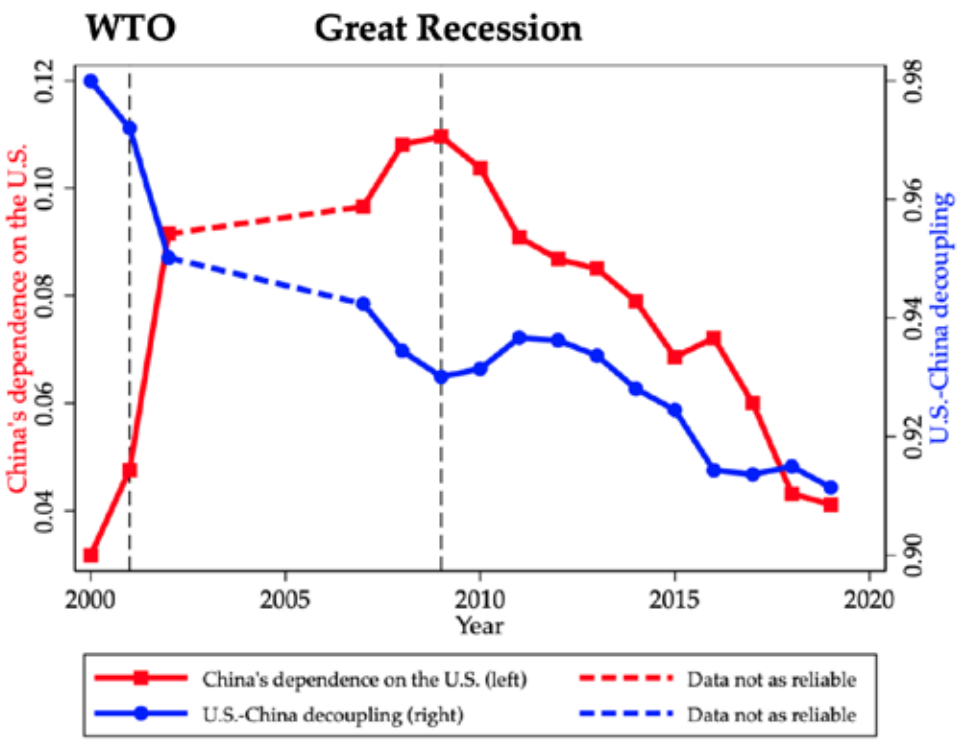
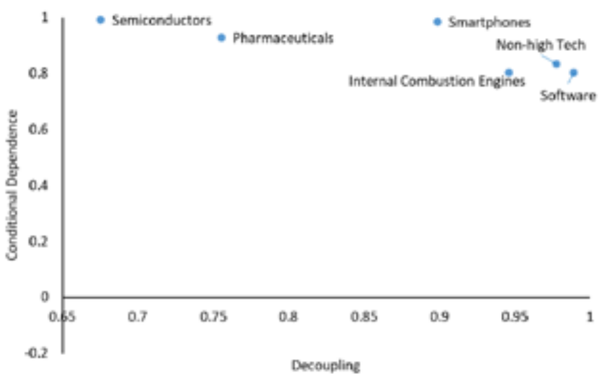
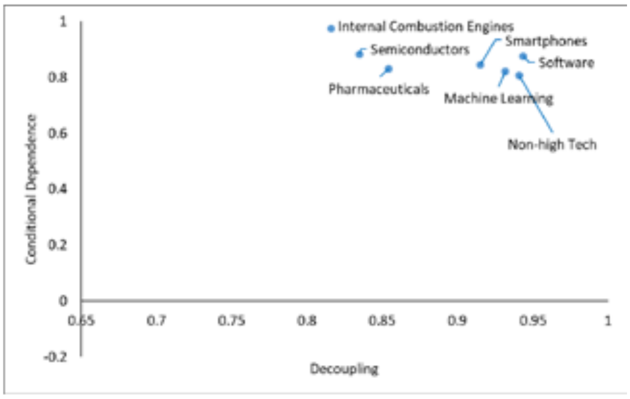


Figure 5: **Decoupling and dependence, ten high-tech fields**

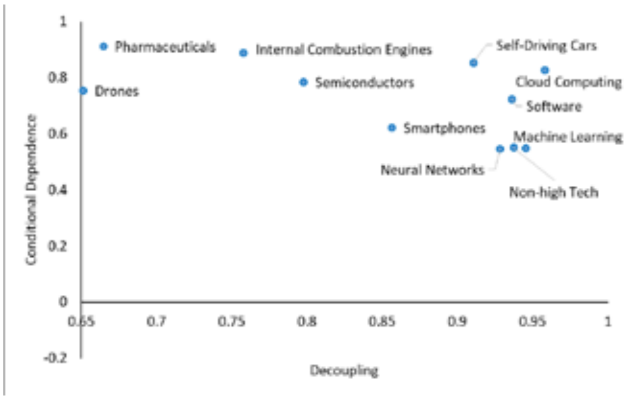
In this figure, we plot the states of decoupling and conditional dependence (both measures are defined in Section 2.3) in selected years of 2000, 2009, 2015, and 2019. The ten high-tech fields are defined by Webb et al. (2019). All other patents are grouped into the "non-high tech" field.



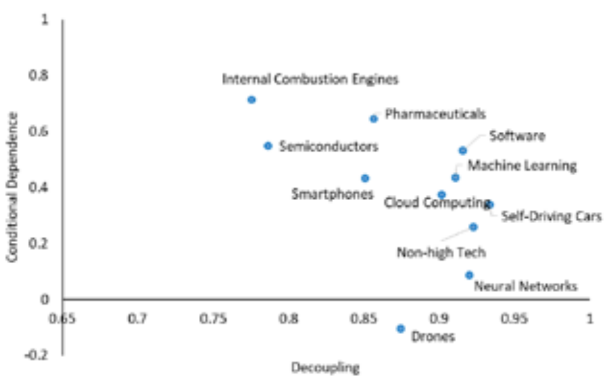
(a) Year: 2000



(b) Year: 2009



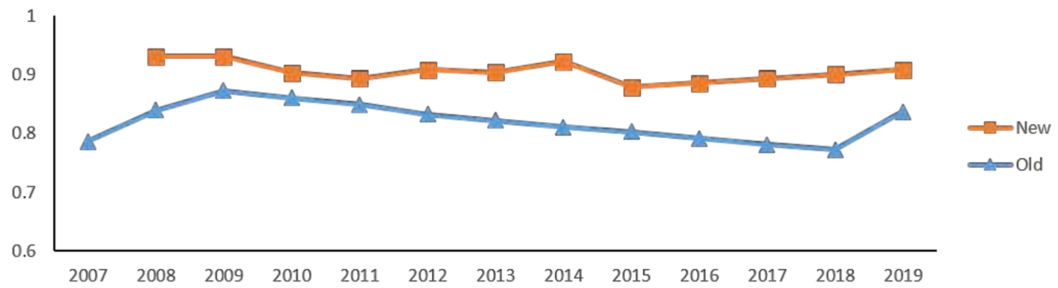
(c) Year: 2015



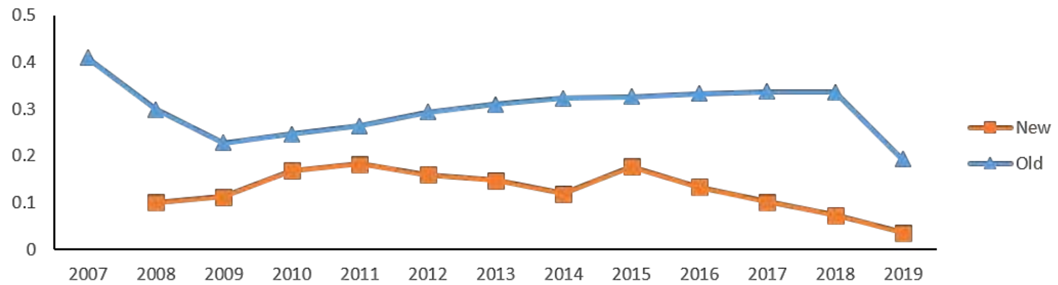
(d) Year: 2019

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

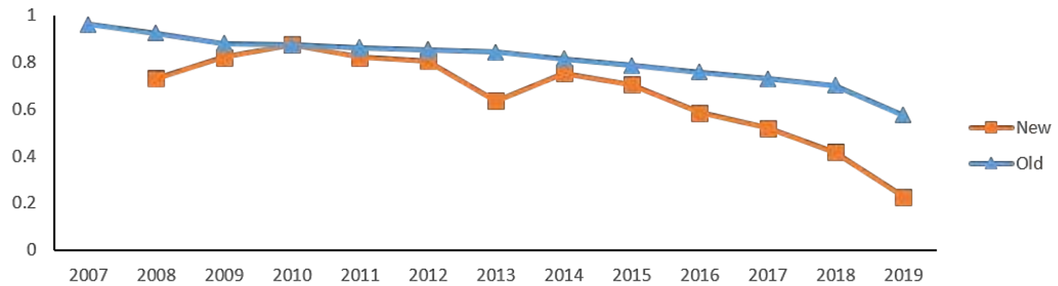
In this figure, we compare the states of decoupling, dependence, and conditional dependence between new and old technologies among the ten high-tech fields. The ten high-tech fields are defined by Webb et al. (2019). A technology is considered new if the grant year of its first patent is after 2008, 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



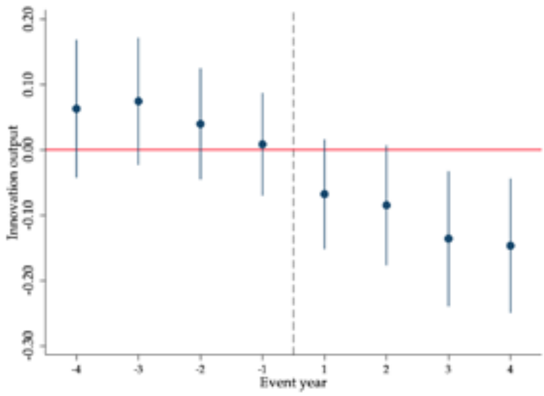
(c) Conditional Dependence

Figure 7: **SEI policy and firm performance, dynamic effects**

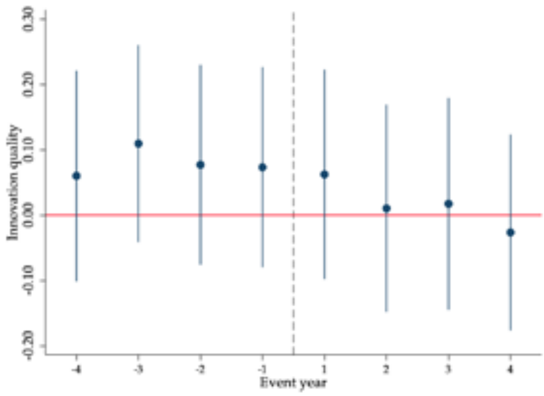
We trace the dynamics of the SEI policy in the following regression at the firm (i)-year(t) level covering the period of 2007–2019:

$$y_{i,j,t} = \sum_{\tau}(\beta_{1,\tau} \times SEI_j \times High\ Subsidy_{i,j} \times T_\tau) + \sum_{\tau}(\beta_{2,\tau} \times SEI_j \times T_\tau) + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t}$$

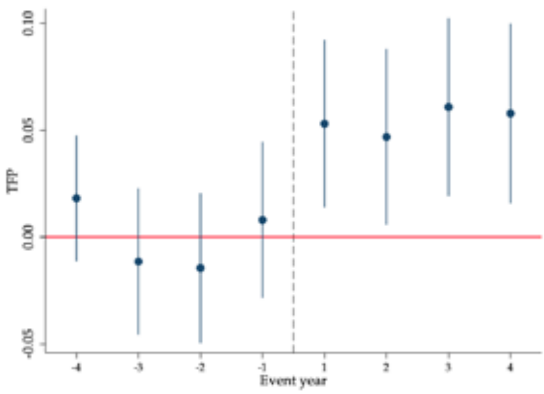
Firms are also indexed by technology class (j) so that each of them could be matched to their primary technology class. SEI_j equals one if technology class j is promoted as an SEI and zero otherwise. Within the SEI-promoted technology sectors, $High\ Subsidy_{i,j}$ equals one if the subsidy-to-sales ratio of firm i is above the sample median. T_τ is a set of year dummies ranging from four years before to four years after the SEI policy shock. All other variables are defined in Table A1. The Figures plot the estimates for $\beta_{1,\tau}$ for the following dependent variables: *Innovation Output* in Figure 7a, *Innovation Quality* in Figure 7b, TFP in Figure 7c, and $1/Q$ in Figure 7d.



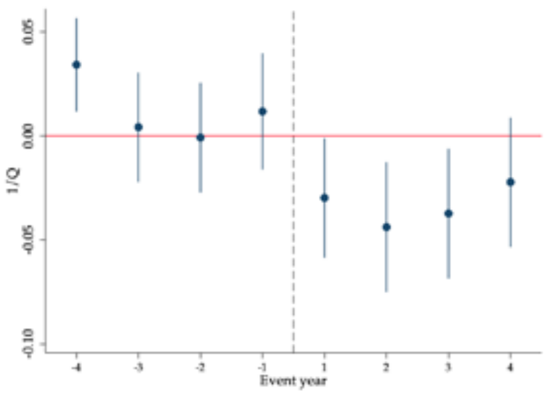
(a) Innovation Output



(b) Innovation Quality



(c) Firm TFP



(d) Inverse of Tobin's Q

Figure 8: **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.

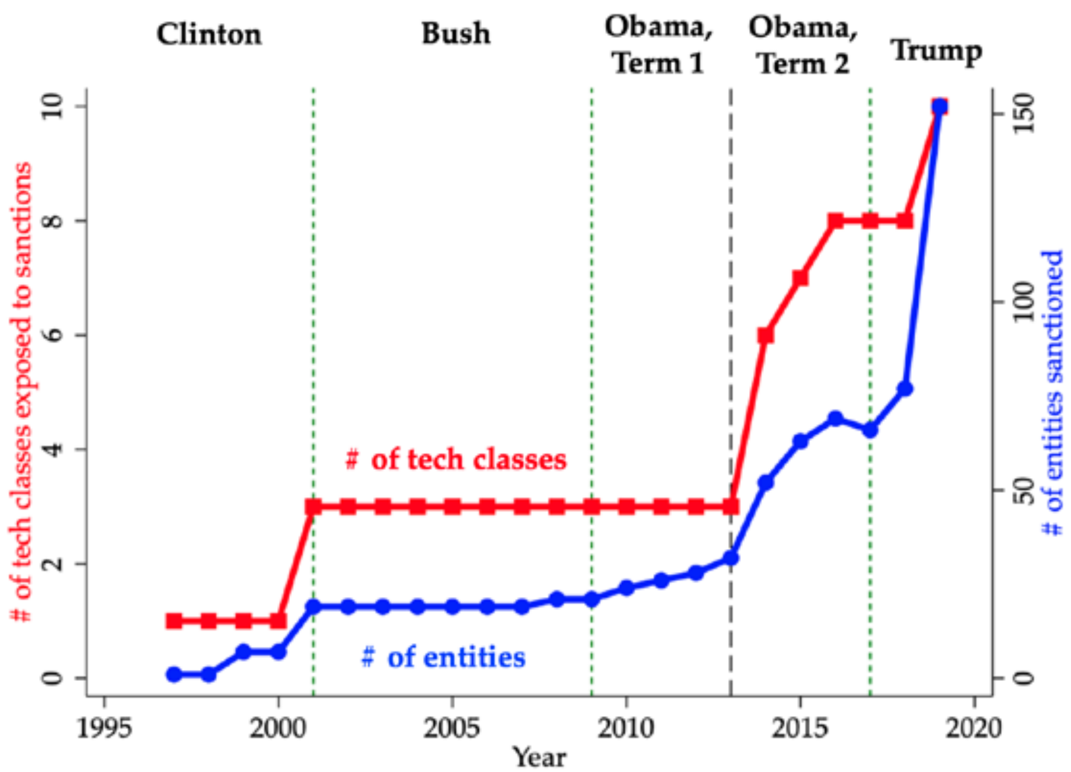


Table 1: Technology Decoupling and Dependence, Panel VAR

This table reports estimation results from the following panel VAR model:

$$y_{i,t} = y_{i,t-1}B_1 + y_{i,t-2}B_2 + \cdots + y_{i,t-p}B_p + \gamma_i + \epsilon_{i,t},$$

where $y_{i,t}$ is a (1×2) vector of dependent variables (i.e., technology decoupling and dependence as defined in Table A1). In columns (1) and (2), both the decoupling and dependence measures are in their original scale. In columns (3) and (4), the variable "dependence" is residualized against "decoupling." γ_i is a (1×2) vector of technology-class-specific panel fixed effect and $\epsilon_{i,t}$ is a (1×2) vector of the error terms. $B_1, B_2, \cdots, B_p$ are (2×2) matrices to be estimated and we assume they are common across all technology classes. We make the following assumptions about the innovations: $\mathbb{E}(\epsilon_{i,t}) = \mathbf{0}$, $\mathbb{E}(\epsilon'_{i,t}\epsilon_{i,t}) = \Sigma$, and $\mathbb{E}(\epsilon'_{i,t}\epsilon_{i,s}) = \mathbf{0}$ for all $t > s$. The panel fixed effects are removed by forward orthogonal deviation transformation proposed by Arellano and Bover (1995). Standard errors are reported in the parentheses. *** denotes significance at the one percent level, ** at the five percent level, and * at the 10 percent level.

	Decoupling	*Dependence*	*Decoupling*	*Dependence*
	(1)	(2)	(3)	(4)
Decoupling, $t-1$	0.724***	0.286	0.863***	0.564
	(0.214)	(0.471)	(0.287)	(0.693)
Decoupling, $t-2$	0.488***	0.708***	0.466***	0.730**
	(0.114)	(0.261)	(0.118)	(0.292)
Dependence, $t-1$	-0.158**	0.336*	-0.189*	0.239
	(0.0788)	(0.179)	(0.0966)	(0.238)
Dependence, $t-2$	0.155***	0.502***	0.153***	0.545***
	(0.0472)	(0.111)	(0.0476)	(0.123)
Observations	1,055	1,055	1,055	1,055
Residualization	No	No	Dependence	Dependence

Table 2: 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 one percent level, ** at the five percent level, and * at the 10 percent level.

	Innovation Output	*Innovation Quality*	*TFP*	*1/Q*
	(1)	(2)	(3)	(4)
Decoupling, $t-1$	1.906***	0.558	0.0992	0.0403
	(0.566)	(0.655)	(0.140)	(0.0966)
Decoupling, $t-2/3$	0.911	0.852	-0.306*	0.404***
	(0.668)	(0.753)	(0.177)	(0.125)
Assets	0.0647***	-0.0204	-0.0144**	0.124***
	(0.0177)	(0.0189)	(0.00574)	(0.00358)
Age	-0.0739	0.0904	0.0358	-0.0109
	(0.0828)	(0.0804)	(0.0219)	(0.0152)
Capex	-0.0597	0.255	-0.341***	-0.00793
	(0.157)	(0.209)	(0.0447)	(0.0279)
PP&E	-0.183**	0.00552	0.115***	0.0480***
	(0.0834)	(0.101)	(0.0261)	(0.0166)
Leverage	-0.00319	-0.158**	0.0173	-0.0471***
	(0.0607)	(0.0730)	(0.0207)	(0.0128)
R&D	-0.196	-0.122	-0.610***	-0.160***
	(0.301)	(0.358)	(0.0885)	(0.0535)
Subsidy	0.287	-0.123	-0.568***	0.110***
	(0.218)	(0.280)	(0.0704)	(0.0420)
Observations	15,594	15,594	15,594	15,594
Adjusted R-squared	0.607	0.189	0.651	0.810
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Table 3: 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 one percent level, ** at the five percent level, and * at the 10 percent level.

	Innovation Output	*Innovation Quality*	*TFP*	$1/Q$
	(1)	(2)	(3)	(4)
Decoupling, $t-1$	0.080	-1.176	-0.258	-0.212
	(0.574)	(0.738)	(0.238)	(0.159)
Decoupling, $t-2/3$	0.016	-0.338	-0.112	0.222**
	(0.310)	(0.459)	(0.131)	(0.097)
Assets	0.119***	-0.042	-0.015	0.087***
	(0.017)	(0.026)	(0.013)	(0.006)
Age	-0.025	-0.168***	0.010	0.054***
	(0.043)	(0.060)	(0.025)	(0.014)
Capex	0.434*	0.137	-0.184	-0.345**
	(0.235)	(0.269)	(0.213)	(0.164)
PP&E	0.201	-0.121	0.249***	0.257***
	(0.134)	(0.169)	(0.089)	(0.055)
Leverage	-0.185***	-0.068	0.138***	-0.058***
	(0.045)	(0.067)	(0.039)	(0.015)
R&D	0.000	-0.003	-0.022***	-0.001*
	(0.001)	(0.002)	(0.002)	(0.001)
Observations	14461	14461	14461	14461
Adjusted R-squared	0.85	0.34	0.80	0.66
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

TABLE 4: 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 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. The dependent variable is U.S.-China technology decoupling in column (1), China's technological dependence on the U.S. in column (2), and dependence measure residualized against the decoupling measure in column (3). 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 one percent level, ** at the five percent level, and * at the 10 percent level.

	Decoupling	*Dependence*	*Dependence, Residualized*
	(1)	(2)	(3)
SEI × Post	-0.0130***	-0.0190**	-0.0286***
	(0.00389)	(0.00899)	(0.00806)
ln(Patents granted in China)	0.0179***	-0.0396***	-0.0264***
	(0.00411)	(0.00902)	(0.00878)
ln(Patents granted in the U.S.)	-0.0157*	0.0860***	0.0743***
	(0.00833)	(0.0149)	(0.0182)
Observations	1,370	1,370	1,370
Adjusted R-squared	0.732	0.818	0.756
Technology class fixed effect	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes

Table 5: 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:

$$y_{i,j,t} = \beta_1 \times SEI_j \times Post_t \times High\ Subsidy_{i,j} + \beta_2 \times SEI_j \times Post_t + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t}$$

The regression is at the firm (i)-year(t) level but each firm is also indexed by technology class (j) so that it could be matched to its primary technology class. SEI_j equals one if technology class j is promoted as an SEI and zero otherwise. $Post_t$ takes the value of one after 2012 and zero otherwise. Within the SEI-promoted technology sectors, "$High\ Subsidy_{i,j}$" equals one if the subsidy-to-sales ratio of firm i is above the sample median. 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 one percent level, ** at the five percent level, and * at the 10 percent level.

	Innovation Output		*Innovation Quality*		*TFP*		$1/Q$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SEI × Post	-0.122	-0.665***	-0.180**	-0.496***	0.00738	0.119***	0.00928	-0.130***
	(0.101)	(0.0714)	(0.0917)	(0.0699)	(0.0333)	(0.0202)	(0.0247)	(0.0142)
SEI × Post × 1{High Subsidy}		-0.117***		-0.0404		0.0520***		-0.0303***
		(0.0243)		(0.0290)		(0.00627)		(0.00434)
Assets	0.0831***	0.103***	-0.0117	0.00314	-0.0133**	-0.0152***	0.130***	0.133***
	(0.0168)	(0.0176)	(0.0178)	(0.0185)	(0.00547)	(0.00567)	(0.00347)	(0.00366)
Age	-0.0183	0.0196	0.0540	0.0416	0.0311	0.0206	-0.00567	-0.00311
	(0.0778)	(0.0784)	(0.0789)	(0.0797)	(0.0208)	(0.0209)	(0.0147)	(0.0149)
Capex	-0.0690	-0.0490	0.231	0.194	-0.347***	-0.351***	-0.0259	-0.0514*
	(0.150)	(0.163)	(0.196)	(0.210)	(0.0439)	(0.0479)	(0.0272)	(0.0299)
PP&E	-0.139*	-0.176**	0.0247	-0.0355	0.120***	0.117***	0.0572***	0.0585***
	(0.0789)	(0.0826)	(0.0947)	(0.0978)	(0.0250)	(0.0258)	(0.0162)	(0.0171)
Leverage	-0.0306	-0.0352	-0.134*	-0.0738	0.0100	-0.00355	-0.0576***	-0.0552***
	(0.0577)	(0.0607)	(0.0700)	(0.0724)	(0.0200)	(0.0208)	(0.0125)	(0.0133)
R&D	-0.0415	-0.0595	-0.203	-0.362	-0.688***	-0.716***	-0.188***	-0.196***
	(0.292)	(0.306)	(0.343)	(0.359)	(0.0861)	(0.0898)	(0.0531)	(0.0566)
Observations	16,310	13,569	16,310	13,569	16,310	13,569	16,310	13,569
Adjusted R-squared	0.603	0.613	0.190	0.197	0.642	0.641	0.803	0.797
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: U.S. Sanctions and Technology Decoupling

This table reports estimation results from the following regression relating U.S. sanctions against Chinese entities and technology decoupling/dependence covering the period of 2007–2019:

$$y_{j,t} = \beta_1 \times \textit{Post Sanction}_{j,t} + \beta_2 \times \textit{Post Sanction}_{j,t} \times \textit{Escalation Period}_t + \delta' X_{j,t-1} + \gamma_j + \gamma_t + \epsilon_{i,t}$$

The dependent variable features technology decoupling and dependence that are defined in Table A1. *Post Sanction*$_{j,t}$ is equal to one if technology class j had been exposed to U.S. sanctions prior to year t and zero otherwise. *Escalation Period*$_t$ takes the value of one after 2013 and zero otherwise. Odd-numbered columns of the table omit *Post Sanction*$_{i,t}$ $\times$ *Escalation Period*$_t$ while the even-numbered columns report the full regression. 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 one percent level, ** at the five percent level, and * at the 10 percent level.

	Decoupling		*Dependence*		*Dependence, Residualized*	
	(1)	(2)	(3)	(4)	(5)	(6)
Post Sanction	-0.0156***	-0.0162***	-0.00516	0.00881	-0.0167*	-0.00317
	(0.00347)	(0.00397)	(0.00852)	(0.00964)	(0.00988)	(0.0102)
Post Sanction $\times$ *Escalation Period*		0.000574		-0.0145**		-0.0141**
		(0.00306)		(0.00652)		(0.00610)
ln(Patents granted in China)	0.0161***	0.0161***	-0.0412***	-0.0416***	-0.0293***	-0.0296***
	(0.00412)	(0.00413)	(0.00896)	(0.00899)	(0.00880)	(0.00884)
ln(Patents granted in the U.S.)	-0.0125	-0.0126	0.0889***	0.0904***	0.0797***	0.0811***
	(0.00821)	(0.00838)	(0.0152)	(0.0156)	(0.0182)	(0.0187)
Observations	1,370	1,370	1,370	1,370	1,370	1,370
Adjusted R-squared	0.731	0.731	0.817	0.817	0.754	0.755
Technology class fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: U.S. Sanctions and Performance of Chinese Firms

This table reports estimation results from regressions relating U.S. sanctions and the performance of Chinese firms covering the period of 2007–2019:

$$y_{i,j,t} = \beta_1 \times \textit{Post Sanction}_{j,t} + \beta_2 \times \textit{Post Sanction}_{j,t} \times \textit{Escalation Period}_t + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t}$$

The regression is at the firm (i)-year(t) level but each firm is also indexed by technology class (j) so that it could be matched to its primary technology class. *Post Sanction*$_{j,t}$ is equal to one if technology class j had been exposed to U.S. sanctions prior to year t and zero otherwise. *Escalation Period*$_t$ takes the value of one after 2013 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 one percent level, ** at the five percent level, and * at the 10 percent level.

	Innovation Output		*Innovation Quality*		*TFP*		*1/Q*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post Sanction	-0.0867**	-0.0774*	-0.00167	0.0286	-0.0178*	-0.0237**	0.00159	0.0160**
	(0.0388)	(0.0469)	(0.0442)	(0.0537)	(0.00942)	(0.0116)	(0.00639)	(0.00771)
Post Sanction × Escalation Period		-0.0113		-0.0367		0.00716		-0.0174***
		(0.0315)		(0.0368)		(0.00818)		(0.00531)
Assets	0.0828***	0.0830***	-0.0118	-0.0112	-0.0138**	-0.0139**	0.130***	0.130***
	(0.0168)	(0.0168)	(0.0178)	(0.0178)	(0.00544)	(0.00545)	(0.00347)	(0.00347)
Age	-0.0166	-0.0146	0.0545	0.0610	0.0270	0.0257	-0.00516	-0.00204
	(0.0778)	(0.0779)	(0.0789)	(0.0790)	(0.0207)	(0.0208)	(0.0147)	(0.0147)
Capex	-0.0711	-0.0695	0.231	0.237	-0.337***	-0.338***	-0.0273	-0.0248
	(0.150)	(0.150)	(0.196)	(0.196)	(0.0438)	(0.0438)	(0.0272)	(0.0272)
PP&E	-0.141*	-0.141*	0.0222	0.0227	0.121***	0.121***	0.0572***	0.0575***
	(0.0789)	(0.0789)	(0.0946)	(0.0946)	(0.0249)	(0.0249)	(0.0162)	(0.0162)
Leverage	-0.0253	-0.0248	-0.132*	-0.131*	0.0112	0.0109	-0.0578***	-0.0571***
	(0.0577)	(0.0577)	(0.0701)	(0.0700)	(0.0199)	(0.0199)	(0.0125)	(0.0125)
R&D	-0.0832	-0.0751	-0.196	-0.170	-0.581***	-0.586***	-0.203***	-0.190***
	(0.294)	(0.294)	(0.347)	(0.347)	(0.0856)	(0.0858)	(0.0533)	(0.0532)
Subsidy	0.219	0.218	-0.0487	-0.0519	-0.589***	-0.588***	0.0813*	0.0798*
	(0.213)	(0.213)	(0.269)	(0.269)	(0.0698)	(0.0698)	(0.0420)	(0.0420)
Observations	16,310	16,310	16,310	16,310	16,310	16,310	16,310	16,310
Adjusted R-squared	0.603	0.603	0.190	0.190	0.645	0.645	0.803	0.804
Firm fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	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).

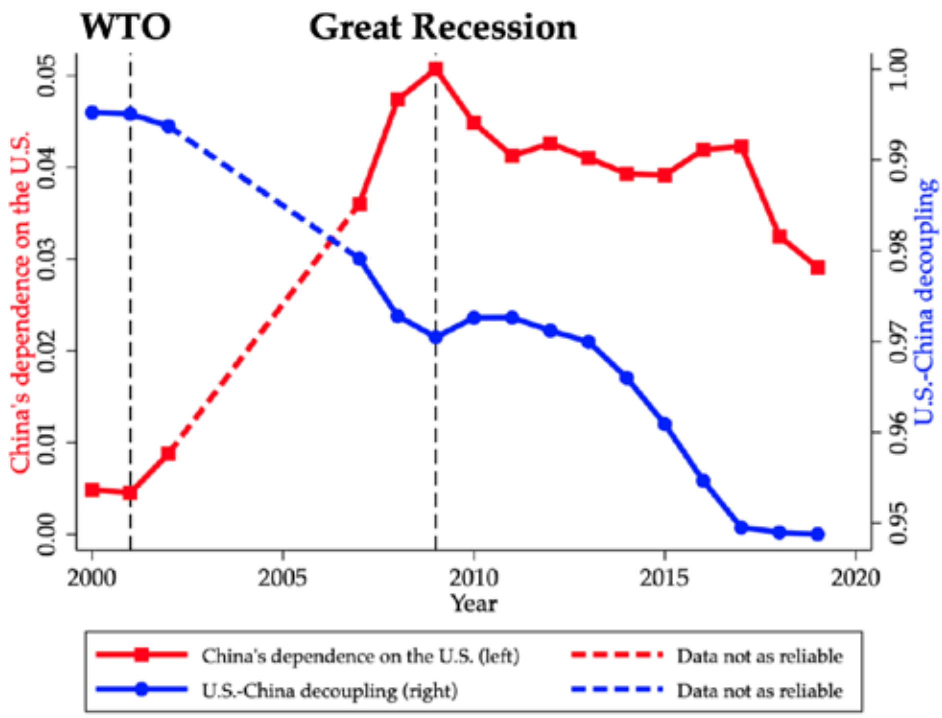


Figure A2: **U.S.-China technology decoupling based on renewed patents**

The sensitivity analysis in this figure targets the concern that a substantial number of Chinese patents are of low quality, are not expected to generate impact, and could thus dilute citation-based measures. In this figure, we restrict 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).

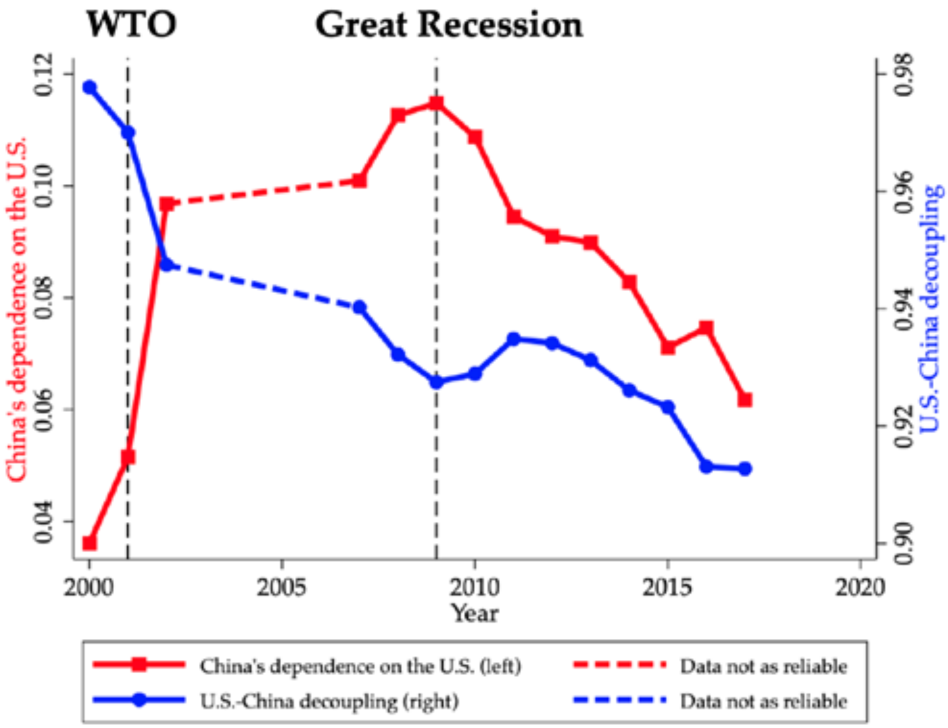


Figure A3: **Technology dependence and Chinese patent share**

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.

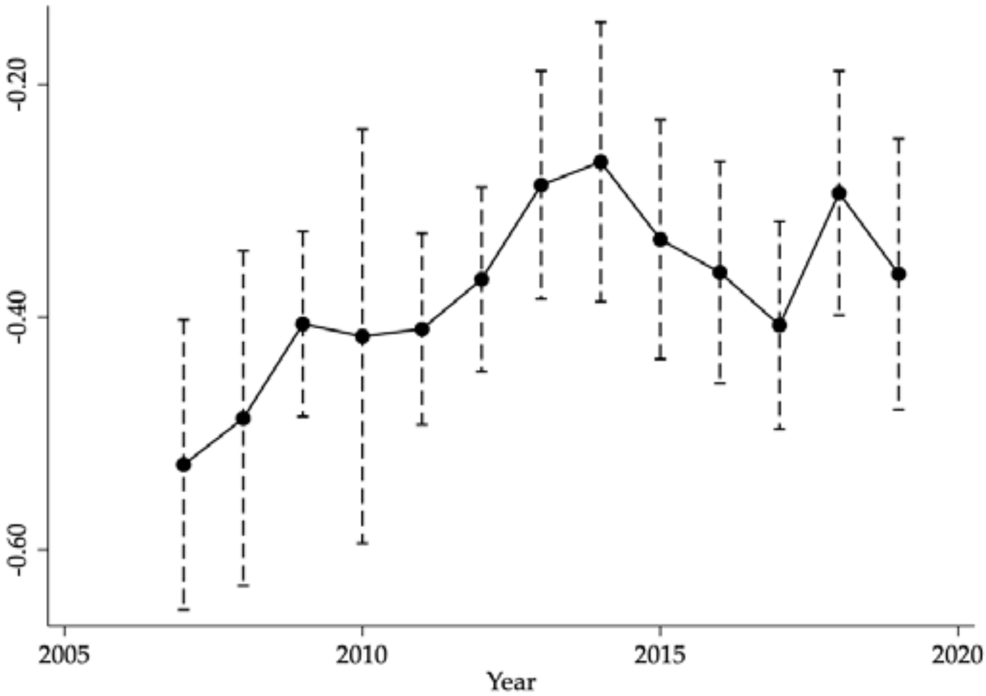


Table A1: Variable Definition

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 has received by 2019, divided by the average number 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, Caves, and Frazer (2015)
$1/Q$	The ratio of the sum of the book value of debt and equity to the sum of the market value of equity and book value of debt
Assets	The natural logarithm of the book value of total assets
Age	The natural logarithm of one plus age since founding (IPO) for Chinese (U.S.) firms
R&D	R&D expenditures divided by sales; missing values are imputed zero
Capex	Capital expenditures divided by book value of total assets
PP&E	Net value of property, plant, and equipment divided by book value of total assets
Leverage	Book value of total debt divided by book value of total assets
Subsidy	The amount of government subsidies divided by sales

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. 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	0.0309	0.896	0.924	0.942	16,310
Innovation Output (number of patents)	3.855	10.27	0	0	2.500	16,310
Innovation Quality	0.426	0.881	0	0	0.526	16,310
Assets (billion RMB)	10.74	28.22	1.396	2.859	7.005	16,310
Age (number of years)	14.58	5.435	11	14	18	16,310
R&D	0.0371	0.0417	0.00228	0.0316	0.0487	16,310
Capex	0.0577	0.0495	0.0212	0.0435	0.0792	16,310
PP&E	0.230	0.153	0.112	0.198	0.319	16,310
Leverage	0.408	0.206	0.242	0.398	0.561	16,310
Subsidy	0.0273	0.0383	0.00538	0.0138	0.0316	16,310
$1/Q$	0.538	0.262	0.328	0.501	0.722	16,310
TFP	0.136	0.288	-0.0444	0.124	0.307	16,310

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. All potentially unbounded variables are winsorized at the 1^{st} and 99^{th} percentiles.

	Mean	Standard Deviation	p25	Median	p75	Observations
Decoupling	.916	.0304	.895	.918	.937	19833
Innovation Output (number of patents)	30.1	106	0	1	10	19918
Innovation Quality	.579	1.19	0	0	.69	19918
Assets (billion USD)	9.21	24.6	.133	.718	4.64	19918
Age (number of years)	22.3	19.3	9	17	30	19918
R&D	1.29	6.56	.00693	.0543	.181	19320
Capex	.0377	.0417	.0129	.0258	.0487	19898
PP&E	.19	.19	.0545	.123	.259	19916
Leverage	.211	.236	.00369	.161	.318	19791
$1/Q$	.556	.354	.291	.489	.748	19918
TFP	2.17	1.2	1.57	2.2	2.65	19118

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.[57] 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–IA14.

[Insert Figure IA4–IA14 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 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

[57]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.

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 IA18. 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 IA18 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 IA18 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.

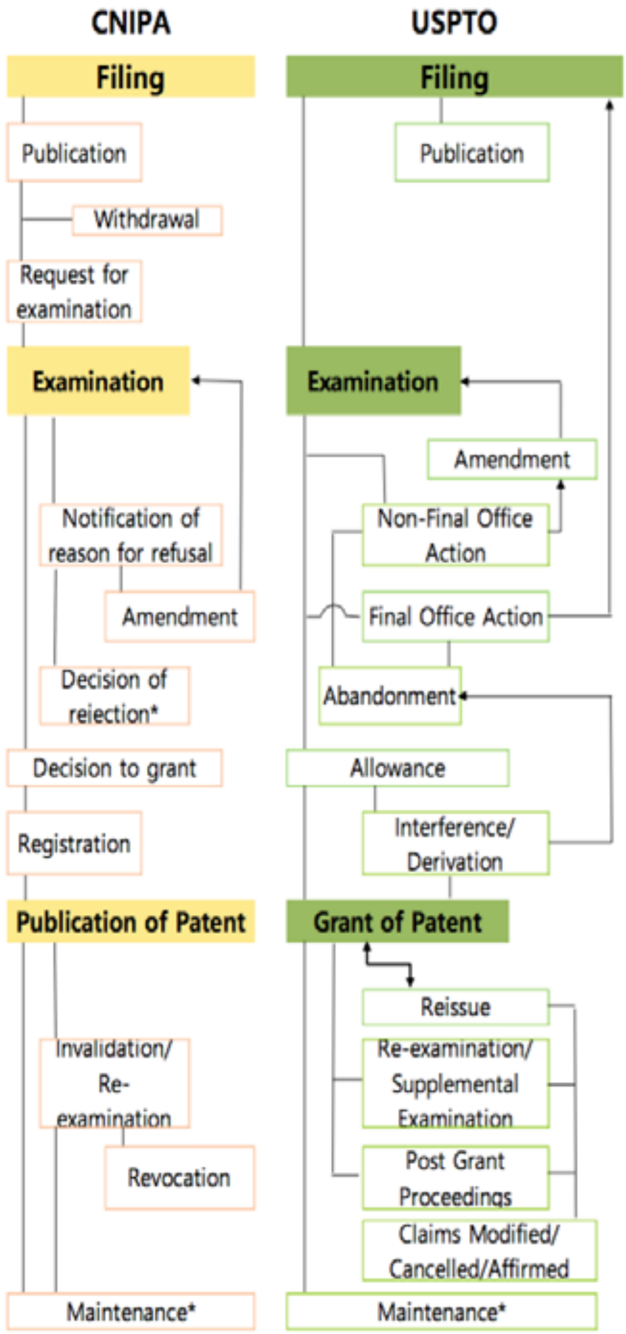
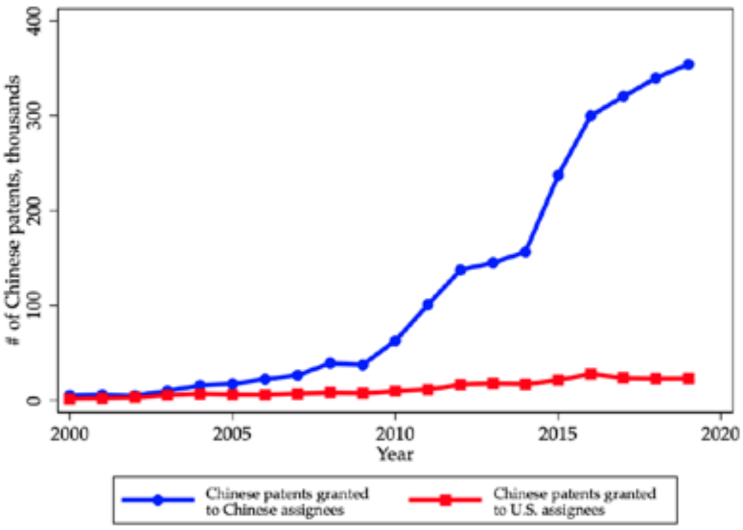
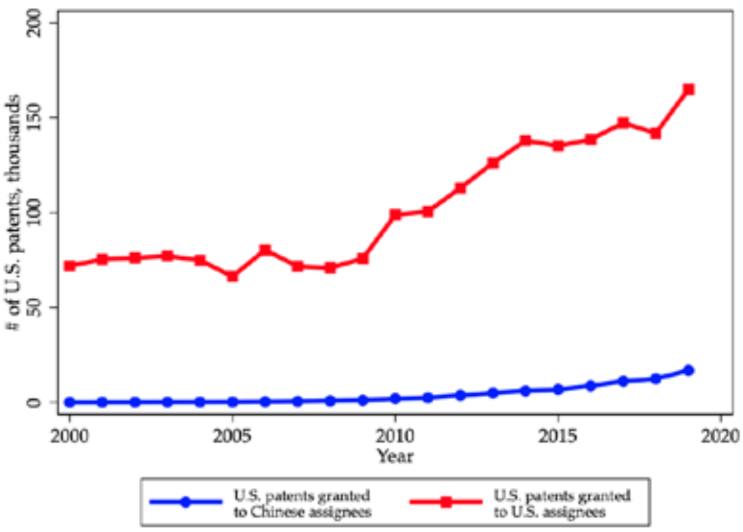


FIGURE IA2: **Patents granted, Chinese vs U.S. assignees**

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:

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

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.

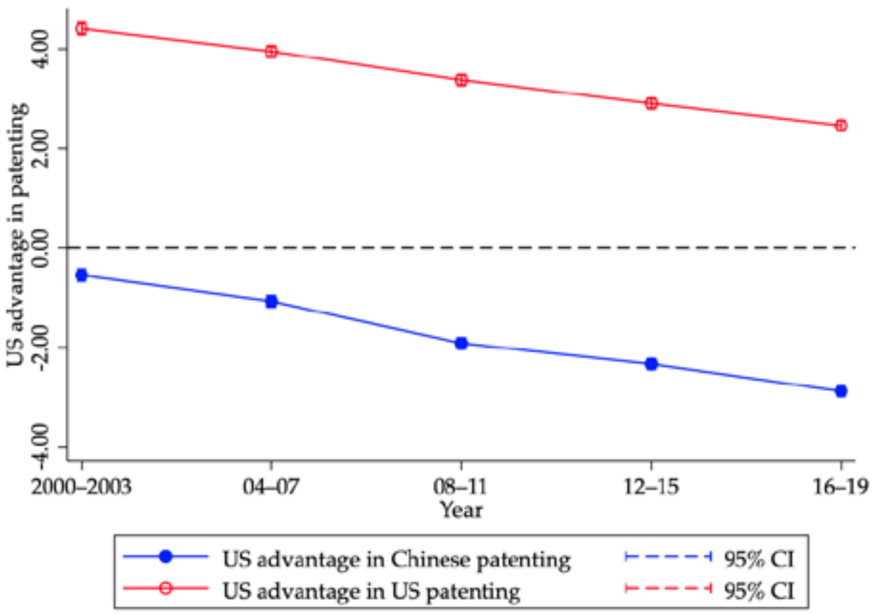


FIGURE IA4: **U.S. advantage in patenting, tech class heterogeneity**

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).

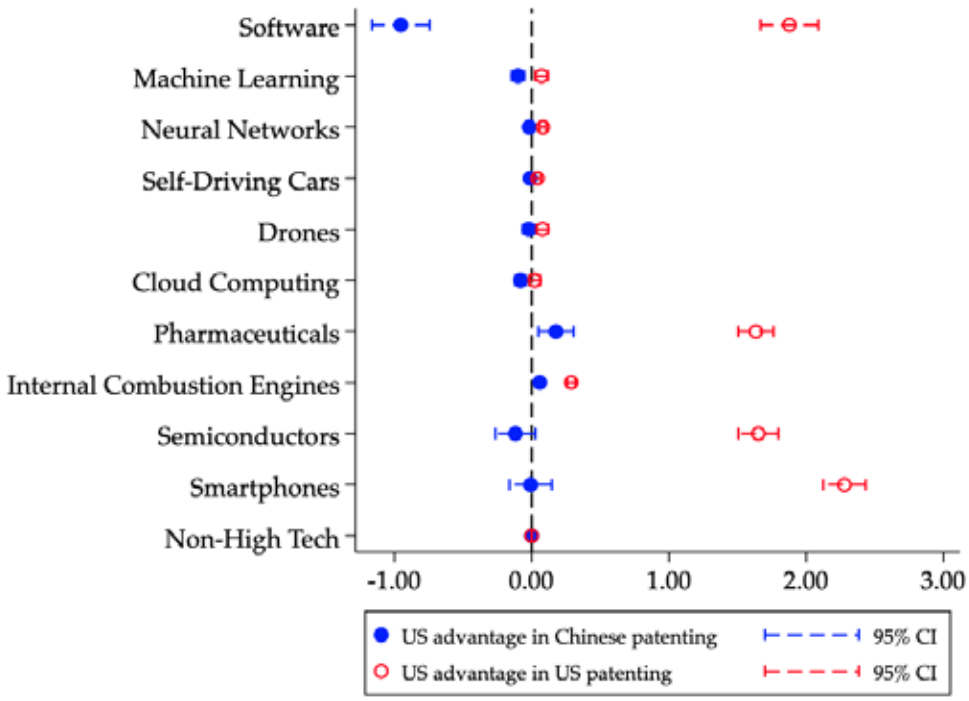


Figure IA5: **U.S. patenting advantage, software**

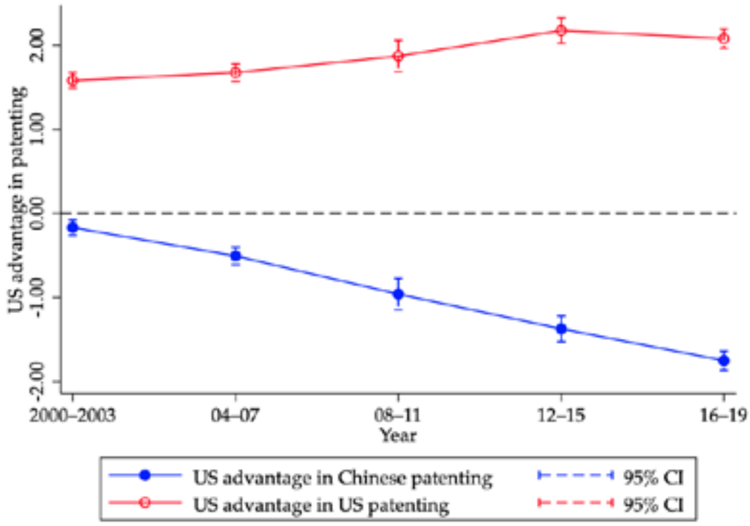


Figure IA6: **U.S. patenting advantage, machine learning**

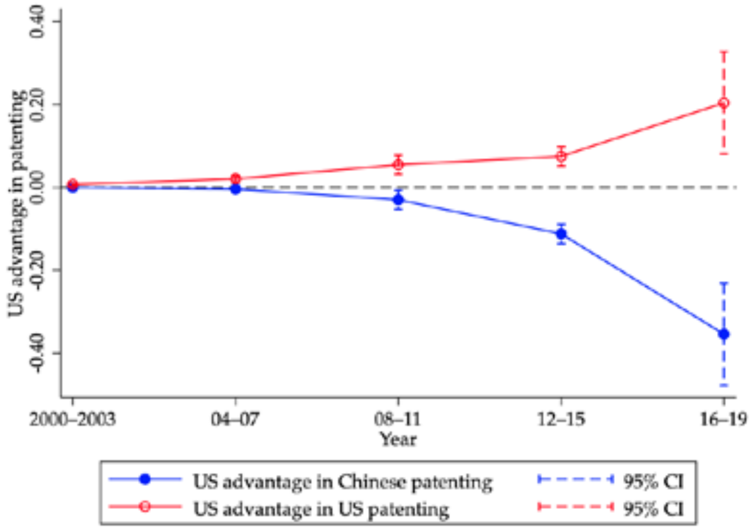


Figure IA7: **U.S. patenting advantage, neural networks**

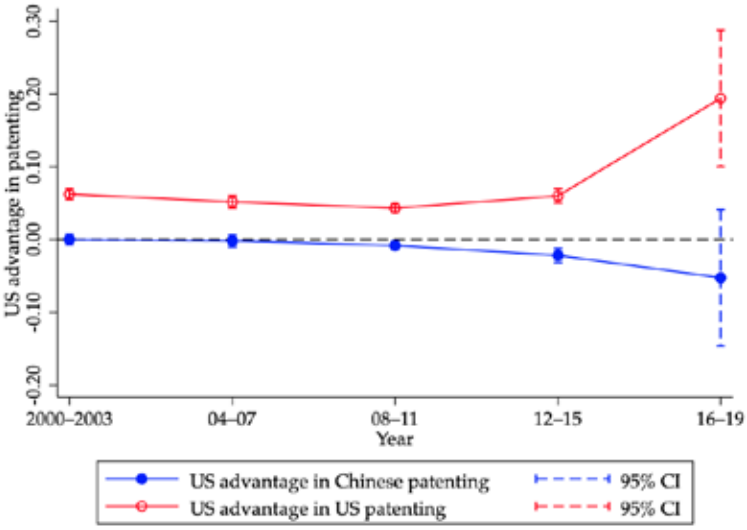


Figure IA8: **U.S. patenting advantage, self-driving cars**

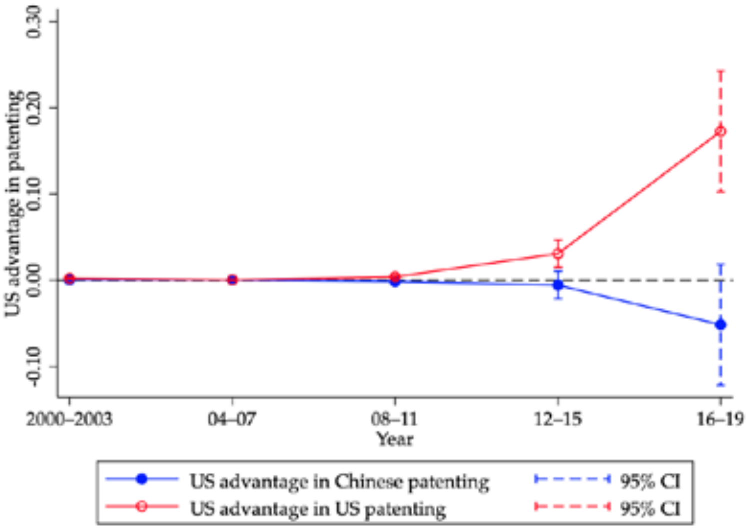


FIGURE IA9: **U.S. patenting advantage, drones**

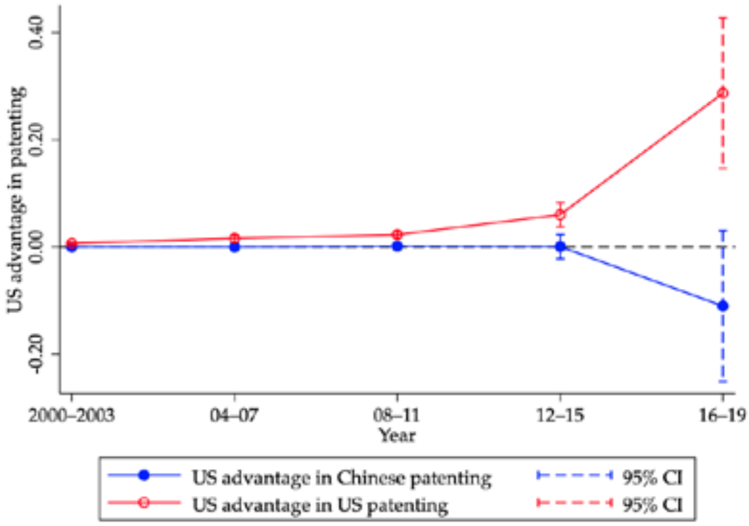


FIGURE IA10: **U.S. patenting advantage, cloud computing**

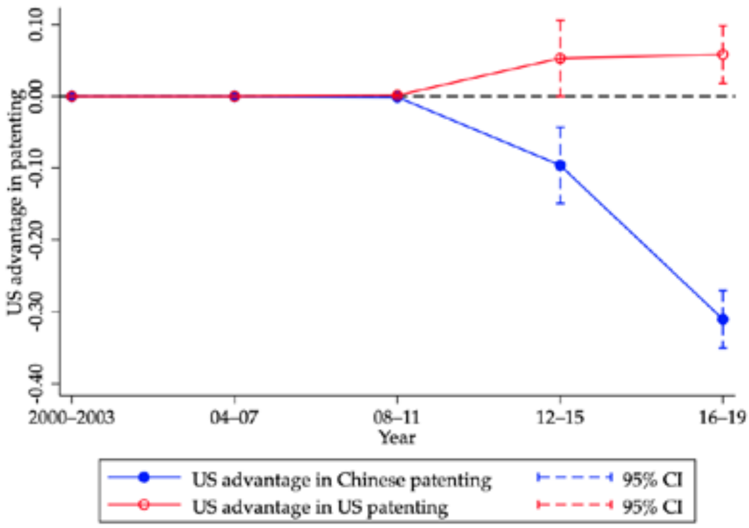


Figure IA11: **U.S. patenting advantage, pharmaceuticals**

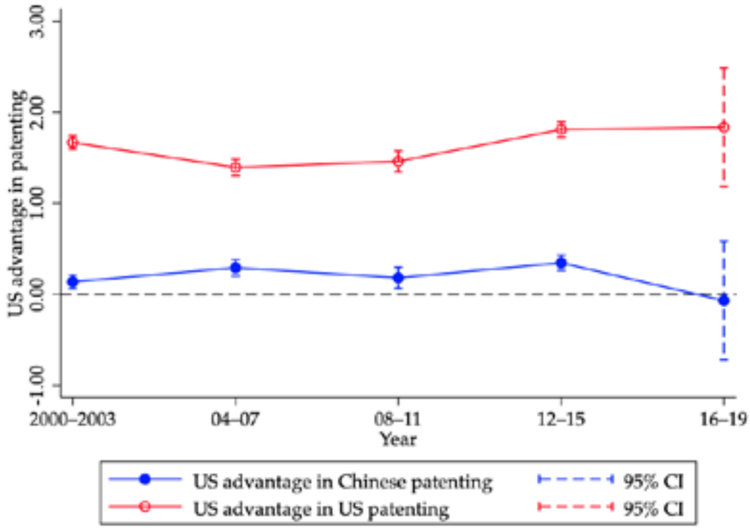


Figure IA12: **U.S. patenting advantage, internal combustion engines**

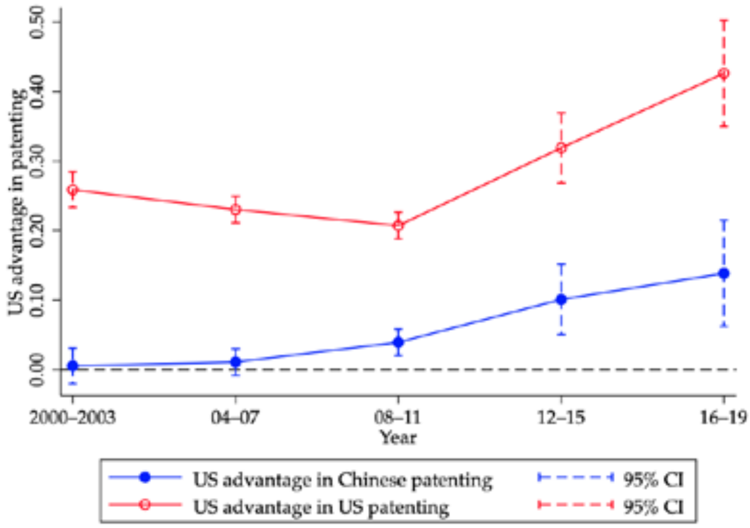


Figure IA13: **U.S. patenting advantage, semiconductors**

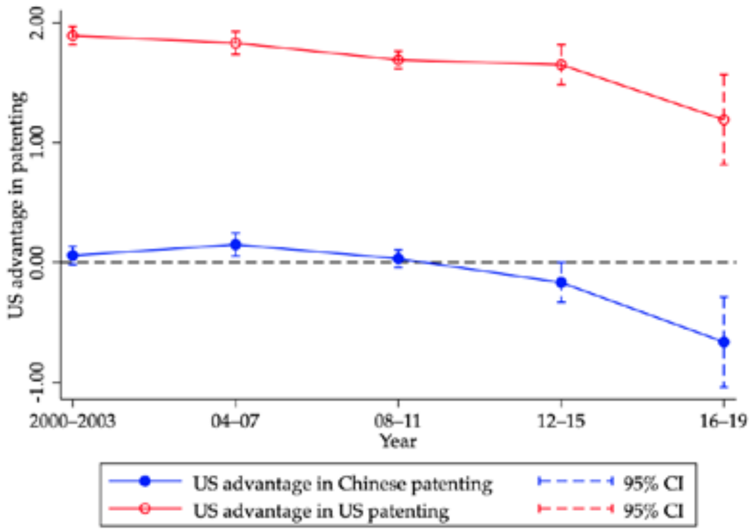


Figure IA14: **U.S. patenting advantage, smartphones**

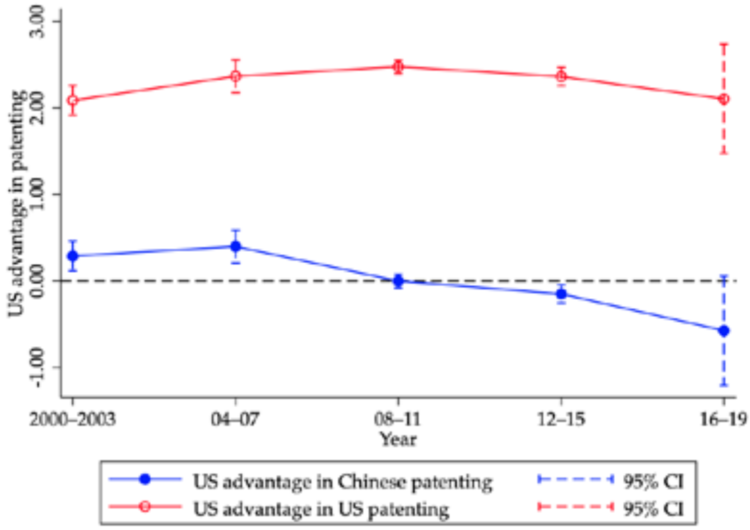


Figure IA15: **External validity checks with academic journals**

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.

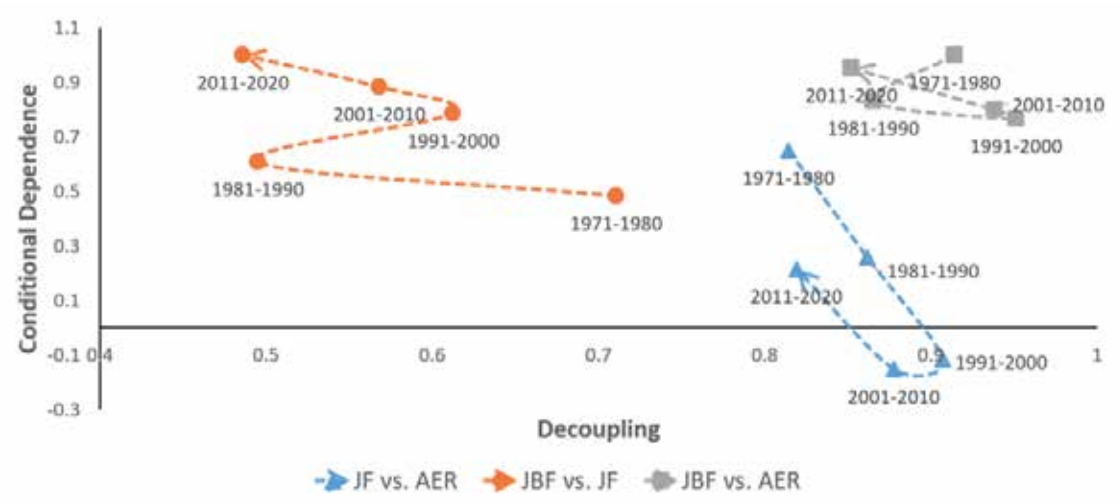


Figure IA16: **U.S.-China technology decoupling, SOEs vs private firms**

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.

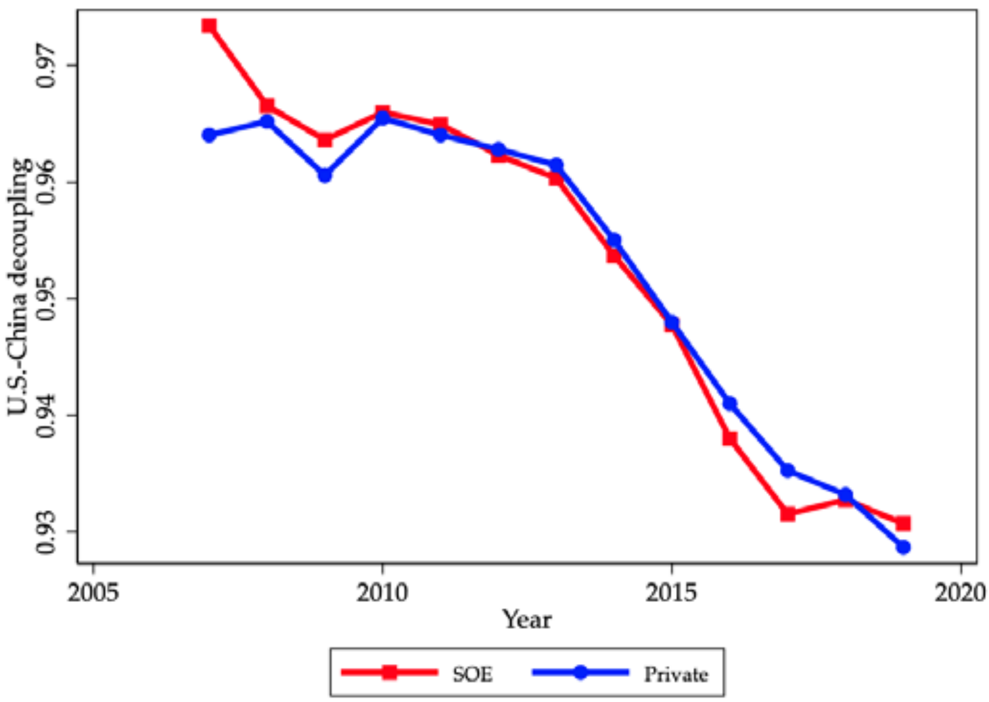
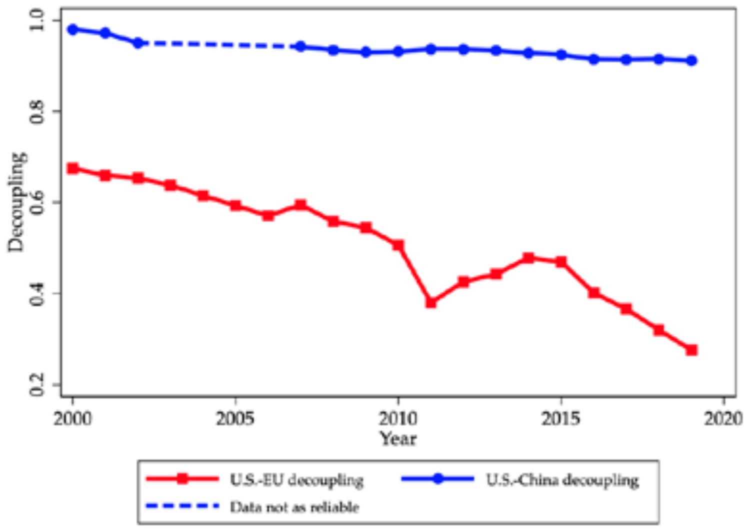
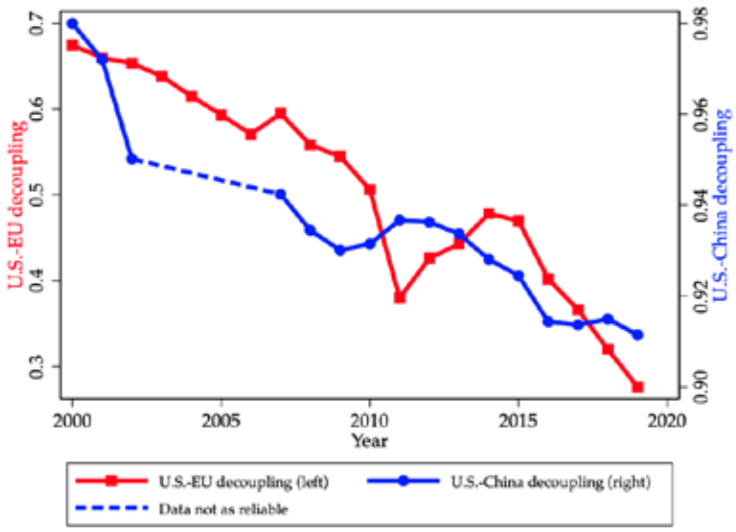


Figure IA17: **Technology decoupling, U.S.-China vs U.S.-EU**

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 IA17a and they are plotted on two separate axes in panel IA17b.



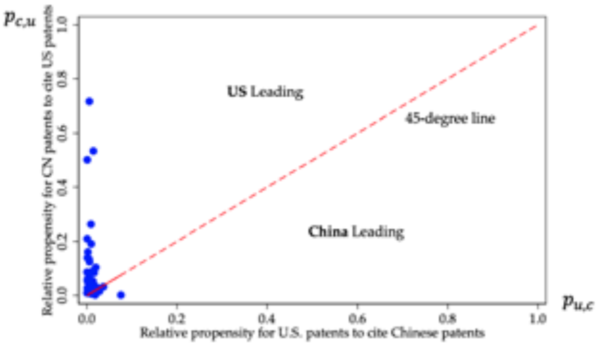
(a) Decoupling comparison on one common axis



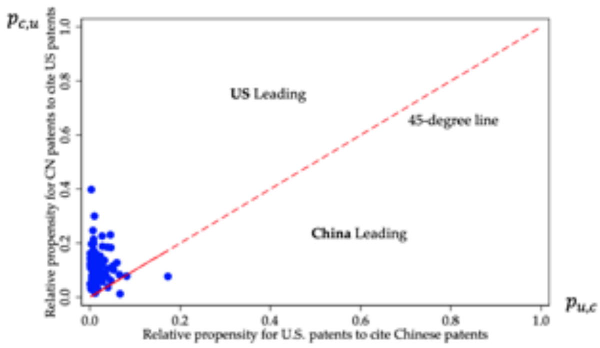
(b) Decoupling comparison on two separate axes

Figure IA18: **Propensity to cite foreign patents relative to citing domestic patents**

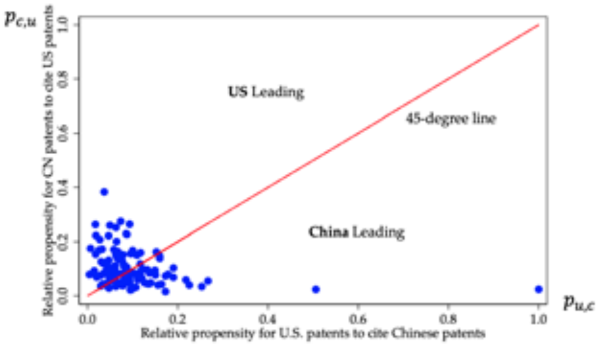
In this figure, we plot $p_{c,u}$ against $p_{u,c}$ for each technology class at three-digit IPC codes. In each figure, the vertical axis ($p_{c,u}$) is a proxy of the propensity for Chinese patents to cite a U.S. patent relative to citing a Chinese one. The horizontal axis ($p_{u,c}$) is a proxy of 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



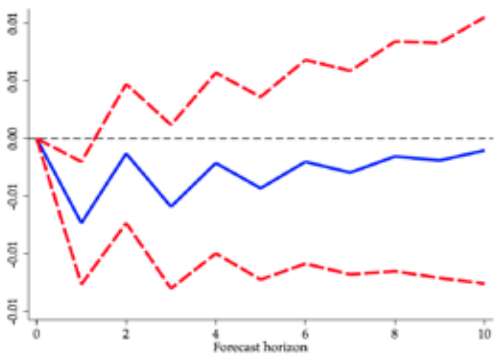
(B) 2009



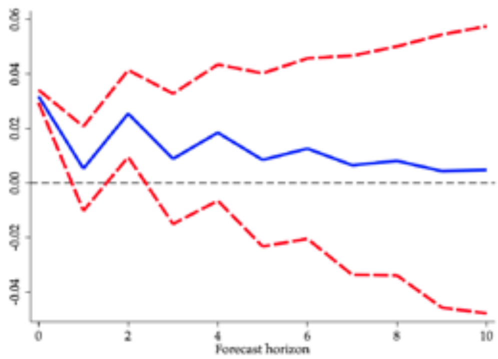
(C) 2019

Figure IA19: **Technology decoupling and dependence, impulse response functions**

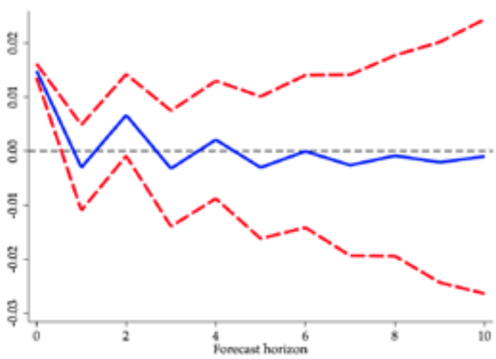
To visualize the dynamic interactions between technology decoupling and dependence, we plot the results of the impulse-response functions (IRF) in this figure. All sub-figures are orthogonalized IRF results based on Cholesky decomposition. To address the concern for concurrent correlation between these two measures, the IRF analysis is based on the residualized measure of technology decoupling and dependence. The exogenous shock is the innovation of decoupling in Figure IA19a and IA19b, and the exogenous shock is the innovation of dependence in Figure IA19c and IA19d. We evaluate how China's technological dependence on the U.S. affects U.S.-China decoupling in Figure IA19a and IA19c, and we assess how U.S.-China decoupling affects China's technological dependence on the U.S. in Figure IA19b and IA19d.



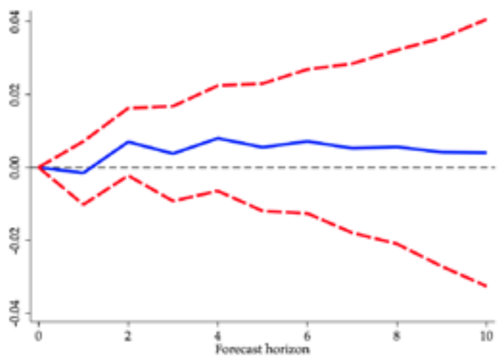
(a) Effect of Dependence On Decoupling
Shock: Innovation of Decoupling



(b) Effect of Decoupling On Dependence
Shock: Innovation of Decoupling



(c) Effect of Dependence On Decoupling
Shock: Innovation of Dependence



(d) Effect of Decoupling On Dependence
Shock: Innovation of Dependence

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

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

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

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. 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.

	ln(# of Patents + 1)					
	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: Technology Decoupling and Dependence, OLS

The regressions in this table are based on panel data at the three digit IPC-year level and the sample period is 2007-2019. All regressions in this table are based on OLS models. We incorporate technology class fixed effects and year fixed effects in all regressions. The dependent variables in regression (1)-(3) are our measure of U.S.-China technology decoupling. The dependent variables in regression (4)-(6) are our measure of China's technological dependence on the U.S. 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)	(3)	(4)	(5)	(6)
Dependence, $t-1$	-0.0822	-0.130*	-0.0968*			
	(0.0576)	(0.0753)	(0.0573)			
Dependence, $t-2$		0.0625	0.129**			
		(0.0526)	(0.0563)			
Dependence, $t-3$			-0.0447			
			(0.0384)			
Decoupling, $t-1$				-0.321	-0.548	-0.398
				(0.262)	(0.340)	(0.255)
Decoupling, $t-2$					0.247	0.592**
					(0.240)	(0.255)
Decoupling, $t-3$						-0.273*
						(0.145)
Observations	1,309	1,176	1,055	1,309	1,176	1,055
Adjusted R-squared	0.676	0.722	0.718	0.746	0.786	0.794
Technology class fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes