Mapping US-China Technology Decoupling, Innovation, and Firm Performance*

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First Draft: December 2020; This Draft: February 2021

Abstract

Based on the combined patent data from the U.S. and China, we quantify the technology decoupling and dependence between the two countries. The first two decades of the 21st century witnessed a continuing increase in technology integration (or less decoupling), but China's technology dependence on the U.S. increases (decreases) during the first (second) decade. A panel VAR analysis suggests that a higher level of decoupling in a given technology field predicts more dependence of China on the U.S., which in turn predicts less decoupling. Decoupling is associated with more patent outputs in the given sector in both countries, lower firm productivity and valuation in China, but no significant impact on U.S. firms. Finally, China's innovation-oriented industrial policies are associated with both more integration with and less dependence on U.S. technology down the road, trading off the inherent conflict between the two main policy objectives of promoting indigenous innovation versus enhancing firm competitiveness.

Keywords: Technology Decoupling, International Economic Order and Integration, Innovation, R&D, Patent, Industrial Policy
JEL Classification Numbers: O31, O33, F02, O25

*We are grateful to Ufuk Akcigit, Joao Gomes, Jeremy Greenwood, Bronwyn Hall, Zhiguo He, Peter Klenow, Josh Lerner, Yao Lu, David Robinson, Mike (Zheng) Song, Fabrizio Zilibotti, and participants of Guanghua International Symposium on Finance and Tsinghua-CUHK joint macro workshop and CKGSB finance seminar for helpful comments and suggestions.

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1 Introduction

Over the past two decades, China emerged as a global technology power, building on its economic miracle fueled by investment and production since its "open-door" policy started in 1978. While the U.S. share of world 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.[1] After ending a 110-year-long US lead to become the top manufacturing nation in 2010, China made to another milestone in 2019 to file the largest number of international patent applications at the World Intellectual Property Organization.

China's technological progress benefited from its integration with the developed world, especially the United States. Science and technology are naturally more fluid at national borders than other production factors. Internet protocols, hardware design and manufacturing, software development and deployment, and IT services and standards have been, to varying degrees, evolved in a global system. The last few years, however, have seen a rise in mutual distrust and actions to unwind from 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 empirical study mapping out the current state and dynamics of competition and decoupling in technology between the two countries, as well as the motives and impact of recent policies that directly or indirectly aim at decoupling.

In this study, we develop novel measures to assess the degree of US-China technology decoupling (or integration) over time and its intricate relation with China's technology dependence on the U.S. We then assess the economic outcomes at the technology field level and at the firm level. Our study builds on the patent data obtained from the United States Patent and Trademark Office (USPTO) and the Chinese National Intellectual Property Administration (CNIPA). Merging the two databases at the technology class (by the three-digit codes of the International Patent Classification (IPC) system) and year level, we first provide an overview of the competitive landscape. While the United States still maintain an overall advantage in innovation, China has been rapidly

[1] R&D expenditures of both China and the United States are measured in constant 2005 PPP dollars. The source of data is the Educational, Scientific, and Cultural Organization of the United Nations.

catching up in both R&D expenditures and patenting activities.

A central mission of this paper is to map out technology decoupling between the two nations over time. We calibrate decoupling by the propensity for a domestic patent to cite a foreign patent relative to citing a domestic one. In simplified language, the extreme situation of "complete decoupling" implies that patents filed in one country never cite any patents in the other country, suggesting two separate ecosystems of innovation. In the other extreme of "complete integration," patents in either country cite patents in the other with the same probability as citing domestic patents. While the extent of decoupling is symmetric with respect to both countries, one nation might depend more on technology on the other than the other way around. We thus construct a measure for China's technology dependence on the U.S. (which is the negative value of U.S. dependence on China) 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 US-China technology decoupling kept declining over time since 2000, the year before China acceded to the World Trade Organization (WTO). In other words, growing integration of the two technological systems is the main theme in the first two decades of the twenty-first century. China's technological dependence on the US, on the other hand, is hump-shaped with the peak point being 2009, the end of the Great Recession. Therefore, from China's perspective, the time period 2000-2009 was characterized by dependence-*deepening* integration with the U.S.; while the next decade featured dependence-*declining* integration. Toward the end of our sample (since 2018), we observe signs of increasing decoupling, but the time period is too short to offer definitive inferences.

We next conduct a panel vector autoregressive (panel VAR) analysis at technology field-year level data from both countries. The analysis yields two empirical relations: First, a lower level of China's dependence on the U.S. predicts a higher level of decoupling in the next year; and second, a higher level of decoupling predicts a higher level of dependence two years down the road. Such an interactive relation echoes a technology-adoption-driven narrative of China's recent technological progress. More specifically, China's technological advancement in recent decades relied heavily on adopting the cutting-edge technologies developed at the global frontier, particularly the United

States. The integration accelerates learning and innovation, followed by a declining dependence on the U.S. technology after the initial adoption. Afterward, stronger domestic technological capability of China enables a higher level of technology decoupling with the US. This process is consistent with the first finding.

On the other hand, technology decoupling creates a barrier for Chinese companies to further learn from their foreign counterparts and to acquire knowledge to continue the progress at the same or fast pace as the outside world. In due time, Chinese companies could lag behind again when a new wave of technologies emerged 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.

At the firm level, the impact of technology decoupling is *a priori* ambiguous due to two opposing forces. On the one hand, global technology integration facilitates knowledge spillover, which complements and spurs domestic innovation (a *"complementarity effect"*). On the other hand, technology decoupling shelters domestic firms and at the same time force them to create instead of merely following. Both factors provide stronger incentives for domestically-oriented innovation (*"substitution effect"*). Our empirical analyses indicate that heightened US-China technology decoupling is followed by higher patenting outputs for both U.S. and Chinese firms, supporting the substitution effect. However, firm efficiency and valuation suffer in China, suggesting a cost for "reinventing the wheel" in a decoupling world. Decoupling has not inflicted any damages on U.S. firm productivity and valuation, presumably because they are still in the leading position in most fields.

Given the asymmetric effects of decoupling on firms in China, we explore the motives and consequences of China's industrial and technology-promoting policies especially the "strategic emerging industries" (SEI) initiative launched in 2012. 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 Administration and the Trump Administration, the major goal of China's innovation-promotion industrial policies is to achieve "self-sufficiency" by "domestic substitution of foreign technologies."[2] The Chinese government, however, indicated that its policies were attempting to achieve self-sufficiency *without* deviating from the global technical standards or advancing along a different technological trajectory.[3] The empirical results lend more support to SEI being associated with both more technology *integration* instead of decoupling between China and the United States, and China's technological *independence* from the US. We further document that firms in technology fields that are promoted by the SEI policy and receive government subsidies are associated with lower patenting output of Chinese firms, but with higher firm efficiency and market valuation. The combined results reveal an inherent trade-off between fostering "indigenous innovation" in China and enhancing firm competitiveness.

Our paper contributes to two broad pieces of literature. The first is on US-China economics relations. Most of the studies on U.S.-China economic relations work in areas related to production and trade. Autor, Dorn, and Hanson (2013) and Pierce and Schott (2016) find that rising Chinese imports cause higher unemployment and lower wages in the US. Amiti, Redding, and Weinstein (2019) provide suggestive evidence that the U.S. tariffs imposed during the 2018 "trade war" were almost completely passed through into US domestic prices. Cen, Fos, and Jiang (2020) document that both high birth rates of Chinese firms and high Chinese subsidy predict same-industry firm exits and lowered employment in the US. In terms of the impact on the Chinese side, Brandt, Van Biesebroeck, Wang, and Zhang (2017) document that cuts in China's output tariffs reduce markups but raise productivity, whereas cuts in China's input tariffs raise both markups and productivity. Tombe and Zhu (2019) demonstrate that reductions in China's internal trade and migration costs are more important than reductions in external trade costs. In contrast, the focus of this study is on technology and innovation. While trade is a crucial aspect of the US-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

[2]For instance, see the United States Chamber of Commerce (2010) under the Obama Administration and the United States Chamber of Commerce (2017) under the Trump Administration.

[3]A quote from China's State Council (2010) said that "we will vigorously enhance integrated innovation and actively participate in the international division of labor. We will strengthen the adoption, digestion, and absorption of foreign technologies, making full use of global innovation resources." See *"Decision of the State Council On Accelerating the Cultivation and Development of Strategic Emerging Industries"* published by the State Council. This is the source link to this reference.

combined data.

The second literature is one on innovation, which has been largely based on single-country (usually the U.S.) experience, taking shocks from another country as given. 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. Autor, Dorn, Hanson, Pisano, and Shu (2020) document that US patent production declines in sectors facing greater competition from Chinese import, and rising exposure to Chinese import reduces sales, profitability, and R&D expenditure of US firms. Though the evidence on the Chinese side is relatively scarce, the literature has been emerging. Fang, Lerner, and Wu (2017) show that innovation increases after China's state-owned enterprises are privatized and this increase is larger in cities with stronger protection for intellectual property rights. Exploiting staggered establishments of patent exchanges in China, Han, Liu, and Tian (2020) find that patent trading promotes comparative-advantage-based specialization and enhances firm performance.

The rest of the paper is organized as follows. Section 2 describe both patent systems and characterizes the national competitiveness of innovation for the two countries. Section 3 develops measures quantifying US-China technology decoupling and China's technological dependence on the U.S., and provides novel stylized facts based on the measures. Section 4 evaluates the relationship between US-China technology decoupling and firm performance. In Section 5, we study how China's industrial policies affect US-China technology decoupling and its subsequent consequences on firm performance. Finally, Section 6 concludes.

2 Institutional Background: Patenting in the U.S. and China

The most crucial data inputs of this study are the combined comprehensive patent-level databases in the United States and China, based on the full records by 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 which is commonly considered the default form of patents.[4] The counterparts in the CNIPA system are "invention patents" ("Chinese Patents" hereafter).[5]

Despite differences in many details, the patent examination procedures at USPTO and CNIPA are mostly comparable to each other. Patents at both USPTO and CNIPA can be granted to both domestic assignees and foreign assignees. Neither USPTO nor CNIPA has any discriminations based on the citizenship of applicants upon the eligibility of patent applications. At the USPTO, all foreign nationals are eligible for patent applications, while at the CNIPA, foreign nationals with a habitual residence or business office in China are eligible for patent applications.[6] 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.[7] At both patent offices, domestic and foreign applicants will go through three major phases: filing, examination, and the grant of patents.[8] Patent applicants and examiners in both countries are required to cite the prior art in domestic and foreign patents.[9]

As an overview, Figures 1a and 1b plot the annual time-series of innovation inputs (R&D expenditures)[10] and outputs (patents) of the two countries. Apparent from both charts is that China has rapidly ascended to becoming a global technology powerhouse in recent two decades, and is challenging the U.S. leadership position in terms of these nominal metrics. While the U.S.

[4] The two other less known categories are design patents and plant patents.

[5] The two other less known categories in the Chinese systems 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.

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

[7] 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. The applicants can simultaneously seek protection for an invention in over 150 countries if they follow the PCT route.

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

[9] For instance, see 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.

[10] 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.

R&D expenditures more than octupled China's level in 2000 and has been growing steadily, China closed almost all the gap by 2020 with a steady annual growth rate of 13.9%. It is not surprising that booming R&D in China has translated into patenting activities, contributing to the shrinking and eventual reversal of the US-China gap in patent volumes. 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.[11]

[Insert Figure 1 here.]

In addition to comparing the two nations as patent approval authorities, we also examine the patenting activities based on the nationalities of the assignees. In both China and the U.S., domestic assignees account for the dominant shares of patents granted in their home countries. In 2019, Chinese assignees account for 78.2% of patents granted in China and 4.7% of patents granted in the U.S. Meanwhile, U.S. assignees account for 46.3% of patents granted in the U.S. and 5.1% of patents granted in China. Therefore, we observe a pattern similar to Figure 1b if the analysis is based on the assignee nationality.[12] Moreover, inferences from our main analyses are qualitatively similar if we define nationality based on assignees instead of patenting authorities.

3 Measuring Technology Decoupling and Dependence between U.S. and China

3.1 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--vis the U.S. The dynamics naturally invited the question as 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

[11]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.

[12]For more detail, please see Section IA2 in the Internet Appendix.

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. The level of decoupling does not directly speak to the relative competitiveness of the two nations. For example, Sinovac of China developed its "inactivated vaccine" against covid-19 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 trains and triggers the immune system.

In comparison, the notion of "technology dependence" in this study hinges critically on a country's 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.

3.2 Measuring Technology Decoupling and Dependence

In this section, we map measures of technology decoupling and dependence to the propensity for a domestic patent to cite a foreign patent relative to citing a domestic one, based on the comprehensive patent data from both the U.S. and China. 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. Hence, we tap citations between the U.S. patents and Chinese patents to construct measures of technology decoupling and dependence.

We set up the following notations to prepare for the construction of the 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 U.S. patents (Chinese patents) receive from Chinese patents, $n_{u,c}$ ($n_{u,u}$) is the number of citations Chinese patents (U.S. patents) receive from U.S. patents. 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 patent office of China and that of the United States. Therefore, $p_{c,u}$ and $p_{u,c}$ are ratios of 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 proceed to develop the measures for both decoupling (or, the lack of integration) and dependence. We start with a visualization, presented in Figure 2, to facilitate intuition. In Panel A, in which the horizontal and vertical axes measure $p_{u,c}$ and $p_{c,u}$, respectively. The state of "complete decoupling" corresponds to the origin, the scenario where domestic patents in either country never cite any patents in the other because 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. Any point interior of the box indicates a partial integration or imperfect decoupling.

[Insert Figure 2 here.]

In Figure 2 the 45-degree line naturally provides the state of parity. At any point on this diagonal line, $p_{c,u}$ is equal to $p_{u,c}$, 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 lands on the latter at point Q. By construction the vector $\overrightarrow{\mathrm{PQ}}$ is orthogonal to the 45-degree line.[13] The norm of $\overrightarrow{\mathrm{QI}}$ (i.e., the projection of $\overrightarrow{\mathrm{PI}}$ onto the par line) captures the degree of US-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 technology dependence on the U.S.

Quantifying the norms of the vectors in the Figure, and hence the resulting measures, now become relatively straightforward. The measure for decoupling is expressed below.

$$Decoupling(\text{US \& CN}) = 1 - \sqrt{(p_{u,c})^2 + (p_{c,u})^2} \times \cos(\theta - \frac{\pi}{4}) \times \frac{\sqrt{2}}{2}, \tag{1}$$

$$\text{where } \theta = \begin{cases} \arctan(\frac{p_{c,u}}{p_{u,c}}) & \text{if } p_{u,c} \neq 0 \\ \frac{\pi}{2} & \text{if } p_{u,c} = 0 \end{cases}$$

$Decoupling(\text{US \& CN})$ is constructed to be $\frac{\sqrt{2}}{2}||\overrightarrow{\mathrm{QI}}||$. A higher value of $Decoupling(\text{US \& CN})$ 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.

[13] 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.

Next, we define the degree of China's technological dependence on the US as:

$$\begin{aligned} \textit{Dependence}(\text{CN v. US}) &= -\textit{Dependence}(\text{US v. CN}) \\ &= \sqrt{(p_{u,c})^2 + (p_{c,u})^2} \times \sin(\theta - \frac{\pi}{4}) \times \sqrt{2}, \qquad (2) \\ \text{where } \theta &= \begin{cases} \arctan(\frac{p_{c,u}}{p_{u,c}}) & \text{if } p_{u,c} \neq 0 \\ \frac{\pi}{2} & \text{if } p_{u,c} = 0 \end{cases} \end{aligned}$$

The dependence measure, bounded between -1 and 1, is asymmetric between the two countries. To be specific, $\textit{Dependence}(\text{CN v. US})$ is, graphically, $\sqrt{2}||\overrightarrow{\text{PQ}}||$ in the US-leading region and $-\sqrt{2}||\overrightarrow{\text{PQ}}||$ in the China-leading region in Figure 2. Hence, a positive sign of $\textit{Dependence}(\text{CN v. US})$ indicates that China depends more on U.S. technology than the other way around, or that the U.S. maintains a leading position. When $\textit{Dependence}(\text{CN v. US}) = 1$ (or -1), the U.S. (or China) is in absolute dominance. For the rest of the paper, "Dependence" refers to China's dependence on the U.S. unless otherwise specified, to ease the notation.

We note that the degree of decoupling poses restrictions 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. Moving from the extreme points toward the middle of the 45-degree line in Figure 2, the range of permissible values of dependence increases. Thus, we 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 $\textit{Dependence}|\textit{Decoupling}(\text{CN v. US})$, to be $\overrightarrow{QP}/||QP'||$, which mathematical expression is as follows.

$$\begin{aligned} \textit{Dependence}|\textit{Decoupling}(\text{CN v. US}) &= -\textit{Dependence}|\textit{Decoupling}(\text{CN v. US}) \\ &= \frac{\textit{Dependence}}{\textit{min}(\textit{Decoupling}, 1 - \textit{Decoupling})} \times \frac{1}{2} \qquad (3) \end{aligned}$$

3.3 US-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 county (U.S. and China), we are able to map their aggregate state in different years into Figure 3. The figure shows three "screen shots" in 2000 (China's entry to the WTO), 2009 (the deep of the Great Recession), and 2019 (the end of our sample period which coincides with open attempts of decoupling). All three observations fall into the lower left corner above the 45-degree line, that is, the two countries have mostly been running separate systems with China exhibiting more dependence on the U.S. technology.[14] The change over time, however, is also informative. Since 2000, China moved first toward more integration with, and more dependent on U.S. technology during the first decade, then reduced its dependence on while furthering integration with the U.S. during the second decade.

[Insert Figure 3 here.]

[Insert Figure 4 here.]

Figure 4 offers a different presentation of the same history, and in more detail. In this chart, the horizontal axis is time in calendar year, and the left (right) 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 dropping steadily. In other words, the general trend is for technologies in the two countries to become more integrated, conforming to the general theme of globalization. China's technological dependence on the US, 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

[14] 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 in 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 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.

century was characterized by dependence-*deepening* integration between the two countries, that is, technology in China became more dependent on U.S. technology during the integration process. During the second decade since 2010, the continued technology integration has been accompanied by China's declining dependence on the U.S.

The aggregate states of decoupling and dependence shown this far may have masked heteorgeneity across different technology sectors. Therefore, we also examine ten high-tech fields defined by Webb, Bloom, Short, and Lerner (2019) which include (by the order of number of total patents): smartphones, semiconductors, software, pharmaceuticals, internal combustion engines, machine learning, neural networks, drones, cloud computing, self-driving cars. For completeness we group all other patents into "non-high tech" field.

Figure 5 plots the states of decoupling (corresponding to $\frac{\sqrt{2}}{2}||\overrightarrow{\mathrm{QI}}||$ 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.[15] 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 new technology sectors, such as neural networks, cloud computing, and self-driving cars, due to a variety of reasons from geopolitical sensitivities to different legal infrastructure.[16] It indicates that the U.S. and China are more decoupled toward the end of our sample, especially among cutting-edge technologies. It is also worth noting that the dependence measure of "drones" turned negative in 2019, suggesting that China overtook the U.S. to be in the leading position in that sector. In fact, one Chinese firm, Da-Jiang Innovations (DJI), accounts for over 70% of the global drones market.

[Insert Figure 5 here.]

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

[15] 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.

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

all tech sectors in 2000, about 42.9% of the tech classes have evolved into China dominance by 2019. The tech fields in which the U.S. retains leadership includes 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, 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.[17]

3.4 Relation between Decoupling and Dependence

The differential patterns in the evolution of decoupling and dependence shown in the previous section suggest that the two concepts capture distinct aspects of the relation between the two nations in the technology space. This section examines the relation between decoupling and dependence in more detail. In particular, we resort to the following panel vector autoregressive (VAR) model to assess the inter-temporal relations between decoupling and dependence:[18]

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

where $y_{i,t}$ is a (1×2) vector of 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 that 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 transforma-

[17] For more detail, please see Section IA3 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 IA15 is the cross-sectional analog of Figure 2 at the three-digit IPC level for years 2000, 2009, and 2019.

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

tion proposed by Arellano and Bover (1995). Results are reported in Table 1.

[Insert Table 1 here.]

In Table 1, the dependent variables are US-China decoupling in odd-numbered regressions and China's technology dependence on the U.S. in even-numbered regressions. Each pair of two regressions are simultaneously estimated. Lagged variables of both measures, up to two lags, appear in all regression. 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 more 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 decoulping results in heightened dependence further down the road, reverting the tendency for decoupling.[19] 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 cutting-edge technologies developed at the global frontier, particularly in the United States. After a wave of learning and adoption, China's technology dependence on the US declined; and a stronger domestic technological capability enables a higher level of technology decoupling with the US. 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.

[19]The impulse-response functions (IRF) from the VAR model using the Cholesky decomposition, plotted in Figure IA16 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 be originated from decoupling (Panels A and B), or assumed to come from dependence (Panels C and D).

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.[20] 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 of building their own high-speed trains, and afterwards built a more decoupled transit system from the original exporting countries.

4 Decoupling and Firm Performance

4.1 Overview of Sample U.S. and Chinese Firms

The ultimate goal of measuring U.S.-China decoupling is to assess its impact on the production of goods and services in both countries. 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.[21] On the China side, the relevant sample includes all firms that are traded on China's A-share stock market, where their financial statement and trading information comes from the China Stock Market and Accounting Research (CSMAR) database. We then merged the CSMAR data with the Chinese patent database by matching company names, accounting for the unique features of the Chinese language during the merging process. On the U.S. side, we merge the U.S. patent database to Compustat using the procedure developed in Kogan et al. (2017).[22] Firm information for both countries is accessed via the Wharton Research Data Services (WRDS). We exclude firms in the financial industry following the common practice.

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

[21] Following Fang et al. (2018), our sampling 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.

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

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. We first compute the relative citation strength at the patent-year level. 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 firm's total factor productivity, TFP, following the method developed in Ackerberg, Caves, and Frazer (2015).[23] The TFP estimation is based on a Cobb–Douglas production function where output is proxied by a firm's total revenue. Inputs include labor and capital, approximated by total assets and total number of employees, and intermediate inputs, approximated by expenditure on labor and capital goods. 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.[24]

While technology decoupling (*Decoupling*) in a sector-year which the firm belongs is the key independent variable, the regressions include the standard firm-year level control variables. Each patent-filing firm is classified into a unique IPC group based on its primary technology class (i.e., the IPC class that hosts the highest number of patents owned by this firm).[25] A patent is attributed pro-rata if there are multiple assignees.[26]

Standard firm characteristics variables included in the regression are defined as follow. *Assets*

[23]Built on Olley and Pakes (1996) and Levinsohn and Petrin (2003), the estimation method proposed in Ackerberg, Caves, and Frazer (2015) addresses the functional dependence problem in previous studies.

[24]We adopt the inverse, rather than the original scale of, Q because the book values may get arbitrarily small or even negative, resulting in erratic Q values.

[25]Since our measure of US-China technology decoupling is based on technology classes at the three-digit-IPC level, we map every firm into a unique technology class to gauge the level of decoupling it is facing. 89.1% of patent-filing Chinese firms can be mapped to a unique IPC by the number of patents it has 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.

[26]When there are N assignees for a patent, we assume each assignee owns $\frac{1}{N}$ share of the patent.

is a firm's book value of assets (in natural logarithm). *Age* is the number of years since a Chinese firm is founded [27] 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 book value of assets. *PP&E* is the ratio of property, plant, and equipment to book value of assets, a measure for asset tangibility. *Leverage* is the ratio of total debt to total assets, both in book value. The detailed definitions of all variables are listed in Appendix A. 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 Appendix B. Table A2 shows that the average patent-filing Chinese firm in our sample is about 15 years old since birth, has a market capitalization of RMB 10.70 billion (about US$ 1.66 billion), and an asset of RMB 10.87 billion (about US$ 1.68 billion). The average Chinese firm in the sample files about 4 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 5.7% of firm assets, 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 U.S. firm in our sample is about 22 years old as a public company, has a market capitalization of US$ 6.96 billion and an asset of US$ 9.21 billion. The average firm faces a technology decoupling measure of also 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.

4.2 Decoupling, Innovative Activities, and Firm Performance

The impact of US-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 knowledge dissemination, allowing firms better access to foreign technology that is state-of-art

[27] Such information is disclosed in China.

and that complements and spurs domestic innovation. We term this negative effect of technology decoupling on domestic innovation as the *"complementarity effect."* On the other hand, some domestic firms may strengthen their local dominance by fending off foreign competition, and may innovate by "reinventing the wheel" in a more sheltered setting. We define this positive effect of technology decoupling on 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:

$$y_{i,j,t} = \text{Decoupling}_{j,t-1} \times \beta_1 + \text{Decoupling}_{j,t-2} \times \beta_2 + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \quad (4)$$

In equation (4), the dependent variable $y_{i,j,t}$, indexed by firm i, technology class j, and year t, is one of the following performance metrics: $InnovationOutput$ (the logarithm of total number of patents filed that were eventually approved), $InnovationQuality$ (the relative citation strength), TFP (total factor productivity, in logarithm), and $1/Q$, the inverse of Tobin's Q. The key independent variables are *Decoupling*, our measure of US-China technology decoupling, measured at the technology class-year level, lagged by one and two years, respectively. X represent the vector of firm characteristics variables introduced in Section 4.1, and are set to lag the dependent variable by one year. γ_t refers to year fixed effect that absorbs shocks to the aggregate economy, and γ_i refers to firm fixed effect which absorbs unobserved and time-invariant firm heterogeneity. $\epsilon_{i,j,t}$ is the error term. The estimation results are reported in Tables 2 and 3 for Chinese firms and U.S. firms respectively.

[Insert Table 2 here.]

[Insert Table 3 here.]

Starting with Chinese firms, 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, reveals 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 (significant at the 10% level) and valuation (significant at the 5% level) two years ahead. To put the estimates into context, consider a hypothetical increase of US-China technology decoupling of 0.069 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 14.2% increase of Chinese firm patenting activity one year later, but a 2.7% drop in firm TFP and an increase of inverse Tobin’s Q by 0.017 (or 3.1% of the sample average) two years down the road.

The effects of technology decoupling on the U.S. firms, examined in Table 3, appear to be much more moderate. There are no detectable relation between lagged decoupling and innovation quality, productivity, or firm valuation. However, U.S. firms share one common experience with their Chinese counterpart after decoupling: They also increase patent activities (significant at the 5% level) but with a longer lag (in two years’ time) and a lower magnitude (about 65% of the magnitude for Chinese firms). When the two countries pursue different routes in advancing technology in a field, they would each make discoveries on their own track, leading to more patentable inventions. Unlike their Chinese counterparts, however, the U.S. firms do not suffer any productivity and valuation losses having to do more “reinventing the wheel,” presumably because the U.S. firms, so far, are primarily at the world innovation frontier and losing complementary technology from China inflicts little damage on their productivity and valuation. Finally, it is worth noting that U.S.-China decoupling is, for China, a likely proxy (though to the 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 mostly one-sided effect of decoupling on firm productivity and valuation in the two countries.

5 Decoupling and Industrial Policies

As rising income, and hence labor costs, gradually erodes 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. 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.

5.1 Have China's Industrial Policies Encouraged Decoupling?

To sharpen such a test, we focus on China's "Strategic Emerging Industries (SEI)" initiative, a centralized policy for technological development launched in 2012. In the 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 grant 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 US-China technology decoupling. As underlined by the State Council of China, "enhancing the ability of indigenous and independent innovation is key to the SEI-promotion policies."[28] According to the commentaries from both the Obama and the Trump Administrations, the major goal of China's innovation-promotion industrial policies is perceived to be achieving "self-sufficiency" by "domestic substitution of foreign technologies."[29]

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 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-difference

[28]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.

[29]For instance, see the United States Chamber of Commerce (2010) under the Obama Administration and the United States Chamber of Commerce (2017) under the Trump Administration.

setup to quantify the relationship between the SEI-promotion policy and US-China technology decoupling at the technology class (i)-year(t) level for the sample period of 2007-2019:

$$y_{i,t} = \beta_1 \times SEI_i \times Post_t + \delta' X_{i,t-1} + \gamma_i + \gamma_t + \epsilon_{i,t} \tag{5}$$

In equation (5), 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. 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 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 26.9% 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. All four coefficients are significant at the 1% level. The last column of the table presents residualized *Dependence* (see explanations in Section 3.4) as 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 likely contributes to 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."[30] 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-art. For instance, the State Council endorses various measures to foster global scientific and technological cooperation.[31]

Perhaps more importantly, results also indicate that decrease in China's technology dependence on the U.S. drops precipitously (by an average of 26.9%) in industries post SEI coverage, which magnitude far exceeds that in the change in decoupling. That is, strong industrial policy, implemented via integration with the U.S. (and the rest of the developed world) reduces China's technological dependence on the US quite remarkably. This finding is consistent with the U.S. "self-sufficiency" narrative for China's industrial policy, but such self-sufficiency is achieved by China's technology *integration* with the US instead of decoupling.

5.2 Industrial Policies and Firm Performance

In light of the impact of the SEI-promotion policy on US-China technology decoupling and China's technological dependence on the US, we next explore the SEI's impact on firm performance. For this purpose, we collect additional information on government subsidy at the firm-year level from firms' financial statements.[32] We then conduct the following triple-difference regression at the firm (i)-technology class(j)-year(t) level covering the period of 2007-2019:

$$\begin{aligned} y_{i,j,t} = \beta_1 \times SEI_j \times Post_t \times High\ Subsidy_i + \beta_2 \times SEI_j \times Post_t \\ + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \end{aligned} \tag{6}$$

[30] 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.

[31] 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.

[32] 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.

In equation 6, 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 within each SEI-covered technology class, we classify "high subsidy" firms to be those with government subsidies during 2007-2011 (pre-SEI) above sample median. A dummy variable $High\ Subsidy_i$ is coded accordingly, which is a firm-specific and time-invariant indicator. The coefficient of key interest is that of the triple interaction term "$SEI_j \times Post_t \times High\ Subsidy_i$." Table 5 reports the results.

[Insert Table 5 here.]

The coefficient on $SEI_j \times Post_t$ turns 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 on the innovation and general performance of the firms. However, the coefficients associated with the triple interaction terms $SEI_j \times Post_t \times High\ Subsidy_i$ (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 performance among firms that received high level of direct government support. More specifically, the highly subsidized firms operating in SEI-promoted technoligy sector end up filing about 14% fewer patents, but their productivity increases by 10.3% and inverse Q decreases by 0.0298 (or 5.5% of sample average). Such a combination suggests that firms supported by the government in fact allocate fewer resources into original research but instead focusing on production efficiency.

To trace out the dynamics of the SEI policy, we expand equation (6) to the following set up with the triple difference term:

$$y_{i,j,t} = \sum_{\tau}(\beta_{1,\tau} \times SEI_j \times High\ Subsidy_i \times T_\tau) + \sum_{\tau}(\beta_{2,\tau} \times SEI_j \times T_\tau) + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \tag{7}$$

That is, we interact both SEI_j and $SEI_j \times High\ Subsidy_i$ 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 6. Year 0 corresponds to 2012, the event year of the SEI-promotion policy.

[Insert Figure 6 here.]

Figure 6 displays any pre-existing trends before the SEI. It seems that patenting activities were already in the decline and firm TFP were already rising in the highly subsidized SEI targeted sectors, but the changes in the continuing direction only become statistically significant post SEI. In the other two variables, there were no discernable pre-trends. Patent quality does not see significant improvement afterwards. Firm valuation experiences significant up-stick (or inverse Q decreases) right after the policy shock, suggesting a fairly efficient stock market that incorporates all forward-looking information.

The smartphone industry in China in the past decade could serve as a poster-child of the patterns uncovered from aggregate statistics. Rising from humble backgrounds, numerous Chinese smartphone makers (e.g., Huawei, Xiaomi, Vivo, Oppo) have swiftly ascended to be the world industry leaders. Surpassing Apple last year, Huawei became the second-largest smartphone maker in the world (even without any sales in the United States). The spectacular 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. For instance, numerous standard-essential patents of Huawei have been adopted in the 5G standard. By embracing the global technology standard, these Chinese enterprises enjoyed easy access to cutting-edge foreign technologies and key inputs (particularly semiconductors) from foreign suppliers. Though the globally integrated supply chain of semiconductors contributes to accelerating the rise of Chinese smartphone makers, it is also responsible for discouraging their incentives to develop the domestic semiconductor industry. In fact, there is no leading-edge semiconductor manufacturing facility in China and all Chinese smartphone makers rely heavily on foreign suppliers.[33] Eventually, Huawei (the industry front runner touted as the role model for indigenous innovation) had to shut down its production of Kirin 9000 (a high-end chipset) 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.,

[33] China's import of semiconductors amounted to \$301 billion in 2019. As a comparison, it spent \$238 billion on importing crude oil.

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, US-mandated technology decoupling can force Chinese firms into indigenous innovation, but at the costs of sacrificing firm efficiency associated with "reinventing the wheels."

6 Conclusion

Based on combined and comprehensive patent data from the U.S. and China, we developed new measures to quantify technology decoupling and dependence between the U.S. and China, in the aggregate and across different technology classes. We find that the first two decades of the 21st century witnessed a continuing increase in technology integration (or less decoupling), but China's technology dependence on the U.S. increases (decreases) during the first (second) decade. In the cross section, a higher level of decoupling in a give technology field predicts more patent outputs in the same sector in China, but lower firm productivity and valuation in the longer term. Though decoupling is also associated with higher patenting outputs for the U.S. firms, it does not negatively impact their productivity and valuation. Finally, we find that China's innovation-promotion industrial policies are associated with both more integration and 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.

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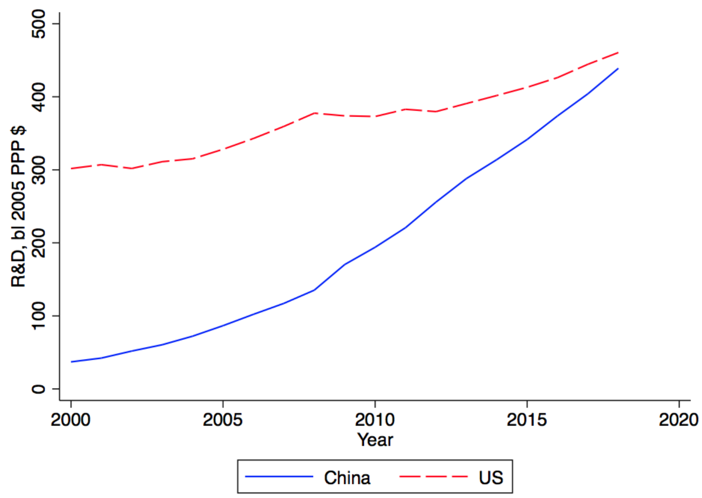
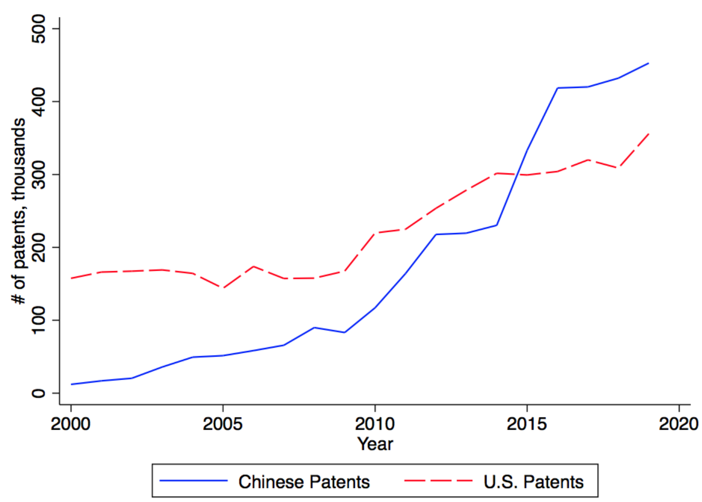
Figure 1: **R&D Expenditures and Patents Granted, US vs China**

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 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 Technology Dependence**

This diagram illustrates how we construct our measures of US-China technology decoupling and China's dependence on the US. $p_{c,u}$ (the vertical axis in this figure) is a proxy of the propensity for Chinese patents to cite a U.S. patent relative to citing a Chinese one. $p_{u,c}$ (the horizontal axis) is a proxy of the propensity for U.S. patents to cite a Chinese patent relative to citing a U.S. one. $p_{c,u} > p_{u,c}$ if a point lies in the region above the 45-degree line, so China depends relatively more on the US than what the US depends on China. In light of this, we define the 45-degree line as the "par line" and we label the region above (below) the 45-degree line as a "US-leading" ("China-leading") region. We project point P to the par line and we decompose the vector $\overrightarrow{\text{PI}}$ into two orthogonal vectors $\overrightarrow{\text{PQ}}$ and $\overrightarrow{\text{QI}}$. The vector $\overrightarrow{\text{QI}}$ (i.e., the projection of $\overrightarrow{\text{PI}}$ on the par line) captures the degree of US-China technology decoupling. The vector $\overrightarrow{\text{PQ}}$ (i.e., the rejection of $\overrightarrow{\text{PI}}$ from the par line) reflects China's technology dependence on the US.

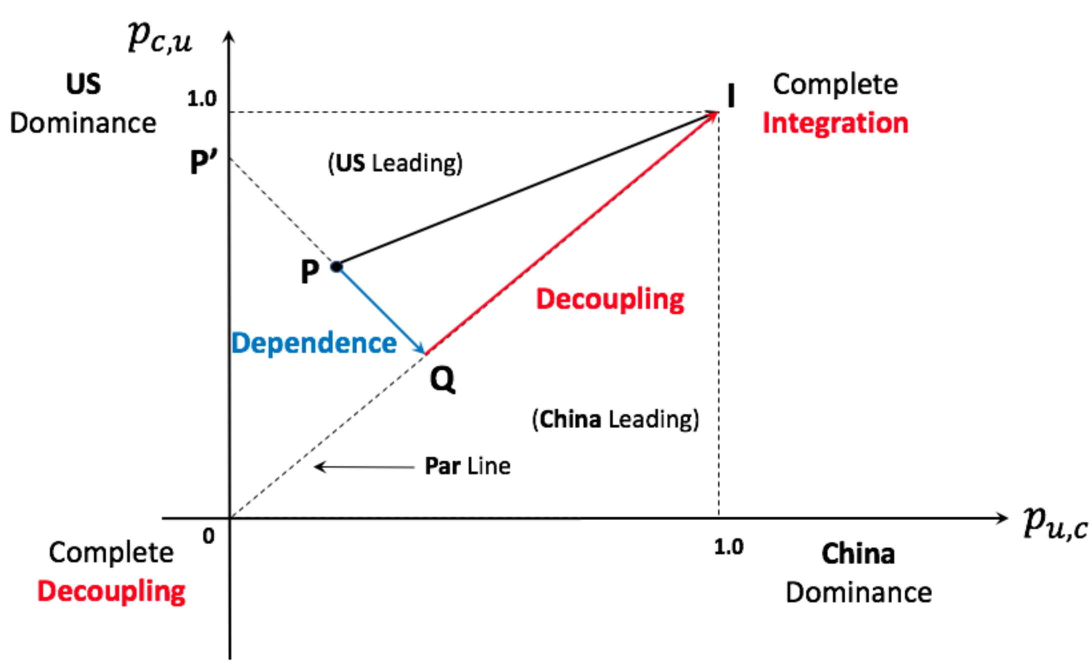


Figure 3: **U.S.-China Technology Decoupling and Dependence: 2000, 2009,and 2019**

This figure is the empirical analog of Figure 2. $p_{c,u}$ (the vertical axis) is a proxy of the propensity for Chinese patents to cite a U.S. patent relative to citing a Chinese one. $p_{u,c}$ (the horizontal axis) 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 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 sampling period). This figure unveils two salient features of technology decoupling and dependence. First, there has been an integration of the technological systems in China and the US, because all the data points tend to move toward the complete integration point $(1, 1)$ over time. Second, China increased its technological dependence on the US after joining WTO, whereas its dependence on the US has declined after the Great Recession.

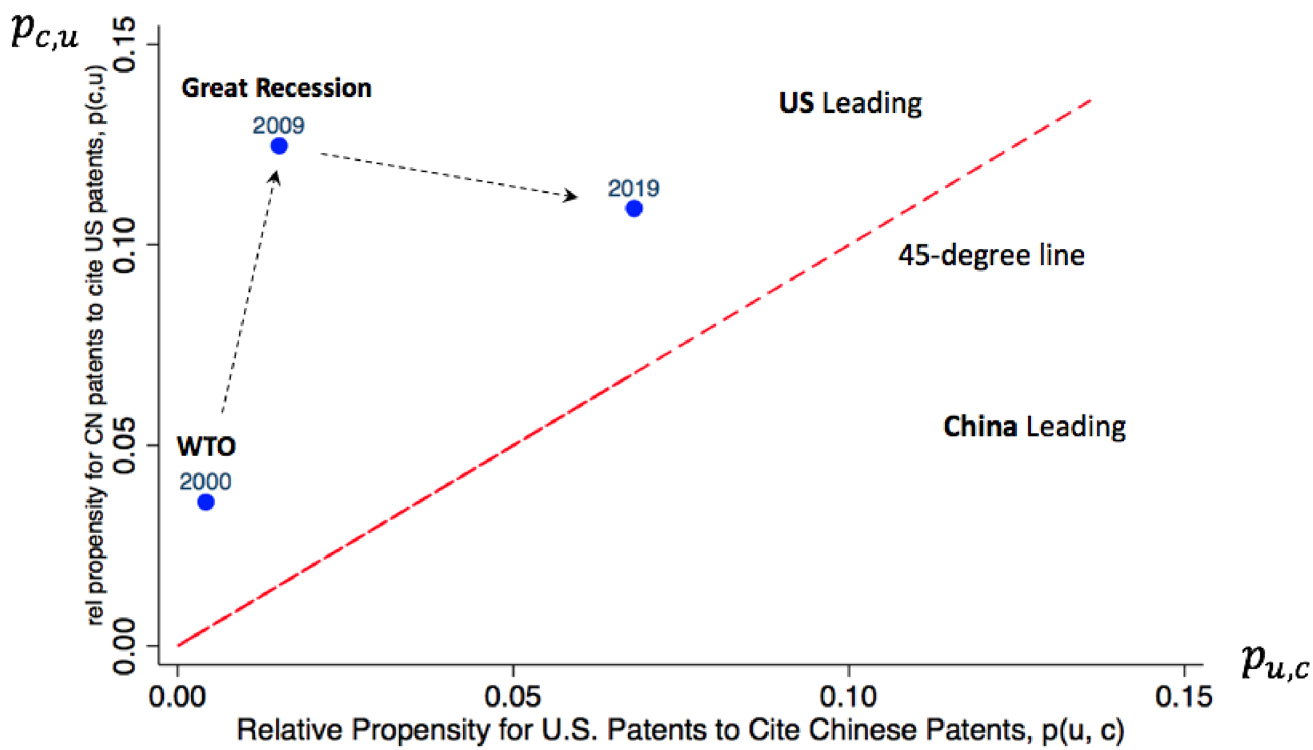


Figure 4: **US-China Technology Decoupling and Dependence: 2000-2019**

In this figure, we characterize how the degree of US-China technology decoupling and China's technological dependence on the US evolved between 2000 and 2019. The right vertical axis in this figure is our measure of US-China technology decoupling, and the left vertical axis is our measure of China's technological dependence on the US. Since China acceded to the World Trade Organization in 2001, the measure of technology decoupling between the two countries kept dropping in a row, so there has been an integration of the two technological systems. China's technological dependence on the US, however, is hump-shaped over time. The first decade of the twenty-first century (2000–2009) was characterized by dependence-*deepening* integration between the two countries. That is to say, China increased its technological dependence on the US during the integration process. As a stark contrast, the second decade of this century (2010–2019) featured dependence-*declining* integration between the two countries, in the sense that China's technological dependence on the US declined while the two technological systems were further integrated.

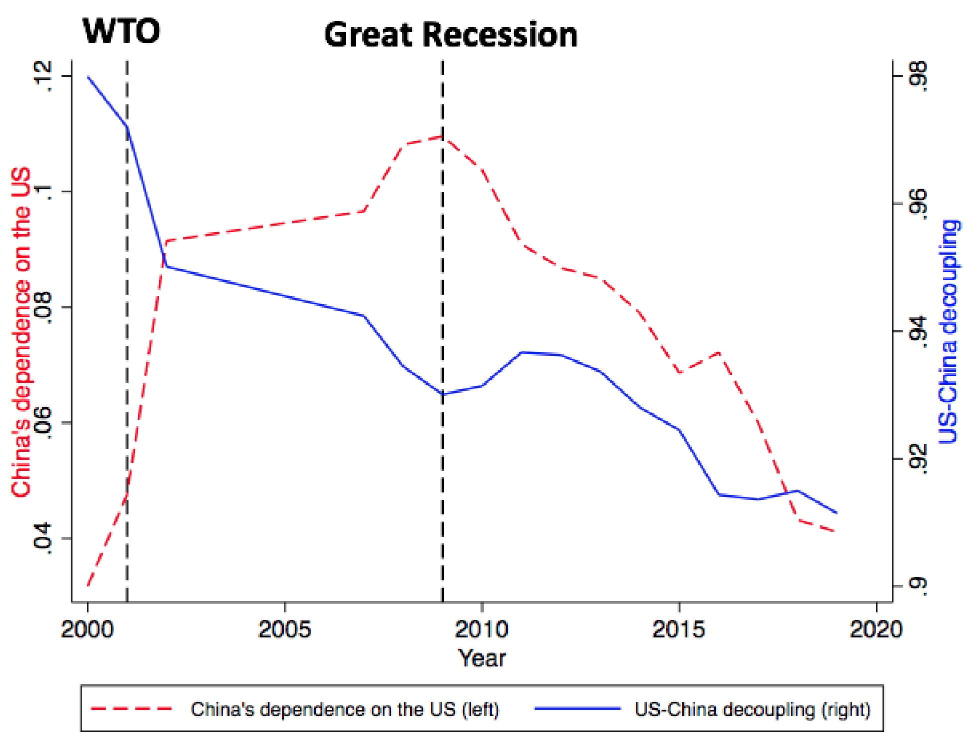
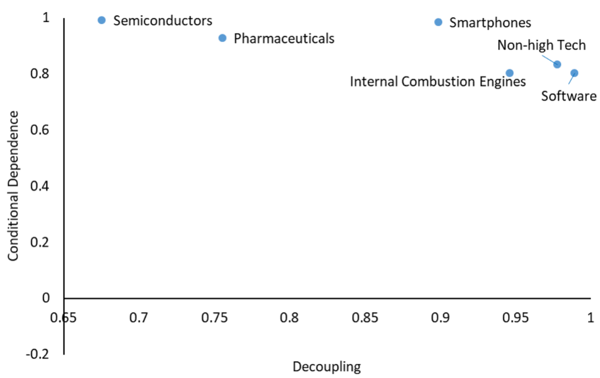
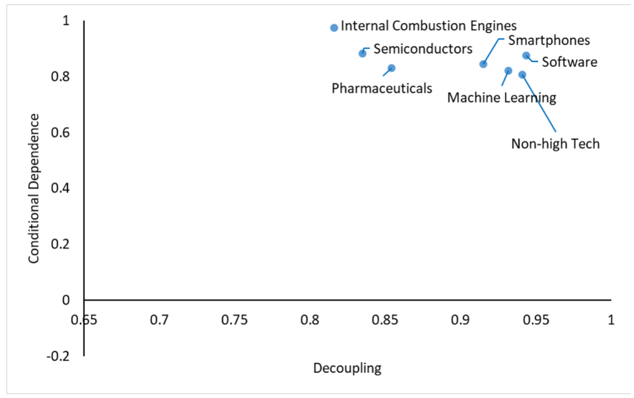


Figure 5: **Decoupling and Conditional Dependence: Ten High-Tech Fields**

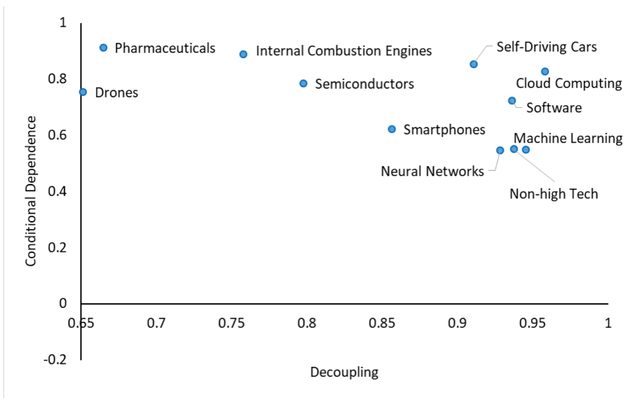
In this figure, we plot the states of decoupling and conditional dependence in years 2000, 2009, 2015, and 2019. The ten high-tech fields are defined by Webb, Bloom, Short, and Lerner (2019). All other patents are grouped into "non-high tech" field.



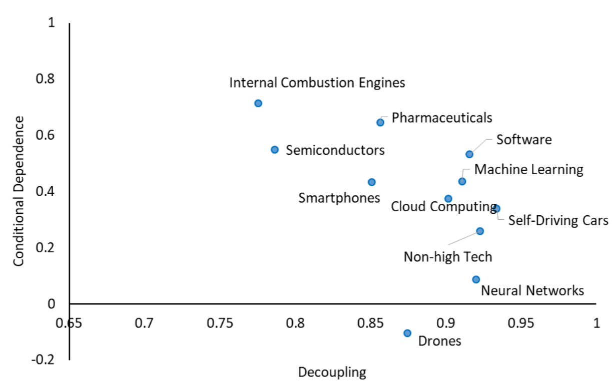
(a) Year: 2000



(b) Year: 2009



(c) Year: 2015



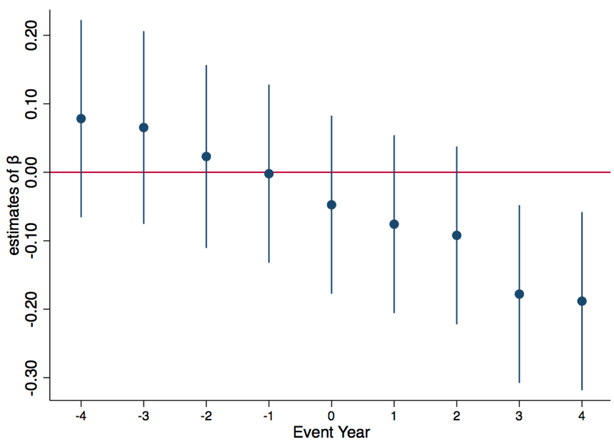
(d) Year: 2019

FIGURE 6: **SEI Policy and Firm Performance, Dynamic Effects**

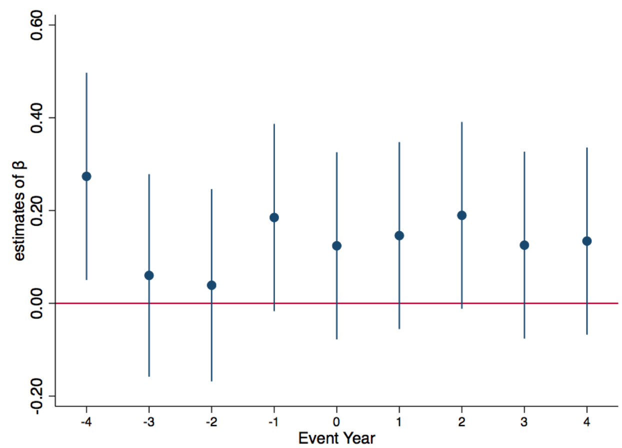
We evaluate the dynamic effects of the SEI policy by the following triple difference setup:

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

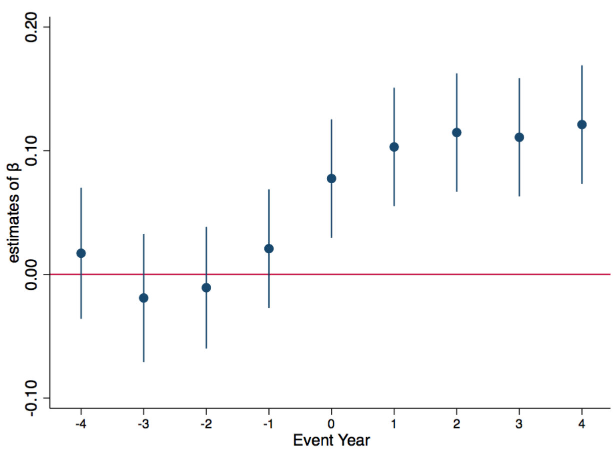
"*SEI_j*" equals one if technology class j is promoted as an SEI and zero otherwise. "*High Subsidy$_i$*" equals one if the subsidy-to-sales ratio of firm i is above the sample median. T_τ is a set of year dummies. We plot the estimates for $\beta_{1,\tau}$ for the following dependent variables: *Innovation Output* in Figure 6a, *Innovation Quality* in Figure 6b, TFP in Figure 6c, and $1/Q$ in Figure 6d.



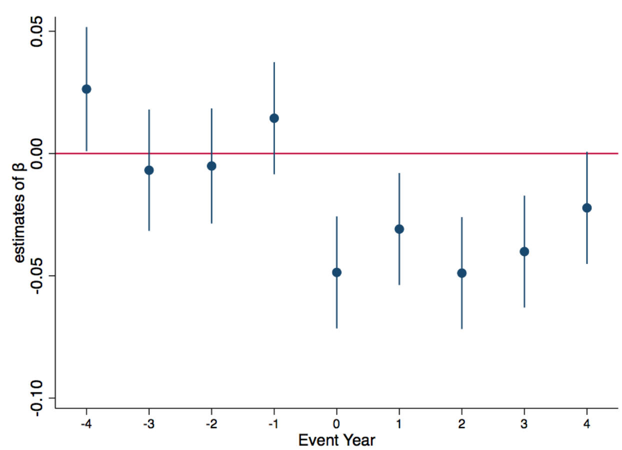
(A) INNOVATION OUTPUT



(B) INNOVATION QUALITY



(C) FIRM TFP



(D) INVERSE OF TOBIN'S Q

Table 1: Technology Decoupling and Technology Dependence, Panel VAR

We estimate the following panel VAR model in this table:

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

$y_{i,t}$ is a (1×2) vector of dependent variables (i.e., technology decoupling and dependence). In regressions (1) and (2), both the decoupling and dependence measures are in their original scale. In regression (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 1 percent level, ** at the 5 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 US-China technology decoupling and the performance of Chinese firms. In all regressions, the independent variables are lagged by one year unless otherwise stated. All regressions in this table include year fixed effect and firm fixed effect. Standard errors are reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Innovation Output	*Innovation Quality*	*TFP*	$1/Q$
	(1)	(2)	(3)	(4)
Decoupling, $t-1$	2.075***	0.661	-0.325	0.0754
	(0.574)	(0.865)	(0.207)	(0.0986)
Decoupling, $t-2$	0.443	0.989	-0.399*	0.248**
	(0.572)	(0.863)	(0.206)	(0.0983)
Assets	0.0557***	0.0157	0.0336***	0.129***
	(0.0170)	(0.0256)	(0.00612)	(0.00291)
Age	0.0483**	0.0290	-0.0115	-0.00945**
	(0.0244)	(0.0368)	(0.00879)	(0.00419)
Capex	-0.105	-0.0614	-0.992***	-0.0141
	(0.158)	(0.238)	(0.0569)	(0.0271)
PP&E	-0.209**	0.109	0.290***	0.0412***
	(0.0844)	(0.127)	(0.0305)	(0.0145)
Leverage	-0.00545	-0.0920	0.215***	-0.0666***
	(0.0636)	(0.0958)	(0.0229)	(0.0109)
R&D	-0.0991	-0.696	-1.816***	-0.140***
	(0.283)	(0.427)	(0.102)	(0.0486)
Constant	-2.407***	-1.620*	1.014***	-0.806***
	(0.575)	(0.867)	(0.207)	(0.0988)
Observations	15,278	15,278	15,278	15,278
Adjusted R-squared	0.609	0.039	0.805	0.811
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 US-China technology decoupling and the performance of U.S. firms. In all regressions, the independent variables are lagged by one year unless otherwise stated. All regressions in this table include year fixed effect and firm fixed effect. Standard errors are reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Innovation Output	*Innovation Quality*	*TFP*	1/*Q*
	(1)	(2)	(3)	(4)
decoupling, $t-1$	-0.296	-0.956	-0.000	-0.232
	(-0.49)	(-1.11)	(-0.00)	(-1.30)
decoupling, $t-2$	1.339**	-0.665	0.055	0.239
	(2.41)	(-0.83)	(0.19)	(1.44)
ln(assets)	0.119***	-0.047**	-0.104***	0.091***
	(7.79)	(-2.15)	(-12.94)	(20.01)
age	0.091***	-0.004	0.004	-0.003
	(7.11)	(-0.21)	(0.67)	(-0.87)
capex ratio	0.453**	0.186	-0.429***	-0.379***
	(2.07)	(0.59)	(-3.73)	(-5.77)
PPE ratio	0.224*	-0.147	0.079	0.317***
	(1.79)	(-0.81)	(1.20)	(8.41)
leverage ratio	-0.181***	-0.080	0.167***	-0.055***
	(-4.16)	(-1.27)	(7.32)	(-4.23)
R&D intensities	0.000	-0.002	-0.017***	-0.001**
	(0.14)	(-1.13)	(-28.55)	(-2.07)
Constant	-0.930	2.348***	0.113	0.634***
	(-1.64)	(2.87)	(0.38)	(3.73)
Observations	14902	14902	14902	14902
Adjusted R-squared	0.85	0.34	0.82	0.66
Firm fixed effect	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes

Table 4: SEI-Promotion Policy and Technology Decoupling

We apply the following DiD setup to disentangle the relationship between the SEI-promotion policy and US-China technology decoupling:

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

The subscript i indexes for technology class and t indexes for year. 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 our measure of US-China technology decoupling in regression (1) and China's technological dependence on the US in regression (2). As a robustness check, the dependence measure is residualized against the decoupling measure in regression (3). In all regressions, the independent variables are lagged by one year. All regressions in this table include year fixed effect and technology class fixed effect. 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*	*Dependence, Residualized*
	(1)	(2)	(3)
$SEI \times Post$	-0.0130***	-0.0190**	-0.0286***
	(0.00403)	(0.00769)	(0.00850)
ln(patents granted in China)	0.0179***	-0.0396***	-0.0264***
	(0.00332)	(0.00634)	(0.00700)
ln(patents granted in the US)	-0.0157***	0.0860***	0.0743***
	(0.00475)	(0.00906)	(0.0100)
Constant	0.967***	-0.0760***	-0.109***
	(0.00986)	(0.0188)	(0.0208)
Observations	1,370	1,370	1,370
Adjusted R-squared	0.732	0.818	0.756

Table 5: SEI-Promotion Policy and Firm Performance

We study the relationship between SEI-promotion policy and firm performance in the following regression:

$$y_{i,j,t} = \beta_1 \times SEI_j \times Post_t \times High\ Subsidy_i + \beta_2 \times SEI_j \times Post_t + \beta_3 \times post_t + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t}$$

The subscript i indexes for firm, j indexes for industry, and t indexes for year. SEI_j equals one if industry j is promoted as an SEI and zero otherwise. $Post_t$ takes the value of one after 2012 and zero otherwise. "$High\ Subsidy_i$" equals one if the subsidy-to-sales ratio of firm i is above the sample median. In all regressions, the independent variables are lagged by one year. All regressions include year fixed effect and firm fixed effect. Standard errors are reported in the parentheses. *** denotes significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.

	Innovation Output		*Innovation Quality*		*TFP*		1/*Q*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SEI × *Post*	-0.120	-0.0534	-0.243	-0.237	0.0779	0.0158	0.00894	0.0328
	(0.134)	(0.139)	(0.203)	(0.217)	(0.0490)	(0.0512)	(0.0234)	(0.0246)
SEI × *Post* × *1{High Subsidy}*		-0.140***		0.00361		0.103***		-0.0298***
		(0.0241)		(0.0375)		(0.00887)		(0.00425)
Assets	0.0843***	0.103***	0.0173	0.0211	0.0374***	0.0343***	0.130***	0.134***
	(0.0155)	(0.0165)	(0.0235)	(0.0257)	(0.00567)	(0.00608)	(0.00271)	(0.00292)
Age	0.0443*	0.0348	0.0553	0.0550	-0.0151*	-0.0229***	-0.0102**	-0.0119***
	(0.0227)	(0.0241)	(0.0345)	(0.0375)	(0.00833)	(0.00887)	(0.00399)	(0.00425)
Capex	-0.0543	-0.0393	0.105	0.118	-1.020***	-1.098***	-0.0239	-0.0538*
	(0.148)	(0.162)	(0.225)	(0.252)	(0.0543)	(0.0595)	(0.0260)	(0.0285)
PP&E	-0.130*	-0.170**	0.113	0.0847	0.281***	0.265***	0.0554***	0.0540***
	(0.0792)	(0.0843)	(0.120)	(0.131)	(0.0290)	(0.0311)	(0.0139)	(0.0149)
Leverage	-0.0270	-0.0212	-0.0290	-0.0124	0.183***	0.145***	-0.0640***	-0.0616***
	(0.0588)	(0.0628)	(0.0893)	(0.0977)	(0.0215)	(0.0231)	(0.0103)	(0.0111)
R&D	-0.0388	-0.0181	-0.816**	-1.009**	-1.788***	-1.910***	-0.184***	-0.193***
	(0.272)	(0.291)	(0.413)	(0.453)	(0.0997)	(0.107)	(0.0477)	(0.0514)
Constant	-0.342	-0.414*	-0.362	-0.409	0.392***	0.523***	-0.236***	-0.234***
	(0.220)	(0.242)	(0.334)	(0.377)	(0.0805)	(0.0891)	(0.0386)	(0.0427)
Observations	16,309	13,669	16,309	13,669	16,309	13,669	16,309	13,669
Adjusted R-squared	0.603	0.613	0.042	0.064	0.798	0.797	0.803	0.797

Appendix

Table A1: Variable Definition

Variable	Definition
Decoupling	a measure of technology decoupling between the US and China
Dependence	China's technological dependence on the US
Innovation Output	the natural logarithm of one plus the number of patent applications a firm files (and eventually granted)
Innovation Quality	the number of citations a patent has received by 2019, divided by the average received by patents in its cohort (i.e., patents applied in the same year and in the same technology class)
TFP	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	firm age
R&D	R&D expenditures divided by sales
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

Table A2: Descriptive Statistics, Chinese Companies

Our empirical analysis is based on all publicly listed Chinese companies that filed at least one patent between 2007 and 2019. To gain a better understanding of these firms, we provide summary statistics for firms in our sample in this table. The variables are defined in Table A1. To alleviate the concerns for outliers, all variables in this table are winsorized at the 1^{st} and 99^{th} percentiles.

	Mean	Standard Deviation	Min	p25	Median	p75	Max	Observations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Decoupling	0.920	0.0308	0.845	0.896	0.924	0.942	0.981	16,010
Innovation Output	3.872	10.32	0	0	0	2.500	61.50	16,010
Innovation Quality	0.162	1.020	0	0	0	0	8.904	16,010
Assets (bl RMB)	10.87	28.37	0.375	1.436	2.905	7.093	211.9	16,010
Market Value (bl RMB)	10.70	17.28	0.990	3.014	5.384	10.33	121.5	16,010
Age	14.63	5.416	3	11	14	18	30	16,010
R&D	0.0369	0.0417	0	0.00215	0.0314	0.0485	0.239	16,010
Capex	0.0573	0.0492	0.00112	0.0212	0.0432	0.0785	0.234	16,010
PP&E	0.230	0.154	0.00687	0.112	0.199	0.319	0.679	16,010
Leverage	0.408	0.206	0.0479	0.241	0.398	0.561	0.912	16,010
$1/Q$	0.541	0.262	0.0918	0.332	0.505	0.725	1.172	16,010
TFP	0.584	0.541	-0.785	0.236	0.573	0.911	1.992	16,010

Table A3: Descriptive Statistics, U.S. Companies

Our empirical analysis is based on all publicly listed U.S. companies that filed at least one patent between 2007 and 2019. To gain a better understanding of these firms, we provide summary statistics for firms in our sample in this table. The variables are defined in Table A1. To alleviate the concerns for outliers, all variables in this table are winsorized at the 1^{st} and 99^{th} percentiles.

	Mean	Standard Deviation	Min	p25	Median	p75	Max	Observations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Decoupling	.916	.0304	.592	.895	.918	.937	.987	19,833
Innovation Output	30.1	106	0	0	1	10	738	19,918
Innovation Quality	.579	1.19	0	0	0	.69	6.95	19,918
Assets (bl USD)	9.21	24.6	.00589	.133	.718	4.64	144	19,918
Market Value (bl USD)	6.96	17.6	.00684	.193	.878	4.32	108	19,918
Age	22.3	19.3	0	9	17	30	85	19,918
Capex	.0377	.0417	7.3e-06	.0129	.0258	.0487	1.46	19,898
PP&E	.192	.193	.000031	.0545	.123	.259	.967	19,916
Leverage	.211	.236	0	.00369	.161	.318	1	19,791
$1/Q$	.556	.354	.0507	.291	.489	.748	1.93	19,918
TFP	1.61	1.12	.0476	.811	1.43	2.16	6.05	19,695

Internet Appendix for "Mapping US-China Technology Decoupling, Innovation, and Firm Performance"

IA1 Patent Examination Procedures, US 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 grant of patents. At both USPTO and CNIPA, patent applicants and patent examiners are required to cite the prior art in both domestic patents and foreign patents.

[Insert Figure IA1 here.]

IA2 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 dominate among China-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 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-difference 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 their U.S. counterparts in Chinese patents, whereas patenting of U.S. assignees is 3.42 times higher than their Chinese counterparts in 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, Bloom, Short, and Lerner (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 US patenting advantage in each high-tech field between 2000 and 2019 and the results are visualized in Figure IA4.[34] 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 US 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.

[34]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.

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

IA3 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 IA15. 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 IA15 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, industries 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 IA15 here.]

Figure IA1: **Patent Examination Procedures, US 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.

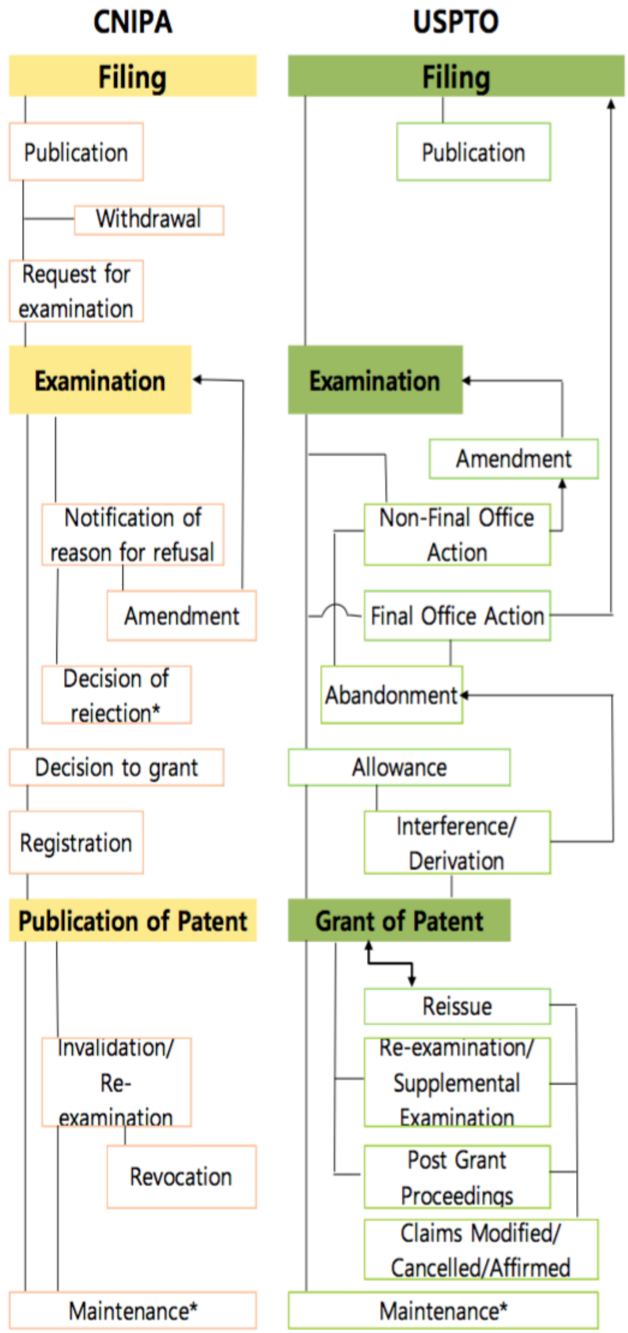
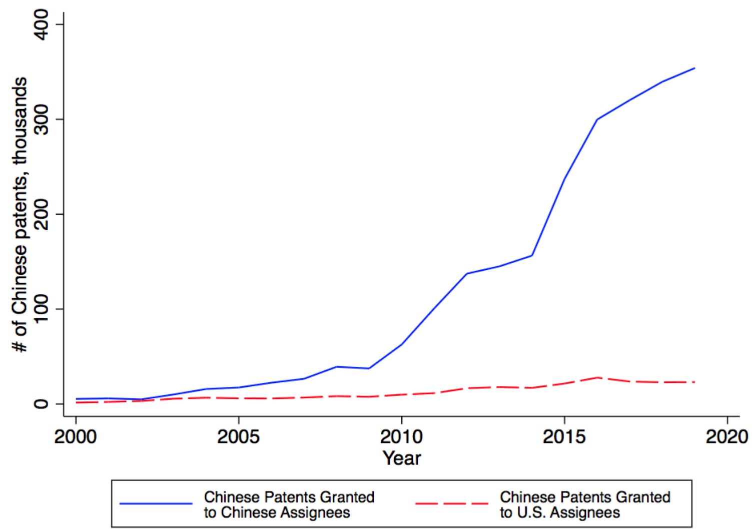
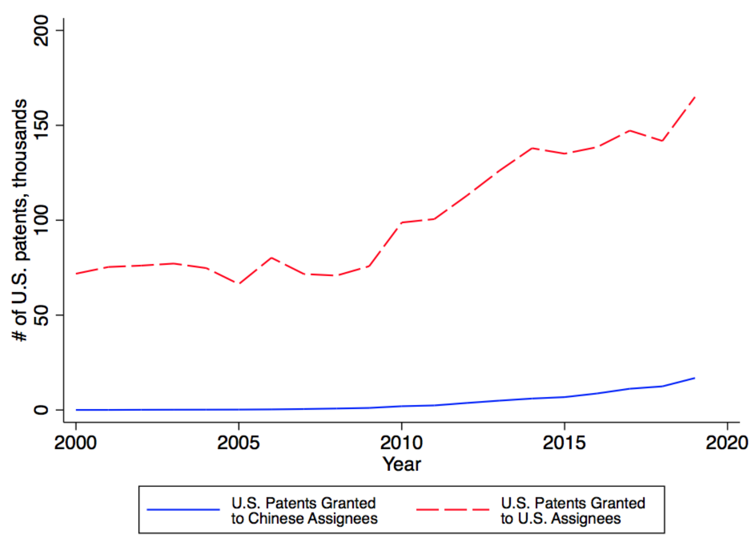


Figure IA2: **Patents Granted, Chinese vs US Assignees**

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 refer to invention patents granted at the Chinese National Intellectual Property Administration (CNIPA). "U.S. patents" in this figure refer 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: **US 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. We focus on patents granted at two patents offices and granted to assignees in two countries, so $p \in \{\text{US Patents}, \text{Chinese Patents}\}$ and $a \in \{\text{US Assignees}, \text{Chinese Assignees}\}$. $1\{\text{US Assignees}\}$ takes the value of one (zero) for the U.S (Chines) patent assignees. $1\{\text{US Patents}\}$ 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. 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.

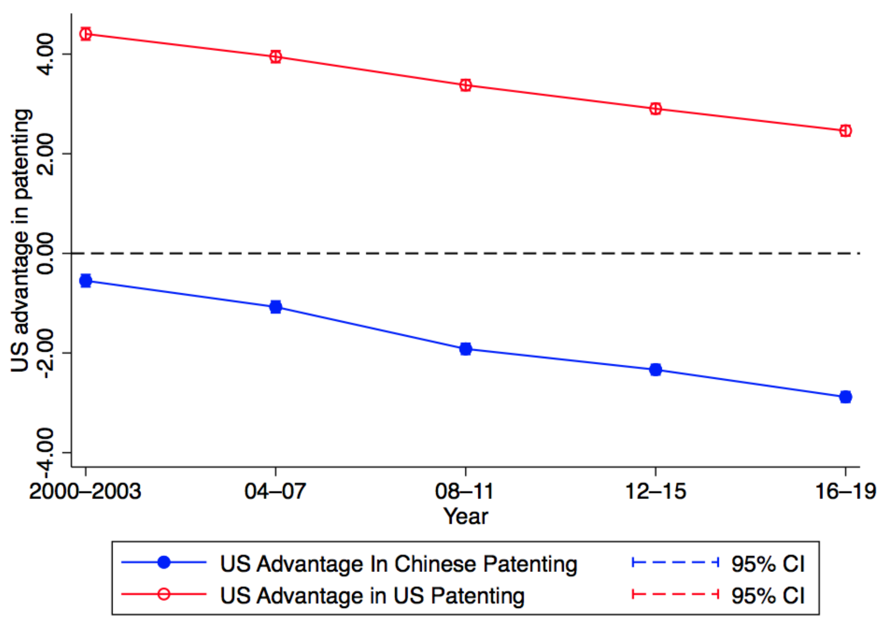


FIGURE IA4: **US Advantage In Patenting, Industry Heterogeneities**

We estimate the U.S. patenting advantage in ten high-technology field 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. Patents granted in other technological fields will be collectively referred to as "low-tech patents." 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 refer to invention patents granted at the Chinese National Intellectual Property Administration (CNIPA). "U.S. patents" in this figure refer to utility patents granted at the United States Patent and Trademark Office (USPTO).

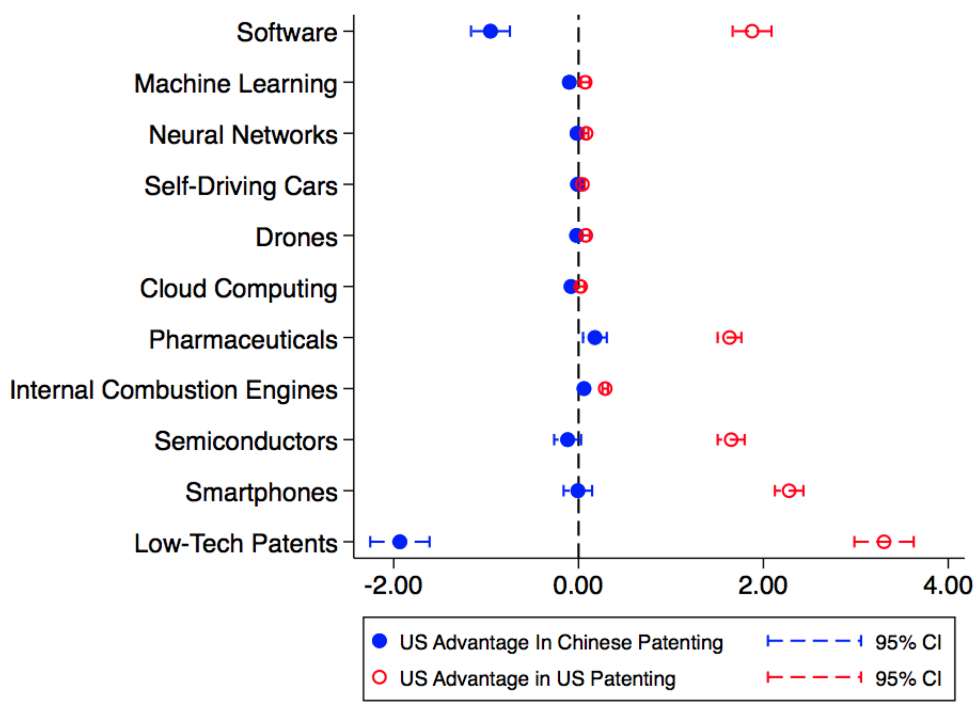


Figure IA5: **U.S. Patenting Advantage, Software**

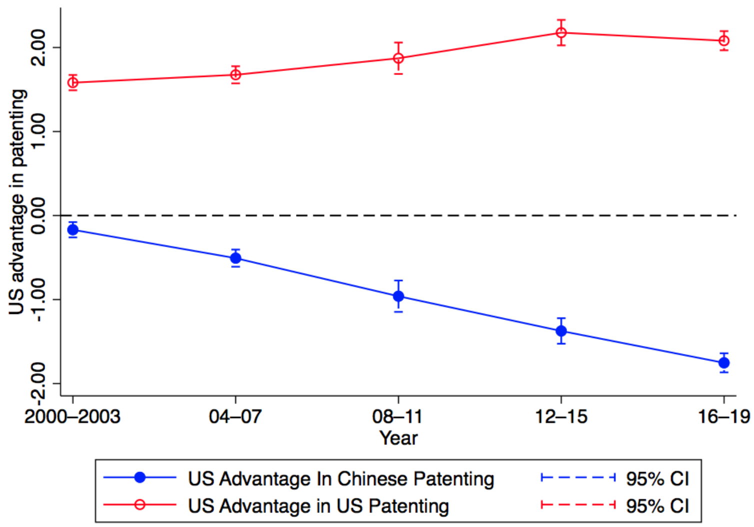


Figure IA6: **U.S. Patenting Advantage, Machine Learning**

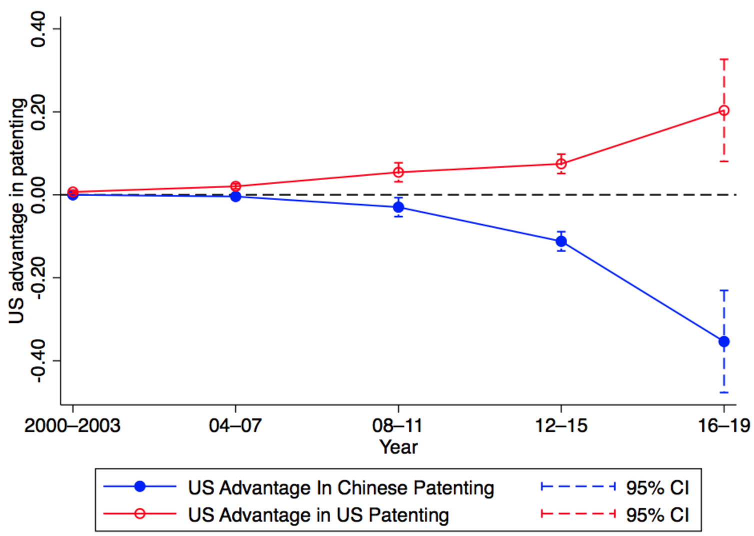


Figure IA7: **U.S. Patenting Advantage, Neural Networks**

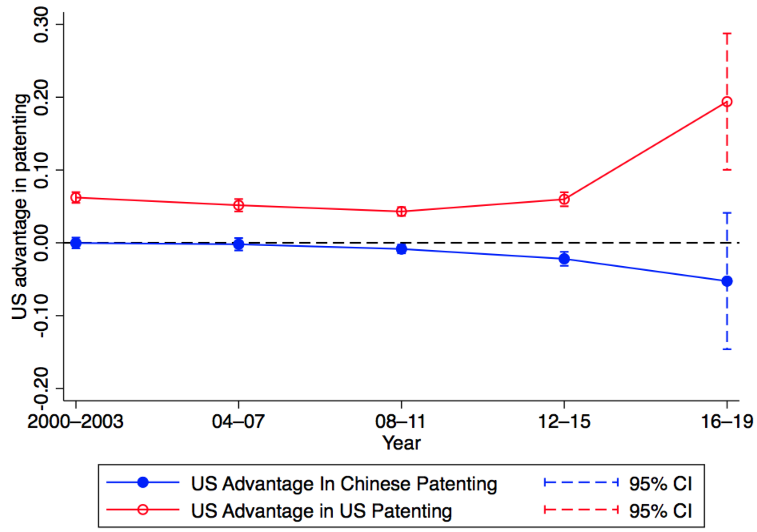


Figure IA8: **U.S. Patenting Advantage, Self-Driving Cars**

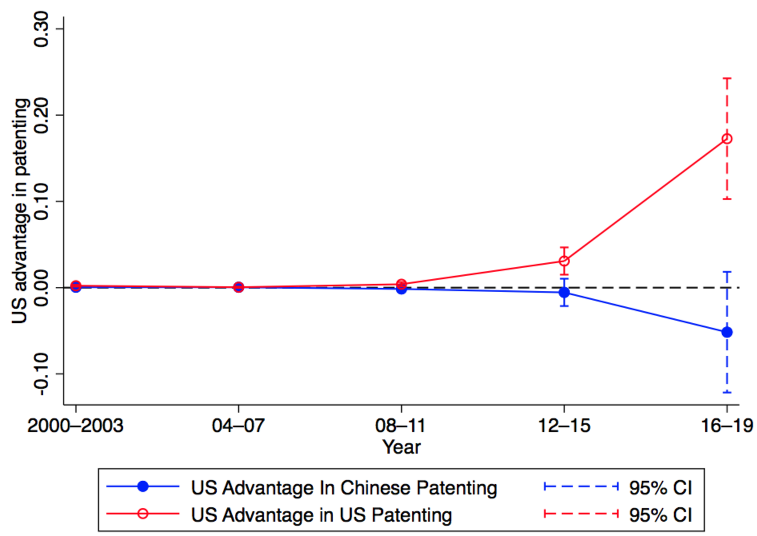


Figure IA9: **U.S. Patenting Advantage, Drones**

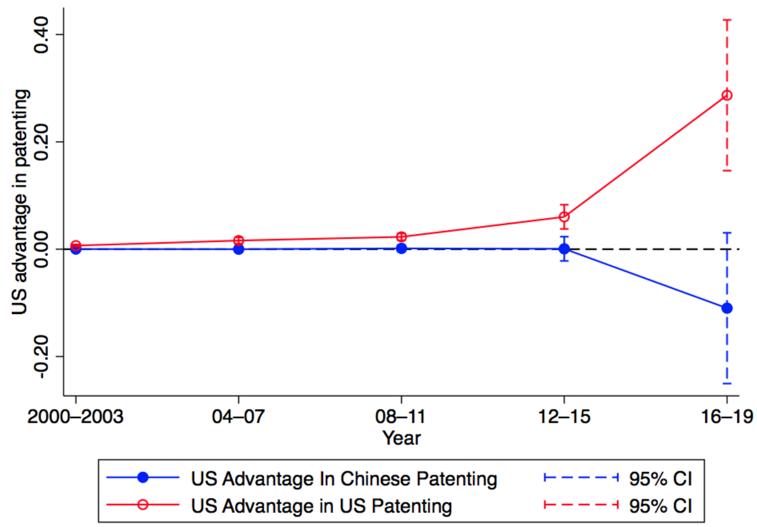


Figure IA10: **U.S. Patenting Advantage, Cloud Computing**

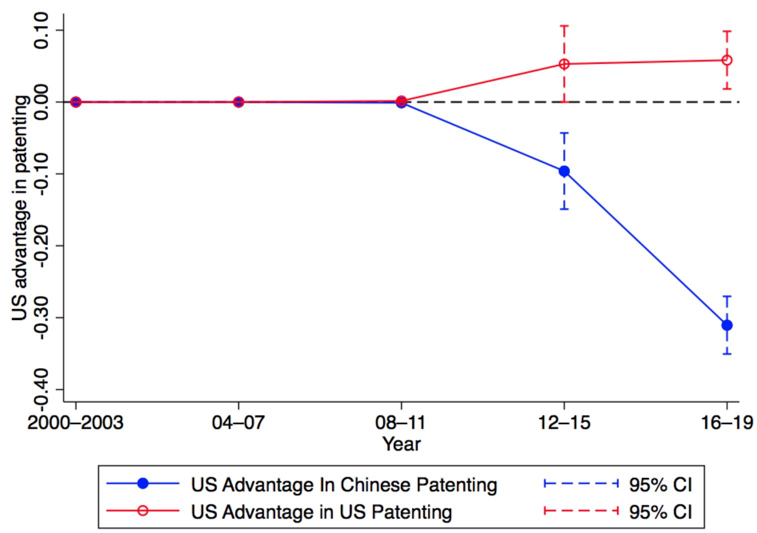


Figure IA11: **U.S. Patenting Advantage, Pharmaceuticals**

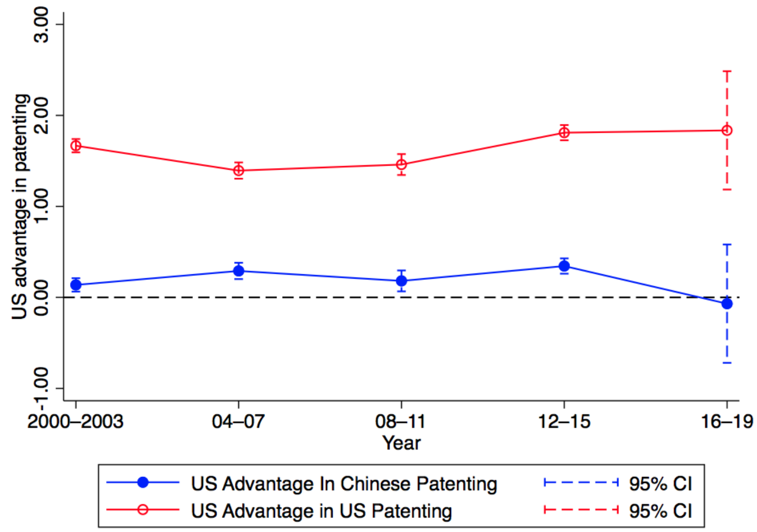


Figure IA12: **U.S. Patenting Advantage, Internal Combustion Engines**

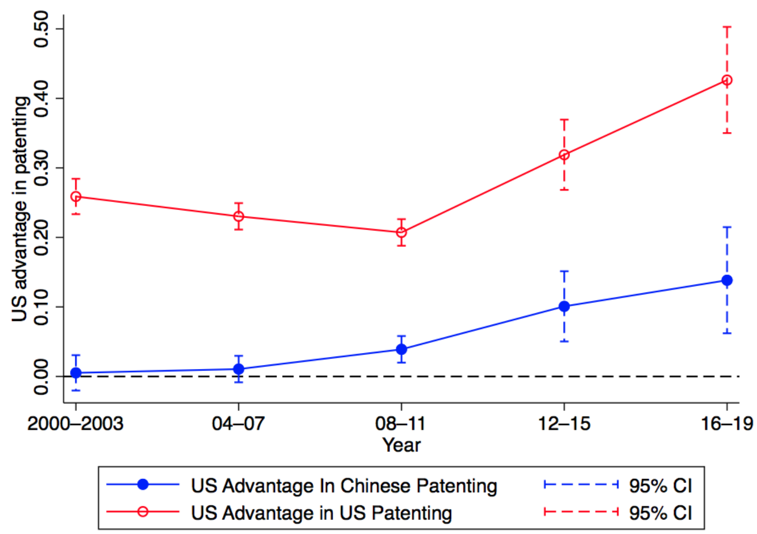


Figure IA13: **U.S. Patenting Advantage, Semiconductors**

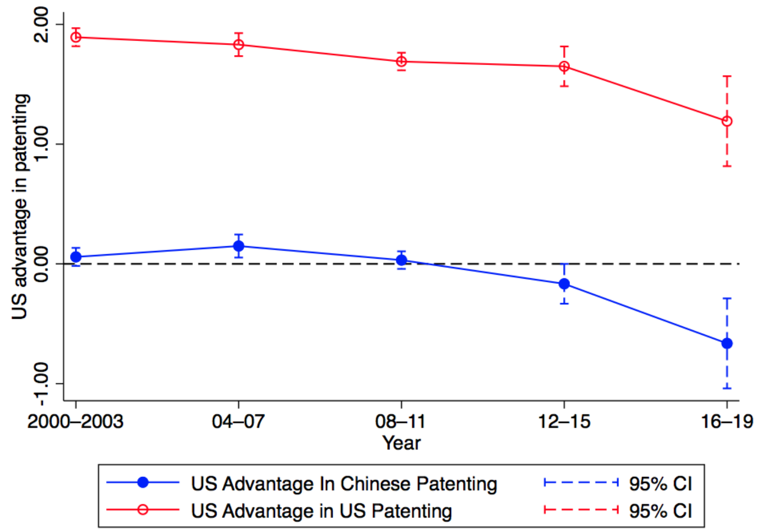


Figure IA14: **U.S. Patenting Advantage, Smartphones**

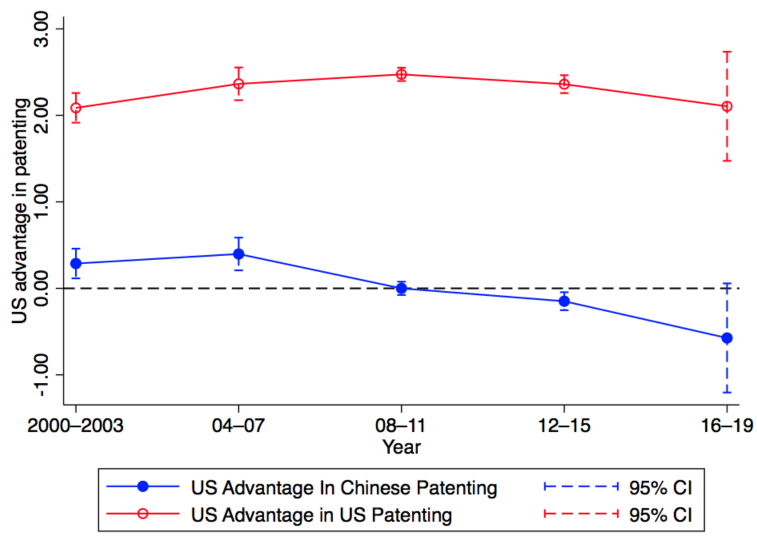
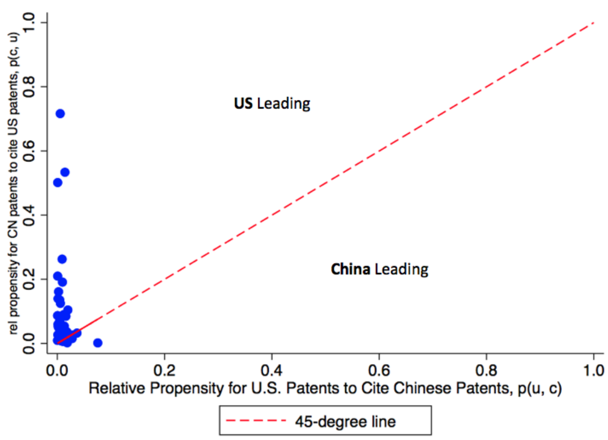
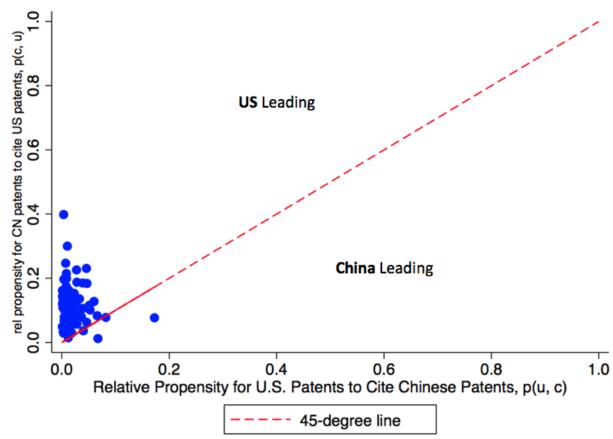


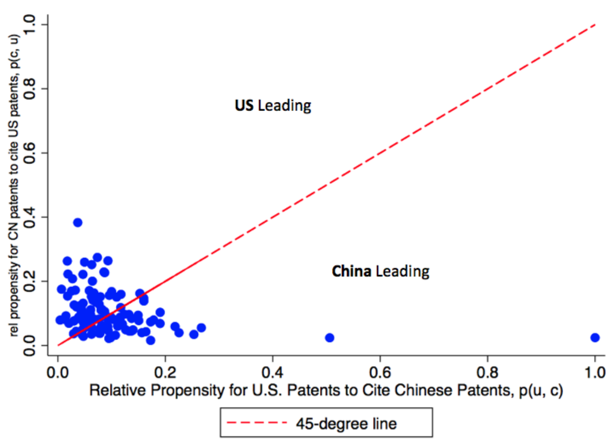
Figure IA15: **Propensity to Cite Foreign Patents Relative to Citing Domestic Patents**
In this figure, we plot $p_{c,u}$ against $p_{u,c}$ for each technology class (at 3-digit IPC codes). $p_{c,u}$ (the vertical axis) is a proxy of the propensity for Chinese patents to cite a U.S. patent relative to citing a Chinese one. $p_{u,c}$ (the horizontal axis) 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 three crucial years: 2000 (the year before China joined WTO), 2009 (the end of the Great Recession), and 2019 (the end of our sampling 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



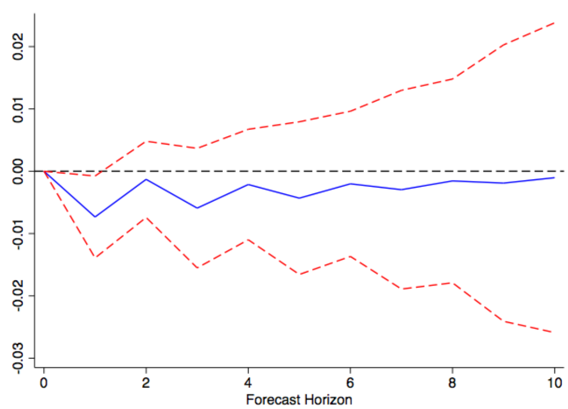
(B) 2009



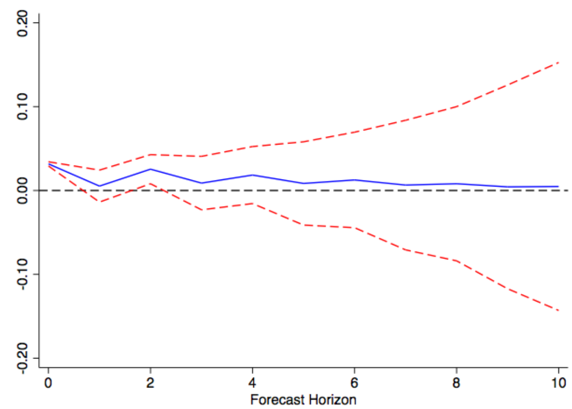
(C) 2019 (Including Outliers)

Figure IA16: **Technology Decoupling and Dependence, Impulse Response Functions**

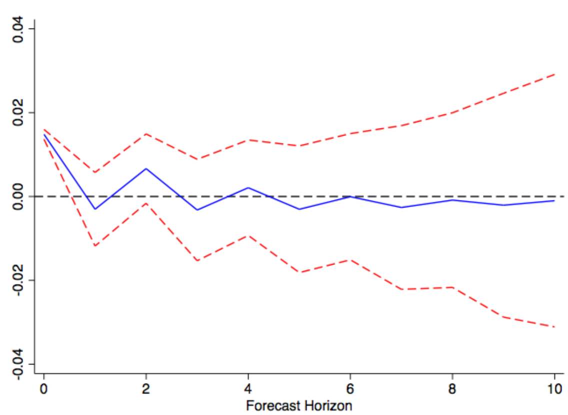
To visualize the dynamic interactions between technology decoupling and dependence, we plot the results of the impulse-response functions (IRF) in this figure. All sub-figures are orthogonalized IRF results based on Cholesky decomposition. To address the concern that these two measures are negatively correlated with each other in a mechanical manner, the IRF analysis is based on the residualized measure of technology decoupling and dependence. The exogenous shock is the innovation of decoupling in Figure IA16a and IA16b, and the exogenous shock is the innovation of dependence in Figure IA16c and IA16d. We evaluate how China's technological dependence on the US affects US-China decoupling in Figure IA16a and IA16c, and we assess how US-China decoupling affects China's technological dependence on the US in Figure IA16b and IA16d.



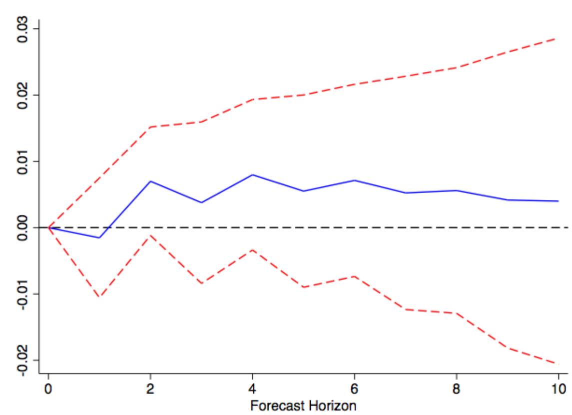
(a) Effect of Dependence On Decoupling Shock: Innovation of Decoupling



(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: US Advantage In Patenting, Dynamics

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

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

In this regression, we stack two samples of patents granted at CNIPA and USPTO into a balanced panel. The subscript i indexes for a technology class, a indexes for the nationality of the patent assignees, p indexes for the patent office, and t indexes for year. The dependent variable $y_{i,a,p,t}$ 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)
Constant	5.324***	4.276***	5.500***	6.338***	7.526***	8.440***
	(0.531)	(0.502)	(0.481)	(0.448)	(0.424)	(0.430)
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
Industry fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Industry × 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: US-Leading vs China-Leading Tech Classes, Top Ten

Panel A reports the top ten US-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. US-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 Technology Dependence, OLS

The regressions in this table are based on a panel data at the three-digit-IPC-year level and the sampling 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 US-China technology decoupling. The dependent variables in regression (4)–(6) are our measure of China's technological dependence on the US. 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***			
	(0.0137)	(0.0149)	(0.0157)			
dependence, $t-2$		0.0625***	0.129***			
		(0.0145)	(0.0166)			
dependence, $t-3$			-0.0447**			
			(0.0184)			
decoupling, $t-1$				-0.321***	-0.548***	-0.398***
				(0.0601)	(0.0657)	(0.0685)
decoupling, $t-2$					0.247***	0.592***
					(0.0635)	(0.0722)
decoupling, $t-3$						-0.273***
						(0.0802)
Constant	0.945***	0.944***	0.929***	0.404***	0.377***	0.172*
	(0.00291)	(0.00313)	(0.00335)	(0.0565)	(0.0793)	(0.102)
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
Tech class fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes