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

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

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

*Corresponding authors

Contact: pengfeihan@gsm.pku.edu.cn, https://orcid.org/0000-0001-5798-4934 (PH); wei.jiang@emory.edu, https://orcid.org/0000-0003-3256-4938 (WJ); dqmei@ckgsb.edu.cn, https://orcid.org/0009-0005-2510-4337 (DM)

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

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Keywords: technology decoupling • innovation • R&D • patent • firm performance

1. Introduction

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

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

The first main mission of this paper is to map out technology decoupling (i.e., the opposite of integration) between the two nations over time, in the aggregate and across different technology classes, based on measures developed anew. We calibrate decoupling by the propensity for domestic patents in a technology area to cite foreign patents relative to citing their own. In simplified language, the extreme situation of "perfect decoupling" implies that patents filed in one country never cite any patents in the other country, suggesting two segregated ecosystems of innovation. In the other extreme of "perfect integration," there is an utter absence of a "home bias" in patent citations as if there were no national borders in technology. Although the extent of decoupling is symmetric with respect to both countries, one nation might depend more on the technology of the other than the other way around. A related measure of China's technological dependence on the United States (which is the negative value of U.S. dependence on China) is based on the propensity of Chinese patents citing U.S. ones relative to citations in the reverse direction.

Applying the measures at the aggregate level, we discover that U.S.–China technology decoupling has been declining steadily since 2000, the year before China acceded to the World Trade Organization (WTO). In other words, growing integration of the two technological systems has been the dominant theme in the twenty-first century. China's technological dependence on the United States, on the other hand, is hump shaped, peaking in 2009 at the end of the Great Recession. Therefore, from China's perspective, 2000–2009 was a decade of dependence-deepening integration with the United States, whereas the next decade featured dependence-relaxing integration. Toward the last two years of our sample (2020–2021, the coronavirus disease 2019 (COVID-19) era), we observe signs of decreasing decoupling despite restrictions on travel and strains on supply chains.

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

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

Regarding policies on the U.S. side, we evaluate the impact of U.S. sanctions imposed via the entity list of the U.S. Department of Commerce, which had hovered at a low level but have escalated since 2014. Perhaps contrary to conventional wisdom, we find that U.S. sanctions against China have not been followed by decoupling in the targeted technology area. It is often said that science and technology do not respect national boundaries, and U.S. government interventions, short of more draconian measures, have not been strong enough to reverse the fundamental forces driving global integration in recent decades. U.S. sanctions have compelled China to pursue more independence-oriented technological development. Although incurring moderate drops in innovation output, profitability, and productivity, Chinese firms exposed to sanctions started to produce more original innovations. Further, valuation of these firms exhibits resilience, possibly helped by support from the Chinese government and businesses as the intensity of sanctions grew.

Technology, by its nature, is fluid at sectoral and national boundaries, with spillovers expected within the broad innovation network. Based on an innovation network built on a patent-citation input-output (IO) table (Acemoglu et al. 2016, Liu and Ma 2022), we find that U.S. sanctions imposed on a sector's upstream are associated with poorer performance of firms in the focal sector in terms of productivity, profitability, and valuation. The focal sector in China seeks more integration with the United States but still suffers in innovation output, efficiency, and impact. Exactly the opposite is true when sanctions are imposed on firms' downstream sectors. As the downstream becomes captive to domestic technologies and supplies after facing restrictions in accessing U.S. technologies and inputs, firms in the focal sector thrive in performance and produce more breakthrough innovations. Our findings indicate that U.S. sanctions can instigate broader impact than was envisioned by the policy makers and prompt potentially unintended consequences via the network spillovers.

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

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

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

2.1. Overview: Patenting in the United States and China

The most crucial data inputs of this study are the combined patent-level databases from the two countries based on the full records from the U.S. Patent and Trademark Office (USPTO) and the Chinese National Intellectual Property Administration (CNIPA). We focus on "utility patents" granted at the USPTO ("U.S. patents" hereafter), which cover inventions that function in a unique manner to produce a useful result and are commonly considered the default form of patents.[8] The counterparts in the CNIPA system are "invention patents" ("Chinese patents" hereafter).[9] Despite differences in many details, the patent examination procedures at USPTO and CNIPA are mostly comparable. USPTO and CNIPA grant patents to both domestic and foreign assignees, and neither of them discriminate based on the citizenship of applicants in regard to eligibility for patent applications. Filing patents at a foreign patent office is critical to protect the applicant's intellectual property there, as the exclusive rights are only applicable in the country or region in which a patent has been filed and granted. At both patent offices, domestic and foreign applicants will go through three major phases: filing, examination, and the granting of patents.[10]

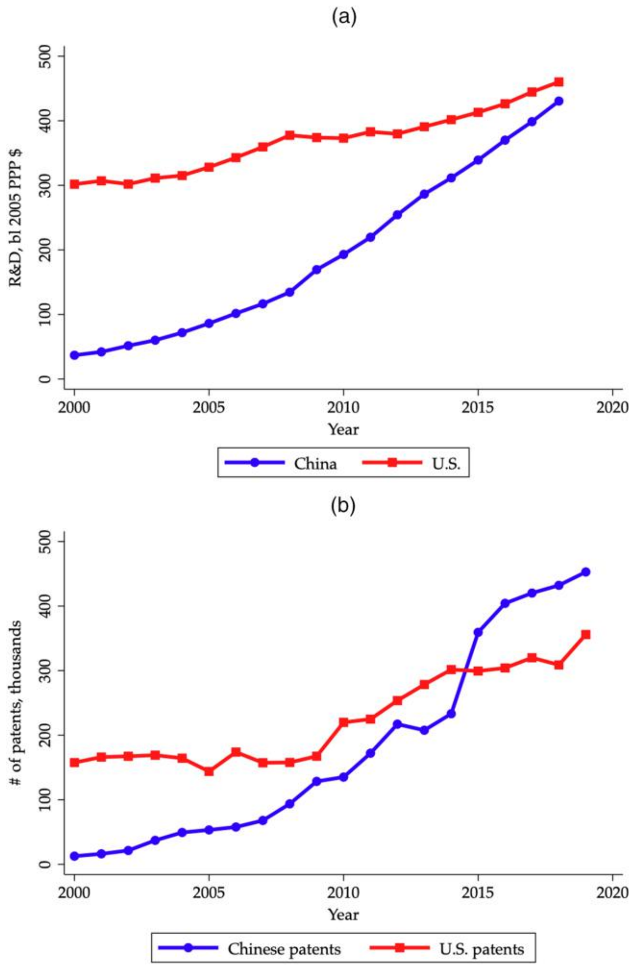
Importantly, patent examiners in both countries are required to search for prior art in both domestic and foreign patents during the patent examination process.[11] The fact that English (but not Chinese) is a global language could contribute to a citation bias in favor of U.S. patents. Nevertheless, the USPTO puts much effort into facilitating U.S. patents to cite foreign ones (from China and other countries). First, the USPTO has access to almost all foreign patent documents through exchange agreements. Second, according to the instruction manual of the USPTO patent examiners, the examiners can request (human) translation of all patents that are cited in the reference or being considered for citation. Third, translations are readily available for virtually all foreign languages (including Chinese) into English. Finally, an English-language advantage, if it exists, should not impact cross-sectional or time-series relations.

As an overview, Figure 1 plots the annual time series of innovation inputs (R&D expenditures)[12] and outputs (patents) of the two countries. Apparent from both charts is that China has rapidly ascended to becoming a global R&D and patenting powerhouse in the two recent decades, challenging the U.S. leadership position at least in terms of these nominal metrics. Although the U.S. R&D expenditures more than octupled China's level in 2000 and have been growing steadily, China had almost closed the gap by 2020, with a steady annual growth rate of 13.9%. Starting from fewer than 1/13 of the U.S. patenting volume at the beginning of the twenty-first century, China managed to surpass the United States in 2015 and has since remained in the lead. In addition to comparing the two nations as patent approval authorities, we also examine the patenting activities based on the nationalities of the assignees, and the results are qualitatively similar.[13]

2.2. Measuring Technology Decoupling and Dependence

Decoupling and dependence are related but also distinct and warrant separate measurements. Technological standards can be different across countries (from issues as simple as the standard voltage), and crossborder technology transfer often faces more friction than

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



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

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

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

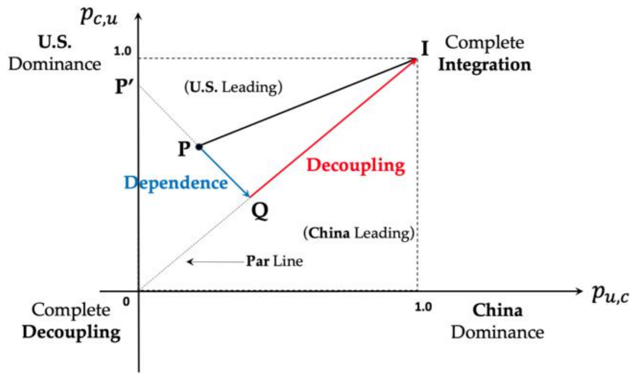
We start with a few notations to build up to the proposed measures. First, $p_{c,u,t}$ is the propensity for Chinese patents approved in year t to cite a U.S. patent relative to citing a Chinese one; analogously, $p_{u,c,t}$ is the propensity for a year-t U.S. patents to cite Chinese patents relative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

$$p_{c,u,t} = \frac{n_{c,u,t}/x_{u,t}}{n_{c,c,t}/x_{c,t}}, p_{u,c,t} = \frac{n_{u,c,t}/x_{c,t}}{n_{u,u,t}/x_{u,t}}. \tag{1}$$

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

With the expressions, we are able to provide a visualization of decoupling and dependence, presented in Figure 2. The horizontal and vertical axes measure $p_{u,c,t}$ and $p_{c,u,t}$, respectively. The state of "complete decoupling," or an absolute lack of integration, is

Figure 2. (Color online) Measures of Technology Decoupling and Dependence



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

associated with the origin and corresponds to the scenario where domestic patents in either country never cite any patents in the other. This is because presumably, each has its own ecosystem that is enclosed from the other. The opposite scenario is zero decoupling or complete integration corresponding to the point I with (1, 1) coordinates (i.e., $p_{c,u,t} = p_{u,c,t} = 1$). At this point, domestic patents cite a patent in the other country with the same probability as citing a domestic patent (i.e., an absence of any "home bias" in technology development).[15] Points interior of the box indicate a partial integration or imperfect decoupling.

The 45° line in Figure 2 is the state of parity (i.e., $p_{c,u,t} = p_{u,c,t}$). Along this line, the propensity for Chinese patents to cite U.S. patents is exactly reciprocated, although the degree of integration/decoupling varies. In the triangular area above the 45° line, Chinese patents are more likely to build on U.S. patents than the other way around or $p_{c,u,t} > p_{u,c,t}$. 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, to illustrate how to quantify such a combination. As a first step, a projection of P onto the 45° parity line arrives at point Q. By construction, the vector $\overrightarrow{PQ}$ is orthogonal to the 45° line. The norm of $\overrightarrow{QI}$ (i.e., the projection of $\overrightarrow{PI}$ onto the par line) captures the degree of U.S.–China technology decoupling, whereas the norm of $\overrightarrow{PQ}$ (i.e., the rejection of $\overrightarrow{PI}$ from the par line) reflects China's technological dependence on the United States. The measure of decoupling simply becomes $\frac{\|\overrightarrow{QI}\|}{\sqrt{2}}$,[16] which based on the geometric relations, could be derived as $1 - (p_{c,u,t} + p_{u,c,t})/2$. Intuitively, measured decoupling is lower if patents from each country cite patents from the other country at a high rate relative to domestic citation. Even though the desire to decouple could be mutual or unilateral, the outcome of decoupling is symmetric between the two countries.

Next, the degree of China's technological dependence on the United States, graphically, becomes $\sqrt{2}\|\overrightarrow{PQ}\|$ in the United States-leading region and $-\sqrt{2}\|\overrightarrow{PQ}\|$ in the China-leading region in Figure 2. Algebraically, it becomes $Dependence(\text{CN on US}) = p_{c,u,t} - p_{u,c,t}$ or the difference in the propensity to cite patents from the other country. For the ease of notation, "dependence" refers to China's dependence on the United States unless otherwise specified in the rest of the paper. Thus, a positive sign of *Dependence* indicates that China depends more on U.S. technology than the other way around or that the United States maintains a leading position. When $Dependence(\text{CN on US}) = 1$ (or -1), the United States (or China) is in absolute dominance.

We note that the degree of decoupling imposes ranges on the level of dependence. In the extreme of perfect decoupling, dependence becomes moot and is hence zero; in the other extreme of perfect integration, the two countries must be on parity, and hence, dependence (which is on a relative scale) is also zero, the neutral value. Moving from the extreme points toward the middle of the 45° line in Figure 2, the range of permissible values of dependence increases. We thus also develop a conditional version of the dependence measure that is free from such a functional restriction. More specifically, let P' be the intersection point of the extension of the vector $\overrightarrow{QP}$ and the vertical axis. Then, $\|QP'\|$ is the maximum level of dependence conditional on the level of decoupling. We thus define the level of dependence conditional on decoupling, or *Dependence* | *Decoupling* (CN on US), to be $\overrightarrow{QP}/\|QP'\|$. It is bounded between -1 and 1 and orthogonal to *Decoupling* (except when the measure is not defined in the two extreme states of perfect decoupling or integration).

Our key measures *Decoupling* and *Dependence* aim at capturing the fundamental economic relations that are not unique to the pairing of the United States and China. In our empirical section, we also explore the time series in U.S.–European Union decoupling during the same time period as a reference point for the relation between two mature economies.[17] For further external validation, we apply them to an out-of-sample setting of which we are informed about the truth so that we can have a "sanity check." Consider the following three representative academic journals: *American Economic Review* (AER; a leading economics journal), *Journal of Finance* (JF; a leading finance journal), and *Journal of Banking and Finance* (JBF; a leading journal in a subfield of finance). Applying the two citation-based measures, we find that the two finance journals are well integrated and that each is more decoupled from AER. Moreover, JBF depends more on JF, whereas the dependence between JF and AER is mutual. Finally, JF and AER became more decoupled during 2001–2010 but have since re-integrated. These findings mirror the evolution of finance academia, a vote of confidence in our measures.[18] We are happy to share the constructed measures *Decoupling* and *Dependence* with interested academic researchers upon request.

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

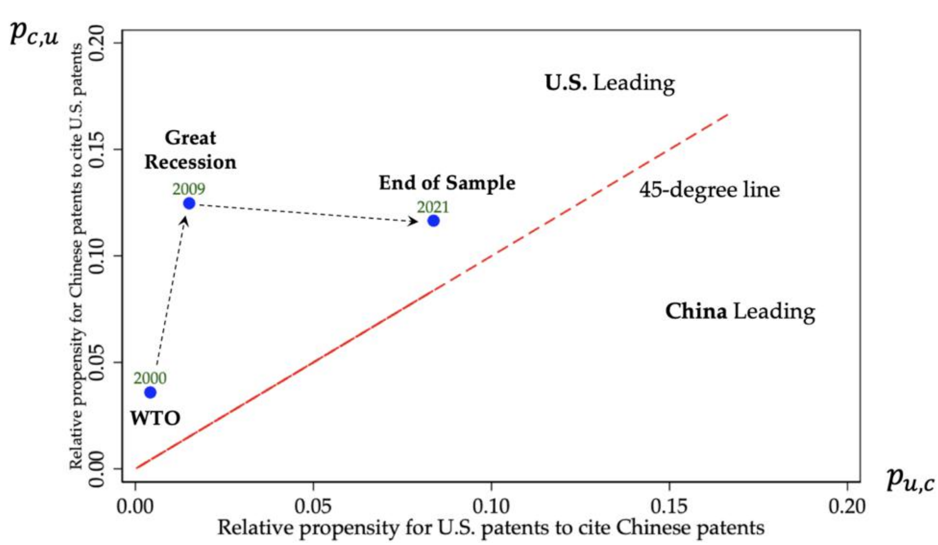
2.3.1. Dynamics of Technology Decoupling: 2000–2021

2.3.1.1. The Time Series. The measures developed in the previous section allow us to quantify the history and the current state of U.S.–China technology decoupling and dependence. Grouping all patents by country (the United States and China), we map the aggregate time series into three "screenshots" in Figure 3: 2000 (the year before China's entry to the WTO), 2009 (the end of the Great Recession), and 2021 (COVID-19 and the escalation of tension between the two nations). All three observations fall toward the lower left above the 45° line, indicating that the two countries have mostly been running separate systems, with China exhibiting more dependence on U.S. technology. The change over time, however, is also informative. Since 2000, China moved first toward more integration with and more dependence on U.S. technology during the first decade and then reduced its dependence while furthering integration with the United States during the second decade.

Figure 4 offers a different presentation of the same history in more detail. In this chart, the horizontal axis is time in the calendar year, and the right (left) vertical axis marks the measure of decoupling (dependence).[19] During the full sample period since 2000, technology decoupling has been falling steadily, conforming to the general theme of globalization. China's technological dependence on the United States, however, is hump shaped over time, with the turning point being around the end of the Great Recession (2009). The combined evidence suggests that the first decade of the twenty-first century was characterized by dependence-*deepening* integration between the two countries; that is, technology in China became more dependent on U.S. technology during the integration process. During the second decade since 2010, the continued technology integration has been accompanied by China's declining dependence on the United States.[20] Although state-owned enterprises (SOEs) play a unique role in China's economy, we verify that patents filed by SOEs and private firms followed very similar dynamics.[21]

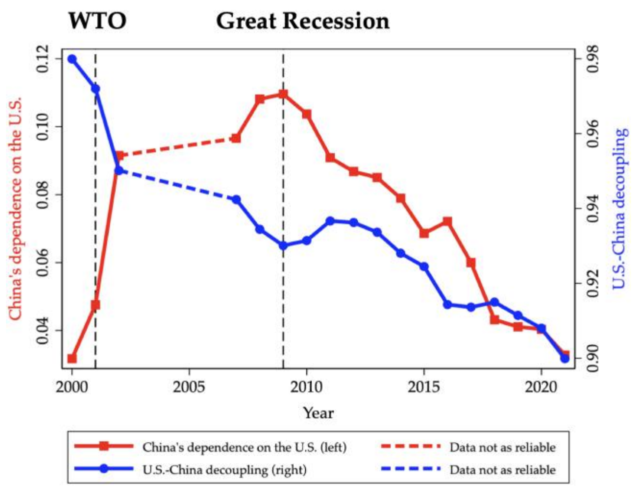
One question that naturally arises is whether the time series of decoupling is unique to the two nations or simply part of the global trend. Because patent

Figure 3. (Color online) U.S.–China Technology Decoupling and Dependence in 2000, 2009, and 2021



Notes. This figure is the empirical analog of Figure 2. The vertical axis ($p_{c,u}$) is a proxy for the propensity for Chinese patents to cite a U.S. patent relative to citing a Chinese one. The horizontal axis ($p_{u,c}$) is a proxy for the propensity for U.S. patents to cite a Chinese patent relative to citing a U.S. one. To highlight critical turning points of the transition, we zoom in on three crucial years: 2000 (the year before China joined the World Trade Organization), 2009 (the end of the Great Recession), and 2021 (the end of our sample period).

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



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

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

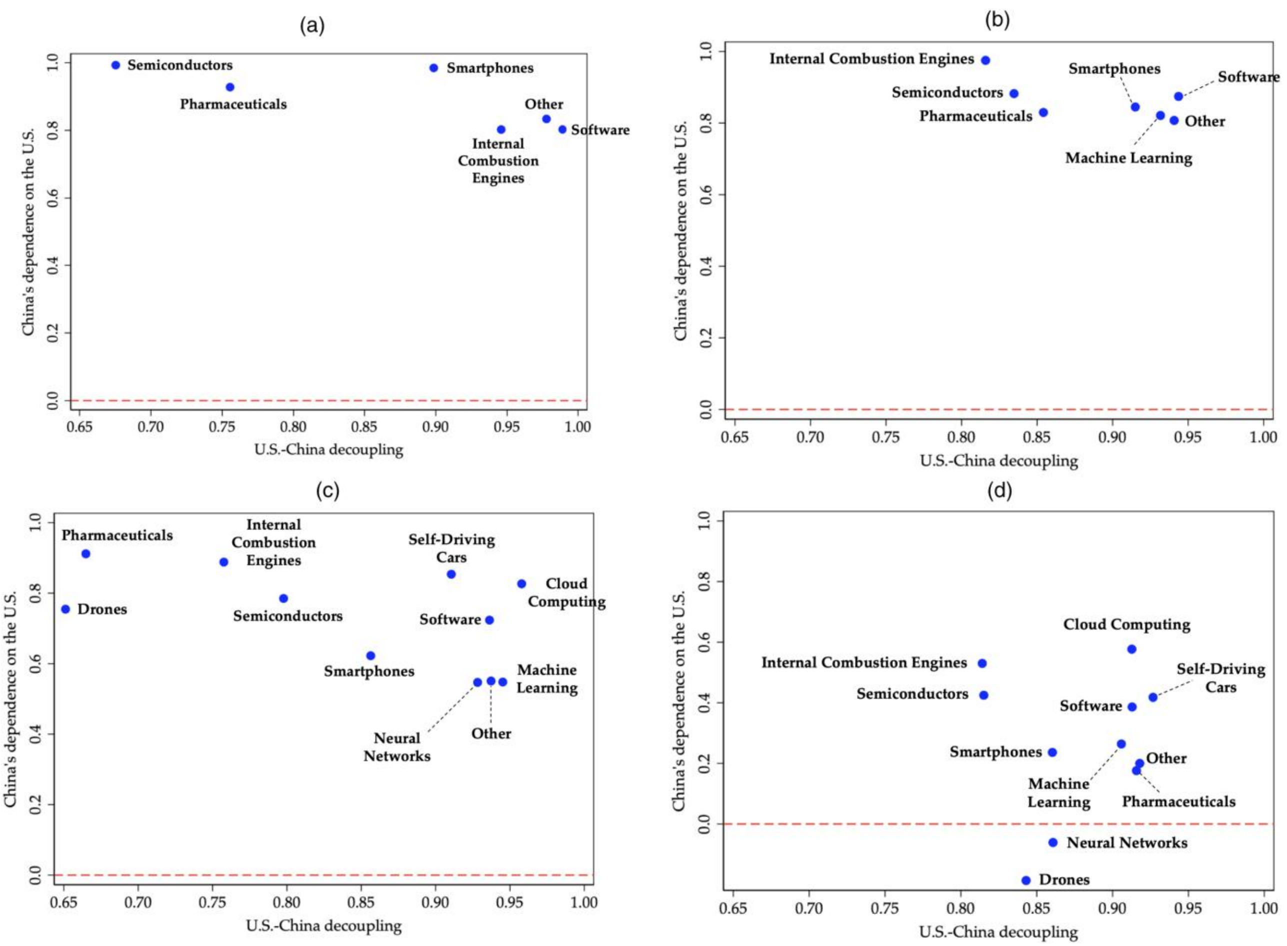
2.3.1.2. The COVID-19 Era. The 2020–2021 segment of the sample period allows us to shed light on the impact of COVID-19 on the technology decoupling between the United States and China, which is ambiguous because of two opposing forces. On the one hand, the development of virtual-based work environment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

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

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

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

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



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

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

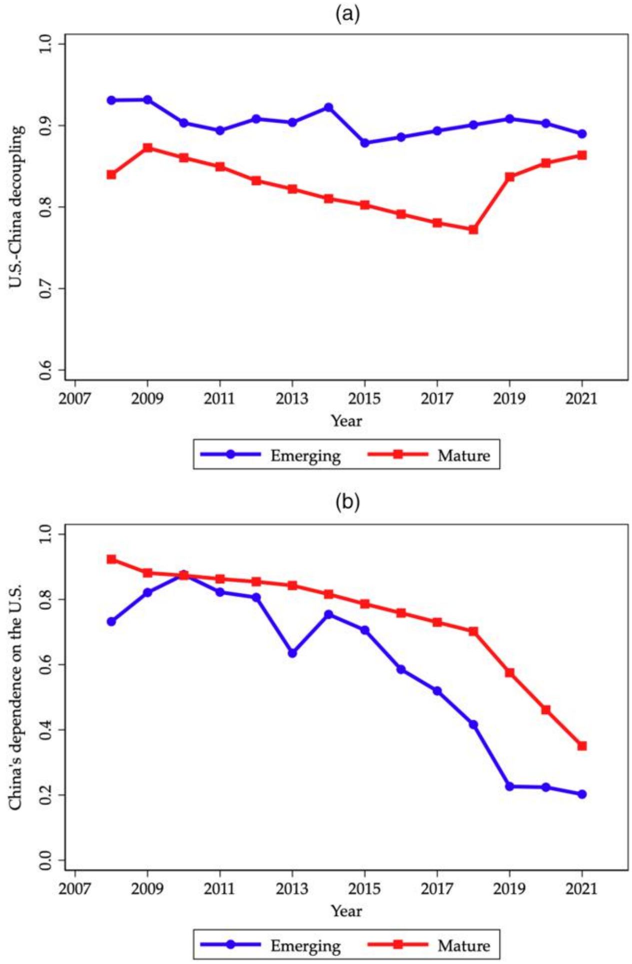
Our findings are mostly consistent with but formalize the anecdotal evidence on both the positive and negative sides regarding China's technological progress. First, China's hard work on reducing dependence in semiconductors seems to have paid off, as shown by the decreased dependence level from 0.55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

2.3.3. Alternative Measures and Sensitivity Checks

2.3.3.1. Discussions of Limitations of Citation Metrics.

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

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



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

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

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

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

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

Two additional methods have been developed based on the content of the patents. Fang et al. (2021) resort to a new-word search in patent abstracts in defining innovation leadership. They find that China made steady progress in the share of patents with "frontier words" during the same sample period, although it is still much lower than the U.S. level. Such a pattern is consistent with our finding on dependence (e.g., in Figure 4). Alternatively, a few recent papers have resorted to "textual similarity" of patents as a proxy for technology similarity or compatibility (Younge and Kuhn 2016, Kelly et al. 2021). We apply the method to U.S. and Chinese patents and discover that the textual similarity between patents filed in the two nations has a cross-sectional correlation (at the technology class-year level) of -0.12 with our decoupling measure (significant at the 1% level) but bears no significant correlation with our dependence measure.[31] Our method could be complementary to the textual-based methods, and more importantly, our method allows an integrated analysis of both decoupling and dependence.

3. Decoupling and Firm Performance: Diagnostics

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

3.1. Overview of Sample U.S. and Chinese Firms

Both the direction of the impact of technology decoupling and its symmetry (or the lack thereof) between the two nations are ambiguous. To investigate these issues, we assemble panels of firms in the United States and China. Given the focus on innovation, the sample comprises publicly traded companies that filed at least one patent between 2007 and 2019. The sample period starts from 2007 because publicly listed firms in China were not required to disclose certain important accounting information (e.g., R&D expenditures) prior to 2007. Other studies (e.g., Fang et al. 2023) follow the same practice. On the Chinese side, financial statements and trading information of firms come from the China Stock Market and Accounting Research (CSMAR) database. We then merged the CSMAR data with the Chinese patent database by matching company names in Chinese. On the U.S. side, we merged the U.S. patent database to Compustat using the procedure developed in Kogan et al. (2017).[32] Firm information for both countries is accessed via Wharton Research Data Services. We exclude firms in the financial industry following the common practice.

Following the literature in corporate finance and innovation, we resort to the following measures as innovation metrics. The first is *Innovation Output*, measured as the natural logarithm of one plus the number of patent applications a firm files (and is eventually granted) in that year. The second measure, *Innovation Quality*, at the firm-year level is the average of relative citation strength over all the patents applied by the firm in a given year. The relative citation strength is defined as the number of citations a patent 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). Quality measured this way is comparable for patents from different time vintages and technology classes.

As for general firm performance, we consider three measures. First, total factor productivity (*TFP*) is the natural logarithm of a firm's total factor productivity. The TFP estimation, following Ackerberg et al. (2015), is based on a Cobb–Douglas production function, where output is proxied by a firm's total revenue. Inputs include capital and labor approximated by total assets and the total number of employees. Intermediate inputs are approximated by cash payments for raw materials and service for Chinese firms following Giannetti et al. (2015). For the sample of U.S. firms, intermediate inputs are calculated as the difference between revenue and operating income before depreciation and amortization, further subtracted of labor expenses. When a firm's labor expense is missing in Compustat, we multiply the industry-average wage per employee by the number of employees with the firm, following Bennett et al. (2020). The second measure *ROIC*, defined as operating income (earnings before interest, taxes, depreciation, and amortization (EBITDA)) divided by invested capital (i.e., the sum of the book value of debt and equity), captures the fundamental earnings power of the firm. Finally, firm valuation is proxied by *Tobin's Q*, approximated by the ratio of the sum of the market value of equity and the book value of debt to the sum of the book value of debt and equity.

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

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

3.2. Decoupling, Innovative Activities, and Firm Performance

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

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

$$y_{i,j,t} = Decoupling_{j,t-1} \times \beta_1 + Decoupling_{j,t-2/3} \times \beta_2 + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t}. \quad (2)$$

In Equation (2), the dependent variable $y_{i,j,t}$, indexed by firm i, technology class j, and year t, is one of the following performance metrics: *Innovation Output* (one plus the number of patents filings that were eventually approved, in logarithm), *Innovation Quality* (the relative citation strength), *TFP* (total factor productivity in logarithm), *ROIC* (return on invested capital), and *Tobin's Q* (in logarithm). The key independent variables are *Decoupling* at the technology class-year level and lagged by one year ($Decoupling_{j,t-1}$) for the short run and the average of lagged two to three years ($Decoupling_{j,t-2/3}$) for the intermediate-run effect. Because the dependent variable (performance) is at the firm level, whereas the key independent variable (*Decoupling*) is at the technology class level, we match a firm to a unique IPC group that hosts the highest number of patents owned by the firm.[33] $X_{i,j,t-1}$ represents the vector of firm characteristic variables introduced in Section 3.1 and is set to lag the dependent variable by one year. γ_t refers to a country-specific year fixed effect that absorbs shocks to the aggregate economy, and γ_i refers to a firm fixed effect that absorbs unobserved and time-invariant firm heterogeneity. $\epsilon_{i,j,t}$ is the error term. The estimation is conducted separately for Chinese firms and U.S. firms, respectively.

Start with Chinese firms reported in Table 1. Column (1) of Table 1 uncovers that increasing technology decoupling in a technology field is associated with significantly (at the 1% level) higher domestic patenting outputs in the same field a year later, and the effect mostly dies out two years down the road. Quantity aside, the patent quality, as measured by the relative citation strength, does not exhibit a significant change, but if anything, the coefficients (in column (2)) are positive on lagged *Decoupling*. Hence, the boom in innovation outputs does not come at the cost of quality. This positive correlation between technology decoupling and firm innovation output could be suggestive evidence that the substitution effect of decoupling is stronger than its complementarity effect for the Chinese firms in the short term (one-year horizon). Columns (4) and (5), however, reveal the potential dark side of technology decoupling in lowered firm *ROIC* and *Tobin's Q*. "Reinventing the wheel" may crowd out firm resources in other productive activities, erode firm profitability, and dampen firm valuation. Consistent with this interpretation, column (3) of Table 1 indicates that intensified decoupling is indeed associated with deteriorating firm productivity over a horizon of two to three years. Perhaps not surprisingly, the effect is stronger among the most innovative firms. By sorting firms into terciles based on their total number of patents, we find that the effects are primarily driven by the most innovative firms.[34]

To put the estimates into context, consider a hypothetical increase in U.S.–China technology decoupling of 0.0685 or 7.4% of the sample mean, a number picked to mimic the reverse of the aggregate change in the level of decoupling from 2000 to 2019. Such a change is

Table 1. Technology Decoupling and Firm Performance, Chinese Firms

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

Notes. Based on firm-year-level regressions for the sample period of 2007–2019, we examine the relationship between U.S.–China technology decoupling and the performance of Chinese firms in this table. All variables are defined in Table A.1. In all regressions, the control variables are lagged by one year. All regressions include year fixed effect and firm fixed effect. Robust standard errors are reported in the parentheses.
*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

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

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

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

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

Table 2. Mandatory vs. Voluntary Decoupling, Chinese Firms

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

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

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

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

	Innovation Output (1)	*Innovation Quality* (2)	*TFP* (3)	*ROIC* (4)	*Tobin's Q* (5)
Decoupling, $t-1$	0.285	−0.741	−0.321	0.052	0.328
	(0.593)	(0.755)	(0.237)	(0.189)	(0.205)
Decoupling, $t-2/3$	−0.085	−0.470	−0.141	−0.148	−0.179
	(0.344)	(0.504)	(0.124)	(0.095)	(0.121)
Assets	0.139***	−0.046	−0.046***	−0.011	−0.134***
	(0.019)	(0.028)	(0.015)	(0.011)	(0.010)
Age	−0.024	−0.155**	0.019	−0.004	−0.133***
	(0.055)	(0.071)	(0.031)	(0.026)	(0.024)
Capex	0.463*	0.228	−0.055	0.097	0.288*
	(0.250)	(0.280)	(0.237)	(0.136)	(0.172)
PP&E	0.151	−0.142	0.247**	−0.097	−0.308***
	(0.139)	(0.176)	(0.099)	(0.088)	(0.069)
Leverage	−0.197***	−0.031	0.146***	0.101**	0.103***
	(0.047)	(0.070)	(0.042)	(0.045)	(0.029)
R&D	0.224***	−0.271*	−0.452***	−0.206**	0.163**
	(0.084)	(0.142)	(0.121)	(0.100)	(0.069)
Observations	13,884	13,884	13,884	13,884	13,884
Adjusted R^2	0.85	0.34	0.79	0.60	0.71
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes

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

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

innovation frontier, and losing complementary technology from China inflicts little damage on their current productivity. Even for the few China-leading technology fields, China does not impose comparable sanctions that restrict technology flow to the United States. Finally, it is worth noting that U.S.–China decoupling is, for China, a likely proxy for its decoupling with the rest of the Western world, whereas the bilateral decoupling has no bearing on the tendency for the United States to decouple with other tech-important nations.

4. Government Policies and Decoupling

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

4.1. Have China's Industrial Policies Encouraged Decoupling?

4.1.1. The Strategic Emerging Industries Initiative and Decoupling. No other centralized industrial policy better showcases China's ambition in technology than the "strategic emerging industries" initiative launched in 2012. In this initiative, the Chinese government identified seven high-tech sectors as "strategic emerging industries:" energy-efficient and environmental technologies, next-generation information technology, biotechnology, high-end equipment manufacturing, new energy, new materials, and new-energy vehicles. Such industries were put in the front row to receive government support from R&D grants to matching benefits in top talent recruiting. These SEI-related industries have since come to the center stage of the ongoing debate on the causes and consequences of U.S.–China technology decoupling. As underscored by the State Council of China, "enhancing the ability of indigenous and independent innovation is key to the SEI-promotion policies."[35] According to the commentaries from both the Obama and Trump administrations, the major goal of China's innovation-promoting industrial policies is perceived to be achieving "self-sufficiency" by "domestic substitution of foreign technologies."[36]

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

$$y_{i,t} = \beta \times SEI_i \times Post_t + \delta' X_{i,t-1} + \gamma_i + \gamma_t + \epsilon_{i,t}. \quad (3)$$

In Equation (3), the dependent variable $y_{i,t}$ features technology decoupling and dependence at the technology class-year level. Because the two variables are correlated in our sample (with a full-sample concurrent correlation coefficient of -0.13), the dependence measure is residualized against the decoupling measure so that the two measures are orthogonalized concurrently by construction. Fixed effects for both technology class and year are included. The dummy variable SEI_i equals one if technology class i is promoted by the SEI and zero otherwise. The dummy variable $Post_t$ takes the value of one after 2012 and zero otherwise. X is a vector of control variables including the number of patents granted at CNIPA and USPTO (both in natural logarithms) in each field and each year, and it lags the dependent variable by one year. Technology class and year fixed effects absorb SEI_i and $Post_t$ on their own. The coefficient β is of key interest as it captures the changes in technology decoupling and dependence after the policy shock of the sectors exposed to the SEI policy relative to the unexposed. Results are reported in Table 4.

Columns (1) and (2) of Table 4 show that the SEI-exposed sectors experienced significantly (at the 1% level) more decline in both decoupling and dependence. In both regressions, variables corresponding to the number of patents granted at CNIPA and USPTO have opposite signs. High patent output in China is followed by more decoupling and less dependence in the following year, but the effect of patent activities in the United States runs in the opposite direction.

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

$$y_{i,t} = \sum_{\tau} (\beta_\tau \times SEI_i \times T_\tau) + \delta' X_{i,t-1} + \gamma_i + \gamma_t + \epsilon_{i,t}. \quad (4)$$

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

Table 4. SEI Promotion Policy and Technology Decoupling

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

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

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

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

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

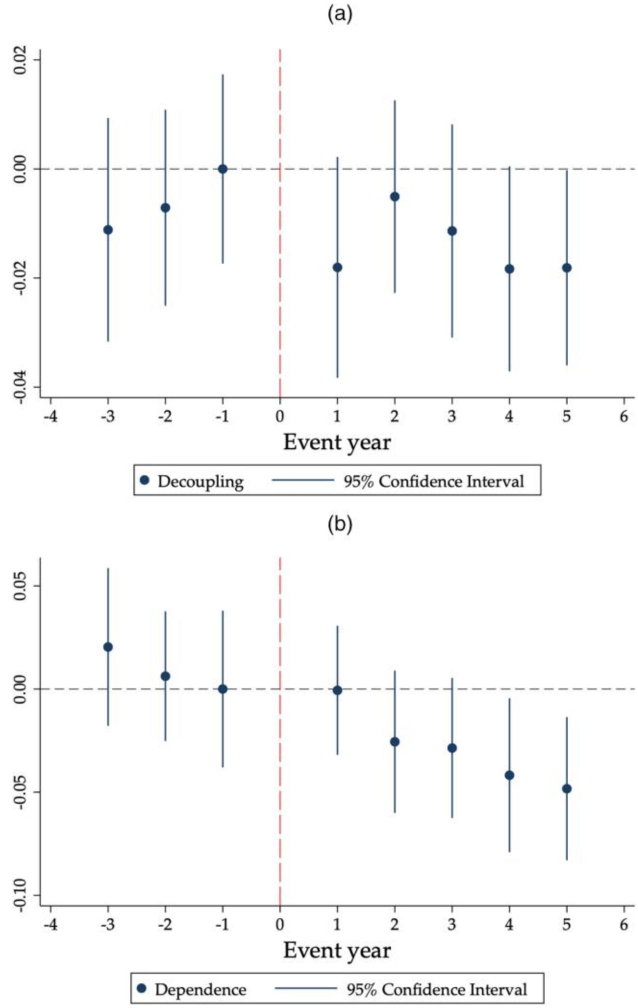
down after the event. Moreover, the decline of decoupling tends to occur faster than that of dependence.

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

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

Because both $Decoupling_t$ and $Dependence_t$ are functions of $p_{c,u,t}$ and $p_{u,c,t}$, the relative propensity for a patent to cite foreign versus domestic patents (see Equation (1)), we can decompose the results in Table 4 by resorting to $p_{c,u,t}$ and $p_{u,c,t}$ as dependent variables in

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



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

Equation (3). On the one hand, we find that U.S. patents are more likely to cite Chinese patents in technology sectors that are encouraged by the SEI policy. It suggests that China moved closer to the global frontier with the boost from government policies. On the other hand, we do not observe any decrease in the propensity of citations from China to the United States, consistent with China's State Council's stated goal, which aims to enhance the technological compatibility between the United States and China. Both findings are consistent with the inferences from the analyses that the SEI policy represented an endeavor by the government to promote both technology integration and self-sufficiency.[39]

4.1.2. SEI and Firm Performance. This section explores the SEI's impact on firm performance. Parallel to our analysis of SEI and technology decoupling in the previous section, we conduct the following DiD regressions at the firm(i)-technology sector(j)-year(t) level covering the period of 2007–2019:

$$y_{i,j,t} = \beta \times SEI_j \times Post_t + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \quad (5)$$

$$y_{i,j,t} = \sum_{\tau} (\beta_\tau \times SEI_j \times T_\tau) + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t}. \quad (6)$$

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

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

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

Table 5. SEI Promotion Policy and Firm Performance

	Innovation Output (1)	*Innovation Quality* (2)	*TFP* (3)	*ROIC* (4)	*Tobin's Q* (5)
SEI × Post	−0.140***	−0.126***	0.00984	0.0138***	0.104***
	(0.0332)	(0.0456)	(0.0103)	(0.00282)	(0.0150)
Assets	0.0918***	−0.0112	−0.00921*	−0.0158***	−0.293***
	(0.0174)	(0.0185)	(0.00553)	(0.00171)	(0.00793)
Age	0.00745	0.0372	0.0283	−0.0141***	−0.0433*
	(0.0631)	(0.0645)	(0.0177)	(0.00498)	(0.0259)
Capex	−0.0569	0.266	−0.389***	−0.0138	−0.0434
	(0.151)	(0.197)	(0.0445)	(0.0114)	(0.0599)
PP&E	−0.117	0.0567	0.117***	0.0426***	−0.109***
	(0.0801)	(0.0966)	(0.0251)	(0.00723)	(0.0357)
Leverage	−0.0307	−0.134*	0.0227	0.00647	0.0864***
	(0.0578)	(0.0705)	(0.0200)	(0.00622)	(0.0270)
R&D	0.634	−1.285*	0.622***	0.182***	1.384***
	(0.611)	(0.670)	(0.150)	(0.0479)	(0.233)
Observations	16,247	16,247	16,247	16,247	16,247
Adjusted R^2	0.603	0.189	0.640	0.435	0.787
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes

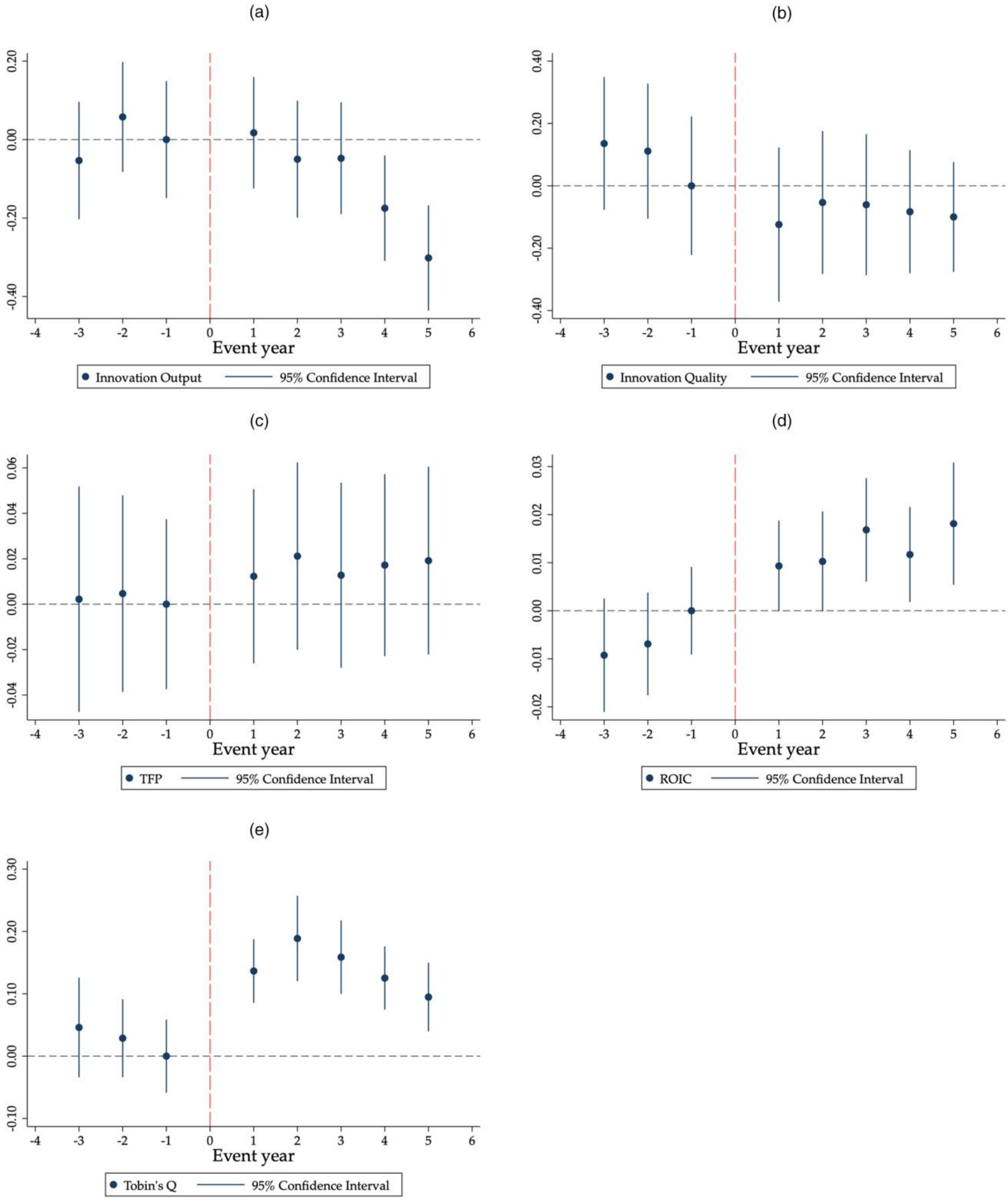
Notes. This table reports estimation results from the following regression relating the SEI policy and Chinese firm performance covering the period of 2007–2019:

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

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

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

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



Notes. This figure examines the dynamics of the SEI policy in the firm-year-level regressions based on Equation (6). We plot the estimates of β_τ in Equation (6) for the following dependent variables: *Innovation Output* in panel (a), *Innovation Quality* in panel (b), *TFP* in panel (c), *ROIC* in panel (d), and *Tobin's Q* in panel (e). All variables are defined in Table A.1. (a) *Innovation Output*. (b) *Innovation Quality*. (c) *Firm TFP*. (d) *ROIC*. (e) *Tobin's Q*.

Table 6. SEI Promotion Policy and Further Evidence on Firm Innovation

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

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

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

The regression is at the firm (i)-year(t) level, but each firm is also indexed by sector (j). SEI_j equals one if sector j is promoted as an SEI and zero otherwise. $Post_t$ takes the value of one after 2012 and zero otherwise. All other variables are defined in Table A.1. In all regressions, the control variables are lagged by one year, and year fixed effect and firm fixed effect are included. Robust standard errors are reported in the parentheses.
*Significance at the 10% level; **significance at the 5% level; ***significance at the 1% level.

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

We acknowledge that the simple quantitative measures in terms of the number of patents and their citations may not adequately capture innovation quality. We adopt the best practice in the literature by examining five established barometers of patenting performance in columns (3)–(7) of Table 6. Following Kerr (2010), we categorize a breakthrough patent as one that breaks into the top 5% in citations among the same cohort (i.e., same technology class and application year). Following patent strength measures proposed by Manso (2011) and developed in subsequent studies (e.g., Brav et al. 2018, Custódio et al. 2019), we categorize a patent to be exploitative if at least 80% of its citations are based on the firm's existing knowledge (i.e., its own patents or patents it cites in the past five years) and a patent to be explorative if at least 80% of its citations are based on new knowledge. Exploitative patents are signs of core competence, whereas explorative patents signal new knowledge creation. Following Hall et al. (2001), we define the patent originality score as one minus the Herfindahl index (at the three-digit IPC) of the number of citations made by a patent to each technology class. Finally, we define the patent generality score as one minus the Herfindahl index of the number of citations received by a patent from each technology class. Originality measures the diversity of knowledge a patent builds on, whereas generality measures the radius of a patent's influences over subsequent innovations. According to the results in Table 6, the SEI has not measurably enhanced the innovation quality along these dimensions, except that firm innovation does become significantly more general (significant at the 1% level) after the policy treatment.[43]

Our findings speak to an intrinsic noncongruence between the two major policy objectives (i.e., indigenous innovation versus firm competitiveness) of the

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

4.2. U.S. Sanctions Against China and Decoupling

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

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

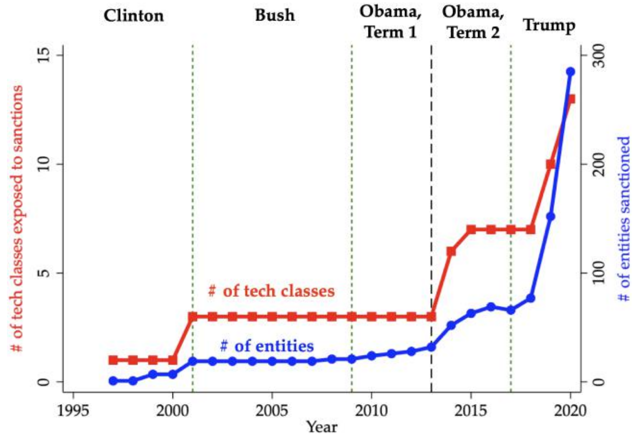
To assess how U.S. sanctions affect U.S.–China technology decoupling, we identify the primary technology class of each sanctioned Chinese entity by merging the entity list with the Chinese patent data using the algorithm delineated in Section 3.1. For all subsidiaries on the entity list, we use their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

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

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

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

Figure 9. (Color online) Number of Entities and Tech Classes Exposed to U.S. Sanctions



Notes. This figure plots the number of sanctioned Chinese entities on the U.S. entity list and the number of technology classes exposed to U.S. sanctions each year. We identify the primary technology class of each sanctioned Chinese entity by the patents they file. We consider a technology class to be exposed to U.S. sanctions in a given year if at least one entity associated with this technology class was sanctioned in that year.

Table 7. U.S. Sanctions and Technology Decoupling

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

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

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

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

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

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

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

The effects of U.S. sanctions on China's technological dependence on the United States are ambiguous because of two opposing forces. By depriving Chinese firms of U.S. technologies, U.S. sanctions may weaken

Table 8. U.S. Sanctions and Technology Decoupling, Dynamic Effects

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

Notes. Based on technology class-year-level regressions for the sample period of 2007–2019, this table traces out the dynamic impact of the U.S. sanctions. The dependent variable features technology decoupling and dependence, which are defined in Table A.1. The dependence measure is residualized against the decoupling measure so that they are orthogonalized concurrently by construction. *Sanction*$(-\tau)$ and *Sanction*(τ) refer to τ years before and after the sanction, respectively. *Sanction*(3+) corresponds to three and more years after the sanction. In all regressions, the control variables are lagged by one year, and year fixed effect and technology class fixed effect are included. Robust standard errors are reported in the parentheses.

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

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

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

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

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

$$\mathit{Upstream\ \ Sanction\ \ Exposure}_{i,t} = \sum_{j \neq i} w(i,j) \times \mathit{Sanction}_{j,t}$$

$$\mathit{Downstream\ \ Sanction\ \ Exposure}_{i,t} = \sum_{k \neq i} w(k,i) \times \mathit{Sanction}_{k,t}.$$

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

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

$$\begin{aligned} y_{i,t} = {} & \beta_1 \times \mathit{Upstream\ Sanction\ Exposure}_{i,t} \\ & + \beta_2 \times \mathit{Downstream\ Sanction\ Exposure}_{i,t} \\ & + \delta' X_{i,t-1} + \gamma_i + \gamma_t + \epsilon_{i,t}. \end{aligned} \tag{8}$$

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

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

4.2.4. Sanctions and Firm Performance. Sanctions, on their own or via spillovers, have implications for the performance of affected firms, which is the subject of this section. Parallel to the technology class-level investigations, we now conduct the following regression at the firm(i)-sector(j)-year(t) level covering 2007–2019:

$$y_{i,j,t} = \beta \times \mathit{Post\ Sanction}_{j,t} + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t} \tag{9}$$

$$\begin{aligned} y_{i,j,t} = {} & \beta_1 \times \mathit{Upstream\ Sanction\ Exposure}_{j,t} \\ & + \beta_2 \times \mathit{Downstream\ Sanction\ Exposure}_{j,t} \\ & + \delta' X_{i,j,t-1} + \gamma_i + \gamma_t + \epsilon_{i,j,t}. \end{aligned} \tag{10}$$

Equations (9) and (10) are analogous to Equations (7) and (8), respectively. Similar to Section 4.1.2, we report the estimation results for the five firm outcome variables in Table 9.

Column (1) in panel A of Table 9 shows that U.S. sanctions are associated with a 12.4% decline (significant at the 1% level) in innovation output for Chinese firms in the sanctioned sectors. Breaking it down, we further discover that the decline can primarily be attributed to falling innovation efficiency instead of innovation input. The drop in firm innovation efficiency amounts to 55.1% of the sample mean (significant at the 1% level), signifying China's reliance on U.S. inputs (including human capital) in converting R&D into patentable technology.[51] Innovation quality exhibits no noticeable change (column (2)). Columns (3) and (4) report that U.S. sanctions are associated with a 2.3% decline in firm *TFP* (significant at the 5% level) and a drop in *ROIC* of 0.99 percentage points (12.5% of the sample mean; significant at the 1% level). Despite suffering in productivity and profitability, affected firms do not experience a significant drop in firm valuation (column (5)). Such valuation resiliency might have benefited from adaptive responses from the Chinese government and businesses as sanctions became more aggressive and widespread.[52] Another bright spot is that innovation by affected firms in China has become more original, suggestive evidence that Chinese firms may have to conduct more discovery-based research after being deprived access to U.S. technologies.[53]

For sensitivity checks, we control for the three general innovation policies described in Section 4.1.2. We also conduct a robustness check based on Poisson regressions to accommodate skewness in patent data. All our findings are robust in these tests.[54]

4.2.5. Sanction Spillovers on Firm Performance. Following the structure of Section 4.2.3 and Equation (10), we analyze the spillover effect of sanctions on firm performance and report the results in panel B of Table 9. Sanctioning upstream sectors is associated with a decline in innovation output, productivity, profitability, and valuation of the focal firm (all significant at the 1% level). In stark contrast, sanctioning downstream sectors features exactly the opposite effects. The example in the previous section regarding the semiconductor sector could put this asymmetry into context. The quality of firm innovation following the sanctions also follows similarly asymmetric paths for firms when the sanction shocks propagate from the upstream or downstream. After an upstream sector is sanctioned, firms in the focal sector tend to experience a significant decrease in R&D as well as R&D efficiency, significantly fewer chances for breakthrough innovation, and an overall decline in the metrics for patent quality. The reverse is the case for firms that face indirect sanction exposure from the downstream. They significantly increase R&D, and they produce significantly more high-impact, explorative, and high-generality patents.[55]

To the extent that U.S. sanctions aim at decoupling China from the West and containing the rise of Chinese firms, our findings uncover some perhaps unintended consequences of the sanctions because of network spillovers. When the United States sanctions a particular technology sector in China, innovation outputs as well as the firm performance of the targeted sector suffer, and so do the downstream sectors and firms in China (that are exposed to sanctions indirectly from the upstream).

Table 9. U.S. Sanctions and Performance of Chinese Firms

	Innovation Output (1)	*Innovation Quality* (2)	*TFP* (3)	*ROIC* (4)	*Tobin's Q* (5)
Panel A: U.S. sanctions and firm performance					
Post Sanction	−0.124***	−0.0235	−0.0229**	−0.00989***	0.0169
	(0.0413)	(0.0477)	(0.0116)	(0.00327)	(0.0160)
Observations	16,247	16,247	16,247	16,247	16,247
Adjusted R^2	0.603	0.188	0.621	0.435	0.786
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes
Panel B: Network spillovers of U.S. sanctions					
Upstream Sanction Exposure	−1.463***	0.230	−0.551***	−0.129***	−1.403***
	(0.511)	(0.667)	(0.136)	(0.0379)	(0.207)
Downstream Sanction Exposure	0.934**	−0.390	0.489***	0.118***	1.319***
	(0.461)	(0.597)	(0.123)	(0.0337)	(0.185)
Observations	16,247	16,247	16,247	16,247	16,247
Adjusted R^2	0.604	0.188	0.622	0.435	0.787
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes	Yes

Notes. Based on firm-year-level regressions for the sample period of 2007–2019, this table reports the estimation results relating U.S. sanctions and the performance of Chinese firms. Panels A and B report the estimation results for Equations (9) and (10), respectively. *Post Sanction* is equal to one for a firm in a year if this firm's sector had been exposed to U.S. sanctions prior to that year and zero otherwise. As delineated in Table A.1, *Upstream (Downstream) Sanction Exposure* is the weighted average of the sanction indicator of all upstream (downstream) technology classes of the focal technology class. In all regressions, the control variables are lagged by one year, and year fixed effect and firm fixed effect are included. Robust standard errors are reported in the parentheses.

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

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

5. Conclusion

By integrating comprehensive patent data from the United States and China, we develop new measures to quantify the time-varying technology decoupling and dependence between the United States and China in the aggregate and in specific technology classes. The first two decades of the twenty-first century witnessed a steady increase in technology integration (or less decoupling), but China's dependence on the United States increased (decreased) during the first (second) decade. Analyzing government policies in both nations, we find that China's innovation-promoting industrial policies are associated with both more integration and less dependence down the road, but the process has not registered improvement in either the productivity or the innovativeness of firms. On the other side, U.S. sanctions against China have not led to U.S.–China decoupling but have spurred more independent and high-impact technological development in China, especially in the upstream sectors of the sanctioned. Knowledge and technology form their own network with complex spillovers across sectors, which are fluid at national boundaries. Sanctions often instigate broader, and often unintended, impact relative to what was envisioned by the policy makers.[56] Our findings provide micro-level evidence for the direct as well as spillover effects that could contribute to the policy debate.

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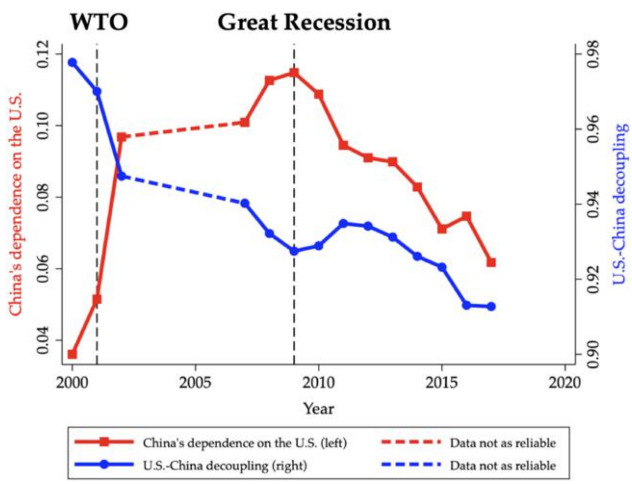
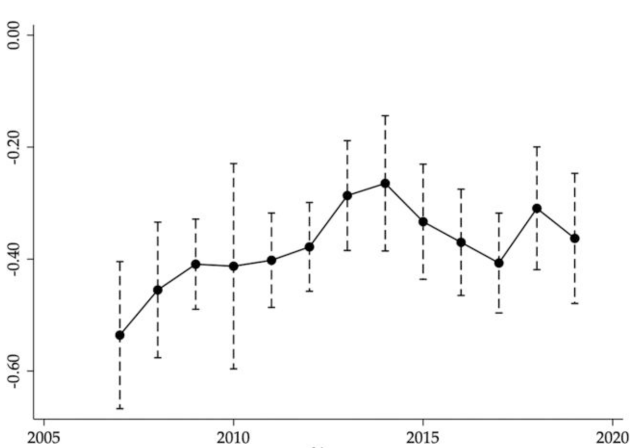
Appendix. Appendix Figures and Tables

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



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

Figure A.2. Technology Dependence and Chinese Patent Share



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

Table A.1. Variable Definition

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

Table A.1. Variable Definition

Variable	Definition
Upstream Sanction Exposure	Weighted average of the sanction indicator of all upstream technology classes of the focal technology class; the weight is the share of citations made from the focal technology class to other upstream technology classes
Downstream Sanction Exposure	Weighted average of the sanction indicator of all downstream technology classes of the focal technology class; the weight is the share of citations the focal technology class receives from other downstream technology classes

Table A.2. Descriptive Statistics, Chinese Companies

	Mean (1)	Standard deviation (2)	25th Percentile (3)	Median (4)	75th Percentile (5)	Observations (6)
Decoupling, $t-1$	0.920	0.0308	0.896	0.924	0.942	16,247
Innovation Output (number of patents)	3.867	10.29	0	0	2.500	16,247
Innovation Quality	0.427	0.886	0	0	0.527	16,247
Assets (billion RMB)	10.75	28.25	1.400	2.861	7.016	16,247
Age (number of years)	14.55	5.429	11	14	18	16,247
R&D	0.0189	0.0191	0.00139	0.0162	0.0273	16,247
Capex	0.0577	0.0494	0.0213	0.0435	0.0791	16,247
PP&E	0.230	0.153	0.112	0.198	0.318	16,247
Leverage	0.408	0.206	0.241	0.398	0.561	16,247
ROIC	0.0791	0.0641	0.0504	0.0767	0.110	16,247
Tobin's Q	2.523	1.707	1.386	1.994	3.044	16,247
TFP	1.196	0.365	0.957	1.133	1.359	16,247

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

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

	Mean (1)	Standard deviation (2)	25th Percentile (3)	Median (4)	75th Percentile (5)	Observations (6)
Decoupling	0.916	0.030	0.895	0.919	0.937	14,839
Innovation Output (number of patents)	31.898	109.588	0.000	1.000	10.000	14,839
Innovation Quality	0.546	1.183	0.000	0.000	0.618	14,839
Assets (billion RMB)	9.899	25.613	0.157	0.817	5.218	14,839
Age (number of years)	23.002	19.730	9.000	17.000	31.000	14,839
R&D	0.101	0.159	0.006	0.041	0.123	14,839
Capex	0.038	0.042	0.013	0.026	0.050	14,839
PP&E	0.194	0.191	0.057	0.126	0.265	14,839
Leverage	0.210	0.232	0.004	0.163	0.315	14,839
ROIC	0.030	0.453	0.021	0.143	0.221	14,839
Tobin's Q	3.020	2.964	1.361	2.052	3.400	14,839
TFP	2.258	1.188	1.655	2.242	2.683	14,839

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

Endnotes

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

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

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

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

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

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

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

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

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

[10] There are two options to file a patent application in a foreign patent office. The applicants can directly file an application at the national patent office of that country, or they can file an application via the Patent Cooperation Treaty (PCT) route. Applicants can simultaneously seek protection for an invention in over 150 countries if they follow the PCT route. Specific steps of the patenting process are illustrated in the flowchart of Figure IA1 in the online appendix. These procedures are based on information from *IP5 Statistics Report*, 2018 edition. The source link to this reference is: https://www.fiveipoffices.org/statistics/statisticsreports.

[11] According to this instruction manual of the USPTO, "a comprehensive prior art search would also include foreign patent publications and non-patent literature (newspapers, magazines, dissertations, conference proceedings, and websites)." At the Chinese patent office, both domestic and foreign prior art should be considered during the examination process for invention patents according to the *Guidelines for Patent Examination* issued by CNIPA.

[12] 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 they are measured in constant 2005 PPP dollars.

[13] See Patenting Activities by Nationalities of Patent Assignees in the online appendix. Figures IA2–IA6 in the online appendix plot the results of the analyses based on the nationalities of patent assignees.

[14] See Propensity of Patent Citations in the online appendix for more detailed explanations.

[15] Although "over-integration" (i.e., $p_{c,u,t}$ and $p_{u,c,t}$ exceeding one) is theoretically possible, empirically it was never the case. Hence, we focus on the scenarios where $p_{c,u,t}$ and $p_{u,c,t}$ are bounded between zero and one.

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

[17] We plot the time series of U.S.–EU decoupling in Figure IA7 in the online appendix. The results in this figure suggest that the U.S.–EU pair has been at a much higher level of integration, with the average decoupling measure of 0.51, in comparison with 0.93 for the U.S.–China pair.

[18] The results are reported in Figure IA8 in the online appendix.

[19] Because the citation information is severely missing for the Chinese patents between 2003 and 2006, these years are dropped in this figure.

[20] We also plot the time series of $p_{u,c,t}$ and $p_{c,u,t}$ in Figure IA9 in the online appendix. Although U.S. patents become more and more likely to cite Chinese ones or $p_{u,c,t}$ increases over time, the propensity to cite U.S. patents by Chinese patents ($p_{c,u,t}$) takes a hump-shaped transition, with the turning point being the end of the Great Recession.

[21] For details, see Figure IA10 in the online appendix.

[22] For details, see Figure IA11 in the online appendix.

[23] For details, see Figure IA12(a) in the online appendix, which reports the number of S&E publications in the world and the share of internationally coauthored publications. Figure IA12(b) in the online appendix tracks the share of internationally coauthored S&E publications in the top five countries by the number of publications (i.e., China, the United States, India, Germany, and the United Kingdom).

[24] 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.

[25] For instance, it took the Semiconductor Manufacturing International Corporation (China's largest semiconductor producer) about two years to advance its production technology from 14- to 7-nm semiconductors, a faster progress than both Taiwan Semiconductor Manufacturing Company and Samsung. See the report in *Bloomberg*: "China's Top Chipmaker Achieves Breakthrough Despite US Curbs" (July 21, 2022).

[26] For example, see the *Harvard Business Review* article titled "Is China Emerging as the Global Leader in AI?" (February 18, 2021).

[27] We have further applied the methodology to more granular levels, such as at the three-digit IPC code level; see Technology Decoupling at the Technology Class Level in the online appendix. Table IA2 in the online appendix reports the top and bottom 10

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

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

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

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

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

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

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

[34] For details, see Table IA4 in the online appendix.

[35] See "Decision of the State Council on Accelerating the Cultivation and Development of Strategic Emerging Industries" published by the State Council. The source link to this reference is: http://www.gov.cn/zwgk/2010-10/18/content_1724848.htm.

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

[37] See "Decision of the State Council on Accelerating the Cultivation and Development of Strategic Emerging Industries" published by the State Council. The source link to this reference is: http://www.gov.cn/zwgk/2010-10/18/content_1724848.htm.

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

[39] For detailed results, see Table IA5, panel A in the online appendix.

[40] For details, see Table IA6 in the online appendix.

[41] For details, please see Table IA7 in the online appendix.

[42] One example regarding such a consequence from this policy can be found in "Policies to Promote High-Quality Development of Integrated Circuit Industry and Software Industry" published by China's State Council.

[43] As a robustness check, we change the threshold for breakthrough patents (to 10%) and modify the definition of explorative and exploitative patents (by using a cutoff value of 60% following Almeida et al. 2013 and Custódio et al. 2019). The results are reported in Table IA8 in the online appendix. Our findings are robust under alternative classification criteria.

[44] See the *CNN* report "New sanctions deal 'lethal blow' to Huawei" (August 18, 2020).

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

[46] The source is the U.S. Census Bureau.

[47] The source is the Ministry of Education of China.

[48] The source is the Institute of International Education.

[49] See the *Wire China* interview "Willy Shih on Why the U.S. Needs to Run Faster" (April 19, 2020). Also, see the *Bloomberg* report "New U.S. Restrictions Will Help Make China Great Again" (December 18, 2020) and *The Economist* report "China courts global capital, on its own terms" (December 11, 2021).

[50] Results are reported in Table IA8 in the online appendix.

[51] For detailed results, please see Table IA9 in the online appendix. As a robustness check, we also change the threshold for breakthrough patents (to 10%) and modify the definition of explorative and exploitative patents (by using a cutoff value of 60% following Almeida et al. 2013 and Custódio et al. 2019). The results are reported in Table IA10 in the online appendix. Our findings are robust under alternative classification criteria.

[52] As U.S. sanctions expanded from specialized military technologies to more civil and commercially oriented technologies, the affected businesses tend to be more nimble in marketplaces, and the Chinese government also started to counter-intervene by bolstering firms targeted by U.S. sanctions. For example, China's Anti-Foreign Sanctions Law passed in June 2021 establishes a legal ground to retaliate against foreign sanctions. Firms sanctioned by the United States in some cases sought "national symbol" status in an ideologized sentiment.

[53] For detailed results, see panel A of Table IA9 in the online appendix.

[54] Results are reported in Tables IA6 and IA11 in the online appendix.

[55] For detailed results, see panel B of Table IA9 in the online appendix.

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

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