INSTITUTE OF DEVELOPING ECONOMIES

IDE Discussion Papers are preliminary materials circulated
to stimulate discussions and critical comments

IDE DISCUSSION PAPER No. 950

Technology Sanction and Firm R&D: Evidence From the US-China Trade Dispute

Kazunobu Hayakawa*, Chih-hai Yang

January 2025

Abstract: The United States has implemented export control regulations targeting China. Specifically, it has included numerous Chinese companies on the Entity List, which comprises parties of concern. Exporters of regulated items or technology to these listed firms must secure permission from the US government, with the possibility of denial. This study investigates how this technology sanction hinders the R&D activities of sanctioned Chinese firms. To achieve this, we apply the matching method to firm-level data from 2015 to 2022. Our findings indicate that technology sanctions do not increase the R&D investment and R&D intensity, even though the total assets of sanctioned firms decline. When we separate the listed firms based on the license review policy (i.e., the nearly strict review), we again observe insignificant effects on R&D investment in either category of sanctioned firms. Notably, less strictly sanctioned firms accumulated more inventories, whereas more strictly sanctioned firms received increased financial support from the government in response to the technology sanctions.

Keywords: US–China trade war, Technology sanction, Innovation
JEL classification: F15, F53

---

* Institute of Developing Economies, JETRO (Kazunobu_Hayakawa@ide.go.jp)

The Institute of Developing Economies (IDE) is a semigovernmental, nonpartisan, nonprofit research institute, founded in 1958. The Institute merged with the Japan External Trade Organization (JETRO) on July 1, 1998. The Institute conducts basic and comprehensive studies on economic and related affairs in all developing countries and regions, including Asia, the Middle East, Africa, Latin America, Oceania, and Eastern Europe.

INSTITUTE OF DEVELOPING ECONOMIES (IDE), JETRO
3-2-2, WAKABA, MIHAMA-KU, CHIBA-SHI
CHIBA 261-8545, JAPAN

Technology Sanction and Firm R&D: Evidence From the US-China Trade Dispute

Kazunobu HAYAKAWA[§]
Bangkok Research Center, Institute of Developing Economies, Thailand

Chih-Hai YANG[*]
Department of Economics, National Central University, Taiwan

***Abstract*:** The United States has implemented export control regulations targeting China. Specifically, it has included numerous Chinese companies on the Entity List, which comprises parties of concern. Exporters of regulated items or technology to these listed firms must secure permission from the US government, with the possibility of denial. This study investigates how this technology sanction hinders the R&D activities of sanctioned Chinese firms. To achieve this, we apply the matching method to firm-level data from 2015 to 2022. Our findings indicate that technology sanctions do not increase the R&D investment and R&D intensity, even though the total assets of sanctioned firms decline. When we separate the listed firms based on the license review policy (i.e., the nearly strict review), we again observe insignificant effects on R&D investment in either category of sanctioned firms. Notably, less strictly sanctioned firms accumulated more inventories, whereas more strictly sanctioned firms received increased financial support from the government in response to the technology sanctions.
Keywords: Technology sanction; Innovation; US-China trade war
JEL Classification: F15; F53

---

1. Introduction

Among the various factors that have contributed to China's remarkable economic growth over the past two decades, the significant increase in innovation activities was a key driver (Boeing et al., 2022; Wu et al., 2017; Xiong et al., 2020). China's ranking in the Global Innovation Index (GII) report climbed from 43rd in 2010 to 17th in 2018 and further rose to 12th in 2021, along with its surge in innovation inputs and outputs.[1] This trajectory

[§] We would like to thank Kiyoyasu Tanaka, Mi Dai, Fukunari Kimura, Miki Hamada, Yuta Watabe, Shujiro Urata, and the seminar participants at JETRO Bangkok, Thammasat University, and the Institute of Developing Economies for their valuable feedback. Hayakawa is also grateful for the financial support provided by the Japan Society for the Promotion of Science (JSPS) through the KAKENHI Grant Number 22H00063. All remaining errors are our own responsibility.
[*] Corresponding author: Professor, Department of Economics, National Central University. 300, Zhongda Road, Zhongli District, Taoyuan 320, Taiwan. Tel: +886-3-4226903. E-mail: chyang@mgt.ncu.edu.tw
[1] The GII report, published annually by the World Intellectual Property Organization (WIPO) since 2007, is calculated by averaging numerous factors. The index comprises two sub-indices: the Innovation Input

illustrates a successful technological leapfrogging and economic catch-up (Lee, 2021). Notably, the telecommunications equipment and computers (IEC) industry outperformed other industries in terms of invention patents and exhibited a higher tendency for strategic patenting during the patenting boom period of 2007–2011 (Hu et al., 2017), suggesting increased technological sophistication within IEC firms. Additionally, China has achieved technological advancements in high-speed railway technologies, electric vehicles, and artificial intelligence, among others. Alongside its technological upgrades, China introduced the 10-year "Made in China 2025" program, with the goal of becoming a manufacturing powerhouse and a global leader in high-tech industries (Chen et al., 2020; Swenson and Woo, 2019).

This development raises serious concerns about China's challenge to US economic dominance. Technological advances, coupled with government support, are gradually empowering Chinese high-tech firms to gain substantial influence in the global market. Specifically, Huawei, a leading figure in the 5G technology for wireless networks, has significantly increased its global presence, becoming a potential supplier of 5G technology in many countries, which will revolutionize network communication (Tekir, 2020). Its market penetration, particularly in Western markets, may be guided and supported by the Chinese government, reflecting geopolitical ambition (Friis and O Lysne, 2021; Tekir, 2020). Adopting Huawei's 5G technology not only results in reliance on equipment potentially influenced by Chinese intelligence service (Kaska et al., 2019) but also raises cybersecurity concerns and sparks debate in the United States (US) and Europe (Friis and O Lysne, 2021; Kaska et al., 2019; Tekir, 2020). China's technological advancements have challenged the US's longstanding dominance in high-tech sectors. Conversely, the increasing tech-geopolitical uncertainty prompts the US to adopt tech-nationalism in its economic rivalry with China (Luo and Van Assche, 2023).

To prevent utilizing the US technology in collaborations between universities, private firms, and the military, and to sever the core supply chains of Chinese high-tech firms, the US government has imposed technology sanctions on Chinese high-tech firms. The US-China trade war, initiated by the US in 2018, was driven by various economic and political concerns.[2] This trade conflict is ongoing and has evolved into a technology war. The US government began utilizing an entity list (EL) to impose sanctions on an increasing number of Chinese technology companies, as discussed in the next section. The US export control regulations have been frequently updated to prevent Chinese firms from obtaining advanced semiconductor chips. China has not yet developed the technological capability to produce these advance technologies independently, which are essential components of many electronics and military products. In light of geopolitical and geo-economic developments, the US has implemented a guardrail strategy and weaponized global value

Index and Innovation Output Index.

[2] For more details, see Swenson and Woo (2019).

chains to target its economic rivals.[3] We refer to this second phase of the US-China trade war as "technology sanction" rather than a "technology war." This is because the restrictions on high-tech product trade were imposed unilaterally by the US, rather than being bilateral.

In the context of this technological rivalry, a key research question arises: how do technology sanctions affect the innovation behaviors of sanctioned firms in China? These policy shocks could influence innovation, even if this innovation effect is unintended, similar to the impacts seen with labor law (Acharya et al., 2013; Yang, 2023) and environmental policy (Löschel, 2002). These technology sanctions are designed to prevent China from acquiring advanced technologies and are expected to directly the technological development of firms on the EL. Alternatively, under these stringent regulations, sanctioned firms may attempt to "swing for the fence" with more radical breakthroughs under this strict regulation (Aghion et al., 2021). Recognizing the importance of leading innovation capabilities in the global market (Chen et al., 2023), China has provided many subsidies and tax incentives to encourage local firm's innovations, with the goal establishing indigenous technological capability. For example, despite being listed on the EL in 2019, Huawei, the most targeted company by technology sanctions, showed an increase in R&D expenditure. Figure 1 illustrates that the R&D expenditure increased from RMB 59.6 billion in 2015 to 101.5 billion in 2018. After the US sanctions, R&D expenditure further increased from 131.6 billion in 2019 to 161.5 billion in 2022. Although the sanctions significantly negatively impacted Huawei's sales and eroded its profit, the increased R&D has led to a notably high R&D intensity (R&D to revenue ratio) since 2021.

[Figure 1]

This study aims to empirically investigate how US technology sanctions affect Chinese firms' R&D. In the academic literature, only a few number of studies have examined the innovation effect of export control in Chinese firms. Examples are those of Anwar et al. (2024), Cao et al. (2024), and Shen et al. (2024). However, most of their study periods focus on US technology sanction based on the old act rather than the recent one. As discussed in the following section, the recent sanction is qualitatively different from the previous sanctions. Conversely, Hu et al. (2024) targeted the recent sanction compared with the above three studies. In our empirical analysis, we utilize a panel dataset of manufacturing and information technology firms from 2015 to 2022. Similar to previous studies, we employ the difference-in-differences (DID) method. Furthermore, unlike Hu et al. (2024), we account for the selection mechanism in the EL. It is evident that the US government does not randomly include Chinese firms in the EL; these firms are considered potential threats to US national security if they import advanced technologies. Such firms may exhibit different innovation behaviors compared to those not included in the EL. Thus, we applied the propensity score matching (PSM) method along with the DID method.

---

[3] It also prevents China from developing and producing advanced armaments, fighter aircrafts, and others.

There are two novelties that distinguish our study from existing research. First, we differentiate EL firms based on the license review policy (i.e., case-by-case or presumption-of-denial). The likelihood of obtaining export permission for high-end or dual-use products varies between these review types. EL firms categorized under a case-by-case basis are more likely to import these products compared to the presumption-of-denial firms. We investigate the effects of inclusion in the EL for these two types of EL firms separately. That is, how both types of EL firms respond to this technology sanction may vary significantly. Another novelty of our study is the investigation of various outcome indicators. In particular, we examine the effect on R&D expenditure rather than its ratio to total assets or sales (R&D intensity). This is because the latter indicator does not indicate whether sanctioned firms alter the *size* of their operations. In addition, we believe that R&D can be a more appropriate measure of innovation than patents because firms can quickly adjust R&D activity to respond to external shocks, whereas a time lag from R&D to patent applications exists.[4] In addition to R&D expenditure, the mechanisms mediating this shock are examined. Specifically, we investigate the effects on labor productivity, total income, inventory amount, and government subsidy amount.

Our study is related to two strands of literature. The first one is the literature on the US-China tariff war. Many studies have examined the direct effects of tariffs on the US economy (Amiti et al., 2019; Amiti et al., 2020; Blanchard et al., 2024; Cavallo et al., 2021; Egger and Zhu, 2020; Fajgelbaum et al., 2020; Handley et al., 2024) or China's economy (Chor and Li, 2024; Cui and Li, 2021; Ma et al, 2021). Other studies have investigated the trade effects on third economies (Fajgelbaum et al., 2024; Hayakawa et al., 2024; Yang and Hayakawa, 2023). Another focus is on the effects of other policy measures on innovation, particularly in China.[5] For example, Chen et al. (2023) and Kong et al. (2024) examined the effect of the US-China tariff war and found that it led to a reduction in the number of patent applications in Chinese firms. Huang et al. (2024) examined how antidumping sanctions imposed by the US government on Chinese exports affected the innovations of Chinese exporters. They found that these sanctions significantly increased the number of targeted firms' patent applications. Additionally, some studies have examined the effects of broader sanctions (i.e., not limited to those by the US) on innovation in China, revealing significantly negative impacts on innovation (Fu et al., 2023; Wen et al., 2024a).

Our major findings are as follows. First, while previous studies indicated a significant rise in the ratio of R&D expenditure to total assets, we observed a significant decrease in total assets but an insignificant change in R&D expenditure. This suggests that sanctioned Chinese firms do not necessarily increase their innovation. The positive effect on the R&D intensity reported in previous studies may be due to the decrease in total assets rather than

[4] Li et al. (2020) and Yang (2023) discussed the reasons why R&D is a more adequate indicator of innovation than patents in China.

[5] Wen et al. (2024b) covered 91 countries and confirmed a significantly negative impact of overall international sanctions on innovation in the target countries.

the expansion of R&D activities. Second, among other performance indicators, we found that inclusion in the EL leads to a gradual rise in labor productivity and a one-time rise in government subsidies. The increase in labor productivity might suggest that US sanctions motivate sanctioned firms to improve their cost efficiency. Third, we observed varying results based on sanction types. Case-by-case firms tend to increase inventory, likely in preparation for future stricter restrictions, whereas presumption-of-denial firms receive more government subsidies, indicating that the Chinese government prioritizes subsidies to more severely sanctioned firms.

The remainder of this paper is organized as follows. Section 2 provides conceptual discussions on the relationship between technology sanctions and innovative activities in firms. Section 3 outlines the data and empirical model. Section 4 presents and discusses the estimation results. The final section concludes the paper.

2. Technology Sanctions and Shocks to Innovation

This section provides a brief overview of US technology sanctions against China and discusses the conceptual framework for understanding their impact on corporate innovation.

2.1. Overview of the US Export Controls and the Literature Review

Export control is a widely used method for protecting the domestic economies in many countries. The US introduced the Export Administration Act (EAA) in 1979, serving as the primary authority for US export control regulations. Its main purpose was to control exports for national security interests, foreign policy objectives, and short supply. With significant changes in the international economic and technological landscape, the EAA was replaced by the Export Administration Regulations (EAR) in 2018. The EAR focuses on controlling the exports of sensitive technology, software, and equipment to maintain national security and prevent intellectual property leaks. The Bureau of Industry and Security (BIS) of the US Department of Commerce is responsible for implementing and enforcing the EAR.

The BIS has published and updated the EL over time. According to the BIS website, the EL was first published in 1997 as part of efforts to inform the public about entities involved in activities that could increase the risk of exported, reexported, or transferred (in-country) items being diverted to weapons of mass destruction programs.[6] The entities in the EL are those believed to be involved, or posing a significant risk of being or becoming

[6] https://www.bis.doc.gov/index.php/policy-guidance/deemed-exports/deemed-exports-faqs/faq/105-what-is-the-background-and-purpose-of-the-entity-list

involved in, activities contrary to the national security or foreign policy interests of the US. These firms are restricted from importing certain critical intermediate goods, technologies, and products from the US. The BIS evaluates license applications to any listed entity based on the policy outlined in the "License Review Policy" column of the EL, which includes "case-by-case" or, most commonly, "presumption of denial."

Despite experiencing a persistent trade deficit over the past few decades, the US did not frequently use the EL as a regulatory tool before 2018 (Hu et al., 2024). For instance, the total number of sanctioned Chinese entities was 42 during the 1997–2010 period (Anwar et al., 2024).[7] However, the second phase of the US-China trade prompted the US to intensify targeted technology sanctions against Chinese high-tech firms by including them in EL. Specifically, the US revised the EL 30 times between 2018 and 2022 (Hu et al., 2024). This decision implies its strong intention to use this tool to prevent sanctioned firms from importing sensitive and advanced technology from the US, thereby safeguarding its intellectual property and technologies.

Table 1 presents the 29 Chinese entities newly added to the EL in 2018. With the intensification of the US-China trade war, the number of newly sanctioned entities surged to 85 in 2019 and 148 in 2020. In 2021 and 2022, the US Department of Commerce added 81 and 68 new entities, respectively, resulting in a total of 411 new entities from 2018 to 2022. Most of the entities are reviewed under the "presumption of denial" policy.[8] While sanctioned entities include individuals, enterprises, universities, research institutions, and government and private organizations, the majority are high-tech firms. The targeted technological fields primarily include semiconductors, artificial intelligence, and auto driving, which are crucial for the success of the "Made in China 2025" program.

[Table 1]

How do US-imposed export controls affect firms' innovation in China? Extant studies are limited. Anwar et al. (2024) and Shen et al. (2024) examined the impact of export controls on innovation in Chinese and high-tech firms using data during 1997-2021 and 2007-2020, respectively. These studies compared innovation activities between "treated" (firms included in the EL) and "nontreated" firms. They found that firms on the EL exhibited increased innovations in terms of "R&D expenditure divided by total assets (R&D intensity)" or "the number of applied or invention patents." Conversely, Cao et al. (224) focused on firms added to the EL during 2013-2019 and found a decrease in innovation in terms of the number of patents. As discussed previously, the main functions of EAA and EAR vary significantly; most of their study periods are periods fall under the EAA.

Hu et al. (2024) adopted the DID method to analyze how EL firms alter their

[7] Listed entities include individuals, enterprises, universities, research institutions, and government and private organizations.

[8] §744.2(d) of the EAR specifies several factors to determine whether to grant or deny license applications. One example is whether the commodities, software, or technology to be transferred are appropriate for the stated end-use and whether that stated end-use is appropriate for the end-user.

innovation (R&D intensity and patents) using a firm-level panel dataset from 2013 to 2022, encompassing a substantial period of the EAR. They found that technology sanctions lead EL firms to increase R&D intensity, whereas the inclusion into the EL has little or no effect on firms' number of patents. However, the study does not differentiate between types of sanctions and does not consider the effect on absolute magnitude of R&D.[9] Thus, further research is needed to provide new and detailed evidence.

2.2. Conceptual Discussion

Policy shocks, even if not directly related to innovation, can unintentionally affect innovation (Acharya et al., 2013). The technology sanctions imposed by the US on Chinese firms through export controls are clearly intended to hinder the development of Chinese high technology firms. This significant regulation is expected to impact the innovation behaviors and performance of the target firms, but the actual effect depends on firms' responses.

Unlike firms in technology-leading countries that primarily rely on their own technological capabilities for innovation, firms in developing countries heavily depend on external technology imports for production and innovation. Compared with R&D, technology transfer is less time-consuming and less risky; it can also immediately fit the required technological demand of production and enhance firm productivity. Specifically, technology imports generally complement rather than replace R&D in fostering innovation in firms in emerging economies, thereby improving their technological capabilities. This complementarity relationship is also observed in Chinese firms (e.g., Fu et al., 2021; Hou and Mohnen, 2013; and Zhao, 1995). Thus, technology sanctions through export controls on key technologies undoubtedly disrupt (break) target firms' production and innovation immediately. Since it is challenging for sanctioned firms to develop these sanctioned technologies in the short run, the lack of complementary technology may interrupt certain ongoing and further R&D projects. Moreover, it increases operating costs and reduces profits, which are essential internal funds for supporting R&D activities. Thus, inclusion in the EL is expected to negatively impact innovation.

Conversely, the impact of market regulation on innovation depends on the proximity to the technological frontier (Amable et al., 2010). A small technology gap indicates that the regulated country has sufficient knowledge stock to learn and assimilate imported technologies. Based on the R&D experience, EL firms might accelerate their R&D efforts to bridge the technological gap. Indeed, China has made significant advancements in several industries, such as information and communication technology, high-speed railways, and electric vehicles. Many high-tech firms may increase their R&D investments and recruit

---

[9] One estimation in Hu et al. (2024) investigated the effect of the sanction on R&D expenditure, which was found to be significantly positive. However, they do not control for the selection effects.

more returning Chinese talent to drive innovation. Therefore, technology sanctions could potentially have a positive innovation effect in China.

Moreover, technology sanctions may not change the target firms' innovation behaviors for several reasons. First, firms may indirectly acquire technologies through nontreated firms, despite that this violates the EAR (Gupta et al., 2024). Second, they might stockpile large inventories of regulated items or software in advance. Third, regulated items or software may not consider a significant part of the key inputs for target firms. Fourth, the profits reduced by sanctions may be compensated by government subsidies. Consequently, technology sanctions may not change access to technologies in substance, and not changing sanctioned firms' innovation. In general, the US technology sanctions may increase, decrease, or do not affect sanctioned firms' innovation activities in China.

3. Empirical Framework and Data

This section explains our empirical framework. The technology sanctions are captured by the existence of each firm in the EL. Similar with previous studies, we explore R&D expenditure divided by total assets as a proxy for innovation activities. We also separately examine its numerator (R&D expenditure) and denominator (total assets). As firms are not randomly included in the EL, EL firms may have different innovation behaviors from non-EL firms. Therefore, we should address this selection mechanism to evaluate the causal effects of being included in the EL.

Nevertheless, for comparison, we start with the DID method, which does not address the selection effect. Specifically, our basic equation is specified as follows:

$$\ln Y_{fit} = \beta \cdot Sanction_{ft} + \gamma_1 \ln LP_{ft-1} + \gamma_2 \ln KL_{ft-1} + \gamma_3 \cdot SOE\ Dummy_{ft-1} + \gamma_4 \ln Subsidy_{ft-1} + FE_f + FE_{it} + \epsilon_{fit} \quad (1)$$

Here, Y_{fit} represents outcome variables for firm f in industry i in year t, including R&D expenditure divided by total assets, R&D expenditure, and total assets. These outcome variables are obtained in logs. $Sanction_{ft}$ takes a value of one if firm f is included in the EL in year t. Unless the selection mechanism works, its coefficient (β) indicates the causal effect of the EL on the outcome variables.

We introduce some control variables defined at the firm-level. *LP* is used as a proxy for labor productivity and is computed as the total income divided by the number of employees. *KL* is a capital-labor ratio, namely, tangible fixed assets divided by the number of employees. The *SOE Dummy* is an ownership dummy that is equal to one if the share of state ownership is positive. *Subsidy* is the amount of government subsidy that can facilitate more innovation, particularly for large firms (Zhao et al., 2018). These variables are included in the equation in the one-year-lagged form to address the simultaneity problem.

Additionally, we control for industry-year fixed effects, which captures the R&D effect due to tariff changes (e.g., US additional tariffs against China), and firm fixed effects. ϵ_{fit} is a disturbance term. We estimate this model using the ordinary least square (OLS) method.

We also employ the PSM-DID method to address selection effects. That is, we follow the solution used in standard PSM analyses (e.g., Rosenbaum and Rubin, 1983). To control for the remaining selection bias from unobservable, temporary time-invariant factors, such as common macro effects, we combine the matching method with a DID approach, as described by Heckman et al. (1998). Similar to the above DID analysis, our treatment indicator variable is $Sanction_{ft}$, whereas outcome variables are represented by $\ln Y_{fit}$. After computing the propensity scores for inclusion in the EL, we employ the one-to-one nearest neighbor matching method as the matching algorithm. To evaluate the treatment effect, we use standard errors based on Abadie and Imbens (2016) in the PSM-DID, which consider the fact that propensity scores are estimated and not known when calculating standard errors. Therefore, we use the *teffects psmatch* command in Stata.

The likelihood of being included in the EL is estimated using the logit model, with the control variables in equation (1) as the main covariates; that is, $\ln LP_{ft-1}$, $\ln KL_{ft-1}$, $SOE\ Dummy_{ft-1}$, and $\ln Subsidy_{ft-1}$. Although the exact criteria used by the US government for selecting firms in the EL are unknown, these basic characteristics are associated with the key elements in the selection. Moreover, we include some fixed effects, as explained later. Regarding the outcome variables, we also examine labor productivity, total income, inventory amount, and the amount of government subsidy.[10] These variables could be mechanisms that mediate the R&D effect of technology sanction.

The dataset used in this study comprises panel data of manufacturing and information technology firms listed on Shanghai or Shenzhen A-shares from 2015 to 2022.[11] It is compiled from three sources. First, we obtain firms' R&D information from the Chinese Research Data Services (CNRDS) database. Second, the key variable of interest, sanctioned Chinese firms, is derived from the EL published by BIS in 2018-2022 (i.e., Supplement No. 4 to Part 744 of the EAR). We gather the English names of blacklisted Chinese firms, translate them into Chinese, and cross-reference them with various websites to ensure accuracy. Notably, some sanctioned firms are large enterprise groups with multiple firms listed on Shanghai or Shenzhen A-shares. By visiting these enterprise group websites, we identify the listed firms within these groups. According to the BIS website, the licensing and other obligations imposed on a listed entity do not automatically extend to its subsidiaries, parent companies, sister companies, or other legally distinct affiliates not listed on the EL.[12]

---

[10] We winsorize all variables from the 1%–99% level.

[11] On China's stock market, categories C and I represent manufacturing and information technology firms. Firms included in category I can be manufacturing, technology service, software, internet, and telecommunication firms. Analyses in the literature reviewed also include information technology firms of A-shares.

[12] The BIS website further instructs that if a company, or even an unaffiliated company, serves as an

However, in our empirical analysis, we treat companies within an EL firms' group as sanctioned entities because the responses to this severe punishment is likely shared across the entire group. In our later analysis, we differentiate blacklisted firms based on the case-by-case and presumption of denial policies in the license review process.[13] We match sanctioned firms with Chinese A-share listed manufacturing companies. Third, information on other variables was obtained from the China Stock Market and Accounting Research databases. This data processing resulted in a total of 15,653 firm observations in 2015-2022.[14]

4. Estimation Results

This section reports our estimation results. Table 2 presents the OLS results of equation (1), with standard errors clustered by firm. The dependent variable (i.e., the outcome variable) is R&D expenditure divided by total assets (R&D intensity) in column (I), R&D expenditure in column (II), and total assets in column (III). Specifically, all three columns present insignificant coefficients for *Sanction*. Thus, compared to previous studies, we found an insignificant association between being included in the EL and the R&D-asset ratio. This result could be due to the differences in the sample period or how standard errors are computed. Some control variables showed significant results. In columns (IV)-(VI), we break down the *Sanction* dummy into two variables representing case-by-case firms and presumption-of-denial firms. We again found no significant results for these dummy variables across all outcome variables. Overall, the findings from equation (1) indicate that the positive effect on the R&D-asset ratio observed in the previous studies may not be robust.

[Table 2]

We control for the selection effect in the EL by using the PSM-DID method. The first-stage propensity for inclusion in the EL is estimated using the logit method. The estimation results for EL firms are presented in columns (I) and (II) of Table 3. In column (I), we account for industry and year fixed effects, whereas column (II) includes industry-year fixed effects.[15] Since treated firms are only included in the study sample for the first treated year, the number of observations is smaller than that in Table 2. Meanwhile, the coefficients for

---

agent, a front, or a shell company for the listed entity to facilitate otherwise impermissible, then it is likely violating, among other things, General Prohibition 10, EAR section 764.2(b) (causing, aiding, or abetting a violation) and also possibly other subsections of 764. See https://www.bis.doc.gov/index.php/policy-guidance/deemed-exports/deemed-exports-faqs/faq/134-do-the-license-requirements-and-policies-of-the-entity-list-apply-to-separately-incorporated-subsidiaries-partially-owned-subsidiaries-or-sister-companies-of-a-listed-entity

[13] We drop the EL firms under the review policy of "§744.2(d) of the EAR" because only two firms belong in this category.

[14] The basic statistics for our variables are presented in Table A1 in the Appendix.

[15] Note that, in the logit estimation, we exclude observations for 2015-2017 as we focus on firms sanctioned and included in the EL during 2018-2022 and incorporate year fixed effects.

LP are significantly positive, indicating that more labor-productive firms are more likely to be included in the EL. *Subsidy* has significantly positive coefficients, showing that firms receiving a larger subsidy are more likely to be included in the EL. However, we do not observe significant results in *KL* and *SOE Dummy*. That is, more productive firms supported monetarily by the government are more likely to be included in the EL. For the later analysis, we report the results excluding case-by-case firms in column (III). We exclude presumption-of-denial firms in column (IV) from the study observations. The results for "presumption of denial" firms are similar to those for all EL firms, whereas labor productivity shows an insignificant result for "case-by-case" firms.

[Table 3]

Based on the estimated propensity, we match treated firms with control firms. The underlying assumption for the validity of our empirical procedure is that, conditional on the observable characteristics relevant for the selection of EL firms, the potential outcomes for treated and control firms are independent of the treatment status. Given these characteristics, the matched pairs of treated and control firms should exhibit comparable performance prior to inclusion in the EL. To ensure the matching quality, Figure 2 depicts the density balancing plots of treated and untreated groups before and after matching. Panels (a) and (b) demonstrate the balance tests of models (I) and (II) in Table 3, respectively. Before matching, EL and non-EL firms exhibited a considerable difference in the pattern of the density plots, whereas their density plots in the matched sample became highly overlapped, implying a closely similar distribution pattern. Table 4 presents the standardized differences and variance ratios for each covariate. The row numbers in this table correspond to those in Table 3. In comparison to the raw observations, the standardized difference among the matched observations should be smaller in absolute terms. Similarly, the variance ratio in the matched sample should be close to one. Table 4 demonstrates these trends, indicating successful matching. However, we can observe low matching performance in some variables (e.g., variance ratios in ln *LP* and ln *KL* in model (II)). Overall, our matching is successful. [16]

[Figure 2 & Table 4]

Table 5 (upper panel) presents the second-step PSM-DID results for all firms (i.e., without differentiating case-by-case and presumption of denial). The results reflect the corresponding effects in the first treatment year, and we use standard errors based on Abadie and Imbens (2016). Matching in these columns is based on the propensities estimated in columns (I) and (II) in Table 3. Both cases indicate insignificant impacts on the ratio of R&D expenditure to total assets. We also analyze the numerator and denominator separately. Although the effect on R&D is insignificant, the impact on total assets is significantly negative, with sanctioned firms reducing their total assets by approximately

[16] We also conduct balancing tests based on models (III) and (IV) of Table 3. The density plots of the treated and nontreated groups become highly overlapped after matching.

6% after being listed in the EL. These results imply that the positive effect on the R&D-asset ratio observed in previous studies may be due solely to the decline in total assets rather than an increase in R&D expenditure. Crucially, our results suggest that US technology sanctions do not alter sanctioned firms' innovation expenditures.

[Table 5]

As discussed in Section 2.2, the impact of technology sanctions on R&D is uncertain, with effects ranging from positive, negative, or neutral. One possible reason for this insignificant R&D effect is the variation in technology differences between China and the US for the regulated items or software, resulting in mixed positive and negative outcomes among sanctioned firms. Another reason is that, although targeted firms were blocked from acquiring advanced technologies by the US government, they may indirectly acquire technologies through other nontreated firms or accumulate large amounts of inventories in advance. These firms may continue with innovation activities with the government's monetary support, which could have been funded by disposing some assets, as evidenced by significant reduction in total assets.[17]

We conduct robustness checks on the above results. Specifically, we employ the doubly robust DID method described in Callaway and Sant'Anna (2021) using their Stata package *csdid*. One advantage of this method is that it considers the heterogeneous treatment effects across treatment timing and years. This issue is pertinent to our analysis due to the regular updates of the EL. Furthermore, firms added to the EL earlier may be recognized as threats to national security than those added later, potentially resulting in different performance outcomes. We perform this estimation by comparing treated firms with never-treated firms. The covariates include the same set of explanatory variables in equation (1), in addition to the industry fixed effects. The simple averages of the treatment effects are presented in the lower panel of Table 5.[18] All outcome variables, including total assets, have insignificant results. Thus, the positive R&D effects are found to be not robust again.

We investigate the impacts on other performance indicators. Table 6 presents the results obtained by the PSM-DID. The robust results are the significant increase in government subsidies. That is, sanctioned firms significantly increased the amount of government subsidy by around 23%. Therefore, the Chinese government tends to provide monetary support to sanctioned Chinese firms so that they can overcome the US sanctions. This result supports Hu et al.'s (2024) argument that government subsidies serve as a crucial channel for export controls that stimulate firms' innovation. However, we do not observe significant results in other variables, especially total income and inventory levels. Thus,

[17] Another possible interpretation is that the ongoing US-China trade war has overall generated a same-direction impact on innovation in both treated and nontreated firms. In this case, we did not detect significant differences in changes in innovation activities between the treated and control firms.

[18] We also report in the table the *p*-values for the chi-square test of the null hypothesis that all pretreatments are equal to zero. It is not rejected for R&D intensity and R&D expenditure.

inventory accumulation is unlikely to be the primary reason for the insignificant average result in R&D expenditures.[19]

[Table 6]

We further investigate the overtime changes of these impacts, as presented in Table 7. Due to the small number of observations for EL firms during a post-treated period, we examined the impacts only up to one year after the first treated year. The results are based on the logit specification with industry-year fixed effects (i.e., column (II) in Table 3). Insignificant results in pretreatment years suggest the absence of pretreatment effects. Table 7 also shows significant changes in labor productivity, which gradually rises over time. We also observe a one-time rise in government subsidies (i.e., their rise only in the first treated year). This increase in government subsidies may be associated with the rise in labor productivity. Conversely, the impact on R&D expenditure remains insignificant over time. Thus, we maintain that the recent US technology sanction does not alter sanctioned firms' innovation expenditures. The effects on total income and inventory levels are also insignificant.

[Table 7]

Finally, we investigate the impacts on case-by-case firms and presumption-of-denial firms separately.[20] Table 8 presents the results of the PSM-DID, indicating an insignificant change in R&D expenditure in both types of sanctioned firms. We also observe a significant rise in labor productivity in both types of sanctioned firms. From a quantitative perspective, case-by-case firms increase their productivity more greatly than presumption-of-denial firms. Additionally, case-by-case firms significantly increase the inventory levels, whereas presumption-of-denial firms significantly increase the subsidy. The inventory increase in case-by-case firms may be due to preparing for sudden prohibitions on importing high-end products, prompting these firms to stockpile inventory in advance. The increased inventory provides a longer buffer period between the current R&D projects and adjusted R&D projects in response to potential strict sanctions. The rise in subsidies for presumption-of-denial firms may indicate that the Chinese government may prioritize granting subsidies to more severely sanctioned firms. These sanctioned firms are generally leaders in their technological fields; subsidizing them helps China secure continuous improvement of key technologies. Therefore, insignificant changes in R&D expenditures may be due to inventory accumulation in less strictly sanctioned firms (i.e., case-by-case firms) and the government financial support in more strictly sanctioned firms (i.e., presumption-of-denial firms).

[Table 8]

[19] We also examined the impacts on return on asset, return on equity, and R&D expenditure over income as other indicators, but found insignificant results for all three indicators.

[20] The propensity estimation is reported in Table 3.

5. Concluding Remarks

The ongoing US-China trade war has significantly impacted the global economy, with China being the primary target. This second phase of the US-China trade war involves technology sanctions targeting certain firms that import advanced technologies from the US but potentially threaten US national security. These sanctions also aim to prevent China from becoming a global leader in high technology.

Against this backdrop, the following question arises "does the technology sanction retard the R&D activity of the sanctioned firms?" To answer this, we examine the R&D effect of technology sanctions on sanctioned firms using a panel dataset of listed firms from 2015 to 2022. Our PSM-DID estimates show that, unlike existing studies, technology sanctions do not enhance the R&D investment and R&D intensity. Nevertheless, we found that sanctioned firms' total assets declined after being listed on the EL. This may lead to an increased R&D intensity since R&D expenditure remains unchanged. When separating EL firms according to the license review policy, we again found insignificant effects on R&D investment in both less and more strictly sanctioned firms. Furthermore, we observed a significant accumulation of inventories in less strictly sanctioned firms and a significant increase in government financial support in more strictly sanctioned firms.

Based on our analyses, technology sanctions do not alter the R&D behavior of Chinese EL firms. They may maintain stable R&D activities through inventory accumulation or government subsidies. However, as the number of sanctioned firms increases over time, it is not fiscally sustainable for the Chinese government to continue providing these subsidies. Furthermore, less strictly sanctioned firms that accumulate inventories may soon face a presumption of denial review policy, rendering their inventories technologically outdated. In short, both strategies are temporary solutions, and a sustainable approach to handling technology sanctions is necessary.

References

Abadie, A. and G.W. Imbens (2016), Matching on the estimated propensity score, *Econometrica*, 84, 781-807.

Acharya, V.V., R.P. Baghai and K.V. Subramanian (2013), Labor laws and innovation, *Journal of Law and Economics*, 56, 997-1037.

Aghion, P., A. Bergeaud and J. Van Reenen (2021), The impact of regulation on innovation, NBER Working paper, No. 28381.

Amable, B., L. Demmou and I. Ledezma (2010), Product market regulation, innovation, and distance to frontier, *Industrial and Corporate Change*, 19(1), 117-159.

Amiti, M., S.J. Redding and D.E. Weinstein (2019), The impact of the 2018 tariffs on prices and welfare, *Journal of Economic Perspectives*, 33(4), 187-210.

Amiti, M., S.J. Redding and D.E. Weinstein (2020), Who's paying for the US tariffs? A longer-term perspective, *AEA Papers and Proceedings*, 110, 541-546.

Anwar, S., B. Hu, Q. Luan, and K. Wang (2024), Export controls and innovation performance: Unravelling the complex relationship between blacklisted Chinese firms and U.S. suppliers, *The World Economy*, 47(7), 2995-3033.

Blanchard, E.J., C.P. Bown, and D. Chor (2024), Did Trump's trade war impact the 2018 election?, *Journal of International Economics*, 148, 103891

Boeing, P., J. Eberle and A. Howell (2022), The impact of China's R&D subsidies on R&D investment, technological upgrading and economic growth, *Technological Forecasting and Social Change*, 174, 121212.

Callaway, B. and P.H.C. Sant'Anna (2021), Difference-in-differences with multiple time periods, *Journal of Econometrics*, 225(2), 200-230.

Cao, Y., F. De Nicola, A. Mattoo, and J. Timmis (2024), Technological decoupling? The impact on innovation of US restrictions on Chinese firms, Policy Research Working Paper; 10950, Washington, DC: World Bank.

Cavallo, A., G. Gopinath, B. Neiman and J. Tang (2021), Tariff pass-through at the border and at the store: Evidence from US trade policy, *American Economic Review: Insights*, 3(1), 19-34.

Chen, A.W., J. Chen and R. Dondeti (2020), The US-China trade war: Dominance of trade or technology? *Applied Economics Letters*, 27(11), 904-909.

Chen, Y., S. Zhang and J. Miao (2023), The negative effect of the US-China trade war on innovation: Evidence from the Chinese ICT industry, *Technovation*, 123, 102734.

Chor, D. and B. Li (2024), Illuminating the effects of the US-China tariff war on China's economy, *Journal of International Economics*, 150, 103926.

Cui, C. and L.S. Li (2021), The effects of the US-China trade war on Chinese new firm entry, *Economics Letters*, 203, 109846.

Egger, P.H. and J. Zhu (2020), The US-China 'trade war': An event study of stock-market responses, *Economic Policy*, 35(103), 519-559.

Fajgelbaum, P.D., P.K. Goldberg, P.J. Kennedy and A. K. Khandelwal (2020), The return to protectionism, *Quarterly Journal of Economics*, 135(1), 1-55.

Fajgelbaum, P.D., P.K. Goldberg, P.J. Kennedy, A. Khandelwal and D. Taglioni (2024), The U.S.-China trade war and global reallocations, *American Economic Review: Insights*, 6(2), 295–312.

Friis, K. and O. Lysne (2021), Huawei, 5G and security: Technological limitations and political responses, *Development and Change*, 52(5), 1174-1195.

Fu, Q., Q. Gong and X.X. Zhao (2023), The effects of international sanctions on green innovations, *Technological and Economic Development of Economy*, 29(1), 141-164.

Fu, X., B. McKern and J. Chen (2021), *The Oxford Handbook of China Innovation*, Oxford University Press, Oxford, U.K.

Gupta, R., L. Walker, and A.W. Reddie (2024), Whack-a-Chip: The Futility of Hardware-Centric Export Controls, arXiv preprint, arXiv:2411.14425.

Handley, K., F. Kamal and R. Monarch (2024), Rising import tariffs, falling export growth: When modern supply chains meet old-style protectionism, Forthcoming in the *American Economic Journal: Applied Economics*.

Hayakawa, K., J.H. Pyun, N. Yamashita and C.H. Yang (2023), Ripple effects in regional value chains: Evidence from an episode of the US–China trade war, *World Economy*, forthcoming.

Heckman, J., H. Ichimura, J. Smith, ad P. Todd (1998), Characterizing selection bias using experimental data, *Econometrica*, 66(5), 1017–1098.

Hou, J. and P. Mohnen (2013), Complementarity between in-house R&D and technology purchasing: evidence from Chinese manufacturing firms, *Oxford Development Studies*, 41(3), 343-371.

Hu, H., S. Yang, L. Zeng and X. Zhqng (2024), U.S.–China trade conflicts and R&D investment: evidence from the BIS entity lists, *Humanities and Social Sciences Communications*, 11, 829.

Hu, A.G.Z., P. Zhang and L. Zhao (2017), China as number one? Evidence from China's most recent patenting surge, *Journal of Development Economics*, 124, 107-119.

Huang, K.G., N. Jia and Y. Ge (2024), Forced to innovate? Consequences of United States' anti-dumping sanctions on innovations of Chinese exporters, *Research Policy*, 53(1), 104899.

Kaska, K., H. Beckvard and T. Minárik (2019), Huawei, 5G and China as a security threat, NATO Cooperative Cyber Defence Centre of Excellence (CCDCOE). Retrieved from https://ccdcoe.org/uploads/2019/03/CCDCOE-Huawei-2019-03-28-FINAL.pdf

Kong, D., C. Liu, P.K. Narayan, and S.S. Sharma (2024), The US–China trade war and corporate innovation: Evidence from China, *Financial Management*, 53, 501–541.

Lee, K. (2021), *China's technological leapfrogging and economic catch-up: A Schumpeterian perspective*, Oxford University Press, Oxford, United Kingdom.

Li, J. Y. Shan, G. Tian and X. Hao (2020), Labor cost, government intervention, and corporate

innovation: Evidence from China, *Journal of Corporate Finance*, 64, 101668.
Löschel, A. (2002), Technological change in economic models of environmental policy: A survey, *Ecological Economics*, 43(2-3), 105–126.
Luo, Y. and A. Van Assche (2023), The rise of techno-geopolitical uncertainty: Implications of the United States CHIPS and Science Act, *Journal of International Business Studies*, 54, 1423-1440.
Ma, H., J. Ning and M. Xu (2021), An eye for an eye? The trade and price effects of China's retaliatory tariffs on U.S. exports, *China Economic Review*, 69, 101685.
Rosenbaum, P. and D. Rubin (1983), The central role of the propensity score in observational studies for causal effects, *Biometrika*, 70, 41–55.
Shen, H., Y. Gao, X. Cheng, and Q. Wang (2024), The impact of the U.S. export controls on Chinese firms' innovation: Evidence from Chinese high-tech firms, *International Review of Financial Analysis*, 95(C), 103510.
Swenson, D. and W.T. Woo (2019), The politics and economics of the U.S.-China trade war, *Asian Economic Papers*, 18(3), 1-28.
Tekir, G. (2020), Huawei, 5G networks, and digital geopolitics, *International Journal of Politics and Security*, 2(4), 113-135.
Wen, J., S. Wang, S. Yang and X. Chen (2024a), International sanctions and innovation: Empirical evidence from China's A-share listed companies, *Emerging Markets Finance and Trade*, 60(2), 263-281.
Wen, J., X. Zhao and C.P. Chang (2024b), The impact of international sanctions on innovation of target countries, *Economics & Politics*, 36(1), 39-79.
Wu, Y., X. Guo, and D. Marinova (2017), Productivity, innovation and China's economic growth, In Song, L., R. Garnaut, C. Fang and L. Johnston (eds.), *China's New Sources of Economic Growth*: Vol. 2: *Human Capital, Innovation and Technological Change*, Australian National University Press, Acton, Australia.
Xiong, A., S. Xia, Z.P. Ye, D. Cao, Y. Jing and H. Li (2020), Can innovation really bring economic growth? The role of social filter in China, *Structural Change and Economic Dynamics*, 53, 50-61.
Yang, C.H. (2023), R&D responses to labor cost shock in China: Does firm size matter? *Small Business Economics*, 61, 1773-1793.
Yang, C.H. and K. Hayakawa (2023), The substitution effect of U.S.-China trade war on Taiwanese trade, *The Developing Economies*, 61(4), 324-341.
Zhao, H. (1995), Technology imports and their impacts on the enhancement of China's indigenous technological capability, *Journal of Development Studies*, 31(4), 585-602.
Zhao, S., B. Xu and W. Zhang (2018), Government R&D subsidy policy in China: An empirical examination of effect, priority, and specifics, *Technological Forecasting and Social Change*, 135, 75-82.

Table 1. Number of New Sanctioned Chinese Entities by License Review Policy, 2018-2022

License Review Policy	2018	2019	2020	2021	2022
Case-by-case	2	27	23	18	5
Presumption of denial	27	58	123	63	63
§744.2(d) of the EAR			2		
Total	29	85	148	81	68

Source: Authors' own calculation based on the BIS, Department of Commerce, the US.

Table 2. The Results of the DID

	(I) R&D/Asset	(II) R&D	(III) Asset	(IV) R&D/Asset	(V) R&D	(VI) Asset
Sanction	0.017	0.041	0.024			
	[0.030]	[0.045]	[0.032]			
Case-by-case				-0.009	0.074	0.083
				[0.071]	[0.137]	[0.083]
Presumption of denial				0.02	0.038	0.018
				[0.032]	[0.047]	[0.034]
ln *LP*	0.058**	0.222***	0.164***	0.058**	0.222***	0.164***
	[0.024]	[0.030]	[0.019]	[0.024]	[0.030]	[0.019]
ln *KL*	-0.056***	-0.036**	0.021	-0.056***	-0.035**	0.021
	[0.015]	[0.018]	[0.013]	[0.015]	[0.018]	[0.013]
SOE Dummy	-0.019	0.037**	0.057***	-0.019	0.037**	0.057***
	[0.014]	[0.016]	[0.012]	[0.014]	[0.016]	[0.012]
ln *Subsidy*	0.014**	0.103***	0.089***	0.014**	0.103***	0.089***
	[0.007]	[0.009]	[0.006]	[0.007]	[0.009]	[0.006]
Number of observations	15,653	15,653	15,653	15,653	15,653	15,653
Adjusted R-squared	0.858	0.901	0.93	0.858	0.901	0.93

Notes: This table reports the OLS results. Standard errors are clustered at a firm-level. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively. In all specifications, we control for firm fixed effects and industry-year fixed effects.

Table 3. Estimation of the Propensity of EL

	(I) All	(II) All	(III) Presumption	(IV) Case
ln *LP*	0.348**	0.335*	0.392**	-0.609
	[0.171]	[0.171]	[0.177]	[0.723]
ln *KL*	0.04	0.031	0.041	0.04
	[0.109]	[0.112]	[0.119]	[0.366]
SOE Dummy	0.357	0.377	0.358	0.642
	[0.263]	[0.268]	[0.277]	[0.989]
ln *Subsidy*	0.541***	0.531***	0.500***	0.961***
	[0.100]	[0.101]	[0.105]	[0.267]
Industry FE	X			
Year FE	X			
Industry-year FE		X	X	X
Number of observations	8,369	5,124	4,962	1,165
Pseudo R-squared	0.181	0.154	0.158	0.157

Notes: This table reports the estimation results of the logit model. Robust standard errors are reported. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Table 4. The Balancing Tests

	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
Model (I)				
ln *LP*	0.268	0.210	0.942	0.956
ln *KL*	0.085	0.042	0.890	0.981
SOE Dummy	0.352	0.023	1.826	1.026
ln *Subsidy*	0.705	0.008	1.321	1.248
Model (II)				
ln *LP*	0.334	-0.008	0.944	0.890
ln *KL*	0.167	0.043	0.831	0.693
SOE Dummy	0.333	-0.109	1.747	0.898
ln *Subsidy*	0.664	-0.104	1.318	1.187
Model (III)				
ln *LP*	0.355	-0.055	0.959	0.780
ln *KL*	0.164	-0.153	0.871	1.086
SOE Dummy	0.324	-0.162	1.722	0.859
ln *Subsidy*	0.632	-0.088	1.343	1.097
Model (IV)				
ln *LP*	-0.164	-0.112	0.640	0.670
ln *KL*	-0.077	-0.474	0.511	0.705
SOE Dummy	0.362	-0.279	2.056	0.833
ln *Subsidy*	1.133	0.207	0.940	0.996

Notes: This table reports the results of the balancing tests for the matching conducted in Tables 4, 5, and 7. Row numbers correspond to those listed in Table 2.

Table 5. Impacts on R&D Intensity, R&D Expenditure, and Total Assets

	R&D/Asset	R&D	Asset
PSM-DID			
(i) Industry FE & Year FE			
Sanction	-0.028	-0.061	-0.060**
	[0.045]	[0.053]	[0.028]
(ii) Industry-year FE			
Sanction	0.012	-0.048	-0.068**
	[0.033]	[0.038]	[0.028]
Doubly robust DID			
Sanction	-0.071	-0.007	0.064
	[0.068]	[0.095]	[0.064]
Pretrend (*p*)	0.8091	0.2623	0.0369
Number of obs.	15,600	15,600	15,640

Notes: The upper panel shows the PSM results, while the results using the doubly robust DID method are reported in the lower panel. The standard errors in the PSM are Abadie-Imbens robust errors. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively. "Pretend (*p*)" reports *p*-values for the Chi-square test of the null hypothesis that all pretreatments are equal to zero.

Table 6. Results of PSM-DID for Other Indicators

	LP	Income	Inventory	Subsidy
(i) Industry FE & Year FE				
Sanction	0.092***	0.011	-0.033	0.223***
	[0.031]	[0.041]	[0.052]	[0.073]
(ii) Industry-year FE				
Sanction	-0.001	-0.022	-0.006	0.251***
	[0.034]	[0.034]	[0.043]	[0.083]

Notes: This table reports the PSM-DID results. The standard errors are the Abadie-Imbens robust errors. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Results of PSM-DID: Overtime Impacts

	t-3	t-2	t	t+1
R&D	-0.083	-0.022	-0.059	-0.053
	[0.106]	[0.037]	[0.067]	[0.055]
LP	0.021	0.002	0.069*	0.116**
	[0.038]	[0.027]	[0.040]	[0.050]
Income	-0.053	-0.026	0.001	-0.079
	[0.057]	[0.044]	[0.043]	[0.059]
Inventory	0.027	0.018	0.015	-0.04
	[0.084]	[0.070]	[0.050]	[0.091]
Subsidy	-0.016	-0.013	0.321***	0.108
	[0.124]	[0.024]	[0.082]	[0.085]

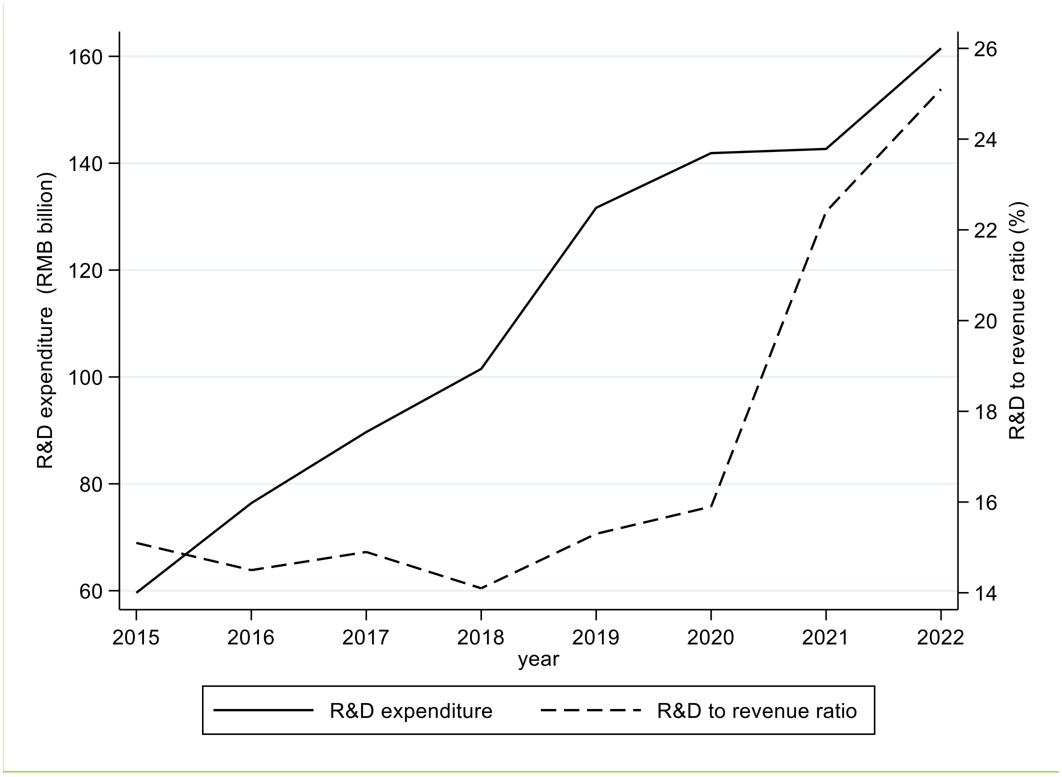
Notes: This table reports the PSM-DID results in the *Sanction* variable. The standard errors are the Abadie-Imbens robust errors. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Results of PSM-DID: Case-by-case and Presumption of Denial

	R&D	LP	Income	Inventory	Subsidy
(i) Presumption of denial					
Sanction	-0.053	0.069**	0.001	-0.032	0.283***
	[0.054]	[0.031]	[0.036]	[0.038]	[0.088]
(ii) Case-by-case					
Sanction	0.219	0.170***	0.116	0.140**	0.113
	[0.155]	[0.065]	[0.125]	[0.071]	[0.197]

Notes: This table reports the PSM-DID results. The standard errors are the Abadie-Imbens robust errors. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively.

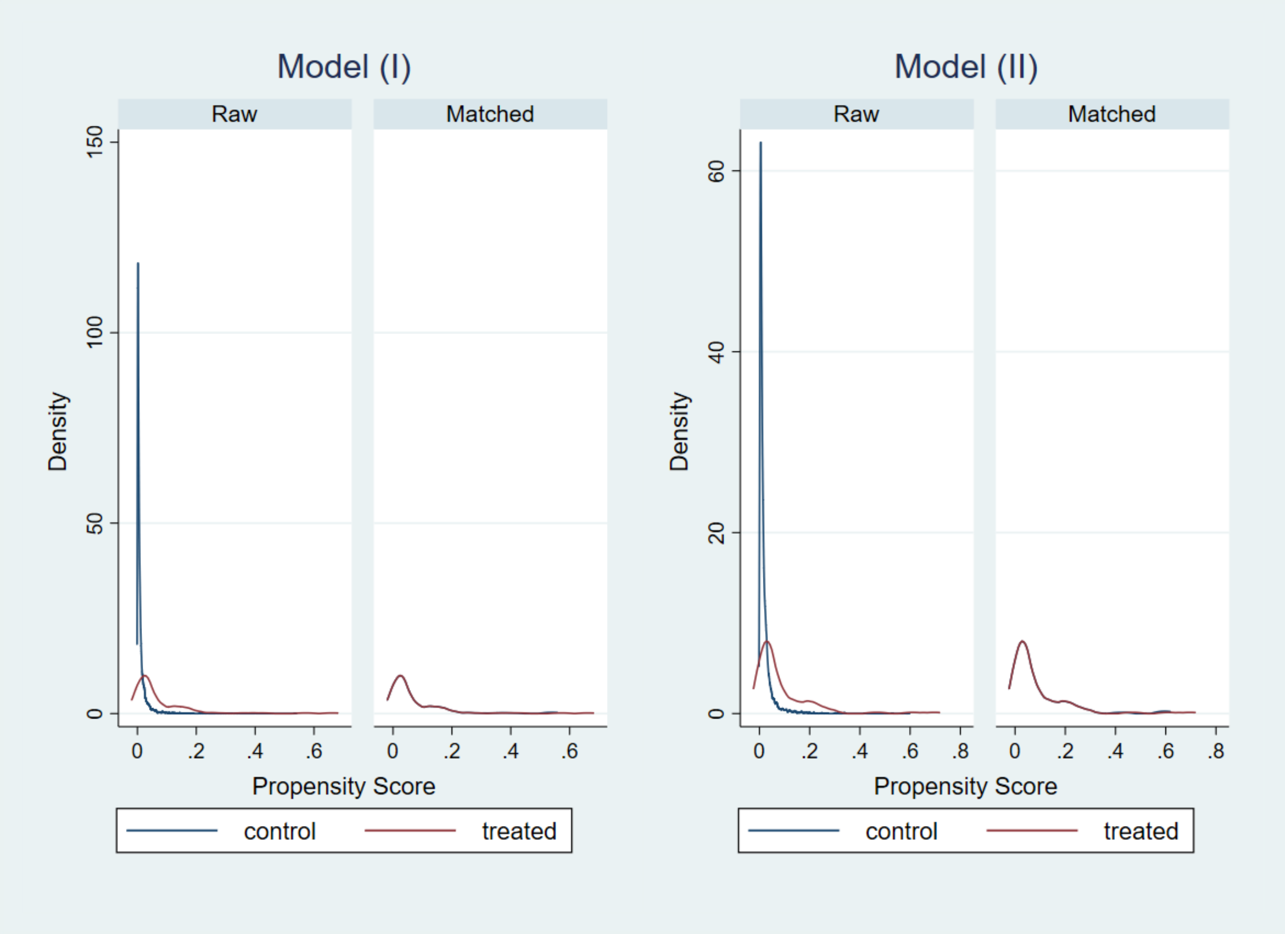
Figure 1. R&D Expenditure and Intensity of Huawei



Source: Huawei Annual Reports.

Figure 2. Balance Tests

Panel (a) Panel (b)



Source: Authors' compilation.

Notes: These figures show the results of the density balancing plots of the treated and untreated groups before and after matching. The model numbers correspond to those in Table 3.

Appendix. Other Tables

Table A1. Basic Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ln *R&D/Asset*	15,653	3.075	0.926	-8.061	5.645
ln *R&D*	15,653	18.259	1.279	7.720	22.571
ln *Asset*	15,653	15.184	1.043	12.577	19.468
Sanction	15,653	0.018	0.134	0	1
Case-by-case	15,653	0.002	0.040	0	1
Presumption of denial	15,653	0.017	0.129	0	1
ln *LP*	15,653	6.838	0.686	3.543	10.094
ln *KL*	15,653	5.613	0.966	0.525	9.574
SOE Dummy	15,653	0.148	0.356	0	1
ln *Subsidy*	15,653	9.705	1.305	4.895	13.490

Source: Authors' compilation.