Export Restrictions and the Ripple Effect: Evidence from U.S.-China Trade Networks

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Abstract

We examine the direct and indirect economic effects of U.S. export control policies, particularly the inclusion of Chinese firms on the BIS Entity List, on both Chinese and U.S. companies. Our event study reveals that U.S. suppliers of sanctioned Chinese firms experience negative cumulative abnormal returns (CARs) around the announcements of their customers' addition to the Entity List, indicating anticipated revenue losses and operational disruptions due to reduced business with these clients. In contrast, Chinese upstream suppliers exhibit positive CARs, reflecting market expectations that they can replace U.S. suppliers in providing intermediate goods to sanctioned firms, thereby expanding their market share over time. Disruptions in trade networks may also influence innovation behavior on both sides by affecting market size, knowledge diffusion, and the degree of market competition. Our analysis of innovation inputs and outputs shows that Chinese firms listed on the Entity List, along with their industry peers, measured by import data, and upstream suppliers, significantly increased R&D investments and patent filings, particularly invention patents. Chinese suppliers also expanded their operations and achieved profit growth. Conversely, U.S. suppliers faced profit declines and reductions in patent value. These findings suggest that the export controls have driven Chinese firms to seek local substitutes for intermediate goods, thereby increasing the size of their upstream market and enhancing innovation capacity. At the same time, the uncertainty brought by these policies have led Chinese firms to prioritize supply chain resilience, indirectly accelerating Chinas industrial upgrading.

Keywords: event study, supply chains, innovation, export restrictions

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1 Introduction

International trade can enhance welfare for both exporting and importing countries by expanding market size, increasing market competition, and fostering knowledge spillovers, leading to long-term economic growth driven by innovation (Bloom et al. (2016), Acemoglu et al. (2016), Liu and Ma (2021)). These benefits span from consumer welfare improvements to productivity gains across industries. However, recent waves of protectionist policies have sought to disrupt these processes, raising concerns over the future of global economic integration.

The Entity List, issued by the U.S. Department of Commerce's Bureau of Industry and Security (BIS), has emerged as a pivotal policy instrument in restricting the transfer of sensitive technologies to specific foreign companies. By imposing export controls on firms deemed a threat to U.S. national security, the Entity List aims to limit their access to critical inputs, particularly in high-tech industries. While these sanctions are intended to protect national interests, they also generate significant economic repercussions, particularly by disrupting global supply chains, having resulted in substantial supply chain restructuring and production decoupling (Grossman et al. (2021), Liu et al. (2023)). This shift has caused notable changes in the participation patterns of China and the U.S. in global value chains (GVCs) between 2017 and 2022 (Alfaro and Chor (2023)). Analysis of China's customs data reveals that informal non-tariff barriers accounted for at least 50% of the reduction in China's imports from the U.S. during the height of the trade war (Chen et al. (2022)). Therefore, studying the Entity List policies offers a unique opportunity to understand the broader economic impact of the U.S.-China trade war and to analyze global supply chain security and industrial resilience within the context of a quasi-natural experiment caused by disrupted trade networks.

We examine the direct and indirect impacts of Entity List sanctions on both Chinese and U.S. firms, with a particular focus on stock market reactions, innovation outputs, R&D investments, and financial performance. We find significant asymmetries in how Chinese and U.S. suppliers respond to these sanctions. Chinese firms, particularly those directly included on the

Entity List, demonstrate resilience and adaptability by increasing their patent outputs and R&D spending. In contrast, U.S. suppliers face financial pressures, reduced innovation performance, and declining patent values, reflecting the broader costs of supply chain fragmentation. These findings highlight the unintended consequences of protectionist trade policies, emphasizing the need to consider the long-term economic implications of global supply chain restructuring.

In a steady-state scenario, upstream and downstream relationships within supply chains can lead to lead-lag effects in firms' stock prices (Cohen and Frazzini (2008), Menzly and Ozbas (2010)). When supply chains undergo adjustments due to exogenous shocks, both upstream and downstream firms also react accordingly. Hendricks and Singhal (2003) provide evidence that firm returns decrease following announcements of supply chain disruptions, particularly those involving production or shipment delays. Amiti et al. (2020) demonstrate that U.S.-China tariff announcements induce stock market declines, implying lower returns to capital, which subsequently reduce investment rates. Similarly, Huang et al. (2023) show that around the dates of higher tariff announcements, U.S. firms with greater reliance on exports to and imports from China experienced more substantial declines in market values. We examine the stock price reactions along supply chains to a specific exogenous policy shockthe inclusion of Chinese companies on the U.S. Entity List. Our analysis reveals significant asymmetries in the responses of Chinese and U.S. firms to this supply chain disruption. U.S. suppliers experience negative CARs during the event window [-5, 5], reflecting market concerns about potential revenue losses and operational disruptions stemming from reduced business activities with their Chinese customers. In contrast, Chinese suppliers exhibit positive CARs following the announcement of their clients' inclusion on the Entity List, suggesting that the market anticipates these firms will replace their U.S. counterparts in providing intermediate goods to sanctioned firms. This aligns with the market's expectations regarding adaptive innovation within Chinese supply chains. This divergence underscores the asymmetric impact of protectionist policies. While U.S. suppliers face financial pressures from disrupted supply chains, Chinese suppliers demonstrate resilience and adaptability, effectively positioning themselves to mitigate the adverse effects of supply chain fragmentation.

Supply chains not only facilitate the transfer of intermediate inputs but also serve as channels for knowledge spillovers (Hanlon (2015), Acemoglu et al. (2016), Liu and Ma (2021)). A substantial body of literature explores the relationship between trade and innovation, particularly focusing on which parties in developed-developing trade dynamics can harness trade-induced innovation to achieve sustained economic growth. Melitz and Redding (2021) summarizes four key channels through which international trade influences innovation and economic growth: (1) Market Size Effect, (2) Product Market Competition Effect, (3) Comparative Advantage Effect, and (4) Knowledge Spillover Effect. Following the implementation of U.S. export control policies, U.S. upstream suppliers may experience reduced profits due to the loss of the Chinese market, thereby lowering their R&D investments and innovation outputs. However, as intended by these policies, the restrictions could also hinder knowledge spillover channels and adversely impact the innovation capabilities of Chinese firms targeted by the sanctions. At the same time, Chinese upstream suppliers may replace the intermediate goods previously provided by U.S. suppliers, thereby expanding their market size, increasing profits, and enhancing their capacity to invest in innovation.

We empirically examine the impact of the U.S. export control policies on the relevant industries and upstream supply chains in both China and the U.S. Our findings reveal that Chinese firms directly included on the Entity List exhibit a significant increase in patent outputs, particularly in high-value invention patents, suggesting a strategic shift toward self-reliance in critical technologies. Similarly, non-sanctioned Chinese firms that import the same embargoed products from the U.S. show increased R&D spending and patent outputs, indicating positive spillover effects within the same industry, potentially driven by competition channels or concerns about resilience. Chinese upstream suppliers of the sanctioned firms experienced higher profitability, suggesting that they benefited from the U.S. export control policies by providing inputs that were previously supplied by U.S. firms. Beyond directly affected suppliers, we observe positive spillover effects within the industries associated with these suppliers. Firms in the same industries significantly increased their patent filings and R&D expenditures, indicating efforts to substitute the intermediate goods previously supplied by sanctioned firms and to strengthen China's domestic supply chain resilience. These firms also expanded their workforce, highlighting the potential business opportunities created by the sanctions.

In contrast, U.S. suppliers demonstrate a notable decline in innovation performance. Our analysis reveals significant reductions in both patent value and patent citations among U.S. suppliers, suggesting a deterioration in the quality and influence of their innovations. Furthermore, these suppliers face financial setbacks, including reduced revenue and workforce sizes, indicating that U.S. export control policies may inadvertently harm domestic firms by disrupting established business relationships and limiting access to the Chinese market. This unintended consequence raises important questions about the efficacy of protectionist measures in achieving long-term economic and strategic goals.

Overall, our study underscores the far-reaching and often unintended consequences of export control policies on global supply chains. While sanctions aim to target specific firms or industries, their impact extends beyond the directly affected entities, influencing entire industries and creating ripple effects across international markets. The results suggest that policymakers must carefully consider the broader economic implications of protectionist policies, particularly in highly interconnected global supply chains. In an era of increasing economic interdependence, understanding these complex dynamics is essential to designing effective and sustainable trade policies that balance national security concerns with economic stability.

The remainder of the paper is structured as follows. Section 2 reviews the relevant literature. Section 3 provides the policy background. Section 4 describes the data sources and measurement techniques. Section 5 outlines the empirical methods. Section 6 analyzes the stock market reactions to the embargo policy. Sections 7 and 8 examine the changes in innovation performance and financial outcomes of upstream suppliers in China and the U.S., respectively, following the policy shock.

2 Related Literature

Our study is primarily related to the literature on international trade, innovation, and economic growth. Melitz and Redding (2021) summarizes four key channels through which international trade can influence innovation and economic growth: (1) **Market Size Effect**: International trade expands the market size accessible to firms, thereby spreading fixed costs over a larger base and increasing incentives for innovation. (2) **Product Market Competition Effect**: The impact of competition can be twofold. On the one hand, heightened competition may compel firms to innovate as a means to escape competition (positive effect). On the other hand, increased competition may reduce firms' profits, thereby diminishing their incentives to innovate (negative effect). (3) **Comparative Advantage Effect**: If a country specializes in industries with faster innovation rates, its overall innovation and economic growth rates will rise. Conversely, focusing on industries with slower innovation rates may hinder long-term economic growth. Thus, comparative advantage shapes a country's long-term trajectory of innovation and economic development. (4) **Knowledge Spillover Effect**: Firms engaged in international markets can acquire new technologies and knowledge from foreign firms and markets. These spillover effects can occur through product trade or research collaborations. Existing studies have primarily examined these four channels from both theoretical and empirical perspectives.

The **Market Size Effect** has garnered substantial empirical support. Export markets not only enhance profitability during normal times but also act as a buffer during domestic economic downturns. Lileeva and Trefler (2010) find that Canadian plants, incentivized by tariff cuts, increased exports, improved labor productivity, and engaged in more product innovation. Similarly, Bustos (2011) uses the reduction in Brazilian tariffs on Argentine imports as a proxy for Argentine firms' export opportunities, finding that lower tariffs increase firms' likelihood of entering export markets and stimulate investments in technological upgrades.

However, empirical findings on the **Product Market Competition Effect** present a more nuanced picture. Schumpeterian models posit that heightened competition can erode firm profits, thereby diminishing incentives to invest in innovation. Conversely, Arrow (1972) contends that monopolistic firms have weaker motivations to innovate due to their secure market position. Perla et al. (2021) suggest that reduced trade barriers widen the profit disparity between average and marginal adopters, thereby accelerating technology adoption and yielding substantial welfare improvements. Empirical evidence in this domain remains inconclusive and shows significant variation across countries at different stages of development. Bloom et al. (2016) demonstrate that competition from Chinese imports stimulated technological advancements in European firms, providing partial support for the "trapped factors" hypothesis proposed by Bloom et al. (2013). This theory posits that when firms suddenly face import competition, specialized production factors may become immobilized due to sunk costs, thereby lowering their opportunity costs and encouraging resource reallocation toward innovation. In contrast, Autor et al. (2020) report opposing findings for U.S. firms, indicating that exposure to low-cost Chinese imports resulted in reduced patent filings and R&D investments. For developing countries, Liu and Ma (2020) document a decline in innovation activities in nations such as China following tariff reductions on intermediate goods. The impact of trade exposure also varies across firms: Aghion et al. (2018), Aghion et al. (2009), and Feng et al. (2016) highlight that high-productivity and R&D-intensive firms experience a more pronounced positive response to export demand shocks. Conversely, low-productivity firms may face adverse effects on innovation, as competitive pressures take precedence over innovation incentives.

Regarding the **Comparative Advantage Effect**, Liu and Qiu (2016) attribute the decline in Chinese innovation following its WTO accession to the reduced opportunity cost of acquiring advanced foreign technologies.

In terms of the **Knowledge Spillover Effect**, the existing literature has focused on the directionality of innovation transmission through international trade. Studies such as Hanlon (2015), Acemoglu et al. (2016), and Liu and Ma (2021) show that upstream imported intermediate goods often guide the innovation direction of downstream industries. Knowledge spillover effects have also been shown to increase the number of non-exporting firms Cui and Li

(2023). Liu and Qiu (2016) highlight that knowledge spillover theory explains how technology-intensive enterprises significantly enhance innovation output through knowledge sharing with partner companies.

One of the primary challenges in the literature on trade and innovation is the identification of causal effects. Our study contributes to this literature by leveraging an exogenous policy shockmandatory export bans imposed by U.S. BIS-to investigate the impact of trade disruptions on innovation through the lens of supply chain interruptions.

Our research also relates to the literature on the economic impacts of protectionist trade policies, intellectual property rights protection, and consumer welfare. The protectionist policies implemented by the U.S. since 2018 have driven significant supply chain restructuring and production decoupling, with notable shifts in the global value chain (GVC) participation patterns of both China and the U.S.(Grossman and Helpman (2020); Alfaro and Chor (2023)). Kopytov et al. (2024) highlight that supply chain uncertainties prompt firms to reorganize their networks by opting for more stable, yet less productive, suppliers. This "flight to safety" behavior reduces macroeconomic volatility but comes at the cost of lower overall GDP. Extensive research has been conducted on the welfare losses caused by tariff war between U.S. and China. Grossman and Helpman (2020) develop a firm-to-firm model and estimate that U.S. tariffs on China result in a 0.12% GDP loss. Similarly, Fajgelbaum et al. (2020) observe that these tariffs are almost entirely passed on to U.S. import prices. Amiti et al. (2019) estimate that the monthly welfare losses from these tariffs amount to approximately $1.4 billion. Empirical financial studies further reveal that investors perceive tariff impositions as negative market signals. Huang et al. (2023) document significant stock return declines for U.S. firms with ties to China following tariff announcements, while Amiti et al. (2020) estimate that these announcements correspond with a $1.7 trillion reduction in the market value of U.S.-listed firms. Rogers et al. (2024) report that heightened U.S.-China tensions also suppress U.S. corporate investments. Han et al. (2024) examine the decoupling and dependence between Chinese and U.S. technologies since China's WTO accession through patent networks. They find that sanctions targeting upstream sectors reduce Chinese firms' innovation, productivity, and profitability, while sanctions on downstream sectors have the opposite effect. In this study, upstream and downstream relationships are defined through patent citation directions. The Entity List issued by the Bureau of Industry and Security has had a direct impact on global supply chains, prompting discussions on scientific internationalism, supply chain security, and domestic manufacturing substitution. Chen et al. (2022) also show that informal non-tariff barriers accounted for at least 50% of the reduction in China's imports from the U.S. during the peak of the trade war. Therefore, our contribution to this body of literature is to examine the spillover effects of sanction policies from the perspective of global supply chains. We identify the upstream U.S. and Chinese suppliers of sanctioned Chinese firms and analyze how these sanctions indirectly affect the broader supply network. This approach helps to shed light on the unintended consequences of protectionist trade policies.

3 Policy Background

The Entity List, as specified in Supplement No. 4 to Part 744 of the EAR, identifies foreign persons, including businesses, research institutions, government organizations, and individuals, that are subject to specific licensing requirements for the export, reexport, or in-country transfer of certain items. The primary purpose of the Entity List is to impose additional controls on transactions involving listed entities that may pose risks to U.S. national security or foreign policy interests. In 2018, the United States enacted a revised version of the Export Control Reform Act (ECRA), significantly expanding the scope of technology export controls. Building on the existing regulatory framework, the ECRA introduced new areas of control, including 14 categories of "emerging and foundational technologies." The primary aim of this act was to safeguard U.S. technological leadership by restricting the transfer of critical technologies to foreign adversaries.

We manually collected updates to the Entity List from the website of the U.S. Department of

Commerce, documenting the effective dates and reasons for each Chinese company's inclusion on the list.[1]. The first inclusion of Chinese entities occurred in June 1997, when the U.S. Department of Commerce added the Chinese Academy of Engineering Physics, which is primarily engaged in China's nuclear weapons development. This marked the beginning of sanctions targeting China's military and defense industries. During the early 2000s, these sanctions expanded to encompass aerospace and aerodynamics research. The onset of the U.S.-China trade war in 2018 marked a sharp escalation in these restrictions. Notable additions include Huawei and its subsidiaries, which were sanctioned in May 2019 for their involvement in 5G technology and alleged connections to China's surveillance activities. Similarly, DJI, a leading drone manufacturer, was added in 2020, citing national security risks associated with the company's drone technology. The same year, the U.S. targeted SMIC (Semiconductor Manufacturing International Corporation), China's leading semiconductor manufacturer, citing concerns over potential military end-use of its chips. In recent years, the U.S. has focused on the AI sector, listing emerging artificial intelligence companies such as Cambricon and 4Paradigm. By the end of 2023, the U.S. had listed 715 Chinese entities on the Entity List, 670 of which are identifiable companies and research institutions, with many targeted firms operating in critical sectors such as semiconductors and communications. The intention behind these sanctions was to curb China's high-tech advancement by restricting its access to cutting-edge U.S. technologies (as shown in Figure 1).

4 Data Construction and Summary Statistics

4.1 Supply Chain Relationship

To identify the upstream suppliers of Chinese clients affected by the U.S. Department of Commerce's Entity List restrictions, we first needed to accurately recognize the sanctioned firms. We collected historical versions of the Entity List from the official website of the Bureau of

[1]Scraped from https://www.ecfr.gov/current/title-15/subtitle-B/chapter-VII/subchapter-C/part-744/appendix-Supplement%20No.%204%20to%20Part%20744

Industry and Security (BIS), retaining key information such as the English names, addresses, effective dates, and reasons for inclusion of Chinese companies. The Chinese names and their affiliated listed companies were manually identified using Tianyancha, based on the English names and addresses provided in the BIS records. As of December 2023, our dataset includes 670 Chinese firms, of which 60 are A-share listed companies. Notably, 46 of these firms were added to the Entity List during their listing period. We further matched these firms with their International Securities Identification Numbers (ISINs) using the BvD Orbis database, resulting in a total of 1,891 ISIN codes. The number of ISINs exceeds the number of listed companies for two primary reasons: (1) a single firm may hold multiple ISIN codes, and (2) subsidiaries' ISIN codes are also included, as sanctions often extend to affiliated entities.

For the purpose of conducting an event study on stock market reactions, we manually collected news reports to determine the announcement dates for each firm's inclusion on the Entity List. Specifically, for each effective date provided by the BIS, we identified the earliest corresponding news report and used that as the announcement date. In general, the announcement date precedes the effective date by 1 to 13 days. Furthermore, we classified the reasons for inclusion on the Entity List into two categories: technology-related and non-technology-related factors. The technology-related factors include issues such as artificial intelligence, semiconductors, and drones, which the BIS deemed as threats to U.S. national security. The non-technology-related factors primarily involve political issues, such as human rights concerns in Xinjiang and territorial disputes in the South China Sea.

To study the spillover effects of sanctions on peer firms, we manually matched the sanctioned firms on the Entity List with China's customs import and export data to identify the products they imported from the U.S., which we defined as restricted goods. We then identified Chinese listed firms that imported these restricted goods from the U.S., defining them as firms affected by the sanctions. In total, we identified 491 listed firms that imported restricted goods from the U.S.

To identify the upstream Chinese suppliers of sanctioned Chinese firms, we utilized both the top five supplier and top five customer data from the CSMAR supplier database. By leveraging both datasets, we partially addressed the limitations of incomplete supply chain information for Chinese companies. First, we identified suppliers of sanctioned listed companies from the top five supplier data. Next, we cross-referenced the top five customer data by matching the Chinese names of these customers with the names of all sanctioned companies to uncover additional supplier relationships. We then consolidated the suppliers identified from both approaches and retained those that had supplier relationships within a five-year window before or after the sanction event. This comprehensive process yielded a final sample of 126 listed companies, of which 74 were confirmed as suppliers prior to the event.

To identify the U.S. suppliers of Chinese firms listed on the Entity List, we utilized the FactSet Supply Chain Relationships database. This comprehensive resource maps business relationships among global companies, categorizing them into four primary types: customers, suppliers, competitors, and strategic partners. Within this framework, we defined supply relationships to include entities classified as suppliers and partners engaged in distribution, manufacturing, in-licensing, and marketing activities. Conversely, customer relationships encompassed those categorized as customers and partners involved in out-licensing. By applying these criteria, we systematically identified U.S. suppliers associated with the sanctioned Chinese firms.

4.2 Innovation Input and Output

We use the extended patent data up to 2023 from the dataset developed by Kogan et al. (2017), which proposes a measure of the private economic value of new innovations based on stock market reactions to patent grants. The advantage of using financial data is that asset prices are forward-looking and hence provide an estimate of the private value to the patent holder based on ex ante information. This measure of quality, expressed in dollars, allows for comparisons across time and different industries. Kogan et al. (2017) employs a three-day announcement window $[t, t+2]$ around the patent grant date to measure the market value of a patent from the firm's idiosyncratic return, adjusted by the unconditional probability of a successful patent application. This updated dataset includes patent values, forward citations, and a mapping from patent numbers to permno. The value of innovation is calculated as the nominal value of innovation deflated to 1982 (million) dollars using the Consumer Price Index (CPI). The citation data is also updated to 2023. Furthermore, we use the CRSP Tools *Translate to PERMCO/PERMNO* to match ncusip and permno, enabling us to link the patent file to FactSet's Supply Chain data. For missing data, we substitute a value of zero, indicating that the firm had no innovation output in that year.

For the Chinese data, we utilized two sub-tables from the CSMAR patent database: the "Patent Details Table" and the "Domestic and Foreign Patent Application and Acquisition Table." These resources provided annual counts of patent applications and grants for listed companies. Notably, the database distinguishes among three patent types: invention patents, utility model patents, and design patents, detailing their respective application statuses. To assess a company's breakthrough innovations, we specifically focused on the annual figures for invention patent applications and grants, as invention patents typically represent higher levels of novelty and technological advancement.

Additionally, to evaluate the impact of policy shocks on firms' R&D investments, we collected data on the proportion of R&D personnel and R&D expenditures from both the Compustat and CSMAR databases.

4.3 Firm Performance

To examine the economic impact of export sanctions on listed firms in both China and the U.S., we use Return on Assets (ROA) as a measure of firms' operating performance and the number of employees as a proxy for firm size. The U.S. data is sourced from the Compustat database, while the Chinese data is obtained from the CSMAR database. Definitions of the remaining control variables are provided in Table B.1.

4.4 Summary Statistics

Figure 2 depicts the timeline of U.S. suppliers impacted by the addition of Chinese firms to the U.S. Entity List. A significant surge in supplier numbers is observed in May 2019, corresponding to the export restrictions imposed on Huawei. This marked increase underscores the extensive supply chain linkages between Huawei and its U.S. suppliers prior to its designation on the Entity List, with prominent firms such as Qualcomm, Flex, and Micron among the affected entities. The black bars represent the entry of new U.S. suppliers providing intermediate goods or services to Chinese firms within the five-year window preceding the enforcement of export restrictions, while the gray line illustrates the cumulative number of affected suppliers over time.

Figure 3 presents the industry composition of these U.S. upstream suppliers, categorized according to the 4-digit Standard Industrial Classification (SIC) system. The most prominent sector is Semiconductors & Related Devices, accounting for 32.05% of all suppliers (50 firms), followed by Prepackaged Software Services at 7.69% (12 firms) and Radio & TV Broadcasting & Communications Equipment at 5.13% (8 firms). Other notable sectors include Computer Communications Equipment (3.85%, 6 firms) and Electronic Components & Accessories (2.56%, 4 firms). Smaller industries, such as Printed Circuit Boards and Aircraft Parts & Auxiliary Equipment, each account for 1.92% (3 firms). The Others category, comprising various smaller industries, represents 33.33% of the total suppliers. These findings highlight the concentration of U.S. upstream suppliers in technology-intensive sectors, particularly in semiconductors and related industries.

Figure 2 illustrates the timeline of the affected U.S. suppliers of Chinese firms that were subsequently added to the U.S. Entity List. There is a sharp increase in the number of suppliers in May 2019, coinciding with the export restrictions placed on Huawei. This spike reflects the extensive network of U.S. suppliers providing goods and services to Huawei prior to its inclusion on the Entity List, including major companies such as Qualcomm, Flex, and Micron. The black bars represent new U.S. suppliers that provided intermediate goods or services to Chinese firms within the five-year window before the export bans were enforced, while the gray line shows the cumulative number of U.S. suppliers affected over time. Figure 3 presents the industry distribution of U.S. upstream suppliers, classified according to the 4-digit Standard Industrial Classification (SIC) system. The largest share of suppliers is in the Semiconductors & Related Devices industry, which accounts for 32.05% of all suppliers (50 firms). This is followed by Prepackaged Software Services at 7.69% (12 firms) and Radio & TV Broadcasting & Communications Equipment at 5.13% (8 firms). Other notable industries include Computer Communications Equipment and Electronic Components & Accessories, comprising 3.85% (6 firms) and 2.56% (4 firms), respectively. Smaller industries, such as Printed Circuit Boards and Aircraft Parts & Auxiliary Equipment, each account for 1.92% (3 firms). The Others category, which includes a wide range of industries, represents 33.33% of the total suppliers. The data highlights the concentration of U.S. suppliers in technology-intensive sectors, particularly in semiconductors and related industries, indicating the critical role these industries play in the U.S.-China supply chain.

Figure 4 presents the industry distribution of Chinese suppliers to Chinese firms that were added to the U.S. Entity List, covering both the five years before and after the export restrictions were imposed. The data reveals that the largest proportion of Chinese suppliers is in the Specialized Equipment Manufacturing sector, accounting for 35.11% of the total. This is followed by Software and Information Technology Services at 12.77% and Computer, Communication, and Other Electronic Equipment Manufacturing at 11.70%. Other industries include General Equipment Manufacturing (9.57%), Electrical Machinery and Equipment Manufacturing (7.45%), and Professional and Technical Services (7.45%). The Other category represents a diverse range of smaller industries, which collectively account for 35.11% of the total suppliers. The classification of industries is based on different versions of Chinese regulatory standards to align with reporting periods. Data from 2023 onward follows the industry classification system of the China Association for Public Companies (CAPCO). Data between 2012 and 2022 uses the 2012 version of the China Securities Regulatory Commission (CSRC) Industry Classification, while data before 2012 is classified according to the 2001 version of the CSRC Industry Classification. This multi-period classification approach ensures consistency with historical changes in industry classifications and reflects the evolving industrial landscape in China.

Table 1 presents the summary statistics for innovation and performance measures of Chinese firms, comparing the treatment group (Chinese listed firms on the U.S. Entity List) and the control group (other listed Chinese firms). The table shows substantial differences in innovation-related variables between the two groups. Firms in the treatment group exhibit higher average values for patent filings and grants across all categories. For instance, the average number of total patent filings in the treatment group is 32.003 compared to 15.724 for the control group. Similarly, the average number of invention patent filings in the treatment group is 10.303, more than double the control group's 4.804. This pattern is consistent across invention patent grants, with the treatment group averaging 7.607 compared to 2.420 for the control group. Furthermore, the Chinese patent data exhibit significant zero inflation and right skewness. Therefore, we employ negative binomial regression and zero-inflated negative binomial regression models to better fit this type of data. In terms of R&D efforts, the treatment group shows a higher R&D personnel ratio (22.944%) compared to the control group (12.035%), indicating a stronger focus on research activities. Additionally, the treatment group reports significantly higher R&D expenditures, with an average spending of 683.652 million RMB, compared to 198.537 million RMB for the control group. The above results confirm that the U.S. BIS Entity List has effectively targeted high-tech Chinese firms. Regarding firm performance, measured by Return on Assets (ROA), both groups show similar average values, with the treatment group at 0.056 and the control group at 0.058. However, the treatment group has a slightly higher average number of employees (EMP), at 8.061 compared to 7.757 for the control group. Overall, the summary statistics suggest that firms on the Entity List tend to be more innovation-intensive and invest more heavily in R&D compared to their counterparts, though their operational performance, as measured by ROA, does not show a significant difference.

Table B.4 presents the summary statistics for innovation and performance measures of U.S.

suppliers, comparing the treatment group (U.S. upstream suppliers of Chinese firms on the U.S. Entity List) and the control group (other U.S. listed firms). The statistics reveal notable differences between the two groups in terms of innovation output, R&D intensity, and financial performance. In terms of innovation, the treatment group exhibits significantly higher average values for both patent value and patent citations compared to the control group. The mean patent value for the treatment group is 3.195, compared to 1.020 for the control group, while the average number of patent citations is 1.711 for the treatment group, substantially higher than the control group's 0.403. The R&D ratio, which measures the proportion of R&D expenditure to total revenue, is also higher in the treatment group, with an average of 0.104 compared to 0.062 in the control group. This indicates that U.S. suppliers of sanctioned Chinese firms tend to allocate more resources toward research and development. In terms of financial performance, the treatment group shows higher cash flow (0.055 compared to 0.020 in the control group) and revenue (7.193 compared to 6.423 in the control group), suggesting that these firms operate on a larger scale. Additionally, the treatment group reports a higher average number of employees (EMP), at 1.497 compared to 0.683 in the control group. Overall, these statistics suggest that U.S. suppliers to sanctioned Chinese firms are more innovation-driven and larger in scale compared to their counterparts, potentially reflecting their reliance on advanced technologies to meet the demands of Chinese high-tech sectors.

5 Empirical Methods

5.1 Event Study Methodology

We first examine the stock market reactions of Chinese upstream suppliers and U.S. upstream suppliers following their clients being placed on the BIS Entity List. Since stock prices reflect the markets expectations about a companys future prospects, particularly changes in future cash flows, stock market reactions provide valuable insights into the economic impact of policy shocks, especially how U.S. export control policies affect upstream firm values through global supply chains. We identify Chinese and U.S. upstream suppliers from the CSMAR database and the FactSet Supply Chain database within five years prior to the sanction announcements. If an upstream supplier had multiple clients placed on the Entity List at different times, we retain only the first shock date for that supplier. Notably, the official U.S. export control list documents provide only the effective dates of sanctions. However, media reports often precede the effective dates by 1 to 13 days. We manually collected the earliest media reports for each sanction list update and adjusted for the time zone differences to determine the announce date as the event date.

We estimate the abnormal returns over the event window [-5, 5] days using daily return data, including reinvested returns, from the pre-event estimation window [-120, -20] trading days. Three methods are applied to estimate abnormal returns. The first method is raw return AR_{it}^{RAW}, which uses the stock's actual return. This method provides a clear and direct calculation of return changes from the investors perspective and can also be used to calculate changes in a companys market value.

The second method is the Market-Adjusted Model, specified as:

$$AR_{it}^{MA} = R_{it} - R_{mt}, \tag{1}$$

where AR_{it}^{MA} represents the abnormal return for firm i on day t, R_{it} is the actual return of firm i on day t, and R_{mt} is the market return on day t. The market return is typically proxied by a broad market index. For the Chinese market, we use the daily market return calculated as a free-float market capitalization-weighted return that includes reinvested cash dividends. For the U.S. market, we use the value-weighted return on all NYSE, AMEX, and NASDAQ stocks. The Market-Adjusted Model accounts for general market movements, isolating the firm-specific return attributable to the event.

The third method is the Fama-French Three-Factor Model Fama and French (1993), which is specified as:

$$AR_{it}^{FF3} = R_{it} - (\alpha_i + \beta_i MKT_t + s_i SMB_t + h_i HML_t)\,, \tag{2}$$

where AR_{it}^{FF3} denotes the abnormal return for firm i on day t adjusted using the three-factor model. The three factors include the excess market returnMKT_t , the size factorSMB_t , and the value factorHML_t. For the Chinese market, the risk-free rate is proxied by the daily benchmark three-month deposit rate published by the People's Bank of China. For the U.S. market, the risk-free rate is the daily equivalent of the one-month Treasury bill rate. Then we compute the cumulative abnormal returns (CAR) of firm i as

$$CAR_i[-5,+5] = \sum_{t=-5}^{+5} AR_{it}, \tag{3}$$

where AR_{it} is the abnormal return for firm i's equities on date t, calculated using the above three method.

To address the challenges posed by event-induced volatility changes and cross-sectional dependence in stock return event studies, we employ two widely-used test statistics, as demonstrated in recent applications by Chen et al. (2024) and Fisher et al. (2022). Boehmer et al. (1991) propose a methodology that mitigates the impact of event-induced volatility by standardizing abnormal returns using volatility estimates from the event window, thereby incorporating heightened volatility directly into the test statistic. This approach partially addresses cross-sectional dependence by utilizing the cross-sectional mean of standardized abnormal returns to compute the t-value. The primary advantage of this method lies in its ability to adjust for event-induced volatility, thereby enhancing the reliability of the test results when significant fluctuations in stock returns occur. However, it remains sensitive to cross-sectional correlations among firms, which may impact the accuracy of the inferences drawn. Building on this framework, Kolari and Pynnönen (2010) introduce a refinement that accounts for both event-induced volatility and cross-sectional dependence. Their approach retains the standardization process proposed by Boehmer et al. (1991) to adjust abnormal returns for volatility changes but incorporates a correction factor to address cross-sectional dependence more explicitly. This correction factor, proportional to $(1 + (N - 1)\rho)$, where ρ represents the average correlation between firms and N denotes the number of observations, strengthens the robustness of the test statistics. This enhancement is particularly valuable in the presence of industry-wide shocks or macroeconomic events that simultaneously impact multiple stocks, thereby improving the reliability of the results in scenarios characterized by heightened cross-sectional correlations.

5.2 Staggered DID

In assessing the impact of U.S. BIS export controls on the innovation and profitability of Chinese and U.S. upstream companies, a staggered DID framework presents a natural methodological choice, as it accommodates variations in treatment timing across firms. However, recent literature has identified substantial limitations associated with the Two-Way Fixed Effects Difference-in-Differences (TWFEDD) estimator in staggered settings (Goodman-Bacon (2021), Baker et al. (2022), Sun and Abraham (2021), Callaway and SantAnna (2021)).

The TWFEDD estimator constructs a weighted average of all possible 2×2DID comparisons. As demonstrated by Goodman-Bacon (2021), the weights are determined by the size of each timing group and the variance of the treatment indicator within each pairing, with the variance being highest for units treated around the midpoint of the panel period. This mechanism implies that groups receiving treatment in the middle of the observation window exert a disproportionate influence on the overall estimate. One major issue with the TWFEDD estimator is that it can yield biased estimates when treatment effects are heterogeneous across groups or time periods(Callaway and SantAnna (2021)). In such cases, the estimator produces a weighted average of treatment effects, with the weights being non-intuitive. Additionally, in staggered DID settings, the TWFEDD estimator may use early-treated groups as control groups for later-treated ones, inducing a "bad compatisons" (Baker et al. (2022)). This requires an assumption that outcomes for early-treated groups remain unchanged after they receive treatment. If this assumption is violated, the estimator can assign negative weights to early-treated groups, distorting the estimated treatment effects.

In our study on the impact of U.S. BIS export controls on Chinese and U.S. upstream firms, the TWFEDD estimator presents several challenges. The policy's effects on innovation and profitability likely vary across industries and over time. Sectors more reliant on U.S. technology may see immediate impacts, while others may respond with delays, and innovation outcomes often have significant lags. Such heterogeneity violates core TWFEDD assumptions, increasing the risk of bias. Moreover, given our focus on long-term effects, using early-treated groups as controls for later-treated groups is problematic, as the policy induces lasting changes. This misalignment can result in negative weights for early-treated groups, distorting estimates and leading to misleading conclusions. In light of these concerns, we adopt the method proposed by Callaway and SantAnna (2021) to estimate the group-time average treatment effects and apply appropriate weighting schemes to obtain the average treatment effect and event-study-type estimands, allowing us to examine the impact of the export control policy and its evolution over time. Additionally, we employ the Doubly Robust (DR) method introduced by SantAnna and Zhao (2020) to enhance the robustness of our estimates. The primary reason for not adopting the method proposed by Sun and Abraham (2021) is that our dataset is not structured as panel data, whereas the approach of Callaway and SantAnna (2021) is well-suited to handling unbalanced panel data.

Specifically, Callaway and SantAnna (2021) focus on the disaggregated causal parameter referred to as the "group-time average treatment effect" (GTA), defined as the average treatment effect for group $g$at time t. In this context, a "group" is defined by the time period when units are first exposed to the treatment. The GTA parameter is particularly appealing because it does not impose direct restrictions on heterogeneity across observed covariates, the timing of initial treatment exposure, or the temporal evolution of treatment effects.The GTA can be nonparametrically point-identified using the doubly robust (DR) approach as follows:

$$ATT^{new}_{dr}(g,t;\delta) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\frac{p_g(X)C}{1-p_g(X)}}{\mathbb{E}\left[\frac{p_g(X)C}{1-p_g(X)}\right]}\right)\left(Y_t - Y_{g-\delta-1} - m^{new}_{g,t,\delta}(X)\right)\right] \quad (4)$$

where $G_g$represents an indicator for group g, $p_g(X)$denotes the generalized propensity score, $C$is a binary indicatorequal to 1 for control group observations, $Y_t$is the outcome observed at time t, and $Y_{g-\delta-1}$is the lagged outcome for group $g$with a lag of $\delta+1$periods, $m^{new}_{g,t,\delta}(X)$represents the outcome regression results.

The generalized propensity score $p_g(X) = P(G_g = 1|X, G_g + (1-D)(1-G_g)) = 1$reflects the probability of being first treated at time $g$for the never-treated group, conditional on pre-treatment covariates X. Observations from the control group with higher weights indicate a greater likelihood of being comparable to treated units, warranting a higher weighting in the estimation. The outcome regression $m^{new}g,t,\delta(X) = \mathbb{E}[Y_t - Yg - \delta - 1 \mid X, C = 1]$represents the expected difference between current and lagged outcomes conditional on covariates $X$for compliant individuals, commonly referred to as outcome regression. This is called "Double Robust Method", introduced by SantAnna and Zhao (2020), providing an estimator for the GTA parameter that remains consistent as long as either the generalized propensity score model or the outcome regression model is correctly specified. This method entails two primary steps: estimating the generalized propensity score and performing the outcome regression. The generalized propensity score is typically derived using a logit model that incorporates relevant covariates and quadratic terms to predict the possibility of being in a treatment group. In the outcome regression step, OLS is applied to regress the control group's outcome changes on covariates. The resulting coefficients are then used to estimate counterfactual outcome changes for the treated group. This counterfactual represents the expected outcome changes for the treated group had they not received treatment.

To estimate overall treatment effects, dynamic effects, and test the pre-trend parallel trends assumption, Callaway and SantAnna (2021) propose several aggregation approaches. One method to obtain the overall effect of treatment participation is through a weighted average:

$$\theta_W^O = \frac{1}{\kappa} \sum_{g \in \mathcal{G}} \sum_{t=2}^{T} 1\{t \geq g\} ATT(g,t) P(G = g \mid G \leq T), \quad (5)$$

where $\kappa = \sum_{g \in \mathcal{G}} \sum_{t=2}^{T} 1\{t \geq g\} P(G = g \mid G \leq T)$ensures that the weights sum to one. This method assigns more weight to larger groups and avoids issues associated with negative weights

To examine treatment effect heterogeneity based on the time since adoption, they introduce an event-time aggregation method. Let $e$denote event-time, defined as $e = t - g$. The corresponding aggregated parameter to capture heterogeneity with respect to event-time is expressed as:

$$\theta_{es}(e) = \sum_{g \in \mathcal{G}} \mathbf{1}\{g + e \leq T\} P(G = g \mid G + e \leq T) ATT(g, g + e). \quad (6)$$

This parameter reflects the average treatment effect across all groups observed to have been exposed to the treatment for exactly $e$time periods. In this way, we can plot $\theta_{es}(e)$across different values of $e$to gain deeper insights into the dynamics of treatment effects.

5.3 Modeling Patent Count Data

We also analyze the changes in innovation output, measured by patent applications count, among Chinese upstream suppliers following the inclusion of Chinese companies on the Entity List. Patent data often exhibit highly right-skewed distributions with a large number of zero values, which pose significant challenges for regression analysis due to the inefficiency of simple linear regressions. While taking the logarithm of the outcome variable can transform skewed data into a distribution closer to normality, Silva and Tenreyro (2006) show that consistent estimation in log-linear regressions heavily depends on the assumption of homoskedastic errors. Cohn et al. (2022) demonstrate through simulations that log1plus regression coefficients can also have incorrect signs in expectation. Although a simple fixed-effects Poisson model can produce consistent and reasonably efficient estimates under general conditions, it assumes that the conditional mean and variance are equal. Our descriptive statistics on Chinese patent data show that the average number of annual patent applications per firm is 15.96, with a variance of 55.53, and that 73.78% of firm-year observations have zero patent applications, indicating a high prevalence of zero values. Therefore, we employ negative binomial regression and zero-inflated regression models to analyze Chinese patent data.

The negative binomial model shares the same conditional mean as the Poisson model but allows for greater flexibility by relaxing the assumption of equal mean and variance, accommodating overdispersion in the data. Zero-inflated models, on the other hand, address the issue of certain observations being unrelated to the underlying process generating the outcome by modeling the link between exposure and observable factors. These approaches are well-suited for patent count data with a high proportion of zero values.The regression specifications used in our analysis are as follows:

For the negative binomial regression:

$$\log(Patent_{it}) = \beta_0 + \beta_1 \mathrm{Post}_{it} + X_{it}'\gamma + \delta_j + \theta_t + \epsilon_{it} \tag{7}$$

where $Patent_{it}$ represents the dependent variable capturing the patent count for firm i in year t. Specifically, for Chinese firms, we consider four key measures of patent activity: the filing patent count $Patent_{filing}$, the issuing patent count $Patent_{issue}$, the filing invention patent count $Invention_{filing}$, and the issuing invention patent count $Invention_{issue}$ [2]. $Post_{it}$ is a binary variable equal to 1 if the firm is affected by the policy shock and 0 otherwise, X_{it} is a vector of control variables, δ_j denotes industry fixed effects, θ_t represents year fixed effects, and ϵ_{it} is the error term clustered at the industry level.

For the zero-inflated negative binomial regression:

$$\log(Patent_{it}) = \beta_0 + \beta_1 \mathrm{Post}_{it} + X_{it}'\gamma + \theta_t + \epsilon_{it} \tag{8}$$

[2] In China, patents are categorized into invention patents, utility model patents, and design patents. Here, we focus on patents with higher technological content and economic impact, which better reflect the quality of innovation and the firm's technological strength Han et al. (2024)

with the inflation equation specified as:

$$\text{Inflate}(Patent_{it}) = \exp(\alpha_0 + \alpha_j \delta_j) \tag{9}$$

where $\text{Inflate}(Patent_{it})$ models the probability of a structural zero using industry fixed effects δ_j, and the error term ϵ_{it} is clustered at the industry level.

6 Stock Market Reactions to Trade Sanction Interventions

The stock market provides a valuable lens for understanding the economic impact of policy shocks, as it reflects investors' expectations about a company's future profitability. Analyzing stock returns offers critical insights into how the market interprets the implications of U.S. BIS export control policies on upstream suppliers, particularly how these policies affect firms' expected future cash flows. By examining CARs around the inclusion of Chinese firms on the BIS Entity List, we aim to capture how both Chinese and U.S. upstream suppliers react to these sanctions and whether the market perceives these events as detrimental to firm performance.

Our analysis focuses on the CARs of upstream suppliers identified from the CSMAR and FactSet Supply Chain databases within a five-year window prior to the sanctions. For each supplier, we retain the earliest announcement date when one of their Chinese clients was added to the Entity List, ensuring that the event date reflects the initial shock to the supplier's business relationship. We further adjust for differences in time zones and manually collect media reports to determine the earliest announcement date.

Table 3 reveals distinct patterns in the stock price reactions of Chinese and U.S. suppliers. For Chinese upstream suppliers, we observe generally positive cumulative abnormal returns following the announcement of their clients' inclusion on the Entity List. Specifically, over the [-5, +5] event window, Chinese suppliers experience a cumulative average abnormal return (CAARE) of 0.0348. Both the Boehmer et al. (1991) and Kolari and Pynnönen (2010) methods can confirm the statistical significance of these returns for event windows. The positive CARs indicate that the market may perceive Chinese upstream suppliers as being able to capture the demand for intermediate inputs from sanctioned Chinese firms, thereby expanding their market size. This reaction may be attributed to substitution effects, where Chinese suppliers pivot to alternative markets or receive government support to sustain their operations.

In contrast, U.S. upstream suppliers exhibit consistently negative stock market reactions to the same events. Across all event windows, U.S. suppliers experience negative cumulative abnormal returns, with the [-5, +5] window showing a signigicant negative CAR of -0.0270, indicating that the market anticipates adverse consequences for U.S. suppliers following the sanctions. These negative reactions suggest that U.S. suppliers expect a loss of revenue or operational disruptions due to reduced business activities with their sanctioned Chinese clients.

The divergence in market reactions between Chinese and U.S. suppliers highlights the asymmetric impact of U.S. export control policies on global supply chains. While Chinese suppliers possibly benefit from shifting to domestic markets, U.S. suppliers face immediate negative consequences. This asymmetry underscores the interconnected nature of global supply chains, where protectionist policies can generate unintended spillover effects on firms in the sanctioning country.

Figure 5 reinforces these findings by illustrating the CARs for both Chinese and U.S. suppliers across various return adjustment methods. Panels (a) and (b) show the raw returns, with Chinese suppliers experiencing an upward trend while U.S. suppliers face a decline. Panels (c) and (d) present market-adjusted returns, and panels (e) and (f) display returns adjusted using the Fama-French three-factor model. The consistent trends across these different methods highlight the robustness of the results.

These findings carry important implications for policymakers and businesses. The evidence suggests that U.S. export control policies, while intended to curb China's technological advancement, may inadvertently harm U.S. firms by disrupting established supply chains. The negative market reactions for U.S. suppliers indicate that these firms face significant business risks from reduced access to Chinese markets, which could affect their long-term growth prospects. On the other hand, the positive CARs for Chinese upstream suppliers indicate that the market anticipates significant business opportunities for these firms to replace the lost market share previously held by U.S. suppliers. Overall, the results highlight the need to carefully assess the broader consequences of protectionist policies on both domestic and international firms, particularly in the context of highly interconnected global supply chains.

7 Embargo Policy on Chinese Firms

7.1 Analyze Chinese Firms on the Entity List

The baseline results of the impact of the BIS Entity List on Chinese firms' innovation input, patent output, and financial performance are summarized in Tables 4 and Table 5.

Tables 4 provides a detailed analysis of the impact of the Entity List on the patent output of Chinese firms, including different types of patent metrics: total patent filings counts(*patentfiling*), patent grants counts(*patentissue*), invention patent filings counts(*inventionfiling*), and invention patent grants counts(*inventionissue*). For each metric, both negative binomial regression (*nbreg*) and zero-inflated negative binomial regression (*zinb*) models are estimated to account for the zero-inflated and right-skewed nature of the patent count data. The results indicate that the inclusion of firms on the Entity List (*Post_EL*) is associated with a significant increase in patent activity across all types of patents. Specifically, the coefficients for *Post_EL* are positive and statistically significant for both patent filings and patent grants in both the negative binomial and zero-inflated negative binomial models. The results are particularly strong for invention patents, which are often considered a measure of breakthrough innovation. These findings suggest that Chinese firms responded to the sanctions by increasing their efforts in filing and obtaining high-value invention patents.

Table 5 presents the baseline estimates for the R&D investment and financial performance of Chinese firms included on the Entity List. Panel A reports the effects on R&D-related metrics, including the ratio of R&D personnel (*R&D_Person_Ratio*) and total R&D spending

(*R&D_Spend_Sum*). The results indicate a significant positive impact on R&D spending following the inclusion of firms on the Entity List. Specifically, the Wild Bootstrap and Cluster standard errors both show statistically significant increases in *R&D_Spend_Sum* at the 1% level, with coefficients of 194.646 and 247.701, respectively. This finding suggests that Chinese firms responded to the export restrictions by increasing their R&D investments, possibly to reduce their reliance on foreign technologies. Panel B summarizes the financial performance of these firms, measured by return on assets (*ROA*) and the number of employees (*EMP*). The results show that there is no significant change in *ROA* following the sanctions, with coefficients close to zero across all specifications. In contrast, the number of employees (*EMP*) shows a marginal negative effect in the Cluster specification, suggesting a possible adjustment in the labor force as firms shift their focus towards innovation-related investments.

The event study estimates are presented in Figures A.1 and A.2. The results suggest that Chinese firms included on the Entity List responded to U.S. export controls by increasing their R&D investments and patent outputs, particularly in high-value invention patents. These findings imply that the sanctions prompted Chinese firms to enhance their innovation capacity as a way to reduce their dependence on foreign technologies and mitigate the impact of the restrictions. The increase in R&D spending indicates a strategic shift towards self-reliance in critical technologies.

7.2 Analyze Chinese Firms Importing the Embargo Products

Then we focuses on the spillover effects of U.S. export control policies on Chinese firms operating in the same industry as those listed on the Entity List but not directly sanctioned. Specifically, we examine Chinese listed companies that import the same types of products from the U.S. as the sanctioned firms, thereby assessing whether these non-sanctioned firms experience changes in their innovation and financial performance following the sanctions. and summarize the baseline results of these firms' patent outputs and R&D performance, respectively.

shows the impact on patent-related outcomes. The results indicate that non-sanctioned firms in the same industry as the sanctioned firms experienced a significant increase in patent outputs following the sanctions. The coefficients for *Post_IMUS*, which represents the post-sanction period for firms importing embargoed products, are positive and statistically significant at 1% level. These results suggest that the export restrictions have encouraged non-sanctioned firms to increase their patenting activities, possibly as a strategic response to enhance their resilience to supply chain uncertainties or to capture the market share of sanctioned firms.

presents the baseline results for the R&D performance and financial performance of non-sanctioned firms importing embargoed products. Panel A reports the effects on R&D-related metrics, including the ratio of R&D personnel (*R&D_Person_Ratio*) and total R&D spending (*R&D_Spend_Sum*). The results show a significant increase in both metrics at the 10% level. Similarly, *R&D_Spend_Sum* shows a substantial and significant increase at the 1% level. These findings indicate that non-sanctioned firms increased their R&D efforts in response to the policy shock. Panel B of summarizes the financial performance outcomes, including return on assets (*ROA*) and the number of employees (*EMP*). The results show a small but significant positive effect on *ROA* at 10% level, suggesting that these firms may have benefited financially from the sanctions. The number of employees also shows a positive and significant change, indicating that these firms may have expanded their workforce to accommodate the increased demand or to support their innovation-related activities.

The event study estimates are presented in Figures A.3 and A.4. Overall, the results suggest that the U.S. export control policies had unintended spillover effects on non-sanctioned Chinese firms operating in the same industries. These firms appear to have seized the opportunity to increase their innovation output and R&D investments, potentially to fill the market gaps created by the sanctions on their competitors. The positive financial performance outcomes further imply that these firms may have gained a competitive advantage in their respective markets as a result of the sanctions. These findings underscore the broader implications of export control policies, highlighting the complex and often unintended consequences on global supply chains and industry dynamics.

7.3 Analyze Chinese Suppliers of Firms on the Entity List

Then we investigate the impact of U.S. export control policies on Chinese suppliers of firms listed on the BIS Entity List. Table 8 and Table 9 summarize the baseline results for patent outputs and R&D performance, respectively, focusing on how Chinese upstream suppliers responded to the sanctions imposed on their downstream clients.

Table 8 presents the results for different patent-related metrics. These results suggest that the sanctions had a dampening effect on the innovation activities of Chinese upstream suppliers, likely due to the absence of competition from leading international counterparts, these results suggest that Chinese upstream suppliers of sanctioned firms may have experienced a decline in innovation output as a result.

Table 9 further explores the impact on R&D performance and financial outcomes of Chinese suppliers. Panel A reports the effects on R&D-related metrics, including the ratio of R&D personnel (*R&D_Person_Ratio*) and total R&D spending (*R&D_Spend_Sum*). The results indicate a mixed response. The *R&D_Person_Ratio* shows a positive and significant increase in some specifications, with coefficients of 0.364 and 0.374 in the Wild Bootstrap and Cluster methods, respectively. However, *R&D_Spend_Sum* remains largely unaffected by the sanctions, suggesting that while some firms increased their R&D workforce, overall spending levels did not change significantly. Panel B of Table 9 reports the financial performance outcomes, including return on assets (*ROA*) and the number of employees (*EMP*). The results indicate a marginal positive effect on *ROA*, with coefficients of 0.004 in both the Wild Bootstrap and Cluster specifications. This suggests that Chinese suppliers may have expanded their workforce in response to the sanctions, potentially to explore new markets or diversify their client base.The event study estimates for the impact of U.S. Entity List sanctions on Chinese upstream suppliers' R&D investment and financial performance are presented in Figures A.5 and A.6. The pre-treatment coefficients in both figures are not significantly different from zero, confirming that the parallel trends assumption holds for the event study analysis.

7.4 Analyze Chinese Suppliers Industries

The final part of our analysis examines the impact of U.S. export control policies on firms operating in the same industries as the upstream suppliers of sanctioned Chinese firms. These firms are not directly supplying to the sanctioned entities but operate within the same industrial sectors, potentially experiencing indirect effects through changes in market dynamics and competition. Tables 10 and 11 present the baseline results for innovation and financial performance, as well as patent output for these firms.

Table 10 reports the patent-related outcomes, including total patent filings, patent grants, invention filings, and invention grants. The *Post_Supind* variable represents the post-sanction period for firms in supplier industries. The results show a significant positive effect on patent outputs across multiple specifications. For instance, the coefficients for *patentfiling* are 0.159 in the *nbreg* model and 0.426 in the *zinb* model, both significant at 1% levels. Similar patterns are observed for *patentissue* and *inventionfiling*, with positive and significant coefficients across both models. These findings suggest that firms in the same industries as the sanctioned suppliers increased their patenting activities, possibly to capture new market opportunities or mitigate potential supply chain disruptions. The impact on invention-related patents is particularly noteworthy, indicating that these firms engaged in more breakthrough innovation following the sanctions. These findings suggest that Chinese upstream industries are making innovation efforts to serve as substitutes for intermediate inputs previously supplied to sanctioned Chinese firms, thereby strengthening the resilience of China's domestic supply chains.

Table 11 presents the results for R&D and financial performance metrics. Panel A shows that firms in supplier industries increased their R&D efforts following the sanctions. The *R&D_Person_Ratio* shows significant positive coefficients in both the Wild Bootstrap and Cluster methods. Similarly, *R&D_Spend_Sum* shows a significant increase, suggesting that these firms allocated more resources to innovation-related activities. Panel B of Table 11 summarizes the financial performance outcomes, including return on assets (*ROA*) and the number of employees (*EMP*). The results indicate a positive and significant increase in *EMP* at 1% level. This indicates that Chinese upstream industries have benefited from the U.S. export control policies by supplying intermediate inputs to Chinese firms that are subject to the sanctions.

The envent study estimates are displayed in Figure A.7Figure A.8. Overall, the findings indicate that firms in the same industries as Chinese upstream suppliers to sanctioned firms experienced positive spillover effects in terms of innovation and R&D efforts. These firms appear to have responded to the policy shock by increasing their innovation activities and expanding their workforce, potentially to fill the gaps left by the sanctioned suppliers. The results underscore the complex and far-reaching implications of export control policies, highlighting the potential for indirect effects on non-sanctioned firms within interconnected industrial sectors.

8 Embargo Policy on U.S. Suppliers

The analysis also extends to U.S. suppliers affected by the inclusion of their Chinese clients on the BIS Entity List. Table 12 presents the baseline results for the innovation performance and financial performance of these U.S. suppliers. The findings provide valuable insights into how U.S. export control policies have impacted the innovation capacity and financial stability of U.S. firms with exposure to Chinese entities on the Entity List.

Panel A of Table 12 reports the innovation performance metrics, including patent value (*Patent_Value*), patent citations (*Patent_Cite*), and R&D ratio (*R&DRatio*). The results indicate a significant negative impact on the innovation output of U.S. suppliers. For *Patent_Value*, the coefficients are -0.423 and -0.261 in the Wild Bootstrap and Cluster methods, respectively, both significant at the 5% level. Similarly, *Patent_Cite* shows a consistent and substantial decline, with coefficients of -0.628 in the Wild Bootstrap specification and -0.506 in the Cluster specification, both significant at the 1% level. These results suggest that U.S. suppliers experienced a notable reduction in the quality and impact of their patents following the export restrictions, likely due to the loss of a significant portion of their client base in China. Interestingly, the *R&DRatio* remains largely unaffected across all specifications, indicating that while U.S. suppliers may not have reduced their R&D investment relative to total sales, the output and influence of their innovations were adversely affected. The event study estimates are shown in Figure A.9. The post-treatment coefficients for both patent value and patent citations indicate a significant and consistent decline across all specifications, suggesting that the export restrictions had a detrimental effect on the innovation output and quality of U.S. suppliers. In contrast, the R&D expense ratio remains largely unaffected, indicating that U.S. suppliers did not significantly reduce their R&D investments relative to total sales, despite the observed decrease in patent output and impact. The pre-treatment coefficients are not significantly different from zero, confirming that the parallel trends assumption holds.

Panel B of Table 12 summarizes the financial performance outcomes, including cash flow (*CashFlow*), the number of employees (*EMP*), and revenue (*Revenue*). The results show that U.S. suppliers experienced negative financial impacts following the sanctions on their Chinese clients. For *CashFlow*, the coefficients are negative but not statistically significant, suggesting that while there may have been some decline in liquidity, it was not substantial. In contrast, the *EMP* metric shows a significant reduction in the number of employees. The *Revenue* metric also shows a significant decline. The event study estimates are shown in Figure A.10. The post-treatment coefficients indicate a consistent and significant decline across all three performance metrics, particularly in cash flow and revenue, suggesting that U.S. suppliers experienced financial distress following the implementation of export restrictions. The results imply that the loss of Chinese clients impacted the cash inflows and overall business scale of U.S. suppliers. The pre-treatment coefficients are not significantly different from zero, confirming that the parallel trends assumption holds. These findings highlight the financial challenges faced by U.S. suppliers as a consequence of the export control policies. This indicates that the export restrictions resulted in a substantial reduction in the revenue of U.S. suppliers. The negative impact on revenue highlights the economic cost of the export control policies for U.S. firms, particularly those that relied heavily on Chinese clients for a significant portion of their business.

Overall, the findings from Table 12 indicate that U.S. suppliers experienced both innovation and financial setbacks following the sanctions on their Chinese clients. The significant decline in patent value and citations suggests that these firms faced difficulties in maintaining the quality and influence of their innovations, possibly due to reduced collaboration opportunities and market access. Additionally, the reductions in employee numbers and revenue underscore the financial pressures faced by U.S. suppliers in the aftermath of the export control measures. These results highlight the unintended consequences of export control policies, demonstrating that such measures can negatively impact firms in the sanctioning country by disrupting established business relationships and supply chains. The findings suggest that policymakers should carefully consider the broader economic implications of export restrictions, particularly when they affect firms with substantial international exposure.

We further examine the impact of U.S. export control policies on all firms within the same industries (SIC2 level) as the U.S. suppliers of sanctioned Chinese companies. Table 13 presents the baseline results for the innovation and financial performance of these firms, shedding light on the broader industry-wide effects of the export restrictions.

Panel A of Table 13 reports the innovation performance metrics, including patent value (*Patent_Value*), patent citations (*Patent_Cite*), and R&D ratio (*R&D Ratio*). The results reveal a significant negative impact on the innovation output of firms in these industries. For *Patent_Value*, the coefficients are -0.422 and -0.449 across the Wild Bootstrap and Cluster methods, respectively, both significant at the 1% level. Similarly, *Patent_Cite* shows a consistent decline, with coefficients of -0.310 and -0.321, both significant at the 1% level. These findings indicate that the export restrictions not only affected the directly impacted U.S. suppliers but also had broader negative spillover effects on the innovation capacity of firms across the same industries. The *R&DRatio* also shows a significant decline, with coefficients of -0.017 and -0.015 in the Wild Bootstrap and Cluster methods, respectively. This suggests that firms in these industries reduced their R&D expenditures relative to their total sales following the export restrictions. The event study estimates results are shown in Figure A.11. The post estimate results indicate a significant decline in patent value, patent citations and R&D expense ratio, suggesting that the export restrictions negatively impacted the innovation input and output of firms across these industries. The pre-treatment coefficients are not significantly different from zero, confirming the parallel trends assumption. These findings suggest that the export restrictions had broader spillover effects, reducing the innovation capacity of U.S. firms within the same industries as the directly impacted suppliers.

Panel B of Table 13 summarizes the financial performance outcomes, including cash flow (*CashFlow*), the number of employees (*EMP*), and revenue (*Revenue*). The results do not show any statistically significant changes across the three financial performance metrics.

Overall, the findings from Table 13 suggest that the U.S. export control policies had broader industry-wide implications beyond the directly affected suppliers. While firms in these industries experienced declines in their innovation output, they appear to have adjusted their financial strategies, possibly through workforce expansion and revenue generation in other areas. These results highlight the complex nature of policy spillover effects, demonstrating that export restrictions can influence entire industries, leading to mixed economic outcomes. Policymakers should consider these broader implications when designing export control measures to avoid unintended negative consequences on domestic industries.

9 Conclusion

We examine the economic impact of U.S. export control policies on both Chinese and U.S. firms, focusing on stock market reactions, innovation output, R&D investments, and financial performance. By leveraging detailed firm-level data from Chinese and U.S. suppliers, we provide a comprehensive analysis of how the inclusion of Chinese firms on the BIS Entity List influences their upstream suppliers and their respective industries. Our findings underscore the complex and asymmetric effects of trade sanctions on global supply chains, revealing both direct and spillover impacts on firms across different sectors.

First, the stock market analysis shows a clear divergence in cumulative abnormal returns (CARs) between Chinese and U.S. suppliers. Chinese upstream suppliers exhibit positive CARs following the announcement of their customers' inclusion on the BIS Entity List, suggesting that the market believes these firms are capable of absorbing the demand for upstream intermediate goods previously supplied by the sanctioned companies, thereby anticipating profit growth. In contrast, U.S. suppliers face consistently negative CARs across various event windows, indicating that the market anticipates revenue losses and operational disruptions for these firms. This divergence highlights the asymmetric impact of protectionist policies, where Chinese firms display resilience and adaptability, while U.S. firms face significant financial pressures due to disrupted supply chains.

The analysis of innovation and financial performance further corroborates these findings. For Chinese firms directly included on the Entity List, we observe a significant increase in patent output, particularly in high-value invention patents. This suggests that Chinese firms have responded to the sanctions by enhancing their innovation capacity to reduce reliance on foreign technologies. Similarly, non-sanctioned Chinese firms that import the same embargoed products exhibit increased R&D spending and innovation outputs, indicating positive spillover effects within the Chinese economy. These firms appear to have seized the market opportunities created by the sanctions, likely aiming to fill the gaps left by sanctioned firms.

Conversely, U.S. suppliers and their industries show a notable decline in innovation performance following the sanctions. The results indicate a significant reduction in both patent value and patent citations, suggesting that U.S. firms experienced a deterioration in the quality and influence of their innovations. Additionally, U.S. suppliers face financial setbacks, including reduced revenue and employee numbers. These findings imply that U.S. export control policies, while aimed at curbing China's technological advancement, may inadvertently harm U.S. firms by disrupting established business relationships and reducing access to Chinese markets.

The spillover analysis reveals that firms operating in the same industries as both Chinese and U.S. suppliers are also affected by the sanctions. Chinese firms in supplier industries demonstrate increased innovation outputs and R&D investments, suggesting that these firms have adjusted their strategies to capitalize on the market disruptions caused by the sanctions. On the other hand, U.S. firms in supplier industries experience declines in innovation outputs, though some firms manage to maintain positive cash flow and revenue growth, indicating a mixed response to the policy shock.

Overall, the findings highlight the far-reaching and often unintended consequences of export control policies on global supply chains. While the sanctions target specific firms, their impact extends beyond the directly affected entities, influencing entire industries and creating ripple effects across international markets. The results underscore the importance of considering the broader economic implications of protectionist policies, particularly in the context of highly interconnected global supply chains.

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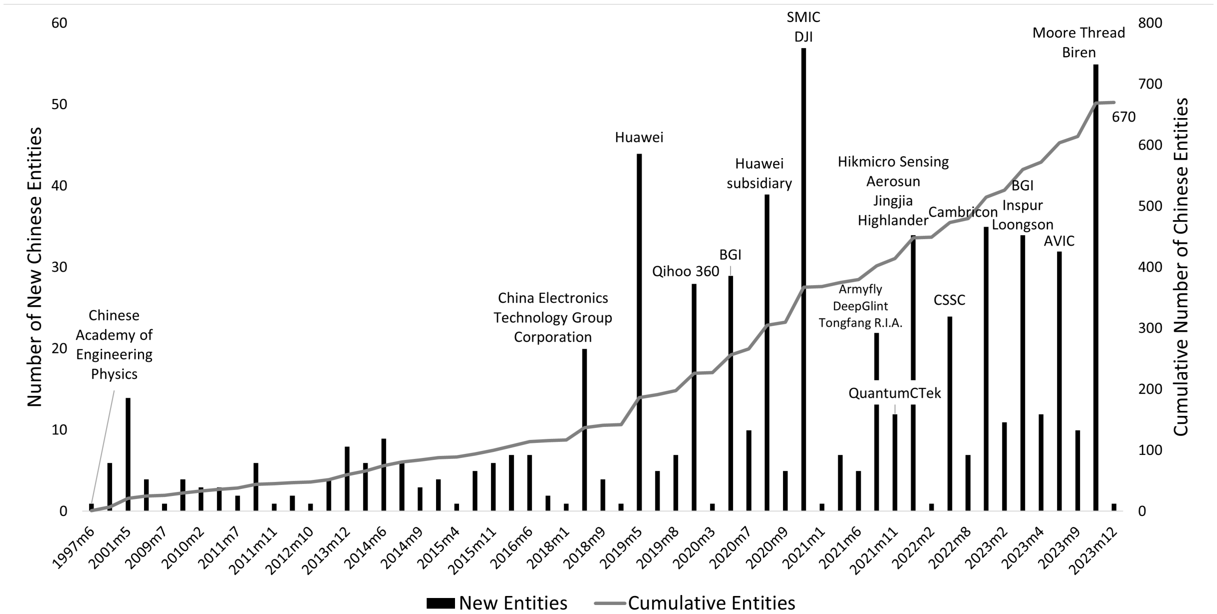


Figure 1: **Chinese Entities Listed in Entity List Over Time** Figure 1 illustrates the monthly number of newly added Chinese entities (left axis) and the cumulative number of Chinese entities (right axis) included in the U.S. Entity List from June 1997 to December 2023. The black bars represent the number of newly sanctioned Chinese entities within each time period, while the grey line indicates the cumulative total. Significant additions of high-profile Chinese companies are labeled, including Huawei, DJI, SMIC, BGI, and DeepGlint, among others. By the end of 2023, a total of 670 Chinese firms were included in the Entity List, with a notable concentration in high-tech sectors such as semiconductors and telecommunications.

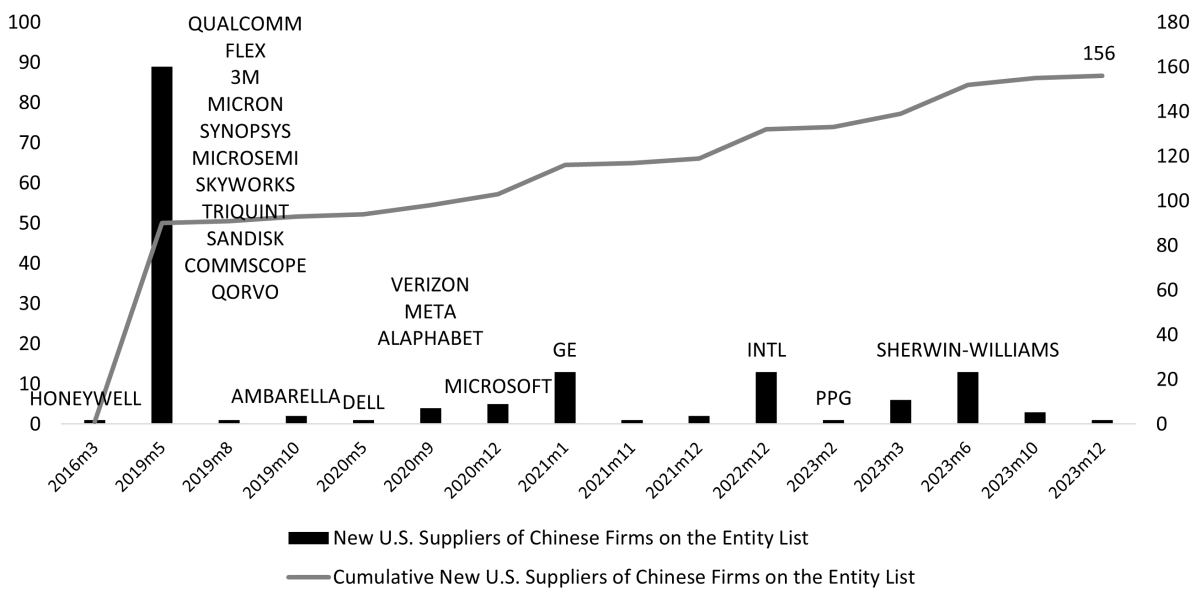


Figure 2: **U.S. Suppliers to Chinese Firms on the Entity List Over Time** Figure 2 illustrates the U.S. suppliers to Chinese firms in the five years prior to these firms being added to the U.S. Entity List. The black bars represent new U.S. suppliers that provided goods or services to these Chinese firms within the five-year window before the export bans were enforced. The gray line indicates the cumulative number of U.S. suppliers impacted over time. Key suppliers include major U.S. technology companies such as Qualcomm, Micron, Synopsys, and Microsoft.

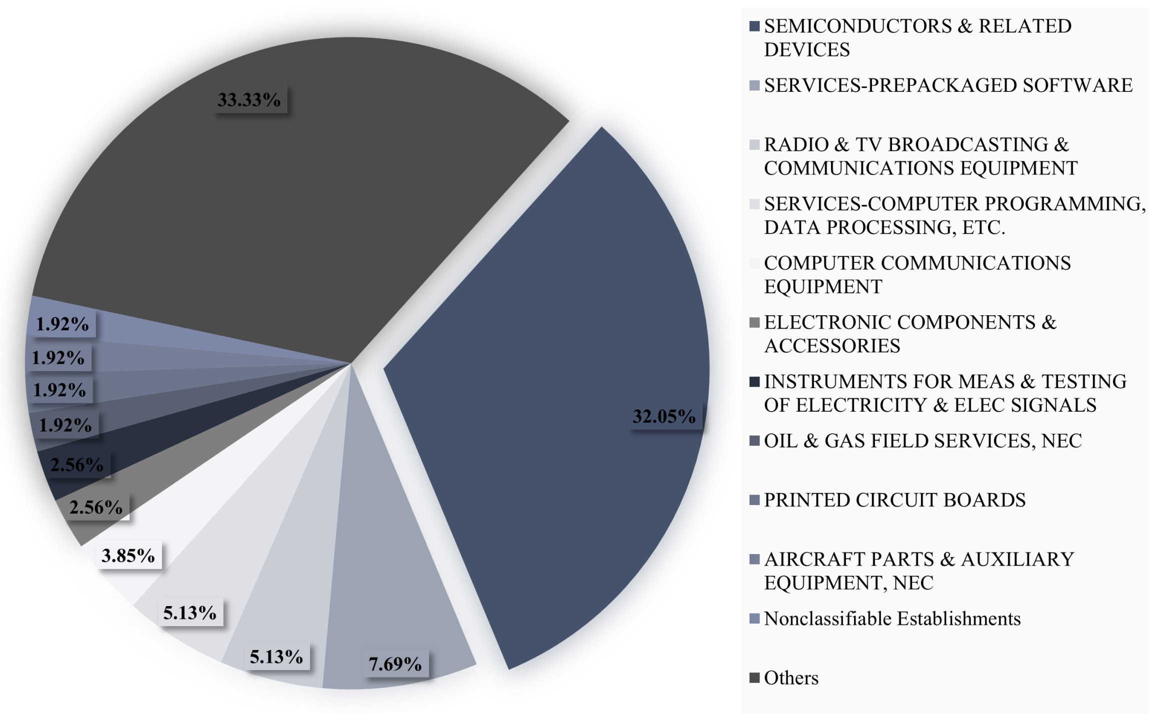


Figure 3: **Industry Distribution of U.S. Upstream Suppliers to Chinese Firms on the Entity List (SIC-4 Classification)** Figure 3 illustrates the industry distribution of U.S. upstream suppliers to Chinese firms that were added to the U.S. Entity List. The industries are classified according to the 4-digit Standard Industrial Classification (SIC) system. The largest industry is Semiconductors & Related Devices, accounting for 32.05% of all suppliers (50 firms), followed by Prepackaged Software Services at 7.69% (12 firms) and Radio & TV Broadcasting & Communications Equipment at 5.13% (8 firms). Smaller industries, such as Printed Circuit Boards and Aircraft Parts, each account for 1.92% (3 firms). The Others category, comprising several industries with fewer suppliers, accounts for 33.33% of the total. This distribution highlights the concentration of key suppliers in the technology and electronics sectors.

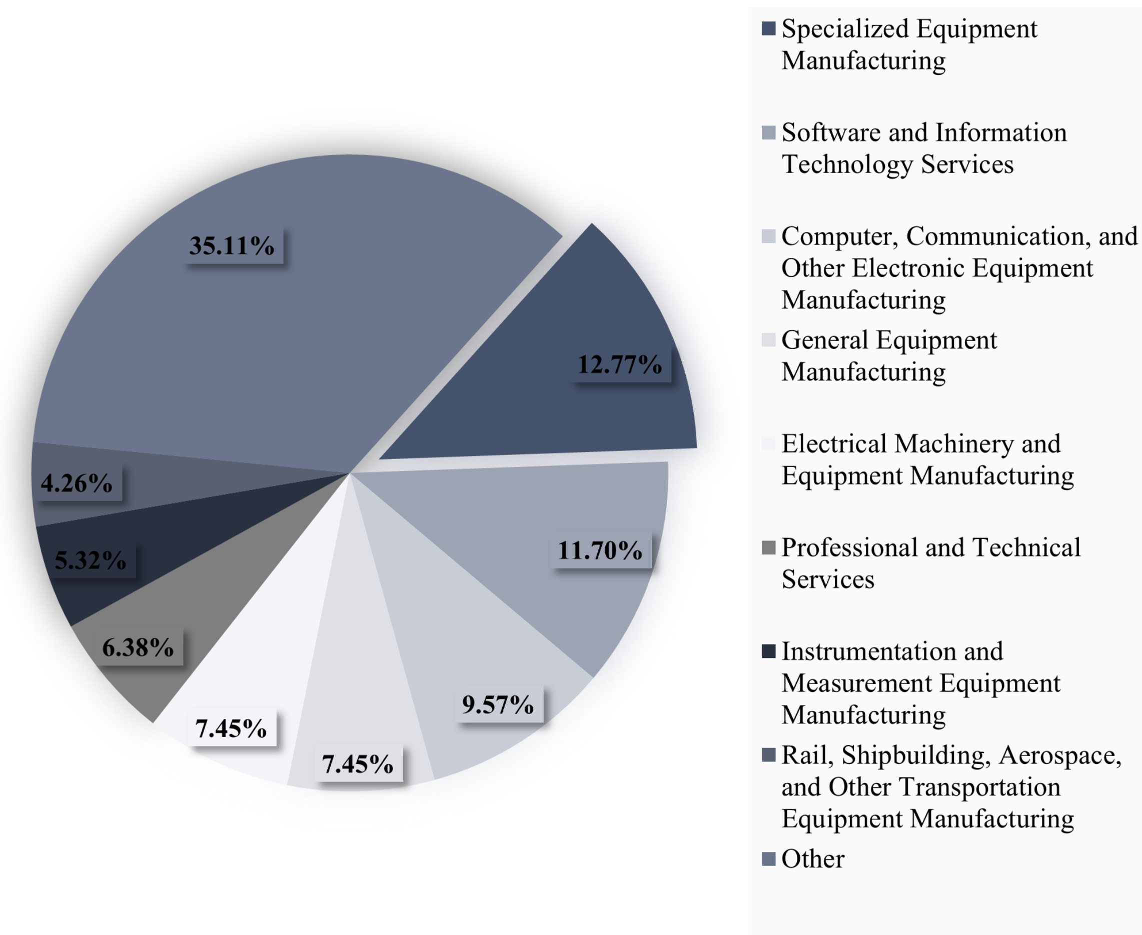
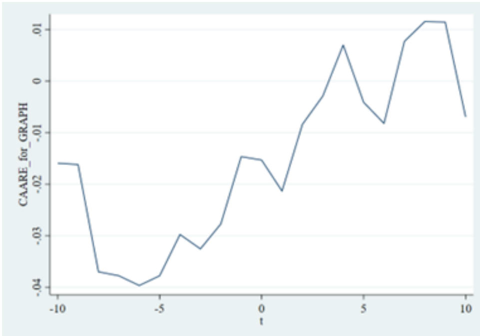
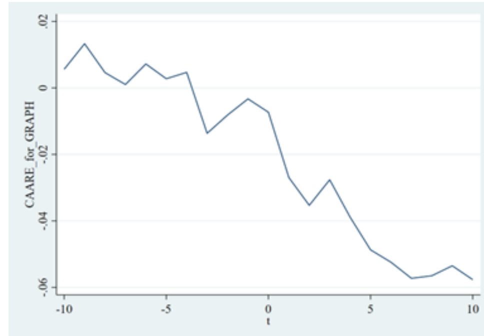


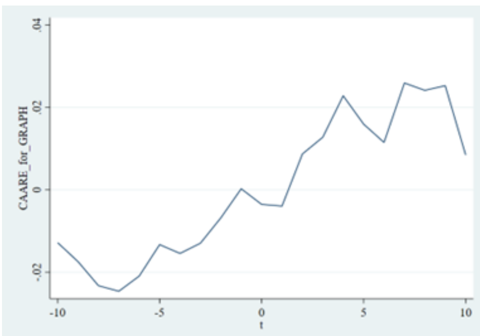
Figure 4: **Industry Distribution of Chinese Suppliers to Chinese Firms on the U.S. Entity List** Figure 4 shows the industry distribution of Chinese suppliers to Chinese firms that were added to the U.S. Entity List, covering both the five years before and after the export restrictions were imposed. Including suppliers after the policy announcement highlights the shift in supply chains as these Chinese firms turned to domestic suppliers for intermediate goods after facing restrictions from U.S. suppliers. The largest sector is Specialized Equipment Manufacturing, accounting for 35.11% of Chinese suppliers, followed by Software and Information Technology Services (12.77%) and Computer, Communication, and Other Electronic Equipment Manufacturing (11.70%). The industry classification is based on three different versions of the Chinese regulatory standards to ensure consistency with the reporting periods. Data from 2023 onward follows the industry classification method of the China Association for Public Companies (CAPCO). Data between 2012 and 2022 uses the 2012 version of the China Securities Regulatory Commission (CSRC) Industry Classification, while data before 2012 is based on the 2001 version of the CSRC Industry Classification. Specifically, the 2012 CSRC classification is applied when the reporting date aligns with the implementation period of the 2012 version. This multi-period classification approach ensures that the industry labels accurately reflect the evolving regulatory framework over time.



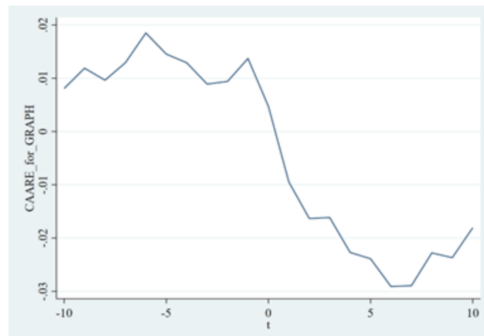
(a) Raw Return of Chinese Suppliers



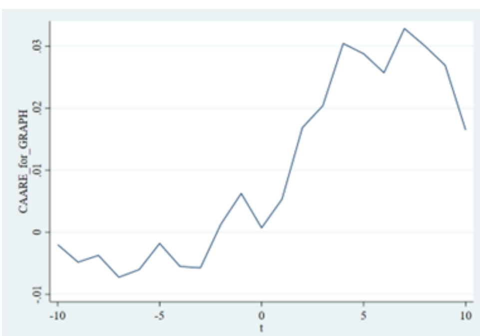
(b) Raw Return of U.S. Suppliers



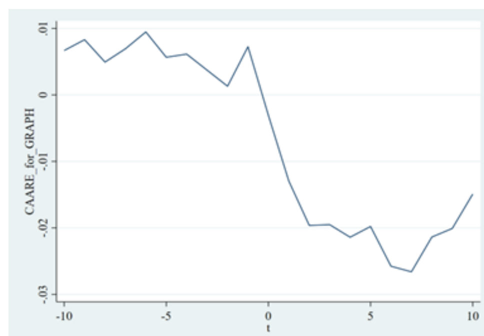
(c) Market Adjusted Return of Chinese Suppliers



(d) Market Adjusted Return of U.S. Suppliers



(e) FF3 Return of Chinese Suppliers



(f) FF3 Return of U.S. Suppliers

Figure 5: **The Cumulative Abnormal Return around Announcement Dates of Suppliers in China and the U.S.** Figure 5 presents the cumulative abnormal returns (CARs) of affected Chinese and U.S. suppliers within a [-10, 10] event window, estimated from a [-120, -20] estimation window. The affected suppliers are defined as companies that had been suppliers to sanctioned entities at any point within the five years preceding their inclusion on the Entity List. Panels (a), (c), and (e) show the CARs for Chinese suppliers based on raw returns, market-adjusted returns, and Fama-French three-factor model-adjusted returns (Fama and French (1993)). Panels (b), (d), and (f) display the corresponding CARs for U.S. suppliers.

Table 1: **Summary Statistics: Innovation and Performance of Chinese Firms** Table 1 provides an overview of the key variables used to measure the innovation and performance of Chinese firms. *Patent_Filing* represents the number of patent applications submitted by a firm during a given fiscal year. *Patent_Issue* reflects the number of patents granted to a firm in a given fiscal year. *Invention_Filing* refers to the number of invention-type patents applied for by a firm, while *Invention_Issue* indicates the number of granted invention patents. *R&D_Person_Ratio* measures the proportion of employees engaged in research and development activities. *R&D_Spend_Sum* captures the total R&D expenditure reported by the firm in million RMB. *ROA* is return on assets. *EMP* represents the natural logarithm of the total number of employees plus one. For detailed definitions of each variable, please refer to the appendix Table B.1

Variable	Count	Mean	Std.Dev.	p25	p50	p75
Patent_Filing						
Treatment	333	32.003	80.728	0.000	0.000	12.000
Control	22,995	15.724	53.003	0.000	0.000	2.000
Patent_Issue						
Treatment	333	22.018	53.428	0.000	0.000	13.000
Control	22,995	11.695	39.670	0.000	0.000	1.000
Invention_Filing						
Treatment	333	10.303	30.027	0.000	0.000	1.000
Control	22,995	4.804	18.507	0.000	0.000	0.000
Invention_Issue						
Treatment	333	7.607	18.708	0.000	0.000	1.000
Control	22,995	2.420	8.964	0.000	0.000	0.000
R&D_Person_Ratio						
Treatment	333	22.944	21.681	0.000	17.930	40.450
Control	22,995	12.035	13.030	0.120	10.260	16.650
R&D_Spend_Sum						
Treatment	333	683.652	984.001	86.240	232.898	775.419
Control	22,995	198.537	503.721	25.972	61.916	152.879
ROA						
Treatment	333	0.056	0.049	0.024	0.043	0.072
Control	22,995	0.058	0.045	0.024	0.047	0.080
EMP						
Treatment	333	8.061	1.292	7.098	8.055	9.090
Control	22,995	7.757	1.174	6.924	7.654	8.486

Table 2: **Summary Statistics: Innovation and Performance of US Suppliers** Table B.4 presents the summary statistics for innovation and financial performance measures of U.S. suppliers, comparing the treatment group (U.S. firms supplying to sanctioned Chinese companies) and the control group (other U.S. firms). The variables include $Patent\_Value$ is calculated using the method proposed by Kogan et al. (2017). $Patent\_Cite$ represents the forward citation count of a firm's patents, adjusted by the average annual citation count for patents of the same year. $R\&DRatio$, defined as the ratio of a firm's R&D expenditures to its total assets. $CashFlow$, calculated as the ratio of operating income before depreciation (OIBD) minus interest expenses (XINT) and taxes (TXT) to total assets. EMP is the natural logarithm of the number of employees. $Revenue$ is the natural logarithm of the firm's revenues. For detailed definitions of each variable, please refer to the appendix Table B.2.

Variable	Count	Mean	Std.Dev.	p25	p50	p75
$Patent\_Value$						
Treatment	1,534	3.195	3.322	0.000	2.446	5.964
Control	39,147	1.020	2.133	0.000	0.000	0.213
$Patent\_Cite$						
Treatment	1,534	1.711	2.257	0.000	0.000	3.668
Control	39,147	0.403	1.196	0.000	0.000	0.000
$R\&DRatio$						
Treatment	1,534	0.104	0.111	0.021	0.073	0.152
Control	39,147	0.062	0.126	0.000	0.003	0.064
$CashFlow$						
Treatment	1,534	0.055	0.170	0.032	0.084	0.130
Control	39,147	0.020	0.226	0.006	0.074	0.126
EMP						
Treatment	1,534	1.497	2.228	-0.245	1.589	3.262
Control	39,147	0.683	2.197	-0.860	0.788	2.282
$Revenue$						
Treatment	1,534	7.193	2.361	5.552	7.098	8.848
Control	39,147	6.423	2.391	4.974	6.618	8.058

Table 3: Event Studies of CARs of Chinese and U.S. Suppliers

This table reports the cumulative abnormal returns (CARs) adjusted by the Fama-French three-factor model (Fama and French (1993)) for Chinese suppliers in Panel A and U.S. suppliers in Panel B. CAARE denotes the cumulative average abnormal return over the specified event windows. NBoe and PBoe represent the corresponding t-statistics and p-values calculated using the method of Boehmer et al. (1991), while NKol and PKol represent the t-statistics and p-values obtained through the method of Kolari and Pynnönen (2010).

Panel A: The CARs of Chinese Suppliers						
t	NoFirms	CAARE	NBoe	PBoe	NKol	PKol
[0;0]	62	-0.0056	-0.05	0.96	-0.04	0.97
[-1;1]	62	0.0041	0.95	0.34	0.85	0.40
[-2;2]	62	0.0226	2.75	0.01	2.46	0.02
[-3;3]	62	0.0259	2.12	0.04	1.89	0.06
[-4;4]	62	0.0322	1.58	0.12	1.42	0.16
[-5;5]	62	0.0348	2.25	0.03	2.01	0.05
[0;1]	62	-0.0009	-0.07	0.94	-0.07	0.95
[0;2]	62	0.0106	0.94	0.35	0.84	0.40
[0;3]	62	0.0141	1.03	0.31	0.92	0.36
[0;5]	62	0.0225	1.67	0.10	1.49	0.14
Panel B: The CARs of U.S. Suppliers						
t	NoFirms	CAARE	NBoe	PBoe	NKol	PKol
[0;0]	111	-0.0103	-3.25	0.00	-1.98	0.05
[-1;1]	111	-0.0143	-2.25	0.03	-1.37	0.17
[-2;2]	111	-0.0234	-3.54	0.00	-2.16	0.03
[-3;3]	111	-0.0257	-3.60	0.00	-2.20	0.03
[-4;4]	111	-0.0271	-3.18	0.00	-1.94	0.06
[-5;5]	111	-0.0293	-2.96	0.00	-1.80	0.07
[0;1]	111	-0.0202	-4.05	0.00	-2.47	0.02
[0;2]	111	-0.0269	-4.62	0.00	-2.82	0.01
[0;3]	111	-0.0268	-4.70	0.00	-2.87	0.01
[0;5]	111	-0.0270	-4.56	0.00	-2.78	0.01

Table 4: Baseline Results - The Patent Output of Chinese EL Firms

This table presents the baseline results for patent output of Chinese firms affected by export control lists. The analysis includes different types of patent metrics: patent filing, patent issuance, invention filing, and invention issuance. For each metric, both negative binomial regression (nbreg) and zero-inflated negative binomial (zinb) models are estimated. Control variables include firm characteristics, ownership structure, and corporate governance measures. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	patentfiling		patentissue		inventionfiling		inventionissue	
	nbreg	zinb	nbreg	zinb	nbreg	zinb	nbreg	zinb
$Post\_EL$	0.679**	0.506***	0.970***	0.642***	0.573	0.234	1.295***	1.061***
	(0.295)	(0.163)	(0.340)	(0.203)	(0.498)	(0.252)	(0.209)	(0.171)
Age	-0.001	0.021*	0.005	0.025***	-0.019	0.001	-0.014	0.011
	(0.008)	(0.011)	(0.008)	(0.008)	(0.012)	(0.016)	(0.013)	(0.012)
$Asset$	0.000***	0.000***	0.000***	0.000***	0.000**	0.000**	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Leverage$	0.002	0.001	-0.000	0.010	-0.001	0.004	-0.023*	0.000
	(0.013)	(0.010)	(0.011)	(0.008)	(0.015)	(0.010)	(0.012)	(0.008)
$Tobin$	0.013	0.004	-0.041	-0.067***	0.030	0.055*	-0.024	0.037
	(0.025)	(0.022)	(0.032)	(0.019)	(0.039)	(0.031)	(0.033)	(0.032)
PPE	-0.569	-1.040**	-0.200	-1.143***	-1.053*	-1.313***	-0.194	-0.934**
	(0.471)	(0.489)	(0.536)	(0.389)	(0.551)	(0.491)	(0.542)	(0.421)
BIG	-0.153	-0.262	0.103	-0.152	-0.254	-0.259	0.000	-0.241*
	(0.247)	(0.223)	(0.235)	(0.188)	(0.212)	(0.179)	(0.171)	(0.141)
$Growth$	0.195**	0.212**	0.121	0.120*	0.124	0.120**	0.037	0.048
	(0.082)	(0.090)	(0.074)	(0.067)	(0.082)	(0.058)	(0.063)	(0.058)
HHI	-1.278*	-0.418	-1.406**	-0.289	-0.505	-1.133***	-1.365*	-0.960**
	(0.743)	(0.546)	(0.694)	(0.471)	(0.478)	(0.366)	(0.798)	(0.382)
SOE	0.250**	0.097	0.246**	0.009	0.232	0.236	0.479***	0.216*
	(0.115)	(0.158)	(0.118)	(0.095)	(0.154)	(0.177)	(0.184)	(0.129)
$TOP1$	0.003	0.006*	0.005**	0.007***	0.001	0.003	0.000	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)	(0.004)	(0.004)
$DUAL$	-0.016	0.131*	-0.098	0.023	0.017	0.110	-0.115	-0.059
	(0.100)	(0.067)	(0.101)	(0.087)	(0.104)	(0.082)	(0.089)	(0.081)
$EXESHR$	-0.000	-0.005**	0.001	-0.005**	-0.005*	-0.005*	-0.003	-0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
$BOARD$	0.048	0.035	0.078**	0.046**	0.089*	0.116***	0.090**	0.079***
	(0.033)	(0.022)	(0.035)	(0.021)	(0.046)	(0.029)	(0.041)	(0.025)
$Direct\_Ind$	-0.001	0.008	0.002	0.006	0.012	0.027***	0.007	0.019***
	(0.009)	(0.011)	(0.009)	(0.008)	(0.011)	(0.008)	(0.008)	(0.006)
N	23328	23328	23328	23328	23328	23328	23328	23328
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inflate	No	Industry	No	Industry	No	Industry	No	Industry

Table 5: Baseline Results of Chinese EL Firms

This table presents the baseline results for Chinese EL firms. Panel A reports the R&D performance metrics, including R&D personnel ratio and R&D spending. Panel B summarizes the financial performance measures, including return on $Assets$ (ROA) and EMP count. The estimations are conducted using both the Wild Bootstrap and Cluster methods. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The R&D Performance				
	Wild BootStrap		Cluster	
Outcome	(1)	(2)	(3)	(4)
$R\&D\_Person\_Ratio$	1.949	-0.017	1.949	-0.017
	(2.350)	(0.955)	(2.571)	(1.026)
$R\&D\_Spend\_Sum$	194.646**	247.701***	194.646***	247.701***
	(85.743)	(89.976)	(69.235)	(62.660)
Panel B: The Financial Performance				
	Wild BootStrap		Cluster	
Outcome	(1)	(2)	(3)	(4)
ROA	-0.003	0.001	-0.003	0.001
	(0.007)	(0.008)	(0.007)	(0.008)
EMP	0.015	-0.025	0.015	-0.025
	(0.052)	(0.044)	(0.029)	(0.034)
Covariates	No	Yes	No	Yes

Table 6: Baseline Results - The Patent Output of Chinese Firms Importing the Embargo Products

This table presents the baseline results for patent output of Chinese firms affected by import embargoes. The analysis includes different types of patent metrics: patent filing, patent issuance, invention filing, and invention issuance. For each metric, both negative binomial regression (nbreg) and zero-inflated negative binomial (zinb) models are estimated. Control variables include firm characteristics, ownership structure, and corporate governance measures. All specifications include year fixed effects, and nbreg specifications additionally include industry fixed effects. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	patentfiling		patentissue		inventionfiling		inventionissue	
	nbreg	zinb	nbreg	zinb	nbreg	zinb	nbreg	zinb
$Post\_IMUS$	0.305**	0.533***	0.512***	0.559***	0.244	0.417***	0.433***	0.491***
	(0.126)	(0.137)	(0.116)	(0.104)	(0.150)	(0.145)	(0.095)	(0.077)
Age	-0.002	0.019*	0.004	0.025***	-0.019	0.001	-0.014	0.012
	(0.009)	(0.011)	(0.008)	(0.007)	(0.011)	(0.016)	(0.012)	(0.011)
$Asset$	0.000***	0.000***	0.000***	0.000***	0.000**	0.000**	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Leverage$	0.001	-0.003	-0.001	0.008	-0.000	0.003	-0.021*	0.001
	(0.013)	(0.009)	(0.010)	(0.007)	(0.015)	(0.010)	(0.012)	(0.007)
$Tobin$	0.012	0.004	-0.052*	-0.075***	0.031	0.056*	-0.032	0.031
	(0.025)	(0.021)	(0.030)	(0.018)	(0.040)	(0.031)	(0.032)	(0.030)
PPE	-0.590	-0.998**	-0.288	-1.189***	-1.053*	-1.255**	-0.320	-1.003**
	(0.468)	(0.490)	(0.526)	(0.370)	(0.555)	(0.506)	(0.534)	(0.400)
BIG	-0.160	-0.294	0.105	-0.148	-0.231	-0.260	0.053	-0.183
	(0.255)	(0.221)	(0.248)	(0.198)	(0.220)	(0.176)	(0.168)	(0.134)
$Growth$	0.214***	0.226***	0.125*	0.127*	0.140*	0.137**	0.037	0.042
	(0.083)	(0.088)	(0.075)	(0.075)	(0.082)	(0.058)	(0.063)	(0.061)
HHI	-1.299*	-0.363	-1.373*	-0.226	-0.563	-1.151***	-1.326*	-0.937**
	(0.747)	(0.541)	(0.701)	(0.455)	(0.483)	(0.380)	(0.806)	(0.376)
SOE	0.242**	0.070	0.247**	-0.019	0.209	0.195	0.514***	0.205
	(0.117)	(0.147)	(0.118)	(0.093)	(0.157)	(0.163)	(0.191)	(0.130)
$TOP1$	0.004	0.008**	0.005**	0.008***	0.002	0.004	0.001	0.003
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)	(0.004)	(0.004)
$DUAL$	-0.024	0.116*	-0.098	0.023	0.029	0.114	-0.096	-0.044
	(0.101)	(0.065)	(0.104)	(0.082)	(0.106)	(0.081)	(0.087)	(0.074)
$EXESHR$	-0.000	-0.005**	0.001	-0.004**	-0.005*	-0.004*	-0.003	-0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
$BOARD$	0.044	0.035*	0.074**	0.046**	0.093*	0.125***	0.086**	0.082***
	(0.033)	(0.021)	(0.035)	(0.020)	(0.048)	(0.028)	(0.042)	(0.027)
$Direct\_Ind$	-0.001	0.006	0.003	0.007	0.012	0.025***	0.006	0.018***
	(0.009)	(0.011)	(0.008)	(0.008)	(0.011)	(0.008)	(0.008)	(0.005)
N	22995	22995	22995	22995	22995	22995	22995	22995
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inflate	No	Industry	No	Industry	No	Industry	No	Industry

Table 7: Baseline Results of Chinese Firms Importing the Embargo Products

This table presents the baseline results for Chinese firms affected by import embargoes. Panel A reports the innovation performance metrics, including R&D personnel ratio and R&D spending. Panel B summarizes the financial performance measures, including return on $Assets$ (ROA) and EMP count. The estimations are conducted using both the Wild Bootstrap and Cluster methods. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The Innovation Performance				
	Wild BootStrap		Cluster	
Outcome	(1)	(2)	(3)	(4)
$R\&D\_Person\_Ratio$	0.364*	0.374	0.364**	0.374**
	(0.211)	(0.227)	(0.171)	(0.166)
$R\&D\_Spend\_Sum$	41.721**	48.487***	41.721**	48.487***
	(17.027)	(16.093)	(18.584)	(17.945)
Panel B: The Financial Performance				
	Wild BootStrap		Cluster	
Outcome	(1)	(2)	(3)	(4)
ROA	0.004*	0.003	0.004*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
EMP	0.035**	0.016	0.035**	0.016
	(0.017)	(0.016)	(0.014)	(0.012)
Covariates	No	Yes	No	Yes

Table 8: Baseline Results - The Patent Output of Chinese EL Suppliers

This table presents the baseline results for patent output of Chinese suppliers of firms on export control lists. The analysis includes different types of patent metrics: patent filing, patent issuance, invention filing, and invention issuance. For each metric, both negative binomial regression (nbreg) and zero-inflated negative binomial (zinb) models are estimated. Control variables include firm characteristics, ownership structure, and corporate governance measures. All specifications include year fixed effects, and nbreg specifications additionally include industry fixed effects. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	patentfiling		patentissue		inventionfiling		inventionissue	
	nbreg	zinb	nbreg	zinb	nbreg	zinb	nbreg	zinb
$Post\_Sup$	-0.398	-0.193	-0.588**	-0.207	-0.341	-0.091	-0.752***	-0.421**
	(0.276)	(0.232)	(0.260)	(0.230)	(0.398)	(0.293)	(0.210)	(0.178)
Age	-0.001	0.021*	0.004	0.024***	-0.019	0.001	-0.015	0.010
	(0.009)	(0.011)	(0.008)	(0.008)	(0.012)	(0.016)	(0.013)	(0.012)
$Asset$	0.000***	0.000***	0.000***	0.000***	0.000**	0.000**	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Leverage$	0.003	0.002	0.001	0.011	-0.001	0.004	-0.022*	0.001
	(0.013)	(0.011)	(0.011)	(0.009)	(0.015)	(0.010)	(0.012)	(0.008)
$Tobin$	0.012	0.004	-0.041	-0.066***	0.028	0.055*	-0.024	0.040
	(0.025)	(0.022)	(0.032)	(0.019)	(0.040)	(0.031)	(0.033)	(0.031)
PPE	-0.593	-1.062**	-0.243	-1.186***	-1.077**	-1.323***	-0.252	-1.024**
	(0.468)	(0.482)	(0.536)	(0.378)	(0.545)	(0.486)	(0.539)	(0.412)
BIG	-0.155	-0.262	0.101	-0.162	-0.264	-0.264	-0.010	-0.266*
	(0.248)	(0.223)	(0.230)	(0.182)	(0.217)	(0.181)	(0.176)	(0.148)
$Growth$	0.189**	0.207**	0.117	0.118*	0.121	0.118**	0.047	0.050
	(0.082)	(0.090)	(0.074)	(0.068)	(0.082)	(0.058)	(0.066)	(0.064)
HHI	-1.296*	-0.419	-1.421**	-0.296	-0.520	-1.129***	-1.364*	-0.980**
	(0.743)	(0.546)	(0.692)	(0.471)	(0.478)	(0.366)	(0.802)	(0.384)
SOE	0.261**	0.105	0.276**	0.031	0.238	0.239	0.503***	0.245*
	(0.116)	(0.160)	(0.119)	(0.096)	(0.154)	(0.176)	(0.187)	(0.134)
$TOP1$	0.003	0.006*	0.005*	0.007***	0.001	0.003	-0.000	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.005)	(0.004)	(0.004)
$DUAL$	-0.020	0.128*	-0.109	0.018	0.014	0.109	-0.124	-0.069
	(0.099)	(0.067)	(0.099)	(0.087)	(0.104)	(0.083)	(0.088)	(0.080)
$EXESHR$	-0.000	-0.005**	0.001	-0.005**	-0.005*	-0.005*	-0.004	-0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
$BOARD$	0.049	0.036*	0.079**	0.047**	0.091**	0.116***	0.092**	0.081***
	(0.032)	(0.021)	(0.035)	(0.020)	(0.046)	(0.029)	(0.041)	(0.025)
$Direct\_Ind$	-0.001	0.008	0.002	0.007	0.012	0.027***	0.008	0.020***
	(0.009)	(0.011)	(0.009)	(0.008)	(0.011)	(0.008)	(0.008)	(0.006)
N	23328	23328	23328	23328	23328	23328	23328	23328
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inflate	No	Industry	No	Industry	No	Industry	No	Industry

Table 9: Baseline Results of Chinese EL Suppliers

This table presents the baseline results for Chinese suppliers of firms on export control lists. Panel A reports the innovation performance metrics, including R&D personnel ratio and R&D spending. Panel B summarizes the financial performance measures, including return on $Assets$ (ROA) and EMP count. The estimations are conducted using both the Wild Bootstrap and Cluster methods. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The Innovation Performance				
	Wild BootStrap		Cluster	
Outcome	(1)	(2)	(3)	(4)
$R\&D\_Person\_Ratio$	2.209	-0.600	2.209*	-0.600
	(2.065)	(0.715)	(1.330)	(0.838)
$R\&D\_Spend\_Sum$	-16.899	13.893	-16.899	13.893
	(37.858)	(44.805)	(45.395)	(48.518)
Panel B: The Financial Performance				
	Wild BootStrap		Cluster	
Outcome	(1)	(2)	(3)	(4)
ROA	0.003	0.009**	0.003	0.009***
	(0.004)	(0.004)	(0.003)	(0.003)
EMP	-0.040	-0.002	-0.040	-0.002
	(0.042)	(0.042)	(0.038)	(0.046)
Covariates	No	Yes	No	Yes

Table 10: Baseline Results - The Patent Output of Chinese EL Firms' Supplier Industries

This table presents the baseline results for patent output of industries that supply to Chinese firms on export control lists. The analysis includes different types of patent metrics: patent filing, patent issuance, invention filing, and invention issuance. For each metric, both negative binomial regression (nbreg) and zero-inflated negative binomial (zinb) models are estimated. Control variables include firm characteristics, ownership structure, and corporate governance measures. All specifications include year fixed effects, and nbreg specifications additionally include industry fixed effects. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	patentfiling		patentissue		inventionfiling		inventionissue	
	nbreg	zinb	nbreg	zinb	nbreg	zinb	nbreg	zinb
$Post\_Supind$	-0.159	0.462**	-0.009	0.511***	-0.088	0.383***	0.134	0.369***
	(0.125)	(0.180)	(0.107)	(0.145)	(0.146)	(0.147)	(0.124)	(0.075)
Age	-0.000	0.023**	0.004	0.027***	-0.018	0.003	-0.014	0.013
	(0.009)	(0.011)	(0.008)	(0.007)	(0.012)	(0.015)	(0.013)	(0.012)
$Asset$	0.000***	0.000***	0.000***	0.000***	0.000**	0.000**	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Leverage$	0.003	-0.003	0.001	0.006	-0.001	0.001	-0.023*	-0.005
	(0.013)	(0.010)	(0.011)	(0.008)	(0.015)	(0.010)	(0.012)	(0.007)
$Tobin$	0.014	-0.004	-0.041	-0.066***	0.030	0.045	-0.024	0.037
	(0.025)	(0.018)	(0.032)	(0.020)	(0.039)	(0.028)	(0.033)	(0.029)
PPE	-0.588	-0.839	-0.231	-0.857**	-1.069*	-1.150**	-0.252	-0.743*
	(0.469)	(0.511)	(0.534)	(0.386)	(0.549)	(0.516)	(0.538)	(0.409)
BIG	-0.160	-0.314	0.097	-0.174	-0.266	-0.322*	-0.016	-0.296**
	(0.248)	(0.247)	(0.232)	(0.190)	(0.216)	(0.187)	(0.176)	(0.139)
$Growth$	0.186**	0.187**	0.118	0.113*	0.121	0.110**	0.049	0.051
	(0.081)	(0.078)	(0.073)	(0.062)	(0.081)	(0.056)	(0.066)	(0.059)
HHI	-1.340*	-0.077	-1.413**	0.037	-0.546	-0.912***	-1.334	-0.814**
	(0.735)	(0.516)	(0.692)	(0.419)	(0.481)	(0.283)	(0.818)	(0.351)
SOE	0.251**	0.048	0.267**	-0.022	0.234	0.186	0.493***	0.183
	(0.115)	(0.148)	(0.119)	(0.090)	(0.153)	(0.161)	(0.185)	(0.131)
$TOP1$	0.003	0.008***	0.005*	0.008***	0.001	0.004	-0.000	0.002
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
$DUAL$	-0.025	0.132*	-0.104	-0.004	0.010	0.119	-0.118	-0.061
	(0.100)	(0.068)	(0.100)	(0.091)	(0.105)	(0.090)	(0.089)	(0.076)
$EXESHR$	-0.000	-0.006**	0.001	-0.005*	-0.005*	-0.005**	-0.004	-0.003
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
$BOARD$	0.048	0.035	0.079**	0.046**	0.090**	0.117***	0.091**	0.085***
	(0.033)	(0.022)	(0.035)	(0.020)	(0.046)	(0.030)	(0.042)	(0.025)
$Direct\_Ind$	-0.001	0.006	0.002	0.004	0.012	0.024***	0.007	0.018***
	(0.009)	(0.010)	(0.009)	(0.007)	(0.011)	(0.007)	(0.008)	(0.005)
N	23328	23328	23328	23328	23328	23328	23328	23328
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inflate	No	Industry	No	Industry	No	Industry	No	Industry

Table 11: Baseline Results of Chinese EL Firms' Supplier Industries

This table presents the baseline results for industries that supply to Chinese firms on export control lists. Panel A reports the innovation performance metrics, including R&D personnel ratio and R&D spending. Panel B summarizes the financial performance measures, including return on $Assets$ (ROA) and EMP count. The estimations are conducted using both the Wild Bootstrap and Cluster methods. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The Innovation Performance				
	Wild BootStrap		Cluster	
Outcome	(1)	(2)	(3)	(4)
$R\&D\_Person\_Ratio$	4.803***	3.652***	4.803**	3.652**
	(0.419)	(0.368)	(1.896)	(1.485)
$R\&D\_Spend\_Sum$	47.470***	56.331***	47.470	56.331*
	(17.831)	(15.916)	(37.879)	(31.043)
Panel B: The Financial Performance				
	Wild BootStrap		Cluster	
Outcome	(1)	(2)	(3)	(4)
ROA	-0.002	0.001	-0.002	0.001
	(0.002)	(0.002)	(0.003)	(0.002)
EMP	0.098***	0.092***	0.098**	0.092***
	(0.021)	(0.021)	(0.046)	(0.027)
Covariates	No	Yes	No	Yes

Table 12: The Impact of Export Restrictions on U.S. Suppliers

This table presents the baseline results for U.S. suppliers affected by Chinese companies being added to export control lists. Panel A reports the innovation performance metrics, including patent filing value, patent citations, and R&D expenses. Panel B summarizes the financial performance measures, such as cash flow, return on $Assets$ (ROA), EMP count, and revenue. The estimations are conducted using both the Wild Bootstrap and Cluster methods. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: The Innovation Performance of US Suppliers				
	Wild BootStrap		Cluster	
Outcome	(1)	(2)	(3)	(4)
$Patent\_Value$	-0.423***	-0.261**	-0.423***	-0.261
	(0.118)	(0.126)	(0.105)	(0.160)
$Patent\_Cite$	-0.628***	-0.506***	-0.628***	-0.506***
	(0.119)	(0.113)	(0.128)	(0.094)
$R\&DRatio$	0.004	0.001	0.004	0.001
	(0.006)	(0.005)	(0.006)	(0.005)
Panel B: The Financial Performance of US Suppliers				
	Wild BootStrap		Cluster	
Outcome	(1)	(2)	(3)	(4)
$CashFlow$	-0.017	-0.009	-0.017*	-0.009
	(0.011)	(0.011)	(0.009)	(0.008)
EMP	-0.078**	-0.057**	-0.078***	-0.057***
	(0.030)	(0.029)	(0.027)	(0.021)
	-0.147***	-0.105**	-0.147***	-0.105**
	(0.046)	(0.046)	(0.054)	(0.049)
Covariates	No	Yes	No	Yes

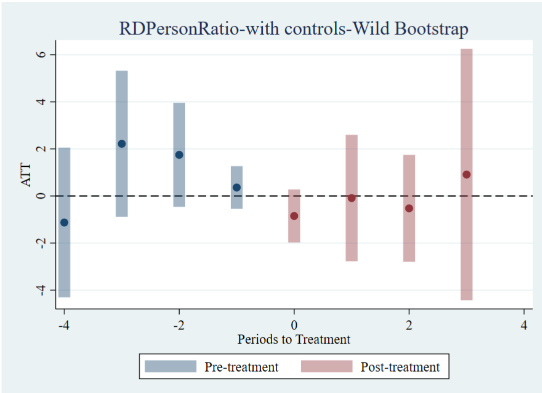
Table 13: The Impact of Export Restrictions on U.S. Suppliers Industry (SIC2)

This table presents the baseline results for U.S. suppliers affected by Chinese companies being added to export control lists. Panel A reports the innovation performance metrics, including patent filing value, patent citations, and R&D expenses. Panel B summarizes the financial performance measures, such as cash flow, return on $Assets$ (ROA), EMP count, and revenue. The estimations are conducted using both the Wild Bootstrap and Cluster methods. Standard errors are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

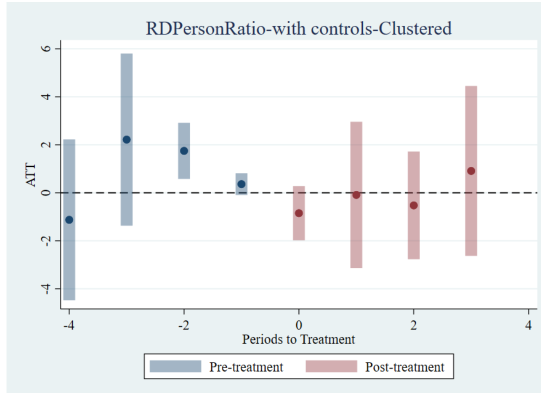
Panel A: The Innovation Performance of US Suppliers				
	Wild BootStrap		Cluster	
Outcome	(1)	(2)	(3)	(4)
$Patent\_Value$	-0.422***	-0.449***	-0.422***	-0.449***
	(0.040)	(0.039)	(0.088)	(0.089)
$Patent\_Cite$	-0.310***	-0.321***	-0.310***	-0.321***
	(0.026)	(0.027)	(0.060)	(0.057)
$R\&DRatio$	-0.017***	-0.015***	-0.017***	-0.015***
	(0.002)	(0.002)	(0.005)	(0.004)
Panel B: The Financial Performance of US Suppliers				
	Wild BootStrap		Cluster	
Outcome	(1)	(2)	(3)	(4)
$CashFlow$	0.027***	0.015	0.027***	0.015
	(0.004)	(0.010)	(0.011)	(0.012)
EMP	0.101***	0.010	0.101***	0.010
	(0.014)	(0.043)	(0.029)	(0.038)
$Revenue$	0.138***	0.008	0.138***	0.008
	(0.020)	(0.053)	(0.050)	(0.057)
Covariates	No	Yes	No	Yes

A Figure Appendix

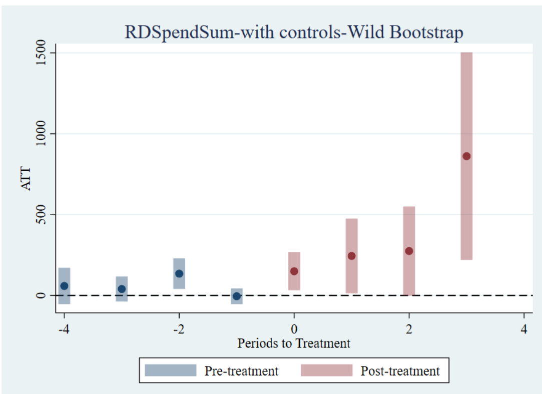
This appendix presents a series of figures illustrating the event study estimates of the impact of U.S. Entity List sanctions on Chinese and U.S. firms and their associated industries. The figures are organized into several categories, covering R&D investment, financial performance, and innovation outcomes for both Chinese and U.S. suppliers, as well as firms operating in related industries.



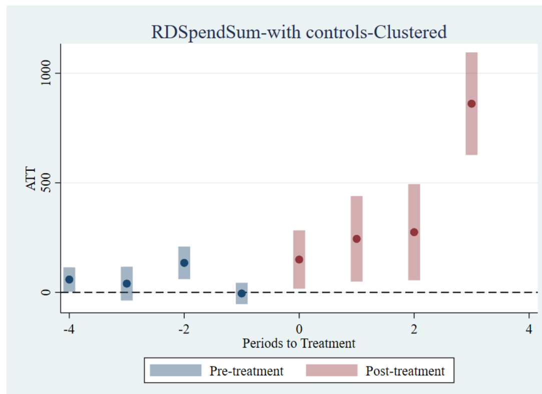
(a) R&D Person Ratio_Wboot



(b) R&D Person Ratio_Cluster

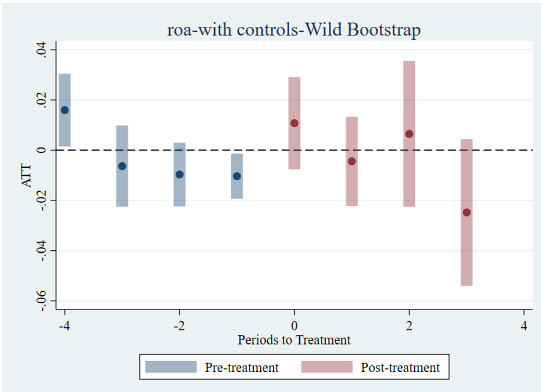


(c) R&D Spend_Wboot

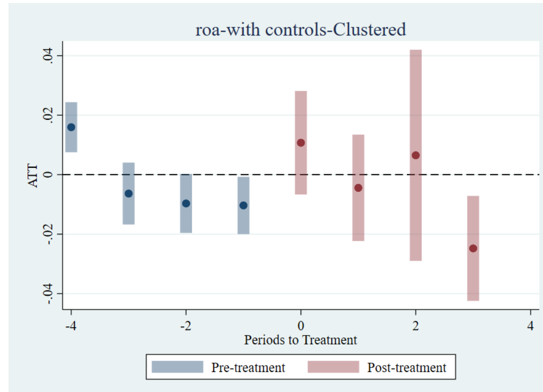


(d) R&D Spend_Cluster

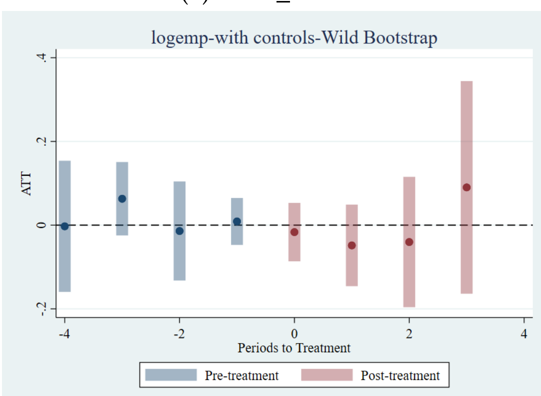
Figure A.1: **The R&D Investment of CN EL Firms** Figure A.1 illustrates the event study estimates of the average treatment effects (ATT) on R&D investment for Chinese firms placed on the U.S. Entity List. Panel (a) and (b) present the estimated coefficients for the ratio of R&D personnel (*R&D_Person_Ratio*) over the pre- and post-treatment periods, with Wild Bootstrap and Cluster standard errors, respectively. Panel (c) and (d) show the corresponding results for total R&D spending (*R&D_Spend_Sum*). The shaded bars indicate the pre-treatment and post-treatment periods, with blue representing pre-treatment and red representing post-treatment. The coefficients in the post-treatment period demonstrate a significant upward trend in R&D spending, indicating that Chinese firms substantially increased their R&D investments following their inclusion on the Entity List. The pre-treatment coefficients are not significantly different from zero, indicating that the parallel trends assumption holds. For the ratio of R&D personnel, the changes before and after the policy intervention are not substantial.



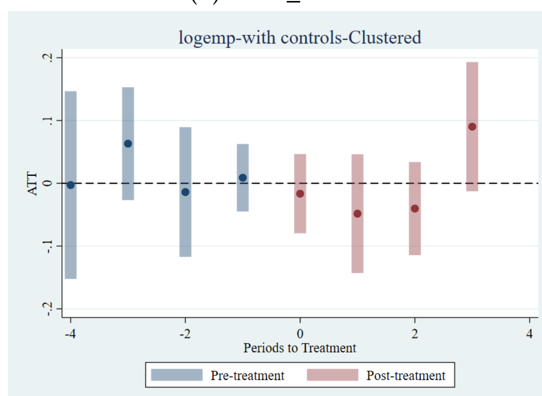
(a) ROA_Wboot



(b) ROA_Cluster

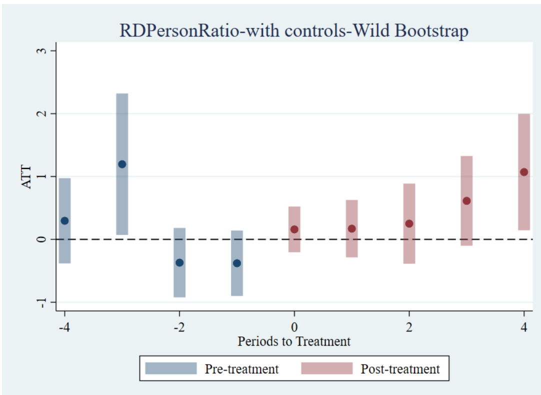


(c) Employee_Wboot

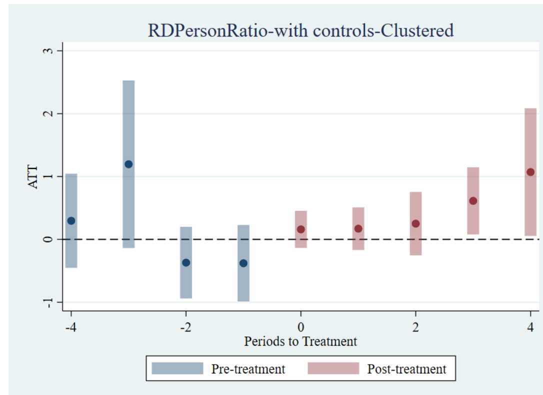


(d) Employee_Cluster

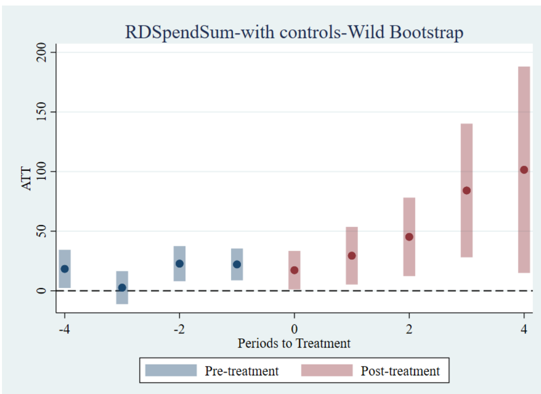
Figure A.2: **The Financial Performance of CN EL Firms** Figure A.2 presents the event study estimates of the treatment effects on financial performance metrics for Chinese firms included on the U.S. Entity List. Panel (a) and (b) display the results for return on assets (*ROA*), while Panel (c) and (d) show the estimates for the number of employees (*Employee*). The pre-treatment coefficients are not significantly different from zero, indicating that the parallel trends assumption holds. In the post-treatment period, both financial performance indicators *ROA* and *Employee* do not exhibit statistically significant changes following the policy shock. The results suggest that Chinese firms did not experience notable declines in profitability or reductions in workforce size as a consequence of their inclusion on the Entity List. These findings imply that the immediate financial impact of U.S. export control policies on Chinese firms' profitability and scale may have been limited.



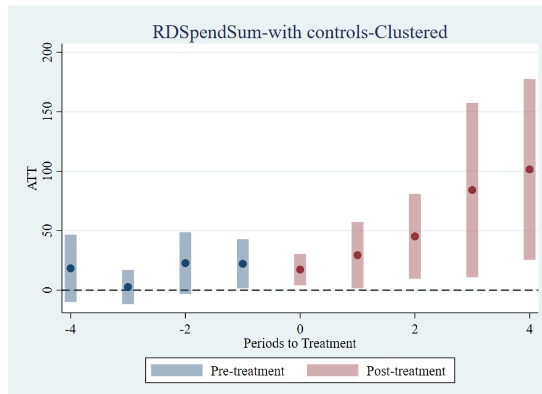
(a) R&D Person Ratio_Wboot



(b) R&D Person Ratio_Cluster

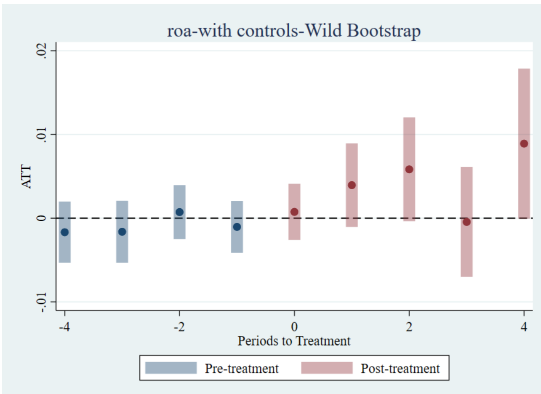


(c) R&D Spend_Wboot

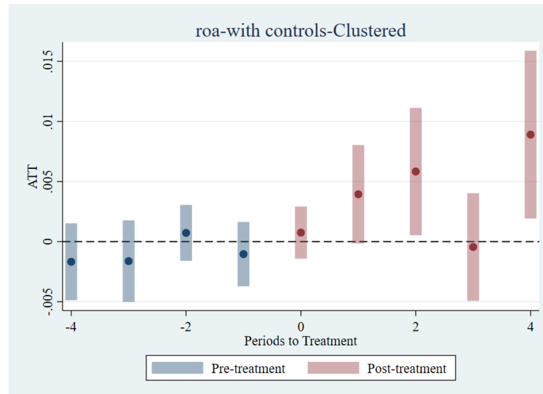


(d) R&D Spend_Cluster

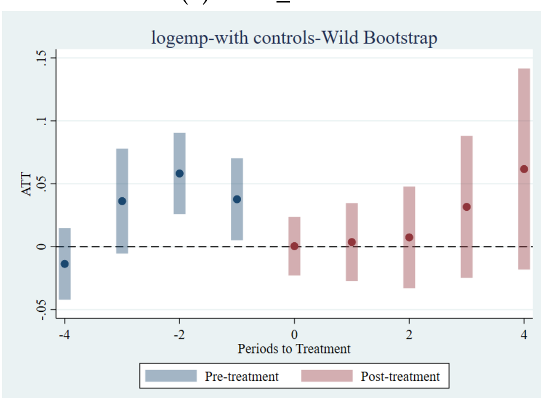
Figure A.3: **The R&D Investment of Chinese Firms Importing the Embargo Products** Figure **??** presents the event study estimates on R&D investment for non-sanctioned Chinese firms importing embargoed products. Panel (a) and (b) display the estimated coefficients for the ratio of R&D personnel (*R&D_Person_Ratio*) over the pre- and post-treatment periods, with Wild Bootstrap and Cluster standard errors, respectively. Panel (c) and (d) show the corresponding results for total R&D spending (*R&D_Spend_Sum*). The post-treatment coefficients indicate a significant upward trend in both metrics, particularly in R&D spending, which shows a substantial increase following the sanctions. These results suggest that non-sanctioned firms importing embargoed products responded to the policy shock by enhancing their innovation efforts, possibly as a strategy to strengthen their resilience to supply chain uncertainties or to capture market share previously held by sanctioned firms. The pre-treatment coefficients are not significantly different from zero, confirming the parallel trends assumption.



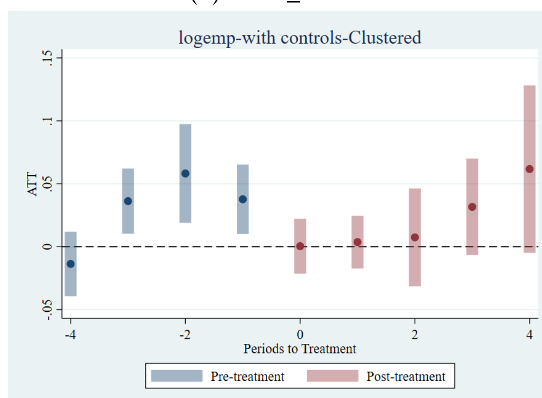
(a) ROA_Wboot



(b) ROA_Cluster

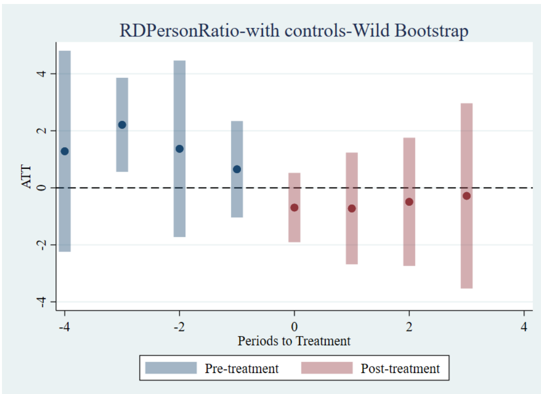


(c) Employee_Wboot

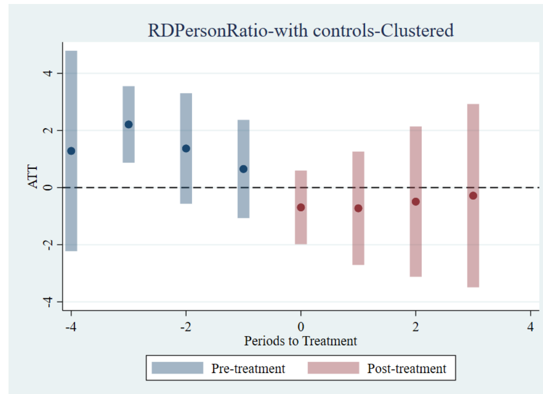


(d) Employee_Cluster

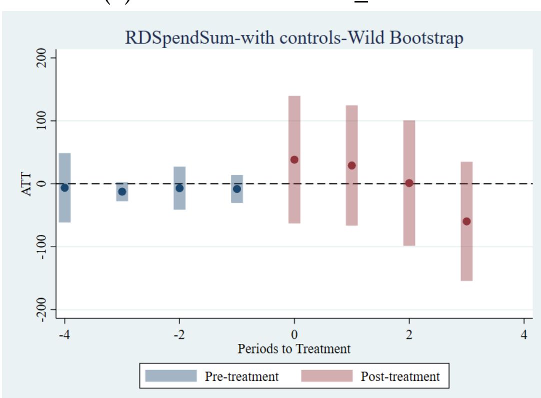
Figure A.4: **The Financial Performance of Chinese Firms Importing the Embargo Products** Figure A.4 presents the event study estimates on financial performance metrics for non-sanctioned Chinese firms importing embargoed products. Panel (a) and (b) display the estimated coefficients for return on assets (*ROA*) over the pre- and post-treatment periods, with Wild Bootstrap and Cluster standard errors, respectively. Panel (c) and (d) show the corresponding results for the number of employees (*Employee*). The post-treatment coefficients indicate a small but significant positive effect on *ROA*, suggesting that these firms may have experienced improved profitability following the sanctions. The pre-treatment coefficients are not significantly different from zero, confirming that the parallel trends assumption holds. These findings suggest that non-sanctioned firms importing embargoed products adapted to the policy shock by improving their financial performance and increasing their workforce size.



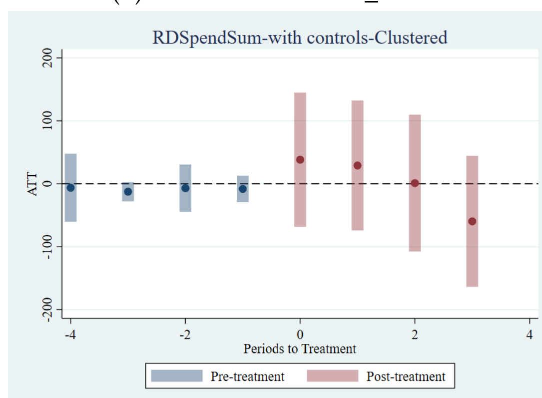
(a) R&D Person Ratio_Wboot



(b) R&D Person Ratio_Cluster

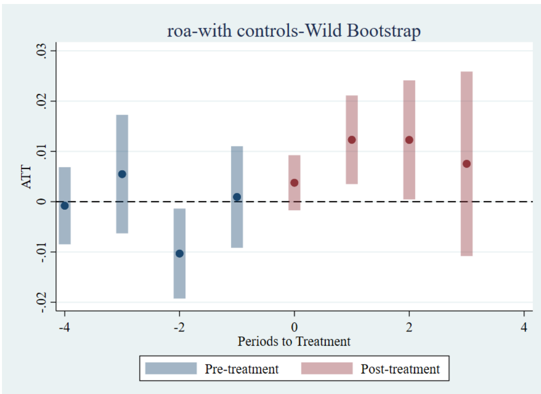


(c) R&D Spend_Wboot

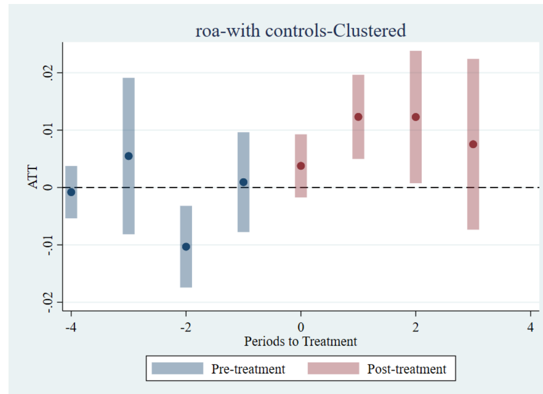


(d) R&D Spend_Cluster

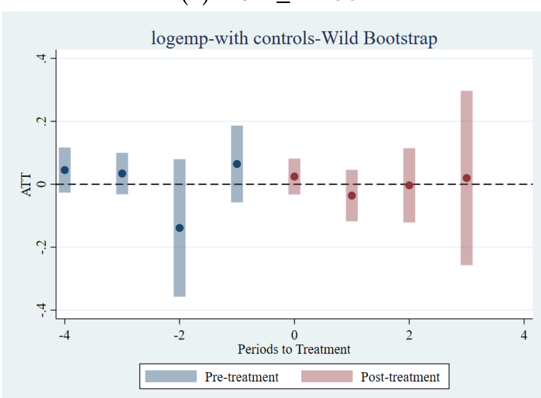
Figure A.5: **The R&D Investment of Chinese EL Suppliers** Figure A.5 presents the event study estimates on R&D investment for Chinese upstream suppliers of firms placed on the U.S. Entity List. Panels (a) and (b) display the estimated coefficients for the ratio of R&D personnel (*R&D_Person_Ratio*) over the pre- and post-treatment periods, with Wild Bootstrap and Cluster standard errors, respectively. Panels (c) and (d) show the corresponding results for total R&D spending (*R&D_Spend_Sum*). The results indicate a mixed response: while the ratio of R&D personnel shows a positive and significant increase in certain specifications, there is no substantial change in total R&D spending following the sanctions. These findings suggest that Chinese suppliers adjusted their R&D workforce but did not significantly alter their overall spending on innovation. The pre-treatment coefficients are not significantly different from zero, confirming the parallel trends assumption.



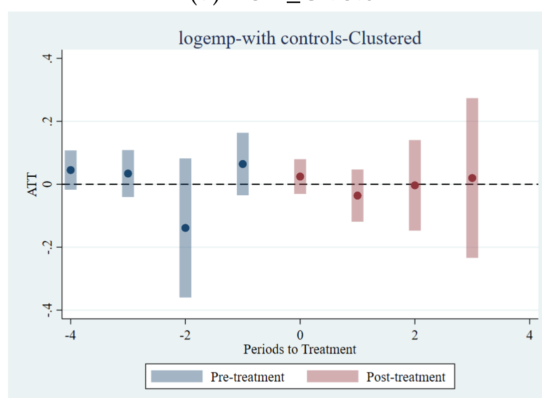
(a) ROA_Wboot



(b) ROA_Cluster

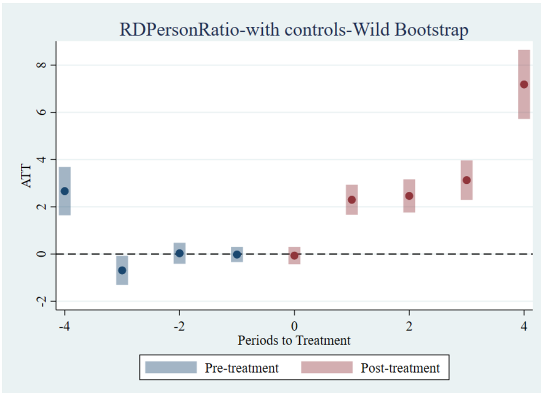


(c) Employee_Wboot

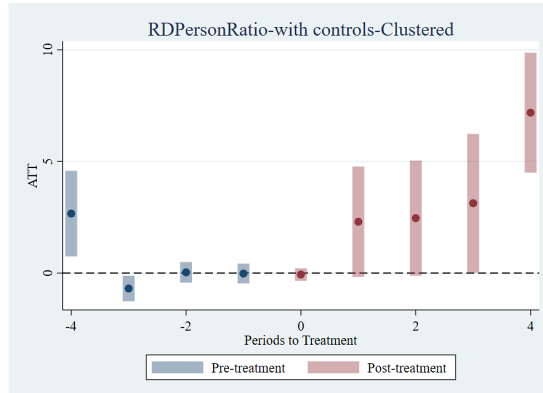


(d) Employee_Cluster

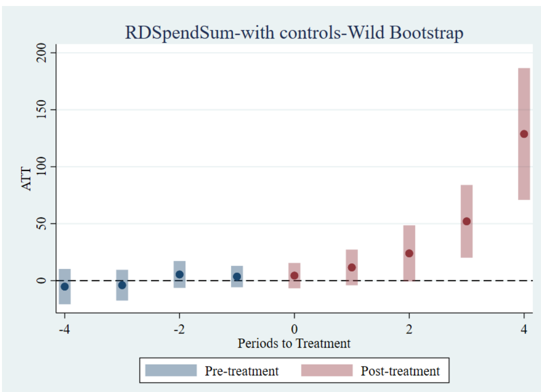
Figure A.6: **The Financial Performance of Chinese EL Suppliers** Figure A.6 presents the event study estimates on the financial performance of Chinese upstream suppliers of firms placed on the U.S. Entity List. Panels (a) and (b) display the estimated coefficients for return on assets (*ROA*) over the pre- and post-treatment periods, with Wild Bootstrap and Cluster standard errors, respectively. Panels (c) and (d) show the corresponding results for the number of employees (*Employee*). The results indicate a marginal positive effect on *ROA*, suggesting that Chinese suppliers experienced a slight improvement in profitability following the sanctions. The pre-treatment coefficients are not significantly different from zero, confirming the parallel trends assumption.



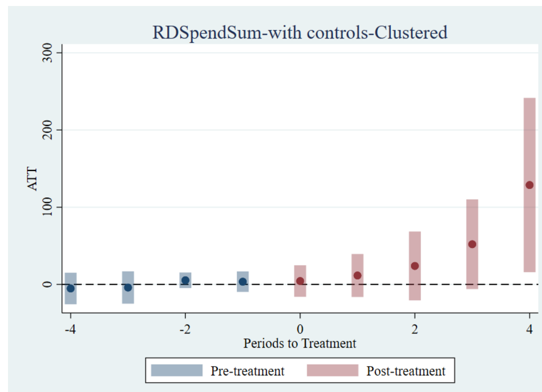
(a) R&D Person Ratio_Wboot



(b) R&D Person Ratio_Cluster

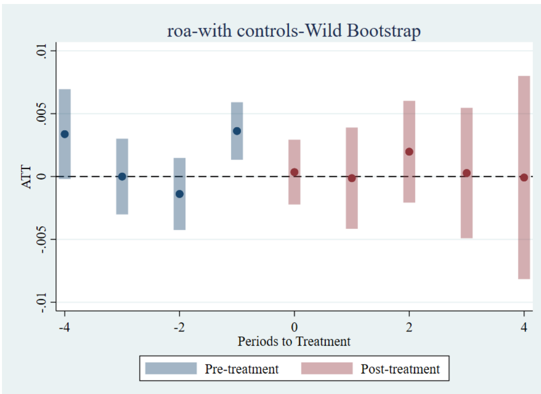


(c) R&D Spend_Wboot

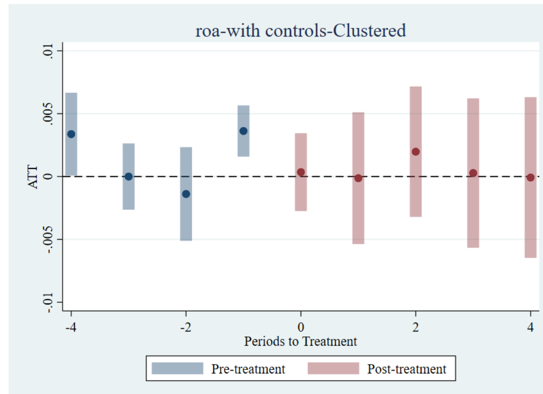


(d) R&D Spend_Cluster

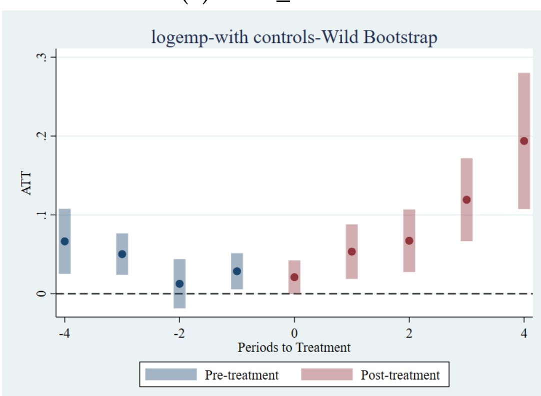
Figure A.7: **The R&D Investment of Chinese EL Firms Supplier Industries** Figure A.7 presents the event study estimates on R&D investment for firms operating in the same industries as the upstream suppliers of Chinese firms placed on the U.S. Entity List. Panels (a) and (b) display the estimated coefficients for the ratio of R&D personnel (*R&D_Person_Ratio*) over the pre- and post-treatment periods, with Wild Bootstrap and Cluster standard errors, respectively. Panels (c) and (d) show the corresponding results for total R&D spending (*R&D_Spend_Sum*). The post-treatment coefficients indicate a significant upward trend in both metrics, suggesting that firms in these supplier industries increased their innovation efforts following the sanctions. This increase in R&D activities may reflect efforts to capture new market opportunities created by supply chain disruptions or to fill the gaps left by sanctioned suppliers. The pre-treatment coefficients are not significantly different from zero, confirming that the parallel trends assumption holds.



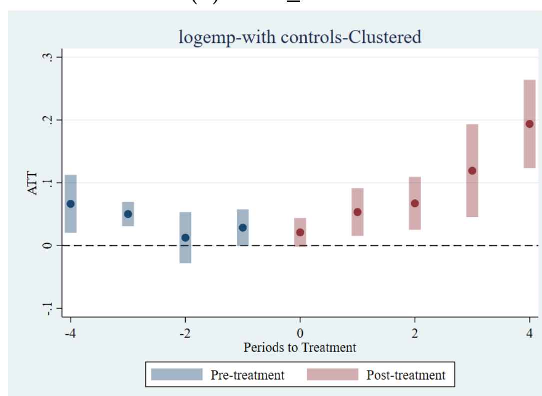
(a) ROA_Wboot



(b) ROA_Cluster

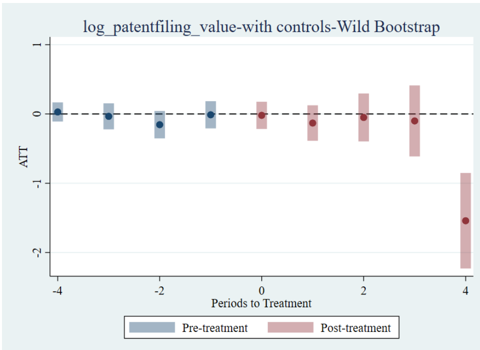


(c) Employee_Wboot

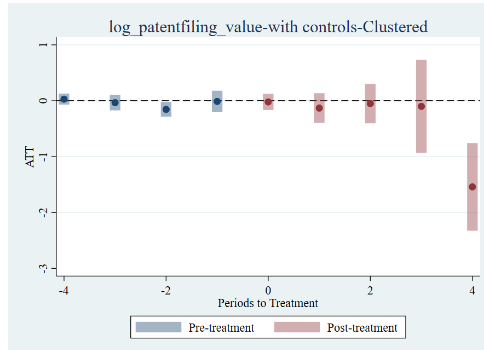


(d) Employee_Cluster

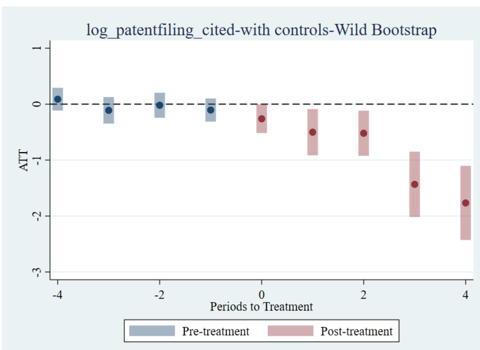
Figure A.8: **The Financial Performance of Chinese EL Firms Supplier Industries** Figure A.8 presents the event study estimates on the financial performance of firms operating in the same industries as the upstream suppliers of Chinese firms placed on the U.S. Entity List. Panels (a) and (b) display the estimated coefficients for return on assets (*ROA*) over the pre- and post-treatment periods, with Wild Bootstrap and Cluster standard errors, respectively. Panels (c) and (d) present the corresponding results for the number of employees (*Employee*). The post-treatment coefficients show a significant upward trend in *Employee*, indicating that firms in these industries expanded their workforce following the sanctions. The pre-treatment coefficients are not significantly different from zero, confirming the parallel trends assumption.



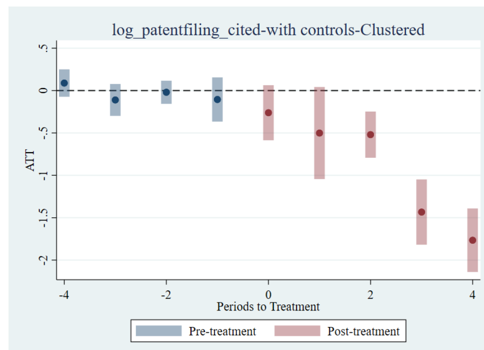
(a) Patent_Filing_Value_Wboot



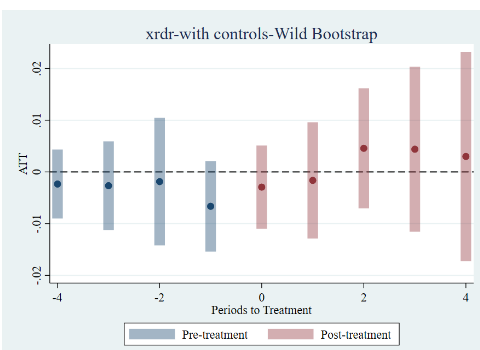
(b) Patent_Filing_Value_Cluster



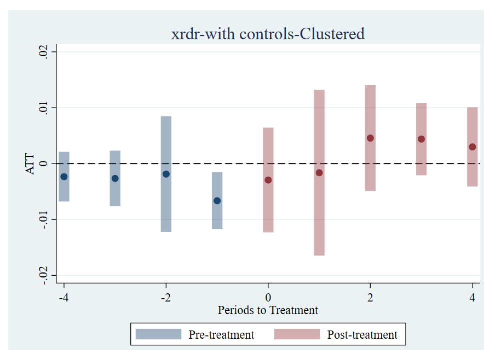
(c) Patent_Filing_Cite_Wboot



(d) Patent_Filing_Cite_Cluster

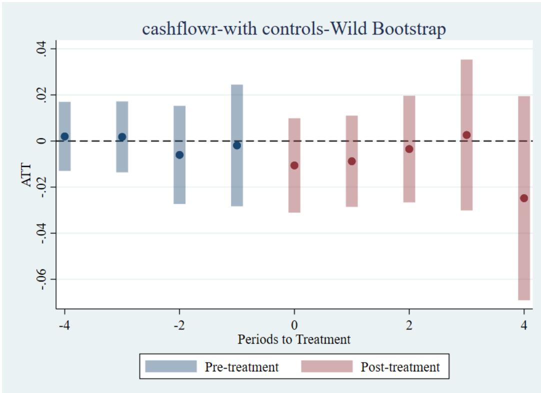


(e) R&D Expense Ratio_Wboot

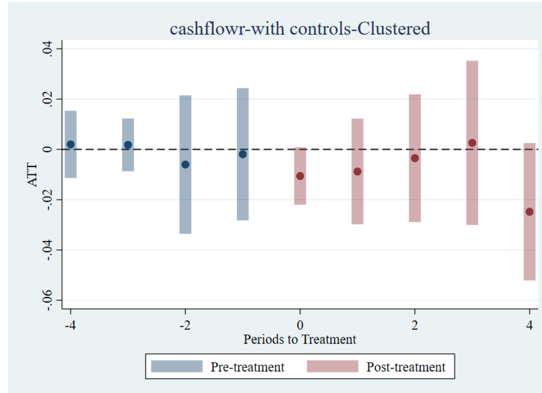


(f) R&D Expense Ratio_Cluster

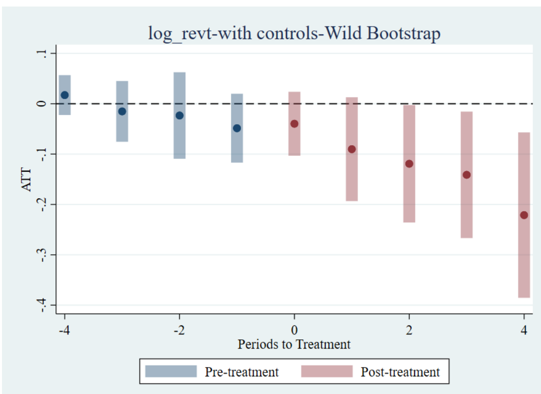
Figure A.9: **The Impact of Export Restrictions on U.S. Suppliers' Innovation** Figure A.9 presents the event study estimates on innovation performance metrics for U.S. upstream suppliers affected by the export restrictions imposed on Chinese firms placed on the Entity List. Panels (a) and (b) display the estimated coefficients for the value of patents (*Patent_Filing_Value*) using Wild Bootstrap and Cluster standard errors, respectively. Panels (c) and (d) present the corresponding results for patent citations (*Patent_Filing_Cite*), while panels (e) and (f) show the R&D expense ratio (*R&D_Expense_Ratio*).



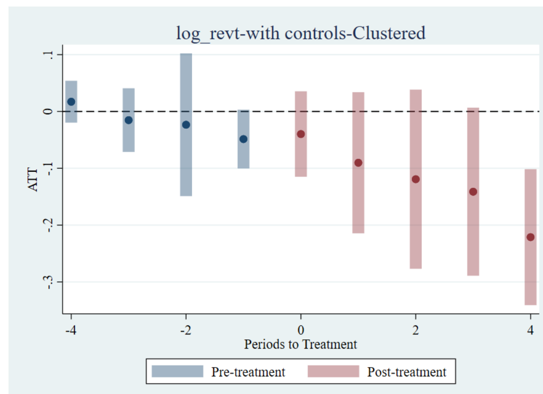
(a) Cash Flow_Wboot



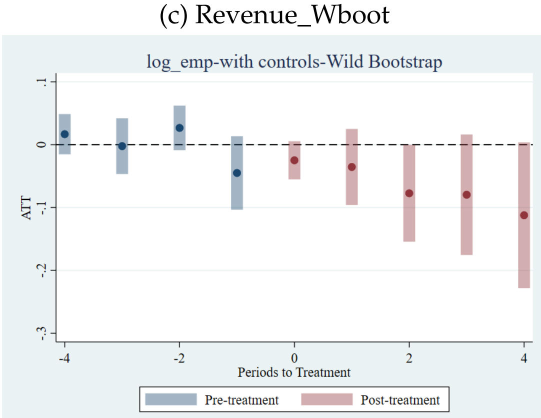
(b) Cash Flow_Cluster



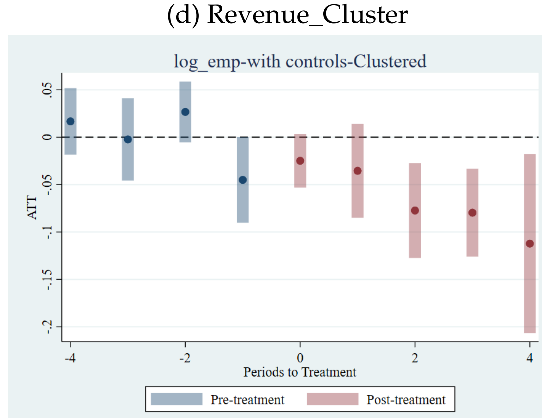
(c) Revenue_Wboot



(d) Revenue_Cluster

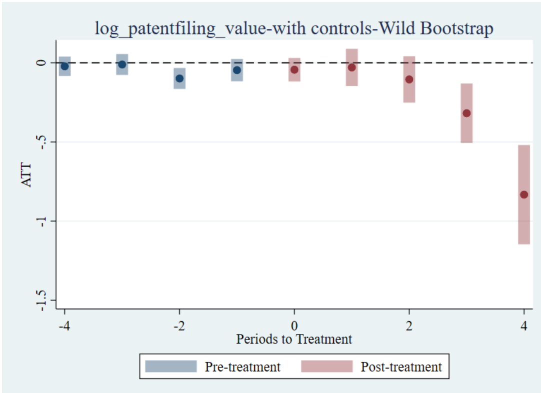


(e) Employee_Wboot

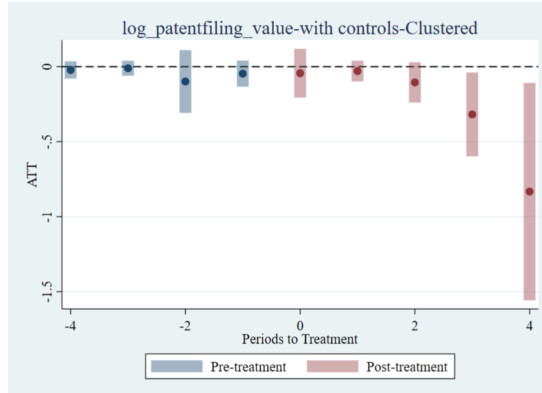


(f) Employee_Cluster

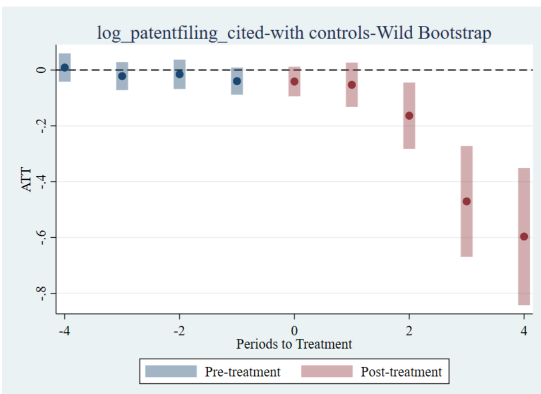
Figure A.10: **The Impact of Export Restrictions on U.S. Suppliers' Performance** Figure A.10 presents the event study estimates on the financial performance metrics of U.S. upstream suppliers affected by the export restrictions imposed on Chinese firms placed on the Entity List. Panels (a) and (b) display the estimated coefficients for cash flow (*Cash_Flow*) using Wild Bootstrap and Cluster standard errors, respectively. Panels (c) and (d) present the corresponding results for revenue (*Revenue*), while panels (e) and (f) show the estimates for the number of employees (*Employee*).



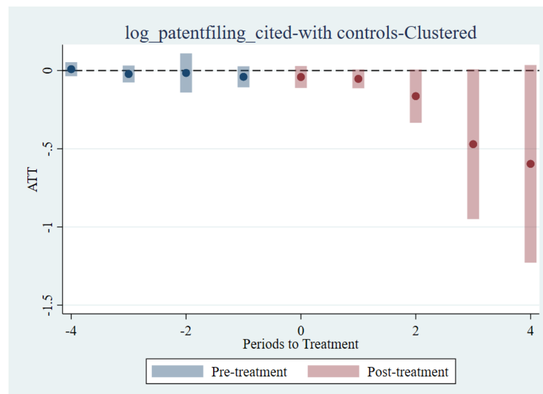
(a) Patent_Filing_Value_Wboot



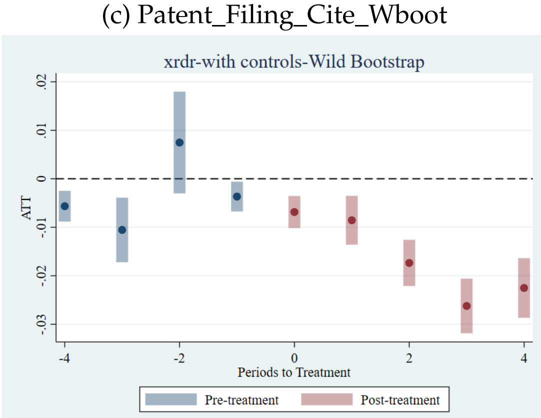
(b) Patent_Filing_Value_Cluster



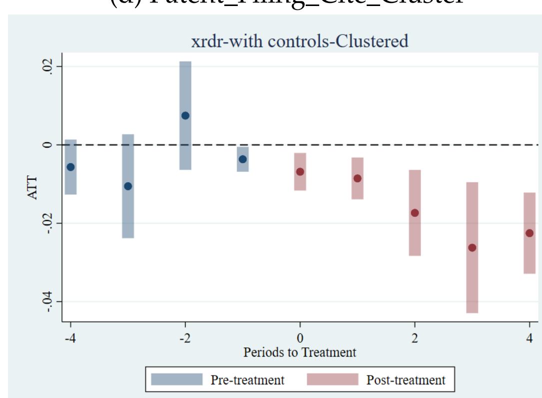
(c) Patent_Filing_Cite_Wboot



(d) Patent_Filing_Cite_Cluster

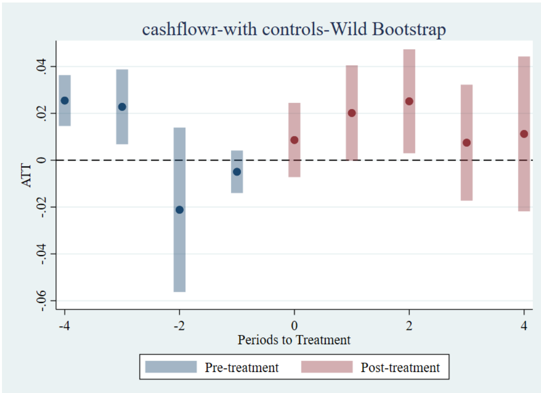


(e) R&D Expense Ratio_Wboot

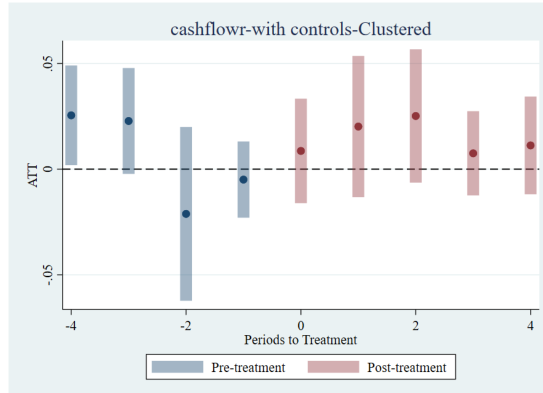


(f) R&D Expense Ratio_Cluster

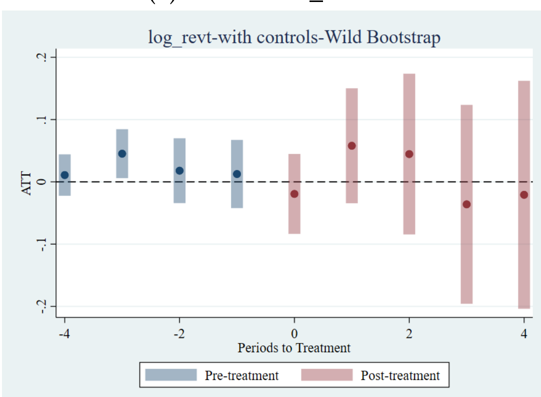
Figure A.11: **The Impact of Export Restrictions on U.S. Suppliers Industry's Innovation** Figure A.11 presents the event study estimates on innovation metrics for U.S. firms operating in the same industries (SIC2 level) as the suppliers of sanctioned Chinese companies. Panels (a) and (b) display the estimated coefficients for patent value (*Patent_Value*), while panels (c) and (d) show the corresponding results for patent citations (*Patent_Cite*). Panels (e) and (f) present the estimates for the R&D expense ratio (*R&D Expense Ratio*).



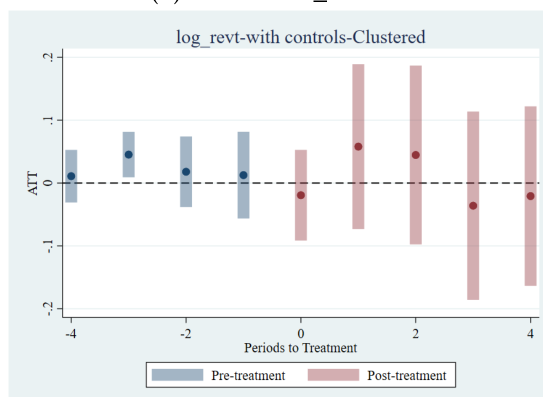
(a) Cash Flow_Wboot



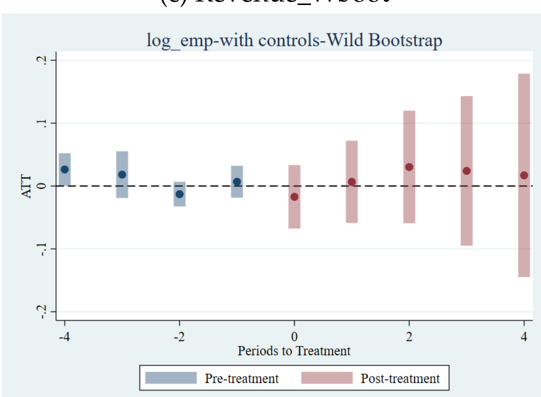
(b) Cash Flow_Cluster



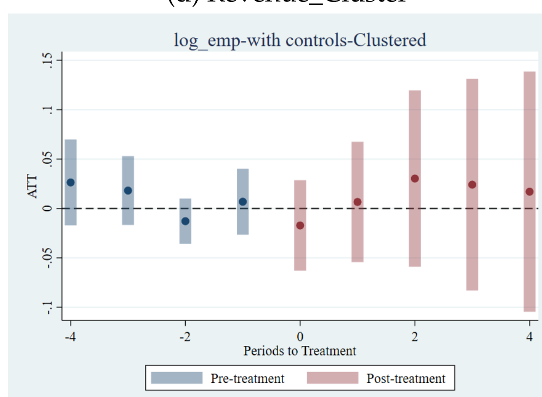
(c) Revenue_Wboot



(d) Revenue_Cluster



(e) Employee_Wboot



(f) Employee_Cluster

Figure A.12: **The Impact of Export Restrictions on U.S. Suppliers Industrys' Performance** Figure A.12 presents the event study estimates on financial performance metrics for U.S. firms operating in the same industries (SIC2 level) as the suppliers of sanctioned Chinese companies. Panels (a) and (b) display the estimated coefficients for cash flow (*CashFlow*), while panels (c) and (d) show revenue (*Revenue*). Panels (e) and (f) present the number of employees (*Employee*).

B Table Appendix

This appendix provides detailed definitions and summary statistics for the variables used in the analysis of Chinese and U.S. firms affected by the U.S. Entity List sanctions. The variable definitions tables (Tables B.1 and B.2) specify the key metrics used to measure innovation, financial performance, and firm characteristics, distinguishing between variables related to Chinese and U.S. firms. Panel A focuses on Chinese firm-level variables such as patent applications, R&D spending, and financial indicators, while Panel B includes variables for U.S. firms, particularly those related to patent value, R&D intensity, and financial metrics.

The appendix also presents summary statistics tables for the control variables used in the analysis. Table B.3 compares the treatment group (Chinese firms listed on the U.S. Entity List) and the control group (other Chinese listed firms) across key control variables such as firm age, asset size, leverage, and return on assets. Similarly, Table B.4 provides summary statistics for U.S. suppliers of Chinese firms on the Entity List, compared to other U.S. firms, covering variables such as cash flow, revenue, and capital expenditures. These summary statistics highlight the differences in firm characteristics between the treatment and control groups, providing essential context for interpreting the empirical results.

Table B.1: Variable Definitions

Variable	Definition
Panel A: Chinese Firm Variables	
$Patent\_Filing$	Number of Patent Applications: The number of patents applied for by a firm during a given fiscal year. Primarily obtained from the CSMAR "Domestic and Foreign Patent Application and Acquisition Table," retaining patents classified as type S5201, supplemented with data from the CSMAR "Patent Details Table."
$Patent\_Issue$	Number of Granted Patents: The number of patents granted to a firm during a given fiscal year. The primary source is the CSMAR "Domestic and Foreign Patent Application and Acquisition Table," retaining patents classified as type S5203, supplemented with data from the CSMAR "Patent Details Table."
$Invention\_Filing$	Number of Invention Patent Applications: The number of "invention-type" patents applied for by a firm during a given fiscal year. This data is primarily sourced from the CSMAR "Domestic and Foreign Patent Application and Acquisition Table.", supplemented with invention patents (type S4901) from the CSMAR "Patent Details Table."
$Invention\_Issue$	Number of Granted Invention Patents: The number of "invention-type" patents granted to a firm during a given fiscal year. The data is primarily sourced from the CSMAR "Domestic and Foreign Patent Application and Acquisition Table.", supplemented with invention patents (type S4901) from the CSMAR "Patent Details Table."
$R\&D\_Person\_Ratio$	Proportion of R&D Employees: The proportion of R&D personnel relative to the total number of employees.
$R\&D\_Spend\_Sum$	R&D Investment: The amount of R&D expenditures in million yuan.
ROA	Return on Assets (ROA): Calculated as net profit divided by the average balance of total assets, where the average balance of total assets is computed as (Total Assets at the End of the Period+Total Assets at the Beginning of the Period)/2
EMP	Employee Number: The natural logarithm of the total number of employees plus one.
Age	Number of Years Since Listing: The number of years since the firm's initial public offering (IPO).
$Asset$	Total Assets (in million yuan): The total asset value of the firm, in million yuan.
$Leverage$	Comprehensive Leverage, calculated as (Net Profit+Income Tax Expense+Financial Expenses+Depreciation+Amortization)/(Net Profit+Income Tax Exposure)
$Tobin$	Tobin's Q Value: Calculated as the ratio of the firm's market value to its total assets.
PPE	Fixed Asset Ratio: The ratio of net fixed assets to total assets.
BIG	Big Four Auditor: A dummy variable indicating whether the auditor is from one of the Big Four accounting firms, 1 for yes, 2 for no.
$Growth$	Revenue Growth Rate: calculated as (Current Period Revenue-Revenue from the Same Period Last Year)/Revenue from the Same Period Last Year

Table B.2: Variable Definitions (Continued)

Variable	Definition
HHI	Industry Herfindahl Index (HHI): calculated as $\sum \left(\frac{X_i}{X}\right)^2$, Where X_i is the revenue of an individual firm and X is the total revenue of the industry to which the firm belongs.
SOE	Ownership Structure: A dummy variable indicating the nature of ownership, 0 represents for Non-state-owned enterprise, 1 represents for State-owned enterprise.
$TOP1$	Shareholding Ratio of the Controlling Shareholder: The percentage of shares held by the controlling shareholder.
$DUAL$	CEO-Chair Duality: A dummy variable indicating whether the firm's CEO and chairperson of the board are the same person, 0 represents not the same person, 1 represents for the same person.
$EXESHR$	Management Ownership Ratio: The percentage of shares held by the firm's management team.
$BOARD$	Board Size: The number of members on the firm's board of directors.
$Direct\_Ind$	Proportion of Independent Directors: The proportion of independent directors on the firm's board of directors.
Panel B: U.S. Firm Variables	
$Patent\_Value$	Economic Value of Firm's Patents: calculated using the method proposed by Kogan et al. (2017).
$Patent\_Cite$	Forward Citation Count of Firm's Patents: adjusted by subtracting the average annual citation count for patents of the same year. The calculation follows the method proposed by Kogan et al. (2017), with citations counted up to the year 2023.
$R\&DRatio$	R&D Ratio: the ratio of a firm's R&D expenditures to its total assets.
$CashFlow$	CashFlow: The ratio of operating income before depreciation (OIBD) minus interest expenses (XINT) and taxes (TXT) to total assets.
EMP	Employee: The natural logarithm of the number of employees, measured in thousands.
$Revenue$	Revenue: the natural logarithm of the firm's revenues, expressed in million dollars.
Age	Number of Years Since Listing: The number of years since the firm's initial public offering (IPO).
$CAPX$	expenditures (capx) divided by lagged asset
MB	Market to Book Ratio
$Sale$	Logarithm of the Sale in $ million
$Leverage$	Financial Leverage Ratio
$PPENT$	Property, Plant and Equipment - Total in $ Million
$Asset$	Assets Total in $ Million

Table B.3: **Summary Statistics: Control Variable of Chinese Firms** Table B.3 presents the summary statistics for control variables used in the analysis, comparing the treatment group (Chinese listed firms on the U.S. Entity List) and the control group (other listed Chinese firms). For detailed definitions of each variable, please refer to the appendix.

Variable	Count	Mean	Std.Dev.	p25	p50	p75
Age						
Treatment	333	9.730	6.727	4.000	9.000	14.000
Control	22,995	9.308	7.333	3.000	7.000	15.000
$Asset$						
Treatment	333	15,969.480	27,994.866	2,526.966	6,301.081	17,387.079
Control	22,995	12,804.354	34,098.872	1,777.354	3,635.898	8,810.796
$Leverage$						
Treatment	333	2.044	1.880	1.200	1.486	2.023
Control	22,995	2.325	2.816	1.197	1.467	2.128
$Tobin$						
Treatment	333	2.423	1.442	1.434	1.931	3.044
Control	22,995	2.073	1.254	1.275	1.672	2.396
PPE						
Treatment	333	0.135	0.103	0.067	0.103	0.180
Control	22,995	0.206	0.140	0.097	0.181	0.286
$Growth$						
Treatment	333	0.226	0.327	0.041	0.167	0.328
Control	22,995	0.192	0.339	0.010	0.130	0.288
HHI						
Treatment	333	0.084	0.063	0.050	0.070	0.089
Control	22,995	0.131	0.139	0.053	0.087	0.153
SOE						
Treatment	333	0.462	0.499	0.000	0.000	1.000
Control	22,995	0.299	0.458	0.000	0.000	1.000
$TOP1$						
Treatment	333	30.482	11.357	21.380	28.130	39.350
Control	22,995	36.455	14.600	25.530	34.980	46.190
$DUAL$						
Treatment	333	0.273	0.446	0.000	0.000	1.000
Control	22,995	0.310	0.463	0.000	0.000	1.000
$EXESHR$						
Treatment	333	16.649	18.975	0.056	11.159	31.477
Control	22,995	16.010	20.446	0.007	3.243	31.098
$BOARD$						
Treatment	333	8.568	1.707	7.000	9.000	9.000
Control	22,995	8.468	1.591	7.000	9.000	9.000
$Direct\_Ind$						
Treatment	333	37.733	5.037	33.330	36.360	42.860
Control	22,995	37.541	5.252	33.330	33.330	42.860

Table B.4: **Summary Statistics: Control Variable of US Suppliers** Table B.4 presents the summary statistics for control variables used in the analysis, comparing the treatment group (U.S. suppliers of Chinese firms on the Entity List) and the control group (other U.S. firms). For detailed definitions of each variable, please refer to the appendix.

Variable	Count	Mean	Std.Dev.	p25	p50	p75
Age						
Treatment	1,534	25.545	20.705	11.000	21.000	34.000
Control	39,147	19.579	18.646	5.000	15.000	27.000
$CAPX$						
Treatment	1,534	0.040	0.045	0.014	0.025	0.047
Control	39,147	0.050	0.062	0.013	0.030	0.062
MB						
Treatment	1,534	2.281	1.652	1.285	1.766	2.604
Control	39,147	2.174	1.760	1.133	1.564	2.489
$Sale$						
Treatment	1,534	7.193	2.361	5.552	7.098	8.848
Control	39,147	6.423	2.391	4.974	6.618	8.058
$Leverage$						
Treatment	1,534	0.213	0.177	0.047	0.206	0.316
Control	39,147	0.269	0.235	0.065	0.239	0.403
$PPENT$						
Treatment	1,534	3,799.738	11,087.707	40.384	243.918	1,643.096
Control	39,147	2,524.470	7,907.801	22.828	172.043	1,082.613
$Asset$						
Treatment	1,534	18,006.863	38,317.508	345.423	1,783.967	10,455.693
Control	39,147	7,549.048	20,663.471	231.177	1,046.400	4,498.376