Who Strikes the Most? The Impact of China-US Tariff War on the Survival of Chinese Enterprises*

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Abstract

This paper investigates the impact of the China-US trade war on the survival of Chinese enterprises from 2014 to 2019, with a focus on the differential effects across firm sizes and their roles in subcontracting networks. Using several datasets, we find that enterprises **indirectly** exposed to the tariff shocks experienced significant increase in exit rates, compared to their directly exposed counterparts. We argue that order-subcontracting networks transfer the shock on directly exposed firms to their subcontractors, which are mostly small and medium-sized enterprises (SMEs). These findings highlight the importance of network structures in magnifying the spillover effects of trade policy shocks, particularly for SMEs that rely on large firms for subcontracting orders.

Key Words: Order subcontracting, firm survival, China-US tariff war

JEL code: F14, O19, O44

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1 Introduction

The literature on firm dynamics has extensively documented that small firms are significantly more vulnerable to market exits compared to their larger counterparts, primarily due to their lower productivity (Hopenhayn, 1992; Melitz, 2003; Arkolakis, 2016). While much of this research focuses on firm-level characteristics, it largely overlooks the role of production networks in shaping firms' survival outcomes. This study introduces a novel perspective by examining how the structure of production networks contributes to the higher exit rates of small firms. Specifically, it focuses on the role of order subcontracting networks in transmitting the shock of the 2018–2019 China–US tariff war. The shock had a significant impact on China, markedly increasing trade policy uncertainty (TPU) since 2017 (Benguria et al., 2022; Caldara et al., 2020) and resulting in a notable decline in exports to the US (Jiang et al., 2023). While the tariffs directly impacted large firms exposed to them, these shocks were subsequently propagated to SMEs operating within the same industry. By examining how this cascading effect impacts firm survival, this paper sheds light on the systemic vulnerabilities faced by small firms within interconnected production systems.

Order subcontracting is a widespread practice (Chen and Ross, 2000; Hu et al., 2013; Li and Zhang, 2015; Wu et al., 2014; Guo and Wu, 2018), wherein a firm delegates part of its tasks to a subcontractor, typically within the same industry. The motivations behind order subcontracting include managing demand uncertainty (Van Mieghem, 1999) and reducing production costs, particularly when cost structures are convex (Spiegel, 1993). Based on the 2018 Enterprises Survey for Innovation and Entrepreneurship in China (ESIEC), approximately one-quarter of Chinese enterprises participate in such order subcontracting networks. These networks are directional, with firms often acting as both order givers and order recipients. The survey further reveals that larger firms tend to distribute their orders to SMEs, positioning the latter as net recipients within the subcontracting relationship.

Our study draws on a rich combination of datasets to comprehensively analyze the survival outcomes of Chinese enterprises during the period of 2014-2019. Using the Chinese Customs Transaction Dataset, we identify firms directly exposed to tariff shocks based on their pre-tariff-war export profiles. We integrate this data with firm-level records from the China Business Registration Dataset, which provides detailed information on firm exit, and the National Tax Survey Database, which offers longitudinal data on large enterprises. Additionally, we leverage ESIEC to examine the structure and prevalence of subcontracting relationships across SMEs.

Our main finding shows that firms directly affected by the shock began adjusting their production as early as 2017. This coincides with the US government's launch of the "Section 232 Investigation" to assess whether steel and aluminum imports from China threatened national security. Event study estimates reveal output changes for directly exposed firms of -0.04% in 2017, -0.05% in 2018, and -0.13% in 2019.

Next, we examine the survival status of the entire population of Chinese manufacturers before and during the China–US tariff war. Prior to the shock, directly exposed enterprises were inherently less likely to exit the market, with an exit rate 2.5% lower than that of indirectly exposed enterprises operating in the same county and industry. However, this gap in exit rates widened significantly after 2017: the gap increased to 3.9% in 2017 and further to 4.0% in 2018. A series of robustness checks yielded consistent results. These findings underscore that indirectly exposed firms faced a substantially greater burden after 2017 compared to directly exposed firms and the pre-2016 period.

Finally, we explore the reasons behind the widened gap in exit rates between directly and indirectly exposed firms, focusing on the role of the order subcontracting network. We provide two pieces of suggestive evidence. First, recognizing that SMEs, rather than large firms, are more likely to be net order recipients,

we categorize all manufacturers into three groups based on their registered capital: small firms, medium firms, and large firms. Comparing the exit rates of directly exposed firms within each group, we find that the widened exit rate gap is only evident among small and medium-sized firms. This pattern is consistent with the order subcontracting channel. Second, we analyze the prevalence of subcontracting across the 117 counties surveyed in the ESIEC 2018. Our findings reveal that the exit rate gap between directly and indirectly exposed firms is robustly more pronounced in counties with higher levels of subcontracting activity.

This study contributes to the literature in two key ways. First, it extends the understanding of firms' resilience within production networks. Theoretically, the role of networks in improving or undermining resilience remains ambiguous. For example, Behrens et al. (2020) empirically find that, when facing import competition from China, plants in clusters exhibit lower exit rates compared to others in the short run, but the mechanisms driving this effect are not discussed. Kranton and Minehart (2000) develop a theoretical model suggesting that network structures between suppliers and buyers offer greater resilience than vertically disintegrated firms under demand uncertainty. Similarly, Uzzi (1996) demonstrate that contractors with long-term, ongoing relationships with multiple manufacturers have lower failure rates, attributing this to trust, fine-grained information, and joint problem-solving within such networks. However, unbalanced networks can amplify shocks, particularly when key firms are adversely affected. Uzzi (2018) document that the loss of a core organization in a network has a disproportionately negative impact on the network's overall viability, as non-core firms often struggle to find alternative partners for their specialized investments. Consistently, Martin et al. (2017) find that competitiveness clusters exhibit weaker resilience, likely due to their dependence on a single leading exporter whose failure can destabilize the entire cluster. Similarly, Marzano (2025) report that firms in horizontal clusters suffer disproportionately from catastrophic events, such as earthquakes. This paper builds on these insights by examining how the structure of subcontracting networks mediates the propagation of trade policy shocks, shedding light on the interplay between network inter-dependencies and firm survival.

Second, this paper contributes to the literature on the economic impacts of the China–US tariff war. While the effects of tariff increases on trade volumes (Jiang et al., 2023; Jiao et al., 2024; Sheng et al., 2025) and economic effects (Chor and Li, 2024; Benguria et al., 2022; He et al., 2021; Guo et al., 2024; Cui and Li, 2021) have been widely documented, the heterogeneous impacts of these shocks on firms' survival remain insufficiently understood. This paper builds on this body of work by examining the survival of Chinese enterprises. Specifically, it highlights that indirectly exposed firms bear disproportionate impacts, as shocks propagate through subcontracting networks. By identifying these mechanisms, the study sheds light on the systemic vulnerabilities inherent in interconnected production systems, contributing to our understanding of trade policy's far-reaching effects.

2 Data and Measurements

This study leverages a rich and comprehensive dataset from multiple sources to examine the impact of the China-US trade war on the survival of Chinese enterprises. First, we identify the universe of directly impacted exporters by utilizing the Chinese Customs Dataset in conjunction with data on tariff changes between China and the United States. Second, we rely on a national survey dataset to capture the timing of changes in output among these directly exposed enterprises. Third, we turn to China Business Registration Data, which provides comprehensive coverage of all registered Chinese enterprises. This dataset enables us to track the survival status of firms across different industries, regions, and firm sizes. Finally, we incorporate

a large-scale enterprise survey to explore the differential survival outcomes between directly impacted firms and SMEs. This multi-faceted approach allows us to uncover both the direct and indirect effects of the trade war, as well as the role of firm size and network structures in mediating these impacts.

2.1 Customs Dataset and Tariff Changes Between China and the US

The Chinese Customs Transaction Dataset provides detailed, firm-level export information, including annual export values broken down by product (at the HS6 level) and destination country. To evaluate firms' exposure to the China-US trade war, we incorporate tariff data from the Global Tariff Database: US Trade War Extension (v.2025-10)[1]. This database provides a comprehensive record of US import tariffs during the trade war period, including product-specific tariff changes, the magnitude of tariff increases, and the timing of their implementation. So, we could identify products exported from China to the United States that were directly impacted by tariff hikes during 2018-2019. By integrating the Chinese Customs Dataset with the tariff database, we construct a firm-level binary indicator of trade-war exposure. This measure enables us to quantify the immediate impact of the trade war on directly exposed firms, providing a critical foundation for analyzing the downstream effects on firm production and survival dynamics.

To address potential endogeneity concerns in firms' exposure status, we utilize the 2014 Customs Dataset to predict whether firms would be directly affected by the tariff war. Specifically, we use firms' export products and destination markets in 2014 to forecast their status of being impacted by the tariff changes introduced several years later. The rationale behind this approach is that firms' export destinations are typically persistent over time. This persistence arises because entry into foreign markets requires firms to incur fixed and sunk start-up costs, while continued exporting allows firms to accumulate market-specific knowledge, customer base, and other intangible assets that raise the value of staying in the market (Das et al., 2007; Timoshenko, 2015; Eaton et al., 2025). This makes past export behavior a reliable predictor of future exposure. In this paper, firms are classified as directly exposed to the tariff war shock if their 2014 product-destination combinations appear on the list of products affected by the tariff increases during the China-US trade war.

2.2 National Tax Survey Including Large Enterprises

The National Tax Survey Database, collected by the Chinese State Administration of Taxation, provides detailed firm-level information on two categories of enterprises: (1) large enterprises that contribute significantly to tax revenue and (2) smaller firms that are randomly selected on an annual basis. The former group of enterprises can be longitudinally tracked throughout the dataset, allowing for a more consistent analysis of firm performance over time. This dataset includes comprehensive metrics on firm performance, such as output, employment, investment, and other key operational indicators.

For this study, we utilize data from 2014 to 2019, focusing specifically on manufacturing firms that appear in the dataset at least three times during the observation period. This selection yields approximately 50,000 observations per year between 2014 and 2019. To ensure data reliability, we apply a censoring rule, excluding the top 1% and bottom 1% of firms based on their output values.

To further enrich our analysis, we merge the surveyed firms in this dataset with the 2014 Customs Dataset. This integration enables us to identify whether firms that were active in 2014 would be directly exposed to the China-US tariff war.

[1] See Rodríguez-Clare et al. (2025) and Teti (2024) for technical documentation.

2.3 China Business Registration Dataset

To analyze firm survival, we draw on the complete set of Chinese business registration records. This dataset, compiled by the Chinese State Administration for Market Regulation, provides detailed information on firm entries, exits, and key attributes such as registered capital, industry classification, and geographic location. Our study focuses specifically on manufacturing enterprises that were active at the end of 2014, tracking their survival status over the period from 2015 to 2019. In the following notation, *Exit_XXXX* indicates that the enterprise either canceled or had its registration revoked in the year XXXX. We interpret this action as the enterprise exiting the market. The dataset includes more than 3 million firm-level observations, offering a comprehensive view of survival dynamics within the manufacturing sector.

We also merge this dataset with the 2014 Customs Dataset to obtain each firm's shock exposure status. It turns out that 1.8% of the manufacturers in 2014 are directly exposed to the future China-US tariff war.

2.4 Field Survey Including SMEs

To examine the divergence in survival status between large and smaller enterprises, we leverage a field survey to explore their network structures, specifically focusing on order-subcontract networks. The Enterprises Survey for Innovation and Entrepreneurship in China (ESIEC), conducted by Peking University, provides detailed data on entrepreneurship and firm performance in China through field tracking surveys. In 2018, the ESIEC covered 117 counties across six provinces, with each county randomly sampling 400 business entities. The samples are representative at both the county and provincial levels. In this survey round, over 6,000 enterprises successfully completed interviews.

The 2018 ESIEC survey primarily captured data on enterprises that were active at the time of the survey, documenting their performance in 2017. Notably, the survey collected information on the proportion of subcontracted orders these enterprises received or shared with their peers. For this study, we define two key dummy variables: (1) *subcontract*, which indicates whether a surveyed enterprise engaged in order subcontracting in 2017, and (2) *net-product-giver*, which indicates whether the surveyed enterprise was a net recipient of orders. A detailed description of order subcontracting behavior is provided in the next section. We compute the county-level averages of subcontract and net-product-giver variables, using them as measures of the prevalence of order-subcontract networks within each county.

Table 1 presents the summary statistics for the key variables used in this study. Panel A highlights firms' survival status and their exposure to shocks. It provides insight into the survival dynamics of manufacturers active in 2014: 4.2% exited the market in 2015, while among the survivors, 4.8% exited in 2016. The exit rate continued to rise, reaching 5.4% in 2017, 5.8% in 2018, and 5.7% in 2019. Among the 3 million manufacturers active in 2014, 1.8% are predicted to have been directly exposed to the China-US tariff war. Panel B focuses on large firms in the tax survey dataset, while Panel C examines the county-level prevalence of order-subcontract networks.

3 Background of Order Subcontract

Order subcontracting, also referred to as horizontal subcontracting, involves a firm delegating a portion of its tasks to a subcontractor. This practice is widely utilized across various industries, including airlines (Chen and Ross, 2000; Hu et al., 2013), maritime shipping (Li and Zhang, 2015), vehicle manufacturing [2],

[2]News from Reuters https://www.reuters.com/article/business/mazda-to-produce-toyota-vehicles-at-its-mexico-plant-idUSL3E8M94SF/

Table 1: Summary Statistics

Variable	Obs.	Mean	Std
Panel A. Firm Level: Business Registration Data			
Exit_2015	3,066,069	0.042	0.201
Exit_2016	2,936,392	0.048	0.213
Exit_2017	2,796,579	0.054	0.226
Exit_2018	2,645,346	0.058	0.234
Exit_2019	2,491,804	0.057	0.232
Exposure	3,066,069	0.018	0.131
Panel B. Firm Level: Tax Survey Data on Large Firms			
Ln(output)	287,622	9.793	2.299
Panel C. County Level			
Subcontract Prevalence	117	0.253	0.108
Net-Product-Giver Prevalence	117	0.102	0.055

Notes: This table presents the summary statistics. In Panel A, *Exit_XXXX* is a dummy variable that indicates whether an enterprise active in year XXXX-1 exited the market in year XXXX. *Exposure* is a dummy variable that denotes whether an enterprise is directly exposed to the China-US tariff war. The details of the variable generating process can be found in Section 2.1.

semiconductor manufacturing (Wu et al., 2014), and online platforms, such as hotel overbooking (Guo and Wu, 2018).

The ESIEC 2018 survey sheds light on the widespread adoption of order subcontracting among Chinese enterprises. According to Panel C of Table 1, the average participation rate in order subcontracting across the 117 surveyed counties is 25.3%.

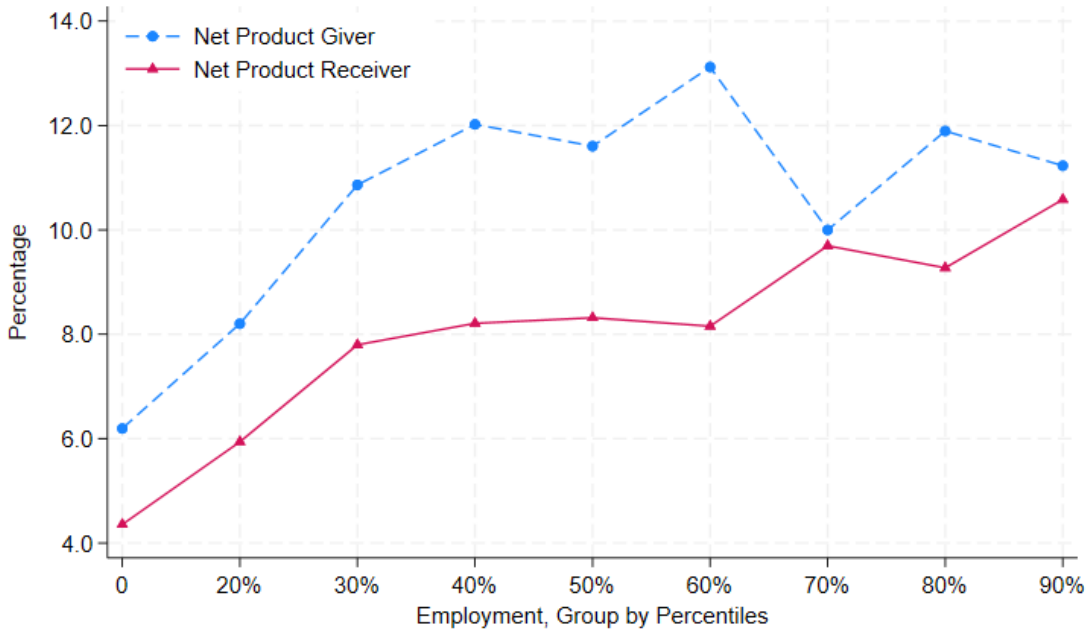
Order subcontracting exhibits a directional nature, with some firms predominantly acting as net recipients of orders (net-product-receivers) and others as net givers of orders (net-product-givers). Figure 1 highlights this role differentiation among firms of varying employment sizes. Firms are categorized into three groups: net product givers, net product receivers, and others. Notably, 91% of firms classified as "others" do not engage in order subcontracting. The figure illustrates the percentages of givers and receivers across different employment-size groups, where employment groups are defined based on employment percentiles (10th to 90th percentile values: 0, 0, 2, 3, 4, 6, 10, 15, 30). Since firms with no employees constitute over 20% of the sample, they are grouped under "0".

Two key patterns emerge. First, among firms with fewer than six employees (below the 60th employment percentile), larger firms are more likely to participate in the subcontracting network. Second, for firms with six or more employees, the likelihood of being a net product giver decreases as firm size increases, while the likelihood of being a net product receiver rises. This suggests that larger firms are more inclined to delegate tasks to smaller firms through subcontracting.

Exporters tend to be significantly larger in size, which leads to an even more pronounced divergence in order subcontracting behavior between exporters and non-exporters, as shown in Figure 2. In the left panel, 18.3% of exporters are identified as net-product receivers, compared to only 11.5% of non-exporters. The right panel focuses exclusively on exporters, dividing them into two groups—large and small exporters—based on the median employment size. Among large exporters, the proportion of net-product receivers rises to 23.5

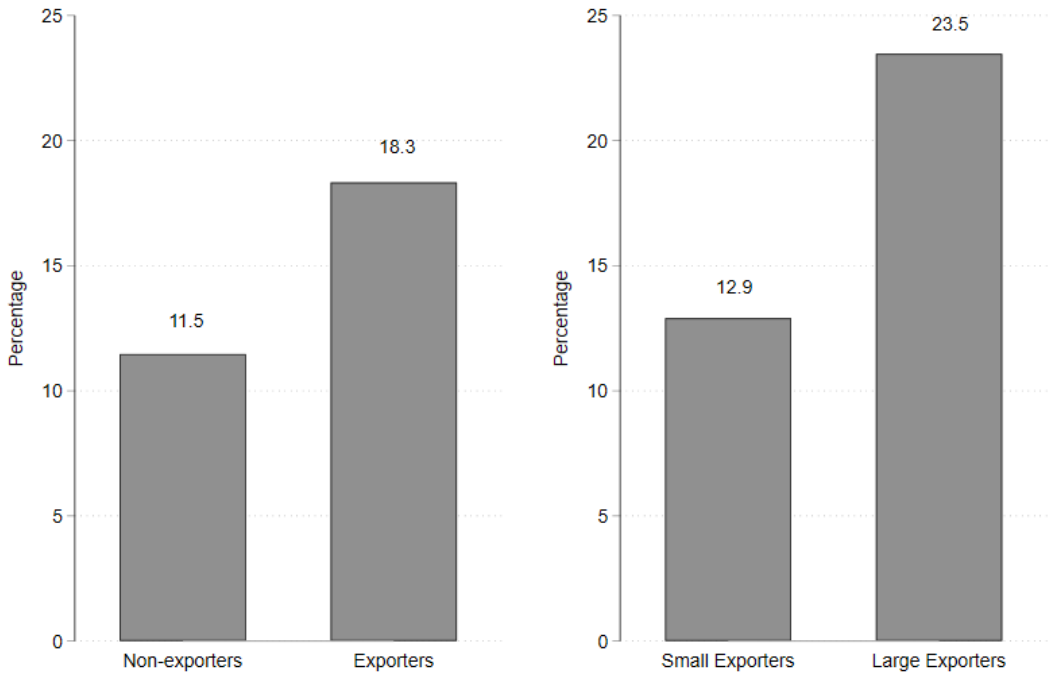
In summary, exporters, particularly large ones, are very likely to delegate portions of their orders to

Figure 1: The Prevalence of Subcontract, by Firm Size



Notes: Firms are classified into three groups: net product giver, net product receiver, and others. 91% of firms in the group of "others" do not engage in order subcontracting. This figure plots the percentage of givers and receivers in each employment-size group of firms. The employment group is classified with the employment percentiles, with the 10th to 90th value as 0, 0, 2, 3, 4, 6, 10, 15, 30, respectively. Since firms without any employment occupy a a share of more than twenty percent, we group those firms as group "0". Group "20%" denotes firms with employment but less than 2, and group "30%" denotes firms with at least 2 employments (the 30 percentile) but less than 3. Finally, group "90%" denotes firms with at least 30 employments (the 90 percentile).

Figure 2: The Prevalence of Subcontract, by Exporter Status



Notes: This figure shows the percentage of enterprises being net-product receivers. The left panel compares exporters and non-exporters. The right panel focuses exclusively on exporters, dividing them into two groups—large and small exporters—based on the median employment size.

other firms, primarily smaller enterprises. This creates a production network within the same industry, where smaller enterprises play a crucial role in fulfilling subcontracted orders from exporters.

4 Identifying the Timing of the Shock

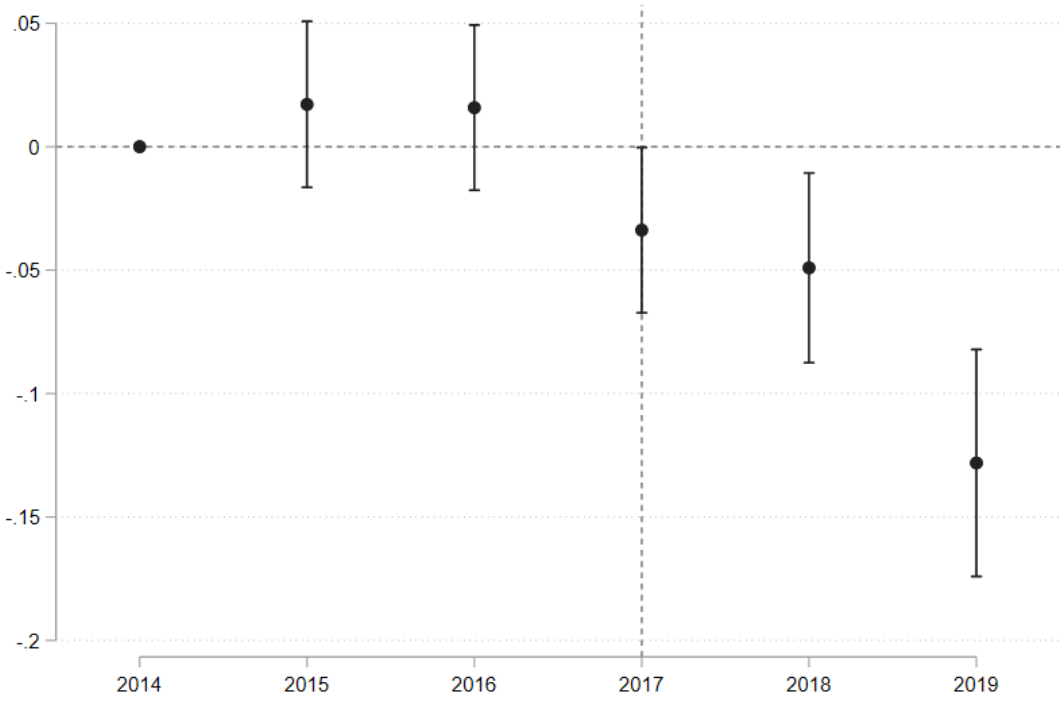
The dynamics of tariff changes during the China–U.S. trade war are well documented in the literature (Jiang et al., 2023; Jiao et al., 2024). A clear pattern emerges: tariffs increased significantly after July 2018. However, firms may have adjusted their production earlier, ahead of the actual tariff hikes. This is likely due to the US government launching the "Section 232 Investigation" in April 2017 to determine if steel and aluminum imports from China posed a threat to national security. To analyze the timing of firms' production adjustments, we estimate the following specification:

$$Ln(output)_{i,t} = \alpha + \Sigma_t \beta_t Exposure_i D_t + \lambda_t + \lambda_i + \epsilon_{i,t}, \tag{1}$$

where $Ln(output)_{i,t}$ denotes firm i's output (in log value) in year t, and $Exposure_i$ is an indicator variable that equals one if firm i exported products to the US in 2014 that would later be subject to tariff increases during the 2018–2019 trade war. D_t is year dummy. λ_t and λ_i are year and firm fixed effects, respectively. standard errors $\epsilon_{i,t}$ are clustered at the firm level. The coefficients of interest, β_t, capture the change in output for exposed firms in each year t relative to a baseline year.

Our analysis draws on tax survey data from 2014 to 2019. We restrict the sample to manufacturing firms

Figure 3: The Decline in Firm Output is Much Smaller in Magnitude Than the Drop in Aggregate Exports.



Notes: This figure plots the estimated β_t in equation 1, with vertical lines as the 95% confidence intervals. We control of year and firm fixed effects. The baseline year is 2014, and the standard errors are clustered at the firm level. The dashed gray line marks the year in which TPU began to rise sharply.

that appear in the dataset at least three times during this period. This selection effectively retains only large enterprises, as only large enterprises that contribute significantly to tax revenue would be longitudinally tracked by the dataset. Consequently, the estimated coefficients β_t capture changes in output for firms directly exposed to the China-US trade war, relative to large firms that were not directly exposed.

Figure 3 plots the estimated β_t coefficients, with 2014 as the baseline year. The estimates for 2015 and 2016 are not statistically different from zero, but they begin to decline in 2017, with sharper drops in 2018 and 2019. This pattern aligns with evidence of rising TPU prior to the imposition of tariffs. Benguria et al. (2022) document a marked increase in firm-level TPU among Chinese listed firms starting in 2017. Similarly, Caldara et al. (2020) report a sharp rise in TPU based on news and earnings calls in the United States during the same period, reflecting escalating trade tensions before actual tariff implementation. As heightened TPU dampens investments (Benguria et al., 2022), forward-looking clients (firms) may have begun scaling back demands (operations) in anticipation of future trade disruptions.

5 Impacts on Firms' Exit Rate

In this section, we examine the divergence in firm dynamics between those directly and indirectly exposed to the China–US tariff shock. Our analysis focuses on firm survival, a key outcome that can be observed across the entire population of Chinese manufacturing enterprises, including SMEs.

5.1 Identification Strategy

Given that firm i is active in year $t-1$ ($Exit_{i,t-1} = 0$), we estimate its probability of exiting the market in year t using the following specification:

$$Exit_{i,t} = \alpha + \gamma_t Exposure_i + \lambda_{c(i),j(i)} + \epsilon_i, \tag{2}$$

where $c(i)$ and $j(i)$ represent firm i's county and SIC-2 industry, respectively. The term $\lambda_{c(i),j(i)}$ denotes county-by-industry fixed effects. Standard errors are clustered at the county by industry level. In this model, γ_t captures the difference in exit probabilities between firms directly and indirectly exposed to the shock in year t. Since county-by-industry fixed effects are included, γ_t essentially reflects the difference in exit rates between directly and indirectly exposed firms within the same county and industry.

We estimate equation 2 for each year from 2015 to 2019, allowing us to track the dynamics of γ_t over time. This enables us to analyze whether the exit rate gap between directly and indirectly exposed firms widens or narrows over the observed period.

5.2 Baseline Results

Figure 4 presents the estimates of γ_t from equation 2 for each year from 2015 to 2019 (left to right). Two key patterns emerge from the results. First, the estimates for γ_{2015} and γ_{2016} are approximately -0.023 and -0.026 respectively. This indicates that even prior to the tariff shock, firms that would later face higher export tariffs were less likely to exit the market. This suggests inherent differences between directly and indirectly exposed firms in the same county and same industry. Nonetheless, the relatively stable estimates around -0.025 imply that this inherent heterogeneity accounts for a roughly 2.5% lower exit rate for directly exposed firms compared to indirectly exposed ones.

Second, following the significant increase in TPU, the estimates of γ_t decline sharply, dropping from -0.026 to -0.039 in 2017, and to -0.040 in 2018. This indicates a widening gap in exit rates between directly and indirectly exposed firms. Considering that the overall exit rate rises during this period (as shown in Panel A of Table 1), these results highlight that indirectly exposed firms experienced a substantially higher exit rate after 2017 compared to directly exposed firms and the pre-2016 period.

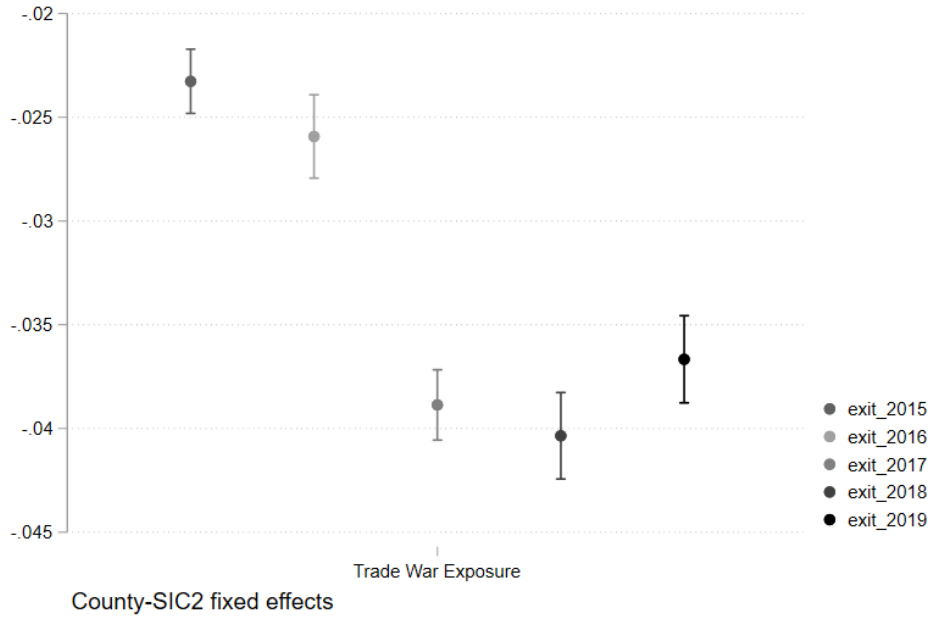
5.3 Robustness Checks

We conducted a series of robustness checks to confirm that the observed exit rate gap reflects differences between directly and indirectly exposed firms, thereby demonstrating the impact of the China-US tariff war. Specifically, these checks aim to address the concern that the observed differences might instead stem from disparities between exporters and non-exporters.

Figure 5 illustrates the logic underlying these robustness checks. Squares represent large enterprises, while triangles denote SMEs. Solid-line squares indicate exporters, with dark-shaded squares representing exporters directly exposed to the China-US tariff war. The figure illustrates two county-SIC2 groups, A and B, where group B contains no firms directly exposed to the tariff shock. Note that the baseline results shown in Figure 4 capture the exit rate gap between shaded and non-shaded enterprises, restricting the comparison to firms within the same county-industry group.

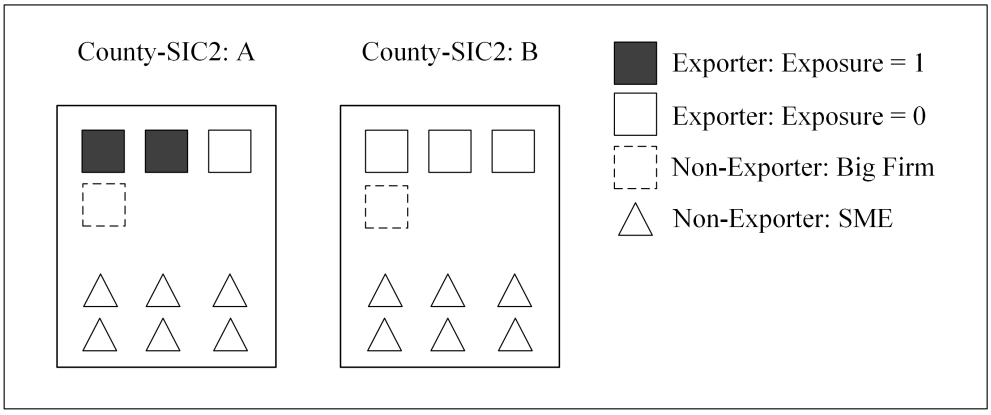
First, we focus on county-industry pairs that have no firms directly exposed to the tariff shock. Specifically, we consider county-industry groups similar to group B in Figure 5 and calculate the exit rate gap

Figure 4: The Uneven Exit Patterns Between Directly and Indirectly Exposed Firms



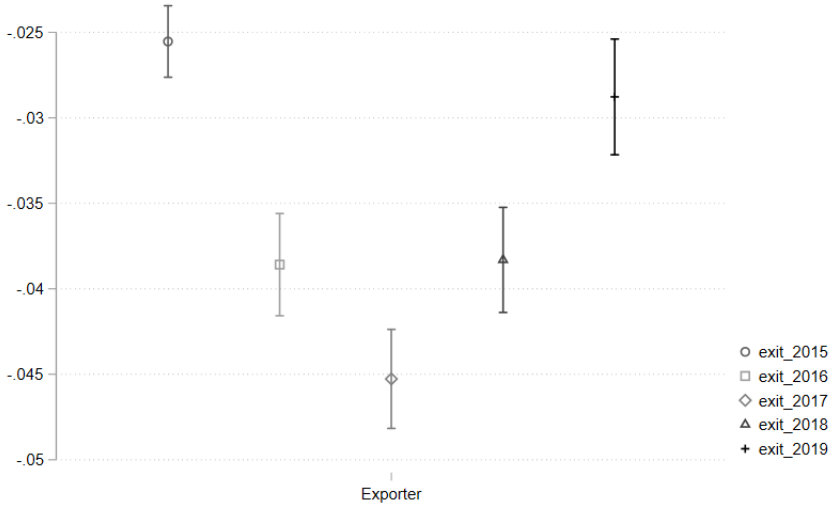
Notes: This figure presents the estimates of γ_t from equation 2 for each year from 2015 to 2019 (left to right), which captures the gap in exit rates between directly and indirectly exposed firms. The vertical lines indicate the 95% confidence intervals.

Figure 5: Illustration of the Robustness Checks



Notes: This figure presents the logic of the robustness checks.

Figure 6: County-SIC2 Without Directly Exposed Firms: The Gap of Exit Rate Between Exporters and Non-exporters



Notes: Firms in county-SIC2 without directly exposed firms are remained for analysis. This figure presents the estimates of γ_t from equation 2 for each year from 2015 to 2019 (left to right), except the independent variable is $Exporter$, a dummy variable indicating firms' export status in 2014. The vertical lines indicate the 95% confidence intervals.

between exporters and non-exporters. The purpose of this check is to address the concern that the observed results in the baseline analysis may simply reflect inherent differences between exporters and non-exporters, rather than the impact of the tariff shock. If this concern holds, we would expect to observe similar patterns when using county-industry pairs like group B. The specification used in this robustness check mirrors equation 2, except the independent variable is $Exporter$, a dummy variable indicating firms' export status in 2014. The estimation results, presented in Figure 6, show that while the coefficients are significantly different from zero, they do not follow the same pattern as the baseline results. This suggests that differences between exporters and non-exporters do not drive the baseline findings.

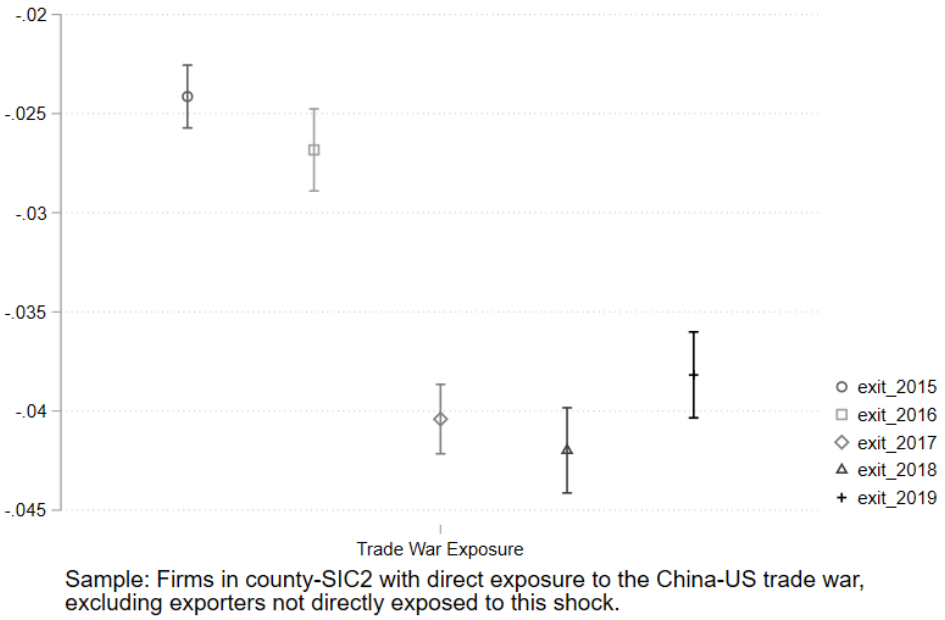
Next, we restrict the sample to county-industry pairs with firms directly exposed to the tariff shock and exclude exporters that are not directly exposed. Here, we compare the exit rates between directly exposed firms and non-exporters, focusing on county-industry groups similar to group A in Figure 5. The specification remains consistent with equation 2. The results, displayed in Figure 7, align closely with those of the baseline analysis.

Overall, these robustness checks confirm that the divergence in exit rates between directly and indirectly exposed firms is indeed driven by the China-US trade war, rather than differences in export status.

6 Mechanism Tests

In this section, we aim to demonstrate that the order subcontracting behavior between directly and indirectly exposed firms can account for the divergence in exit rates. The underlying rationale is that, although increased tariffs lead to reduced demand, directly exposed firms do not necessarily shoulder the entire burden. Instead, they may continue utilizing their own production capacity while allocating fewer orders to their subcontractors, who are often located in the same county and operate within the same industry as

Figure 7: County-SIC2 With Directly Exposed Firms: The Gap of Exit Rate Between Directly Exposed Firms and Non-exporters



Notes: Directly exposed firms and non-exporters within county-SIC2 regions containing directly exposed firms are retained for analysis. This figure presents the estimates of γ_t from equation 2 for each year from 2015 to 2019 (left to right). The vertical lines indicate the 95% confidence intervals.

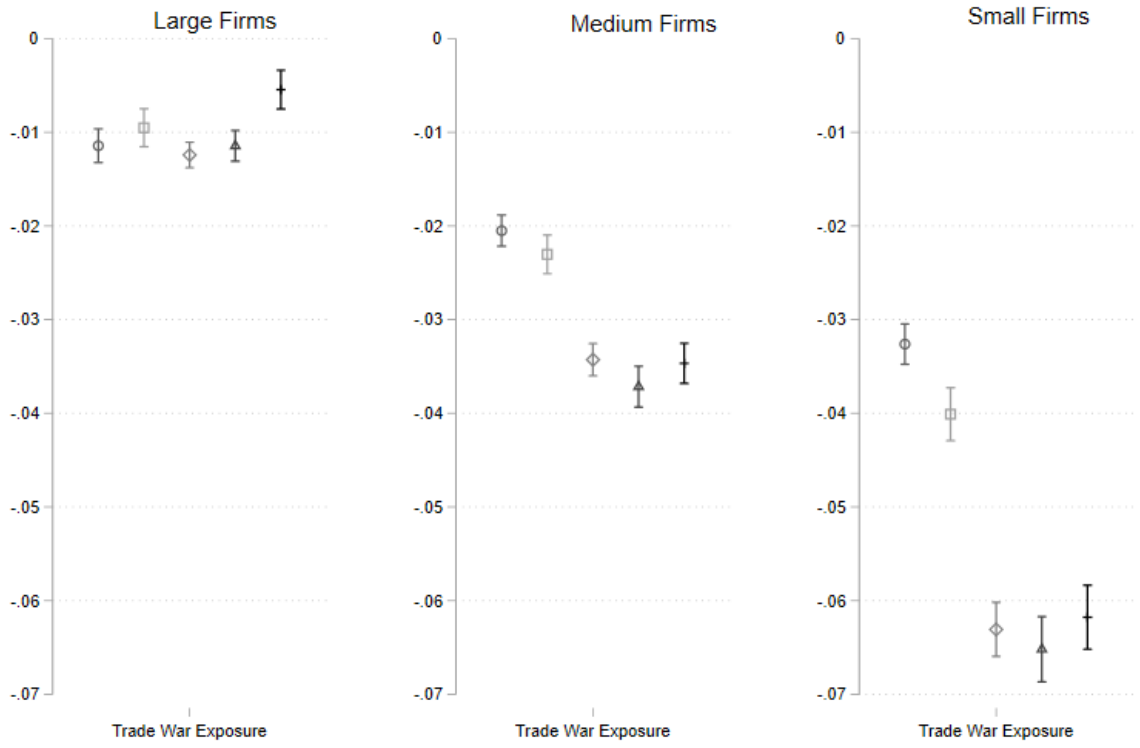
the directly exposed firms. Since these subcontractors tend to be smaller in size, this shift could result in a higher exit rate among smaller firms.

We present two pieces of suggestive evidence to support this perspective. First, as discussed in Section 3, smaller firms are more likely to act as net recipients of orders and are therefore more susceptible to the impact of reduced subcontracted orders. Based on this, we hypothesize that the divergence in exit rates between directly and indirectly exposed firms is primarily driven by the exit rate disparity between directly exposed firms and SMEs, rather than between directly exposed firms and large firms. To test this hypothesis, we categorize all manufacturers into three groups based on their registered capital: *small firms*, with registered capital below the 20th percentile of firms in the same county and industry; *medium firms*, with registered capital between the 20th and 80th percentiles; and *large firms*, with registered capital above the 80th percentile. We then compare the exit rates of directly exposed firms with those of large, medium, and small firms, using the specification in equation 2.

The results are presented in Figure 8. The first panel shows the comparison between directly exposed firms and large firms, revealing no significant divergence in exit rates during the observation period. However, the middle and right panels indicate a notable divergence in exit rates between directly exposed firms and SMEs after 2017. These findings are consistent with the mechanism of order subcontracting.

Second, we hypothesize that indirectly exposed firms in counties with higher prevalence of order subcontracting are more likely to exit the market, whereas directly exposed firms in such counties are less likely to do so. To test this hypothesis, we utilize the ESIEC dataset, which allows us to calculate the prevalence of order subcontracting across 117 surveyed counties. Since the survey was conducted in 2018, when most of the surveyed firms were still operational, the measure of subcontracting prevalence serves as a valid

Figure 8: Heterogeneity in the Gap of Exit Rates



Notes: This figure plots the exit rate gap between directly exposed firms and large, medium, and small firms, respectively, using the specification in equation 2. In each panel, the estimates for each year from 2015 to 2019 are presented left to right. The vertical lines indicate the 95% confidence intervals.

pre-determined variable for analyzing the survival status of firms in 2019. To investigate the influence of subcontracting on firms' exit behavior, we estimate the following linear probability model at the firm level:

$$Exit_{i,2019} = \alpha + \beta_1 Exposure_i + \beta_2 \left(Exposure_i \times SubcontractPrev_{c(i),2018}\right) + \theta_{c(i),j(i)} + \varepsilon_i, \tag{3}$$

where $Exit_{i,2019}$ is an indicator equal to one if firm i exits in 2019 and zero otherwise. $Exposure_i$ is the tariff-war exposure measure. $SubcontractPrev_{c(i),2018}$ is the subcontract prevalence in county c, computed from ESIEC 2018. The interaction term $Exposure_i \times SubcontractPrev_{c(i),2018}$ captures whether the exit response to shock exposure is amplified in counties with denser subcontracting networks. $\theta_{c,j}$ denotes county by SIC2 fixed effects.

Table 2 reports the estimated coefficients for β_1 and β_2 from equation 3, focusing on firms in the surveyed counties that were active in 2018. Column (1) indicates that firms directly exposed to the shock are 2.5% less likely to exit the market in 2019. Notably, in counties with higher subcontract prevalence, the exit rate gap becomes even more pronounced—a 10% increase in subcontract prevalence results in a 0.59% wider gap. These findings remain robust when controlling for industry fixed effects (column 2) or county-by-industry fixed effects (column 3).

Table 2: Indirectly Exposed Firms in Counties With a Higher Subcontract Prevalence Are More Likely to Exit

	(1)	(2)	(3)
	Conditional on survival in 2018: exit in 2019		
Exposure	-0.025***	-0.027***	-0.026***
	(0.005)	(0.005)	(0.005)
Exposure×Subcontract Prevalence	-0.059***	-0.064***	-0.065***
	(0.020)	(0.019)	(0.020)
County FE	Yes	Yes	No
SIC2 FE	No	Yes	No
County×SIC2 FE	No	No	Yes
Observations	502,273	502,273	502,075
Adjusted R^2	0.012	0.016	0.019

Notes: ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table 3 presents the estimates from equation 3, using the variable *net-product-giver prevalence* as an alternative measure of subcontract prevalence. This specification also serves as a robustness check, given that smaller firms are more likely to be net order recipients (or net product givers). The results are consistent with previous findings — the gap in exit rates between directly and indirectly exposed firms is more pronounced in counties where a higher proportion of firms are net product givers.

7 Conclusion and Discussion

This study examines the impact of the China–US tariff war on the survival of Chinese enterprises, with particular attention to the differing effects on large versus small firms and the role of subcontracting networks. Leveraging a rich blend of firm-level customs transaction data, tax survey records, and business registration datasets, we present robust evidence that indirectly impacted firms experience higher exit rates compared to directly impacted firms.

Table 3: Robustness Check: Indirectly Exposed Firms in Counties With a Higher Subcontract Prevalence Are More Likely to Exit

	(1)	(2)	(3)
	Conditional on survival in 2018: exit in 2019		
Exposure	-0.033***	-0.035***	-0.034***
	(0.004)	(0.005)	(0.005)
Exposure#Net-Product-Giver Prevalence	-0.081**	-0.086**	-0.096**
	(0.037)	(0.036)	(0.038)
County FE	Yes	Yes	No
SIC2 FE	No	Yes	No
County×SIC FE	No	No	Yes
Observations	502,273	502,273	502,075
Adjusted R^2	0.012	0.016	0.019

Notes: ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

This counterintuitive finding is explained by the dynamics of order subcontracting between firms, wherein directly exposed firms mitigate the effects of the tariff shock by transferring it to their smaller subcontractors. This underscores the critical dependence of SMEs on the stability and resilience of their larger counterparts, emphasizing the deeply interconnected nature of contemporary production systems. By shedding light on the dynamics of subcontracting relationships, we provide a nuanced understanding of how global trade conflicts can have far-reaching consequences for firm behavior and market structure.

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