# Firm-level evidence of tariffs:
## leadtime, performance, and global sourcing

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**Abstract**

We study how the US tariff imposed on China during 2018Q3 affected the operations of multinational US companies. We focus on 2018Q3 because it concentrates on a sharp rate increase over a brief period of time, which favors econometric evaluation. We used data between 2015 and 2019 to avoid the effect of the Covid-19 pandemic. We use transaction-level import data at the shipment level of imports to the United States. We find that companies have diversified their sources, reduced the share of imports from China, and increased the share of imports from other Asian countries, such as India and Vietnam, and North American countries, such as Canada and Mexico (similar to Alfaro and Chor, 2023). We also observe an increase in lead time in the operations of the company and a negative effect in the company's financial results. We test the causal effect of the tariff war on leadtime and diversification of sources using a Difference-in-Difference. In both cases we find causal evidence. The increase on tariff produced an increase 1.5 more country sources, reduce the supply from the main country in a 0.3%, and finally increases the leadtime in the US supply chain importers of a 0.4%.

# 1 Introduction

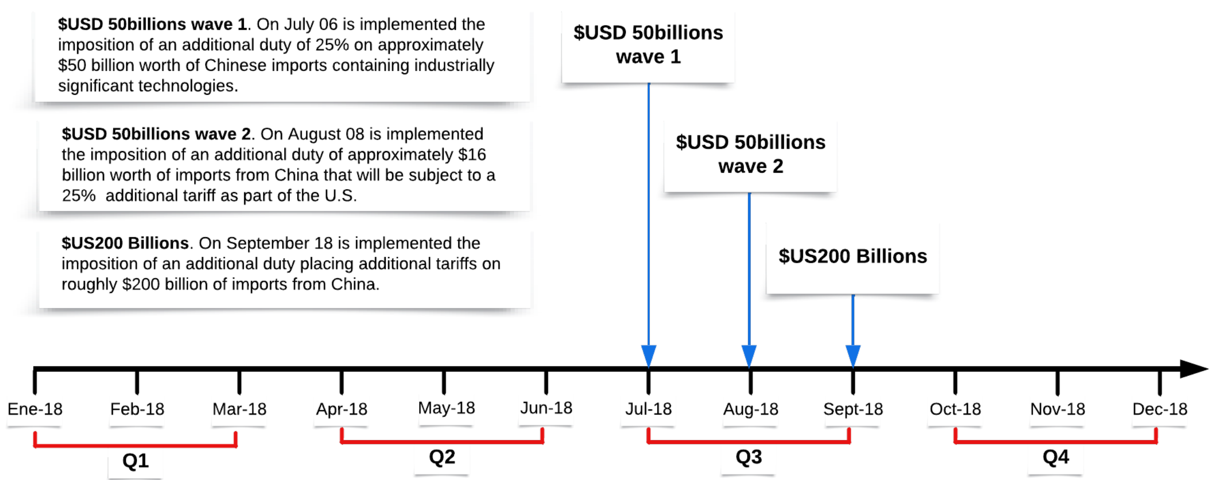
In the dynamic landscape of global commerce, the China–United States trade war has emerged as a focal point, reshaping economic paradigms and challenging established supply chain dynamics. This article attempts to dive into the intricate web of consequences that arises from this geopolitical conflict, with a particular focus on its profound impact on the US supply chain. In particular, this work analyzes how multinational companies importing to the US have restructured their supply chains after the US tariff imposed on China.

For this work, we will consider the following three tariff increases from the US to China. After Section 301 investigation in which the United States Trade Representative (USTR) accused China's acts, policies and practices related to technology transfer, intellectual property, and innovation are unreasonable and discriminatory and burden US commerce. The list of products issued today covers 1,102 separate U.S. tariff lines valued at approximately \$50 billion in 2018 trade values. Due to this, an imposition of an additional 25% duty on approximately 50 billion dollars worth of Chinese imports containing industrially significant technologies. The Office of the United States Trade Representative (USTR) today released a list of approximately 16 billion dollars worth of Chinese imports that will be subject to an additional tariff 25% as part of the U.S. response to China's unfair trade practices related to the forced transfer of American technology and intellectual property.

This second tranche of additional tariffs under Section 301 follows the first tranche of tariffs on approximately \$34 billion of imports from China, which went into effect on July 6. According to the specific direction of the President, the US Trade Representative (Trade Representative) has determined that China's statements and conduct indicated that action at a level of \$50 billion could not be sufficient to eliminate China's unfair and harmful policies. To address this supplementary action were adopted to impose an additional 10% and 25% duty on products from China with an annual trade value of approximately \$200 billion. Therefore, during the third quarter of 2018q3, the Trump administration imposed 3 waves of import tariffs on approximately \$250 billion of US imports, with rates ranging between 10% and 50%. As Figure 1 shows, during the third quarter of 2018 the US tariffs were introduced in three main waves: July 6, August 8, and September 18.

Using aggregate data (no transhipment nor companies level information) we see import values falling by 25-30% after the imposition of the tariffs, implying that the imposition of the tariffs had very large relative effects on the amount of imports for affected countries and sectors. This implies a substantial shock to global supply chains, because it means that at least \$136 billion of trade was redirected as a result of import tariffs (Alfaro and Chor, 2023). Therefore, the global supply chain is restructuring. Alfaro and Chor (2023) argue that Given the fixed costs associated with current supply chains, this reorganization of global value chains is likely to impose large costs on firms that have made investments in the United States and China, as they have to move their facilities to other locations or find alternative sources of import and export destinations.

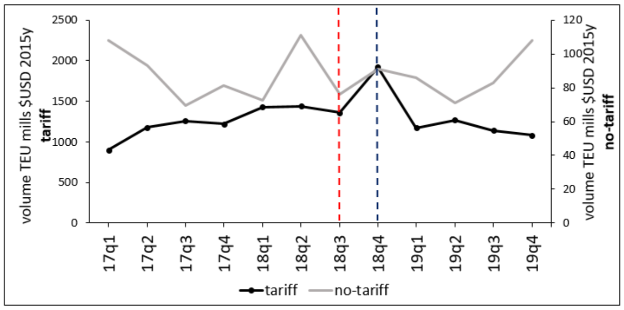
**Figure 1: US waves of import tariffs on US imports from China during the 2018-Q3**



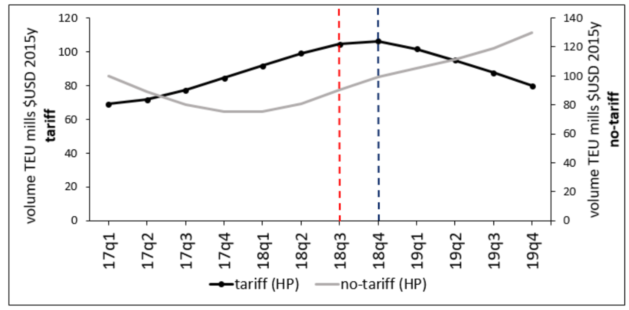

But what is the effect of this reorganization of the supply chain on the supply chain itself at the multinational company level? How does this change in source and diversification affect the operations of the company?In this work, we analyze these questions. If we use transaction-level import data at the shipment level jointly with importing prices, and we plot where US imports are going before and after 2018-Q3 (Figure 2). As we see in Figure 2a and its tendency values in Figure 2b, while no-tariff products have increased their imports from China, tariff products have decreased their imports from China.

As we see in Figure 2b and its tendency values in Figure 2c it happens the opposite way. Tariff products have increased their imports from Europe, and no-tariff products have decreased their imports from Europe. In this work, we study how the US tariff imposed on China during 2018Q3 affected the operations of multinational US companies. We focus on 2018Q3 because it concentrates on a sharp rate increase over a brief period of time, which favors econometric evaluation. We used data between 2015 and 2019 to avoid the effect of the Covid-19 pandemic. We use transaction-level import data at the shipment level of imports to the United States.

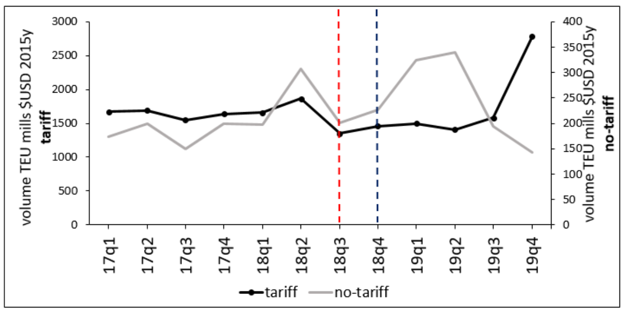
**Figure 2: US Companies trans-shipment imports in $USD year 2015 ($TEU \times Price$)**



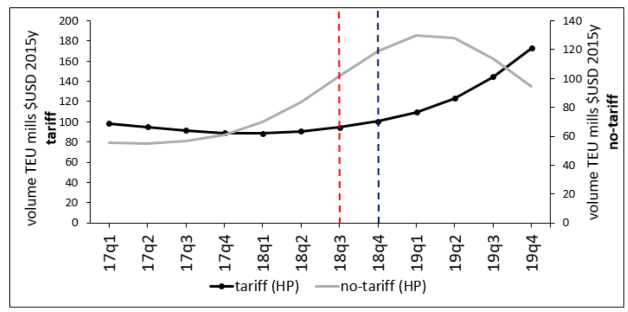

(a) **US trans-shipment imports from China**



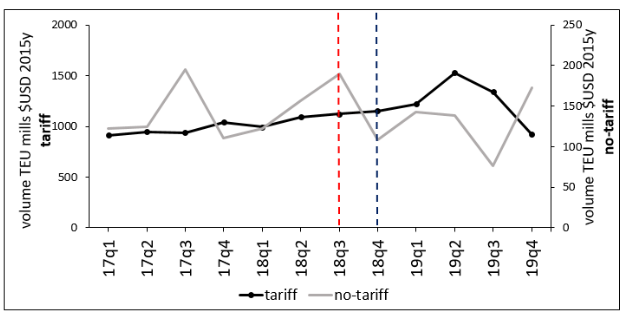

(b) **US trans-shipment imports from tendencies China**



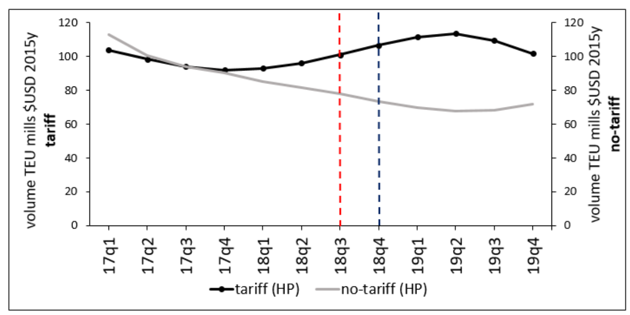

(c) **US trans-shipment imports from Europe**



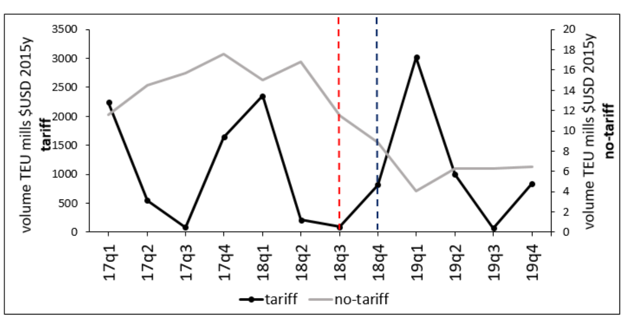

(d) **US trans-shipment tendencies from Europe**



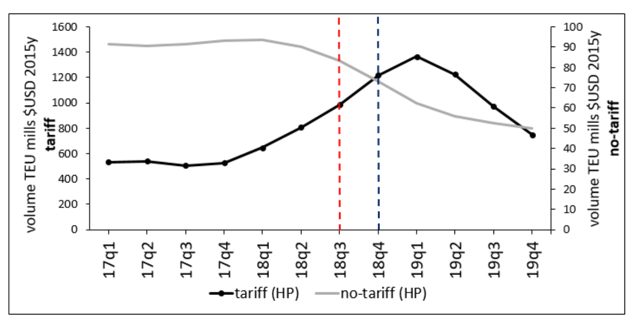

(e) **US trans-shipment from rest of Asia**




(f) **US trans-shipment tendencies from rest of Asia**




(g) **US trans-shipment from Mex/Can**




(h) **US trans-shipment tendencies from Mex/Can**

**Note:** Own elaboration based on Panjiva dataset and Amiti M, Redding S, Weinstein D (2019) (Replication package). Values were obtained using the twenty-foot equivalent unit TEU with the price of the 6-digit HS code product($TEU \times Price$).

We find that companies have diversified their sources, reduced the share of imports from China, and increased the share of imports from other Asian countries, such as India and Vietnam, and North American countries, such as Canada and Mexico (similar to Alfaro and Chor, 2023). We also observe an increase in lead time in the operations of the company and a negative effect in the company's financial results. We test the causal effect of the tariff war on leadtime and diversification of sources. In both cases we find causal evidence. The increase on tariff produced an increase 1.5 more country sources, reduce the supply from the main country in a 0.3%, and finally increases the leadtime in the US supply chain importers of a 0.4%.

# 2 Literature Review

## 2.1 Disruptions, resilience, and strategies for supply chains

The literature on operations management has extensively examined supply chain disruptions (e.g., Bhattacharya et al., 2012; Tang, 2006; Tomlin, 2006). The term "supply chain disruption" is used here to describe the combination of an unintentional and unexpected triggering event that happens at a specific point in the supply chain and the ensuing situation that poses a serious risk to the focal firm's regular business operations (Bode  Wagner, 2015).

Generally speaking, events that have a low probability of happening but a high impact—like natural disasters like the 2011 earthquake, tsunami, and nuclear disaster in Japan [Sheffi, 2017]—man-made accidents like the US coal mining disaster [Madsen, 2009]—and pandemics like SARS [Chou et al., 2004] and Ebola [Calnan et al., 2012]—are what cause disruptions in supply chains. We research how unexpected tariffs can disrupt supply chains.

Resilience is the capacity to bounce back from a setback quickly and efficiently (Behzadi et al., 2020). Due to the fact that disruptions in the supply chain can result in large losses for businesses in terms of both money and operations (Tukamuhabwa et al., 2015), resilience is regarded as a crucial quality that supply chains must have. Moreover, according to Ali et al. (2017), it is dynamic rather than static. Kamalahmadi and Parast (2016) conducted a thorough review of related literature in order to enhance knowledge of resilience for businesses and supply chains. Furthermore, for comparable reviews, we direct the readers to Ali et al. (2017) and Golan et al. (2020).

According to Ali et al. (2017), supply chain resilience is a complicated and multifaceted research topic, and there have been significant efforts made to determine its component parts. Studies have identified a variety of factors, but the main components are as follows:

collaboration (e.g., Christopher  Peck, 2004; Jüttner  Maklan, 2011); information sharing (e.g., Hosseini et al., 2019); flexibility (e.g., Hosseini et al., 2019; Jüttner  Maklan, 2011); agility (e.g., Christopher  Peck, 2004; Hosseini et al., 2019); visibility (e.g., Hosseini et al., 2019; Jüttner  Maklan, 2011); visibility (e.g., Hosseini et al., 2019; Hosseini et al., 2019).

It is possible to assess and analyze practical supply chain resilience by focusing on these elements, which are also referred to as supply chain resilience principles (Kamalahmadi Parast, 2016). As per Pettit et al. (2010), supply chain resilience is primarily influenced by two factors: the supply chains' capabilities, which can be enhanced through management control, and their vulnerabilities, which are dictated by the forces of change.

Using a focus group methodology, seven vulnerability factors and fourteen capability factors were found. Cardoso and colleagues (2015) employed a set of eleven indicators, such as network design, centralization, and operational indicators, to evaluate the resilience of the supply chain.

These factors, however, are not relevant in real life. It is difficult to compute in practice a detailed network structure with flow information, which is necessary for both network design and centralization indicators. In conclusion, no universal indicator exists to assess supply chain resilience in practical situations. The following section goes into further detail on this subject.

## 2.2 Analyzing supply chain resilience in practice

The literature sheds light on how supply chains and businesses can become more resilient. According to Lee (2004), supply chains that perform well should be flexible, nimble, and coordinated in order to enable them to bounce back quickly from unexpected setbacks. In particular, he stressed the value of data and cooperative connections when creating an agile supply chain. Snyder et al. (2006) reviewed and compiled a number of models for creating supply chains that can withstand disruptions. The most often mentioned strategies, based on the components of supply chain resilience, are supply chain agility enhancement, redundancy creation, collaborative supply chain relationship formation, and increased flexibility (Tukamuhabwa et al., 2015).

Theoretical and practical approaches to supply chain resilience differ significantly, though (Tarei et al., 2020; Tukamuhabwa et al., 2015). According to reports, companies most frequently use enhanced forecasting, dual or multiple sourcing, and increased safety stock to handle disruptions (Katsaliaki et al., 2021). While resilience strategies and the concept of resilience are closely related, firms' practical strategies tend to be more aligned with risk management than with resilience. Risk management includes risk sharing techniques like revenue sharing, insurance, cooperation, and public-private partnerships, as well as risk avoidance techniques like supplier evaluation, technology adoption, flexible processes, and information security (Tarei et al., 2020).

As a result, even though a large variety of supply chain resilience strategies have been identified, there aren't many empirical studies that look into the specific practical responses of businesses. A study by Lee et al. (2020), which examined the reflections of organizations during a crisis, is an exception. But rather than addressing the supply chain as a whole, it mostly concentrated on the perspectives of specific companies.

One of the biggest challenges in conducting empirical research to analyze supply chain resilience is defining resilience using firm operational data. The three primary categories of resilience metrics found in theoretical models are: recovery level (such as service level, unfulfilled demand rate), time to recover (such as out-of-service time, on-time delivery), and profit lost during recovery period (Behzadi et al., 2020). For empirical research, comparable indicators are also defined. Time-to-recover (TTR) is a risk exposure index that Simchi-Levi et al. (2014) proposed to measure the effect of a disruption on specific supply chains.

It is the amount of time needed for a specific node to fully function again following an interruption. Time-to-survive (TTS), an index akin to TTR, was introduced by Simchi-Levi et al. (2015) because reliable TTR data is frequently unavailable. It is the longest period of time that a system can operate without experiencing a decrease in performance in the event that a specific node is broken. The two risk exposure models mentioned above helped Ford Motor Company recognize and control its risks.

Baghersad and Zobel (2021) assessed resilience as an overall system performance loss following a disruption, use the theoretical notion of a resilience triangle as their foundation. Retail supply chain examples are rather difficult for this indicator, even though it shows the resilience fluctuation of supply chains with consistent demands. Moreover, the COVID-19 pandemic's protracted disruption negatively impacts prediction accuracy, which impedes the indicator's computation.

Coordination and information exchange are lacking, which creates another serious issue. Research frequently discusses the robustness of entire supply networks, yet in practice, individual supply chain nodes operate independently. In actuality, a supply chain's visibility is limited to the tiers above and below it (Scheibe  Blackhurst, 2018). In this instance, the only method to comprehend the complete supply chain is to conduct interviews with participants in various supply chain nodes. Tarei et al. (2020) conducted interviews with seven supply chain managers occupying various positions in the petroleum industry of India to investigate the variations in risk management techniques and practices.

Supply chain activities under crisis scenarios in Bangladesh were investigated by Shareef et al. (2020) using representative case studies and interviews. The instances included detailed descriptions of landslides, cyclones, and floods, among other disasters. Furthermore, the factors that impact the performance of the supply chain were determined. Ivanov (2018) presented five examples of how Nissan, Toyota, Volkswagen, and ASOS plc—a British online fashion retailer—developed robust supply networks. A detailed description of the supply chain resilience measures was also provided. Nevertheless, each case's total supply chain performance is only partially described by a few key indicators, such sales and inventory level, and the supply chain performance topic was not sufficiently covered.

The practical examination of supply chain resilience remains a significant research subject in spite of the challenges outlined above (Katsaliaki et al., 2021). The few empirical research that are now accessible are mostly cross-sectional and limited to the setting of industrialized nations (Tukamuhabwa et al., 2015). Additionally, case studies and interviews are typically used to gather data. The Panjiva dataset allows it to own the whole retail supply chain and establish direct connections with upstream manufacturers, factories, and customers throughout China. As a result, data from the complete supply chain is accessible. The research adds to the body of empirical work on supply chain resilience analysis. We have conducted the first resilience research using quantitative data taken directly from a company's operating procedures. Furthermore, we minimize the distinction between resilience strategy research and practice by reporting the resilience level and tariffs outbreak tactics empirically.

## 2.3 Supply chain management during COVID-19

Lastly, we examine the literature on supply chain management in light of the COVID-19 pandemic and the ensuing financial downturn. The first body of work is essentially theoretical and is categorized as conventional literature on supply chain disruption. For example, Baqaee and Farhi (2020) modeled COVID-19 as a combination of exogenous shocks to the supply quantity, productivity of producers, and composition of the final demand.

A concept for an entwined supply network, in which all of the market's supply chains are integrated, was put forth by Ivanov and Dolgui (2020). They suggested looking more closely at COVID-19's effects from this fresh angle. A mathematical production recovery strategy was presented by Paul and Chowdhury (2020) for manufacturing supply chains in the event of the COVID-19 pandemic. These studies offer insightful information about supply chain management during a particular epidemic, but their lack of actual data makes them incredibly impractical.

Our research is more in line with those that used empirical estimation to determine how the epidemic affected supply chains. A significant number of studies in this stream have concentrated on the supply chains of medical supplies and personal protective equipment (e.g., Armani et al., 2020; Gereffi, 2020; Ranney et al., 2020). These studies have also highlighted the significance of government guidance (e.g., Ranney et al., 2020) and the adoption of digital technology (e.g., Armani et al., 2020).

The agricultural and food supply chains have received additional attention (see, for example, Aday  Aday, 2020; Gray, 2020; Reardon et al., 2020; Richards & Rickard, 2020). Hobbs (2020), for instance, talked about the COVID-19 shocks to the supply and demand sides and how those impacts affected Canada's food supply systems. The aforementioned studies concur that there are no significant disruptions to the food and agriculture supply chains, and that their logistical services remain efficient. For some supply chains, the situation is less favorable.

Based on expert interviews, Majumdar et al. (2020) examined the apparel supply chain functioning in South Asian nations and discovered that manufacturing, supply, and demand were all totally disjointed and disconnected in this supply chain. McMaster et al. (2020) analyzed global fashion supply networks and provided an overview of current dangers and ways to mitigate them. There have been recommendations for a variety of approaches, including social distancing in factories (Bodenstein et al., 2020), agile supply chains (McMaster et al., 2020), agile sourcing models that incorporate disruption risk sharing (Majumdar et al., 2020), and resilient supply chains (Hobbs, 2020; Singh et al., 2020).

There has been emphasis on the use of data-driven digital technologies, like digital supply chain twins (Ivanov  Dolgui, 2020). Nevertheless, none of the earlier research can guarantee that the suggestions they made will be effective when COVID-19 spreads around the globe.

In general, simulations are often used to examine the effects of disruptions since realistic data are not available. For instance, Ivanov (2020) examined and forecasted the effects of COVID-19 on supply chain performance using a simulation-based methodology. He noted that facility opening and closing hours are anticipated to be important variables. Ivanov and Das (2020) examined possible recovery routes and mitigation strategies for pandemic supply risk using a simulation technique. Some studies were somewhat more narrowly focused, concentrating on specific metrics or industries.

Guan et al. (2020), for instance, examined the effects of COVID-19 lockdowns on supply chains using a global trade-modeling framework. They discovered that there would be less loss from a lengthier lockdown that is capable of eradicating the illness than from shorter ones. A simulation model for a public distribution system network was created by Singh et al. (2020) to illustrate COVID-19 interruptions in the food supply chain.

The present study is distinct from earlier ones in the following ways. Firstly, whereas simulations are frequently used to study the effects of disruptions, we use transshipment data from worldwide supply chains. Furthermore, we go beyond the analysis of the effects of a pandemic and take into account supply chain resilience and the workable resilience plans of enterprises, in contrast to earlier research related to the disruptions outbreak. Lastly, taking into account the features of this retail supply chain, we evaluate and talk about several industries, whereas earlier research focused primarily on particular sectors, such food or medical supply chains (e.g., Hobbs, 2020; Gereffi, 2020).

# 3 Data Description and Variable Definition

We gather information from various sources, primarily relying on import data based on the bill of lading provided by the Panjiva data set. This data set offers comprehensive details regarding US Customs bill of lading (BoL) manifests for public and private US companies. The bill of lading functions as a confirmation of goods loaded, including essential details such as the importer's and overseas supplier's names and addresses, at the 6-digit level of Harmonized Tariff Schedule (HTS6), country of origin, and volume represented in Twenty-foot Equivalent Units (TEU)). With access to this data set, we can monitor all import transactions into the United States facilitated by maritime shipping routes. For importer $i$, product $p$ and period in quarter $t$. We define the number of sources country used for the company $i$ at period $t$ as $S_{it}$. We define the percentage of the volume that represents the first country source $volp_{ipt}$. We define the percentage of imports from relevant sources as follow: the percentage of imports from China ($volchina_{ipt}$), from India ($volindia_{ipt}$) and finally the percentage of imports from Canada and Mexico ($volmexda_{ipt}$). In the following table we present statistics for each diversification variable.

We use CARD Trade War Tariffs Database from the Center for Agricultural and Rural Development Li (2018). we define the variable $\text{tafiff}_p$ as an indicator if the product $p$ is affected by tariff increase as follows:

$$\text{tafiff}_p = \begin{cases} 1 & \text{if } p \text{ has tariff increase.} \\ 0 & \text{if Otherwise.} \end{cases} \tag{1}$$

We define the variable $I_t(t \geq \text{2018-Q3})$ as an indicator for the period starting from 2018q3:

**Table 1: Summary Statistics for US Importer Companies**

| | Mean | SD | p25 | p50 | p75 | N |
|---|---|---|---|---|---|---|
| **Before** | | | | | | |
| $\log(dap)$ | 4.26 | 1.54 | 3.64 | 4.00 | 4.37 | 650,664 |
| $\log(mkvaltq)$ | 8.87 | 2.11 | 7.55 | 8.91 | 10.35 | 587,179 |
| $\log(saleq)$ | 7.42 | 1.90 | 6.21 | 7.46 | 8.69 | 655,144 |
| $ROA$ | 1.20 | 1.88 | 0.33 | 1.20 | 2.13 | 656,040 |
| $ROE$ | 1.02 | 9.34 | 0.66 | 1.22 | 1.80 | 644,715 |
| **After** | | | | | | |
| $\log(dap)$ | 4.30 | 1.40 | 3.69 | 4.06 | 4.42 | 262,616 |
| $\log(mkvaltq)$ | 8.98 | 2.21 | 7.58 | 8.96 | 10.53 | 236,202 |
| $\log(saleq)$ | 7.60 | 1.90 | 6.36 | 7.62 | 8.82 | 264,363 |
| $ROA$ | 1.18 | 1.96 | 0.34 | 1.18 | 2.11 | 264,747 |
| $ROE$ | 1.01 | 19.98 | 0.64 | 1.26 | 2.07 | 261,241 |

**Note:** We left out of this statistics the outliers for variables $ROA$ and $ROE$. Specifically, we left out the lower values for percentiles 1% and larger values for percentiles 99%.

$$I_t(t \geq \text{2018-Q3}) = \begin{cases} 1 & \text{if } t \geq \text{ 2018-Q3} \\ 0 & \text{if Otherwise.} \end{cases} \tag{2}$$

Finally, we can calculate an indicator if the import of product $p$ is affected by tariff and the period is after 2018q3.

$$\text{tariff}_p \times I_t(t \geq \text{2018-Q3}) = \begin{cases} 1 & \text{if } p \text{ has tariff increase and } t \geq \text{2018-Q3} \\ 0 & \text{if Otherwise.} \end{cases} \tag{3}$$

Finally, we collect firm quarter-level financial fundamentals from the Standard & Poor's Compustat. Limiting our analysis to publicly listed firms allows our analysis to control for firm attributes. Following the existing literature (e.g., Rumyantsev, Netessine, (2007); Kesavan S, Kushwaha T, Gaur V (2022)), We define the market value ($mkvaltq_{it}$), sales ($saleq_{it}$), return on assets ($ROA_{it}$) and Return on Equity ($ROE_{it}$). Leadtime measurement is more complex. Lead time data are not publicly available and, in practice, vary both by product and by supplier. Additionally, there are lead times (or delays) both in product deliveries and in payments to suppliers, although classical inventory models only account for the former. As a proxy for a lead time, we use the average number of days of outstanding accounts payable ($dap_{it}$), defined by $dap_{it} = \frac{365}{4} \times \frac{ap_{it}}{cogs_{it}}$. Here, $ap_{jt}$ stands for accounts payable. See Rumyantsev, Netessine, (2007) for a justification for this lead time proxy.

In Table 2 we show descriptive statistics for the variable of performance of the company. Due to the heterogeneity of these values for each sector, in Annex **??** we show the same statistics for each sector. We left out of these statistics the outliers for variables $ROA$ and

*ROE*. Specifically, we cut out the lower values for the percentiles 1% and the larger values for the percentiles 99%. This is done in the statistics for the total sample and for each sector in Annex **??**.

**Table 2: Statistics diversification variables**

| | Mean | SD | min | p10 | p25 | p50 | p75 | p90 | max | N |
|---|---|---|---|---|---|---|---|---|---|---|
| **no-tariff** | | | | | | | | | | |
| *volp* | 95.96 | 11.79 | 13 | 85 | 100 | 100 | 100 | 100 | 100 | 794,929 |
| *S* | 89.45 | 113.46 | 1 | 6 | 17 | 45 | 117 | 231 | 690 | 829,138 |
| *volchina* | 49.98 | 48.63 | 0 | 0 | 0 | 50 | 100 | 100 | 100 | 829,138 |
| *volindnam* | 5.69 | 21.96 | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 829,138 |
| *volmexda* | 2.47 | 14.99 | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 829,138 |
| **tariff** | | | | | | | | | | |
| *volp* | 96.08 | 11.59 | 16 | 86 | 100 | 100 | 100 | 100 | 100 | 328,196 |
| *S* | 87.63 | 113.74 | 1 | 6 | 16 | 44 | 114 | 221 | 685 | 342,479 |
| *volchina* | 48.63 | 48.66 | 0 | 0 | 0 | 31 | 100 | 100 | 100 | 342,479 |
| *volindnam* | 6.35 | 23.14 | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 342,479 |
| *volmexda* | 2.62 | 15.47 | 0 | 0 | 0 | 0 | 0 | 0 | 100 | 342,479 |

The first thing we have to notice is that we are working with different sector classifications, and each of these sectors was affected differently from the tariff. In Table 3 we show the different tariff increases for each sector, considering the number of products affected by these tariff wars. In Table 3 we do not consider the classification Vegetable products because only an 8% of the 6-digit HS code product were affected by tariffs. Neither consider Footwear and Headgear for only having 19% of their products with tariffs.

**Table 3: Classification of Harmonized System Codes 6 (hs6) products by hs2 categories desegregating by tariff and no-tariff products**

| code | Classification | no-tariff | | tariff | | Total(hs6) |
|---|---|---|---|---|---|---|
| | | N(hs6) | % | N(hs6) | % | |
| 01-05 | Animal Products | 128 | 33.5 | 254 | 66.5 | 382 |
| 16-24 | Foodstuffs | 89 | 41.4 | 126 | 58.6 | 215 |
| 25-27 | Mineral Products | 3 | 2 | 145 | 98 | 148 |
| 28-38 | Chemicals | 190 | 21.4 | 696 | 78.6 | 886 |
| 39-40 | Plastics | 29 | 13.2 | 190 | 86.8 | 219 |
| 41-43 | Raw Hides, Skins, Leather | 16 | 23.2 | 53 | 76.8 | 69 |
| 44-49 | Wood Products | 41 | 14.9 | 234 | 85.1 | 275 |
| 50-63 | Textiles | 275 | 34 | 533 | 66 | 808 |
| 68-71 | Stone and Glass | 45 | 22.5 | 155 | 77.5 | 200 |
| 72-83 | Metals | 230 | 40.9 | 333 | 59.1 | 563 |
| 84-85 | Machinery and Electrical | 147 | 18.5 | 646 | 81.5 | 793 |
| 86-89 | Transportation | 16 | 11.1 | 128 | 88.9 | 144 |
| 90-97 | Miscellaneous | 198 | 54.8 | 163 | 45.2 | 361 |
| | Total | 1489 | 28.9 | 3669 | 71.1 | 5158 |

**Note:** We do not consider the classification 06-15 Vegetable products because only an 8% of the 6-digit HS code product were affected by tariffs. Neither consider 64-67 Footwear and Headgear for only having 19% of their products with tariffs.

# 4 Empirical Strategy

As a first step, in Section **??** we estimate the effect of the average increase in tariff on different variables $y_{ipt}$ of diversification, company results and supply chain indicators. Our main specification exploits differences in diversification levels, after the tariff war, compared to times before the tariff existed, controlling for fixed effects for the observation quarter, the year, the sector, the firm. The unit of observation is the import $i$, product $p$, period $t$. We define the specification on Eq. (4) we estimate the OLS:

$$\begin{aligned} y_{ipt} =& \beta \cdot \text{tariff}_p \times I_t(t \geq \text{2018-Q3}) \\ &+ \alpha_i + \sum_{q=1}^{4} \gamma_q \cdot \mathrm{I}(t \in q) + \sum_{s} \eta_p \cdot \mathrm{I}(p \in s) + e_{ipt} \end{aligned} \tag{4}$$

$$\begin{aligned} y_{ipt} =& \beta \cdot \text{tariff}_p \times I_t(t \geq \text{2019-Q3}) \\ &+ \alpha_i + \sum_{q=1}^{4} \gamma_q \cdot \mathrm{I}(t \in q) + \sum_{s} \eta_p \cdot \mathrm{I}(p \in s) + e_{ipt} \end{aligned} \tag{5}$$

The variable $\alpha_i$ are import fixed effects. The variable $\mathrm{I}(t \in q)$ is a dummy variable indicating the quarter.

To identify the impact of a program on its beneficiary population, it is necessary to identify the cause-and-effect relationships between the components produced by the program and the expected results or the variables of interest on which its objectives are defined. Furthermore, it is essential to isolate from the observed benefits all those effects that derive from factors external to the program (state of the economy and national and global political situation, exchange rate, international prices, climatic phenomena, natural disasters, tax rates/tariffs, commercial agreements, etc.), as well as the individual characteristics of each individual, which are available in secondary sources.

The Difference in Differences (DD) Method is a quasi-experimental design that uses series data of time of the treatment and control groups to obtain an appropriate counterfactual to estimate a causal effect. Without a doubt, this analysis methodology constitutes the best tool to achieve an ex post evaluation of a CO. In this study, we will use the DID method to estimate the effect of a merger in the shipping industry on freight prices, comparing changes in prices over time between companies that participated in a merger (the intervention group) and companies to which they did not participate (the control group). For a general explanation of the DID approach, see Angrist and Pischke (2010). For an explanation more linked to its use in ex post evaluations of a CO, see Greenfield in Kwoka (2015).

This method considers that many unobservable characteristics of individuals are more or less constant over time. Thus, by subtracting the situation of the results before from the situation after, the effect of all characteristics that are unique to that individual and that do not change over time is nullified weather. In reality, you are canceling (or controlling) not only the effect of observable characteristics time-invariant, but also the effect of time-invariant unobservable characteristics (Gertler et al, 2011).

The DID method requires data before and after the intervention. The method consists of comparing the difference of the treatment group, with a counterfactual group of equal characteristics, A, with the difference between the counterfactual group and a comparison group, B. Hence the name of the difference-in-differences method, or double differences. This approach eliminates bias in comparisons after the intervention period, between the treatment group and the control group. Likewise, biases are eliminated from comparisons. over time in the treatment group. In this context, the DID can be used to estimate the effect of tariffs on lead time.

As we noted above, the parallel trend assumption is critical to ensure the validity of the DID models, being also the most difficult to comply with. Requires that in the absence of treatment (the merger), the difference between the "treatment" group (companies that merged) and the "control" group (companies that did not merge) is constant over time.

Although there are no proof statistics for this assumption, visual inspection is useful when you have many observations in a time. Violation of the parallel trend assumption will lead to a biased estimate of the causal effect.

Our econometric estimation strategy considers a difference-in-differences estimator conditional, implemented by a fixed-effects panel data regression. In particular, we consider a model of the following type:

To analyze the impact of the change in import source on supply uncertainty, we consider only the series import $i$ and product $p$ that experienced a sudden change in import source and, also, we only consider data during consistency periods $t$. The specification is the following:

As a second step, in Section **??** we estimate causal effects using the difference-in-difference (DID) method.

$$\begin{aligned} y_{ipt} = & \beta \cdot \text{tariff}_p \times I_t(t \geq \text{2018-Q3}) \\ & + \beta_{\text{tariff}} \cdot \text{tariff}_p \\ & + \beta_{\text{after}} \cdot I_t(t \geq \text{2018-Q3}) \\ & + \alpha_i + \sum_{q=1}^{4} \gamma_q \cdot \mathrm{I}(t \in q) + \sum_s \eta_p \cdot \mathrm{I}(p \in s) + e_{ipt} \end{aligned} \tag{6}$$

$$\begin{aligned} y_{ipt} = & \beta \cdot \text{tariff}_p \times I_t(t \geq \text{2019-Q3}) \\ & + \beta_{\text{tariff}} \cdot \text{tariff}_p \\ & + \beta_{\text{after}} \cdot I_t(t \geq \text{2019-Q3}) \\ & + \alpha_i + \sum_{q=1}^{4} \gamma_q \cdot \mathrm{I}(t \in q) + \sum_s \eta_p \cdot \mathrm{I}(p \in s) + e_{ipt} \end{aligned} \tag{7}$$

An assumption for the DID method is that at the beginning of the implementation of the program, the control and treatment groups have similar growth paths (parallel growth). In the next to Figures we see sectors where this is achieved. This is not achieved by the rest (See Annex.) The first figure show the trend for leadtime, and next figure show the trend for sector considering $S$ and volp.

**Figure 3: Parallel before: Leadtime**

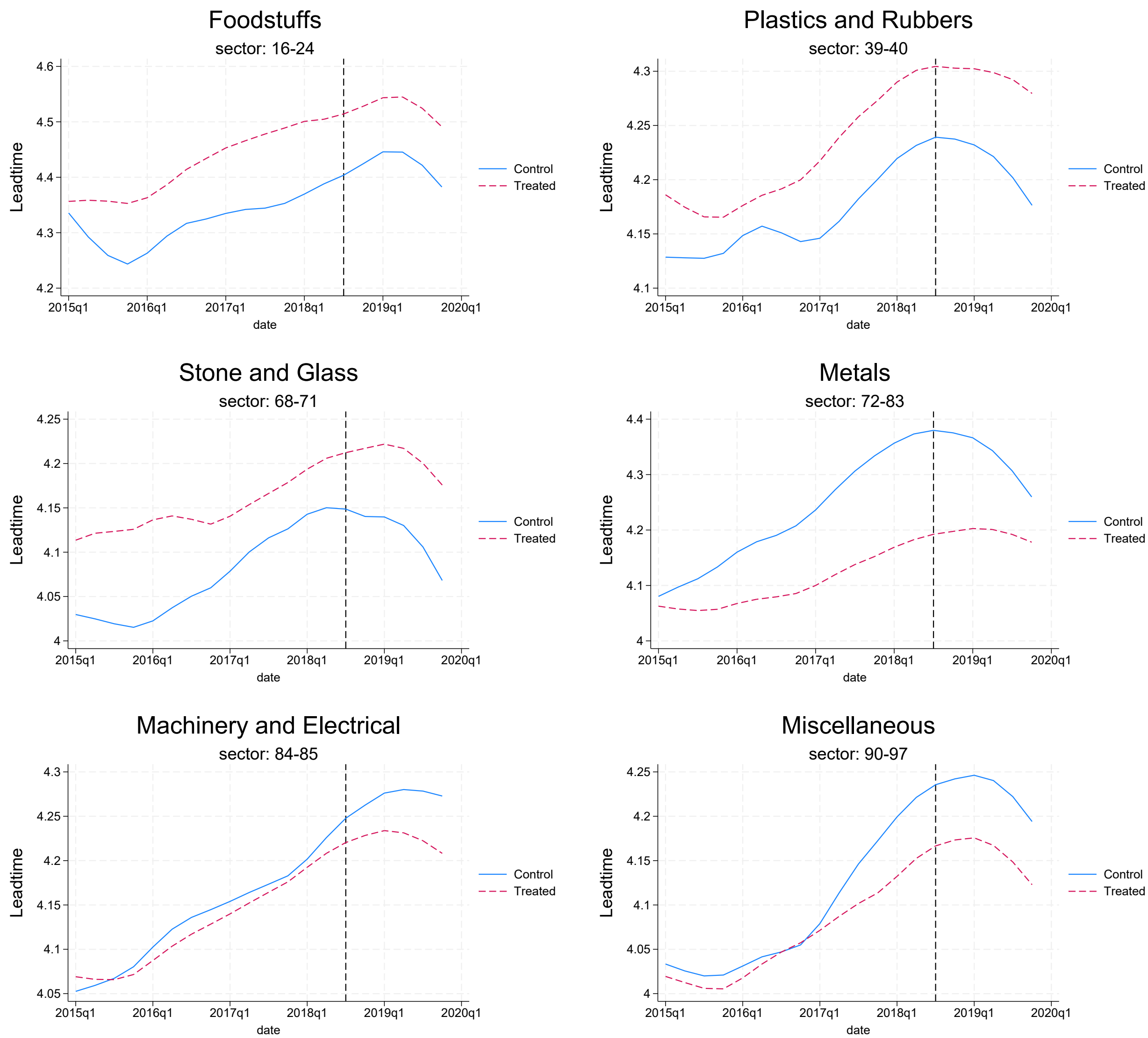
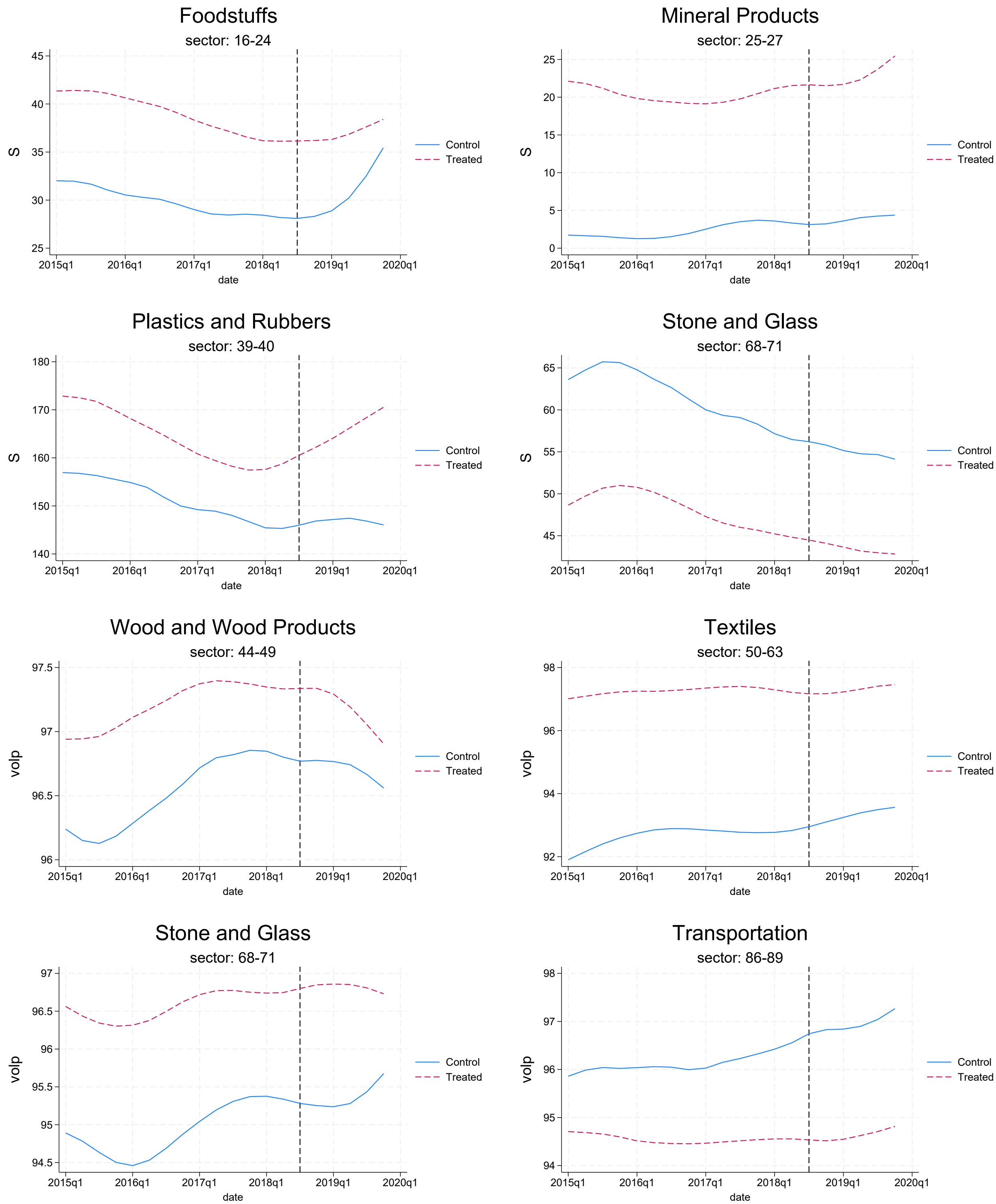


**Figure 4: Parallel before: S and volp**



# 5 Results

In Table **??** we present the estimation results for the Model. We report the estimation results for the average treatment effect on the treated (ATET) and also the coefficient estimation for the control variables. Column 2 in Table **??** provides results for the estimation considering the aggregate data. Columns 3-9 provides estimation results for the model split by product category. The results are heterogeneous. First, we find a negative estimated value of ATET for the case of the aggregate sample. This support the idea that U.S. companies shifting away from China show a reduction on their supply uncertainty. Second, at the disaggregate by categories we find a diverse behaviour. While for electronics and apparel we find a negative estimated value of ATET, we find a negative estimated value for textiles. Results are not statistically significant for the other categories.

**Table 4: Estimation Results**

**Model A1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.32*** | 0.02*** | 0.08*** | -1.94*** | 1.05*** | 0.24*** |
| | (0.01) | (0.00) | (0.00) | (0.10) | (0.05) | (0.03) |
| r2 | 0.333 | 0.962 | 0.408 | 0.315 | 0.134 | 0.125 |
| N | 814,321 | 914,882 | 766,197 | 1,143,775 | 1,143,775 | 1,143,775 |

**Model A2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.02*** | -0.11*** | -2.66*** | 1.52*** | 0.24*** |
| | (.) | (0.00) | (0.00) | (0.22) | (0.11) | (0.08) |
| r2 | 0.333 | 0.962 | 0.407 | 0.315 | 0.134 | 0.125 |
| N | 814,321 | 914,882 | 766,197 | 1,143,775 | 1,143,775 | 1,143,775 |

**Model B1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.16*** | 0.00*** | -0.05*** | -0.21 | -0.47*** | 0.24*** |
| | (0.02) | (0.00) | (0.00) | (0.18) | (0.09) | (0.06) |
| $\text{I}_t(t \geq \text{2018-Q3})$ | 0.00 | 0.02*** | 0.14*** | -0.61*** | 1.18*** | -0.07 |
| | (0.02) | (0.00) | (0.00) | (0.16) | (0.08) | (0.05) |
| $\text{tariff}_p$ | 0.59*** | -0.00** | 0.01*** | -4.27*** | 1.68*** | 0.23*** |
| | (0.01) | (0.00) | (0.00) | (0.11) | (0.06) | (0.04) |
| N | 814,321 | 914,882 | 766,197 | 1,143,775 | 1,143,775 | 1,143,775 |
| r2 | 0.339 | 0.962 | 0.409 | 0.316 | 0.135 | 0.125 |

**Model B2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.00** | -0.09*** | -0.69** | -0.50*** | 0.24** |
| | (.) | (0.00) | (0.01) | (0.29) | (0.15) | (0.10) |
| $\text{I}_t(t \geq \text{2019-Q3})$ | 0.00 | 0.01*** | 0.07*** | -0.91*** | 1.67*** | 0.02 |
| | (.) | (0.00) | (0.01) | (0.25) | (0.13) | (0.09) |
| $\text{tariff}_p$ | 0.61*** | -0.00 | 0.01*** | -4.41*** | 1.68*** | 0.29*** |
| | (0.01) | (0.00) | (0.00) | (0.10) | (0.05) | (0.04) |
| N | 796,531 | 896,379 | 750,967 | 1,120,197 | 1,120,197 | 1,120,197 |
| r2 | 0.338 | 0.962 | 0.407 | 0.315 | 0.137 | 0.125 |

**Table 5: Animal & Animal Products**

**Model A1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq 2018\text{-Q3})$ | 0.16*** | -0.13*** | 0.10*** | -0.99 | 3.67*** | -0.52 |
| | (0.03) | (0.01) | (0.02) | (0.90) | (0.64) | (0.56) |
| r2 | 0.352 | 0.989 | 0.470 | 0.487 | 0.448 | 0.553 |
| N | 7,216 | 6,614 | 5,744 | 9,150 | 9,150 | 9,150 |

**Model A2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq 2019\text{-Q3})$ | 0.00 | -0.06** | 0.03 | -0.72 | 3.22** | 0.87 |
| | (.) | (0.02) | (0.05) | (2.00) | (1.42) | (1.25) |
| r2 | 0.349 | 0.989 | 0.468 | 0.487 | 0.446 | 0.553 |
| N | 7,216 | 6,614 | 5,744 | 9,150 | 9,150 | 9,150 |

**Model B1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq 2018\text{-Q3})$ | 0.01 | -0.12*** | -0.03 | -1.01 | 1.75 | -1.01 |
| | (0.05) | (0.02) | (0.04) | (1.54) | (1.10) | (0.97) |
| $\text{I}_t(t \geq 2018\text{-Q3})$ | 0.08** | -0.01 | 0.15*** | -2.38* | 0.83 | 1.05 |
| | (0.04) | (0.02) | (0.03) | (1.26) | (0.90) | (0.79) |
| $\text{tariff}_p$ | 0.34*** | 0.03** | 0.01 | 8.13*** | 4.46*** | -1.70** |
| | (0.02) | (0.01) | (0.02) | (1.07) | (0.76) | (0.67) |
| N | 7,216 | 6,614 | 5,744 | 9,150 | 9,150 | 9,150 |
| r2 | 0.373 | 0.989 | 0.472 | 0.492 | 0.450 | 0.554 |

**Model B2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq 2019\text{-Q3})$ | 0.00 | -0.05* | -0.10* | -1.08 | 0.29 | -0.57 |
| | (.) | (0.03) | (0.06) | (2.36) | (1.68) | (1.48) |
| $\text{I}_t(t \geq 2019\text{-Q3})$ | 0.00 | -0.05** | 0.13*** | -2.28 | 1.04 | 1.63 |
| | (.) | (0.02) | (0.05) | (1.95) | (1.39) | (1.22) |
| $\text{tariff}_p$ | 0.34*** | 0.00 | 0.01 | 7.97*** | 4.95*** | -1.96*** |
| | (0.02) | (0.01) | (0.02) | (0.98) | (0.70) | (0.62) |
| N | 7,216 | 6,614 | 5,744 | 9,150 | 9,150 | 9,150 |
| r2 | 0.372 | 0.989 | 0.469 | 0.492 | 0.450 | 0.554 |

Table 6: Foodstuffs

**Model A1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | -0.19*** | -0.00 | 0.09*** | 0.44 | 0.47** | -0.57** |
| | (0.03) | (0.00) | (0.01) | (0.40) | (0.20) | (0.27) |
| r2 | 0.294 | 0.977 | 0.449 | 0.471 | 0.293 | 0.273 |
| N | 29,355 | 28,299 | 24,945 | 37,101 | 37,101 | 37,101 |

**Model A2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.01 | -0.04* | 0.53 | 0.39 | 0.14 |
| | (.) | (0.01) | (0.02) | (0.88) | (0.44) | (0.60) |
| r2 | 0.293 | 0.977 | 0.447 | 0.471 | 0.293 | 0.273 |
| N | 29,355 | 28,299 | 24,945 | 37,101 | 37,101 | 37,101 |

**Model B1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | -0.49*** | -0.02* | 0.02 | -1.90*** | 0.78** | 1.48*** |
| | (0.05) | (0.01) | (0.02) | (0.74) | (0.37) | (0.50) |
| $\text{I}_t(t \geq \text{2018-Q3})$ | 0.48*** | 0.01* | 0.09*** | 0.60 | -0.34 | -1.00** |
| | (0.04) | (0.01) | (0.02) | (0.62) | (0.31) | (0.42) |
| $\text{tariff}_p$ | -0.47*** | 0.01 | -0.01 | 5.16*** | -0.04 | -3.36*** |
| | (0.02) | (0.01) | (0.01) | (0.43) | (0.22) | (0.29) |
| N | 29,355 | 28,299 | 24,945 | 37,101 | 37,101 | 37,101 |
| r2 | 0.318 | 0.977 | 0.450 | 0.474 | 0.293 | 0.276 |

**Model B2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.00 | -0.01 | -0.95 | 0.86 | 1.83** |
| | (.) | (0.01) | (0.03) | (1.09) | (0.55) | (0.74) |
| $\text{I}_t(t \geq \text{2019-Q3})$ | 0.00 | -0.01 | 0.03 | -0.23 | -0.21 | -0.66 |
| | (.) | (0.01) | (0.02) | (0.93) | (0.47) | (0.63) |
| $\text{tariff}_p$ | -0.52*** | 0.00 | -0.00 | 4.69*** | 0.10 | -3.11*** |
| | (0.02) | (0.00) | (0.01) | (0.39) | (0.19) | (0.26) |
| N | 29,355 | 28,299 | 24,945 | 37,101 | 37,101 | 37,101 |
| r2 | 0.315 | 0.977 | 0.447 | 0.474 | 0.293 | 0.276 |

**Table 7: Mineral Products**

**Model A1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.26** | 0.02*** | 0.12*** | 0.22 | -0.63* | 0.28 |
| | (0.10) | (0.01) | (0.02) | (0.54) | (0.36) | (0.48) |
| r2 | 0.483 | 0.975 | 0.359 | 0.508 | 0.510 | 0.445 |
| N | 4,747 | 7,902 | 6,739 | 9,555 | 9,555 | 9,555 |

**Model A2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | -0.00 | -0.08* | -1.01 | -1.02 | -0.57 |
| | (.) | (0.01) | (0.05) | (1.17) | (0.79) | (1.04) |
| r2 | 0.482 | 0.975 | 0.356 | 0.508 | 0.510 | 0.445 |
| N | 4,747 | 7,902 | 6,739 | 9,555 | 9,555 | 9,555 |

**Model B1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | -1.40 | 0.01 | -0.01 | 0.92 | -2.16 | -7.40 |
| | (1.77) | (0.07) | (0.20) | (5.34) | (3.61) | (4.72) |
| $\text{I}_t(t \geq \text{2018-Q3})$ | 1.67 | 0.01 | 0.14 | -0.70 | 1.52 | 7.73 |
| | (1.77) | (0.07) | (0.19) | (5.31) | (3.59) | (4.70) |
| $\text{tariff}_p$ | -2.39** | 0.00 | -0.16 | -0.25 | 1.79 | -1.27 |
| | (1.06) | (0.05) | (0.13) | (3.57) | (2.41) | (3.16) |
| N | 4,747 | 7,902 | 6,739 | 9,555 | 9,555 | 9,555 |
| r2 | 0.484 | 0.975 | 0.360 | 0.508 | 0.510 | 0.445 |

**Model B2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | -0.06 | 0.04 | -0.49 | -1.63 | -4.87 |
| | (.) | (0.10) | (0.27) | (7.22) | (4.88) | (6.39) |
| $\text{I}_t(t \geq \text{2019-Q3})$ | 0.00 | 0.07 | -0.05 | -0.05 | 0.86 | 4.22 |
| | (.) | (0.10) | (0.27) | (7.18) | (4.85) | (6.36) |
| $\text{tariff}_p$ | -2.94*** | 0.01 | -0.18* | 0.16 | 1.14 | -3.76 |
| | (0.85) | (0.04) | (0.11) | (2.97) | (2.01) | (2.63) |
| N | 4,747 | 7,902 | 6,739 | 9,555 | 9,555 | 9,555 |
| r2 | 0.483 | 0.975 | 0.356 | 0.508 | 0.510 | 0.445 |

**Table 8: Chemicals & Allied Industries**

**Model A1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq 2018\text{-Q3})$ | -0.51*** | 0.02*** | 0.03*** | -1.59*** | 0.54*** | -0.05 |
| | (0.03) | (0.00) | (0.01) | (0.29) | (0.17) | (0.16) |
| r2 | 0.200 | 0.968 | 0.365 | 0.326 | 0.183 | 0.204 |
| N | 68,221 | 75,411 | 64,853 | 92,606 | 92,606 | 92,606 |

**Model A2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq 2019\text{-Q3})$ | 0.00 | 0.02*** | -0.05*** | -2.22*** | 0.62 | -0.25 |
| | (.) | (0.01) | (0.01) | (0.65) | (0.39) | (0.36) |
| r2 | 0.197 | 0.968 | 0.365 | 0.326 | 0.183 | 0.204 |
| N | 68,221 | 75,411 | 64,853 | 92,606 | 92,606 | 92,606 |

**Model B1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq 2018\text{-Q3})$ | -0.25*** | 0.01** | -0.03** | -1.50** | 0.52 | -0.12 |
| | (0.07) | (0.01) | (0.01) | (0.66) | (0.39) | (0.36) |
| $\text{I}_t(t \geq 2018\text{-Q3})$ | 0.31*** | 0.00 | 0.06*** | 0.29 | 0.49 | -0.15 |
| | (0.06) | (0.01) | (0.01) | (0.59) | (0.35) | (0.32) |
| $\text{tariff}_p$ | -2.87*** | 0.00 | 0.01 | -1.57*** | -1.89*** | 0.93*** |
| | (0.03) | (0.00) | (0.01) | (0.38) | (0.23) | (0.21) |
| N | 68,221 | 75,411 | 64,853 | 92,606 | 92,606 | 92,606 |
| r2 | 0.329 | 0.968 | 0.365 | 0.326 | 0.184 | 0.204 |

**Model B2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq 2019\text{-Q3})$ | 0.00 | 0.03*** | -0.02 | -1.04 | 0.33 | -0.32 |
| | (.) | (0.01) | (0.02) | (1.00) | (0.59) | (0.55) |
| $\text{I}_t(t \geq 2019\text{-Q3})$ | 0.00 | -0.01 | 0.01 | -0.37 | 0.88 | 0.00 |
| | (.) | (0.01) | (0.02) | (0.91) | (0.54) | (0.50) |
| $\text{tariff}_p$ | -2.90*** | 0.00 | 0.00 | -1.90*** | -1.77*** | 0.92*** |
| | (0.03) | (0.00) | (0.01) | (0.35) | (0.21) | (0.19) |
| N | 68,221 | 75,411 | 64,853 | 92,606 | 92,606 | 92,606 |
| r2 | 0.329 | 0.968 | 0.365 | 0.326 | 0.184 | 0.204 |

**Table 9: Plastics and Rubbers**

| **Model A1** | | | | | | |
|---|---|---|---|---|---|---|
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.42*** | 0.03*** | 0.07*** | -2.26*** | 0.67*** | 0.16 |
| | (0.02) | (0.00) | (0.01) | (0.27) | (0.12) | (0.10) |
| r2 | 0.156 | 0.959 | 0.393 | 0.407 | 0.191 | 0.187 |
| N | 81,993 | 95,091 | 79,917 | 118,269 | 118,269 | 118,269 |

| **Model A2** | | | | | | |
|---|---|---|---|---|---|---|
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.01*** | -0.12*** | -2.68*** | 0.89*** | -0.20 |
| | (.) | (0.00) | (0.01) | (0.59) | (0.26) | (0.23) |
| r2 | 0.151 | 0.959 | 0.393 | 0.407 | 0.191 | 0.187 |
| N | 81,993 | 95,091 | 79,917 | 118,269 | 118,269 | 118,269 |

| **Model B1** | | | | | | |
|---|---|---|---|---|---|---|
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.45*** | 0.01 | -0.06*** | -0.56 | 0.06 | 0.23 |
| | (0.05) | (0.01) | (0.02) | (0.71) | (0.31) | (0.28) |
| $\text{I}_t(t \geq \text{2018-Q3})$ | -0.21*** | 0.02*** | 0.14*** | 0.50 | 0.48* | -0.15 |
| | (0.05) | (0.01) | (0.01) | (0.67) | (0.29) | (0.26) |
| $\text{tariff}_p$ | 1.24*** | 0.00 | 0.02*** | - 12.42*** | 0.93*** | 0.37** |
| | (0.02) | (0.00) | (0.01) | (0.40) | (0.18) | (0.16) |
| N | 81,993 | 95,091 | 79,917 | 118,269 | 118,269 | 118,269 |
| r2 | 0.208 | 0.959 | 0.394 | 0.413 | 0.191 | 0.187 |

| **Model B2** | | | | | | |
|---|---|---|---|---|---|---|
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.01 | -0.09*** | -0.18 | -0.44 | -0.01 |
| | (.) | (0.01) | (0.02) | (1.09) | (0.47) | (0.43) |
| $\text{I}_t(t \geq \text{2019-Q3})$ | 0.00 | 0.00 | 0.05** | -0.51 | 1.19*** | 0.02 |
| | (.) | (0.01) | (0.02) | (1.02) | (0.44) | (0.40) |
| $\text{tariff}_p$ | 1.30*** | 0.00 | 0.02** | - 12.56*** | 1.00*** | 0.44*** |
| | (0.02) | (0.00) | (0.01) | (0.36) | (0.16) | (0.14) |
| N | 81,993 | 95,091 | 79,917 | 118,269 | 118,269 | 118,269 |
| r2 | 0.206 | 0.959 | 0.392 | 0.413 | 0.191 | 0.187 |

**Table 10: Raw Hides, Skins, Leather, and Furs**

**Model A1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.15*** | 0.05*** | 0.14*** | -4.92*** | 3.17*** | -0.15 |
| | (0.03) | (0.01) | (0.02) | (0.65) | (0.45) | (0.11) |
| r2 | 0.272 | 0.963 | 0.436 | 0.411 | 0.324 | 0.365 |
| N | 12,782 | 12,820 | 10,385 | 16,981 | 16,981 | 16,981 |

**Model A2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.02* | 0.10*** | -6.38*** | 4.33*** | -0.13 |
| | (.) | (0.01) | (0.03) | (1.40) | (0.96) | (0.24) |
| r2 | 0.270 | 0.963 | 0.432 | 0.409 | 0.322 | 0.365 |
| N | 12,782 | 12,820 | 10,385 | 16,981 | 16,981 | 16,981 |

**Model B1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.12 | -0.01 | 0.03 | -3.81 | 1.09 | -0.81 |
| | (0.40) | (0.08) | (0.22) | (8.02) | (5.50) | (1.40) |
| $\text{I}_t(t \geq \text{2018-Q3})$ | 0.03 | 0.07 | 0.11 | -1.37 | 2.04 | 0.72 |
| | (0.40) | (0.08) | (0.22) | (8.00) | (5.49) | (1.40) |
| $\text{tariff}_p$ | -0.57*** | -0.03 | -0.12 | 29.07*** | 4.78* | -6.62*** |
| | (0.12) | (0.04) | (0.09) | (3.91) | (2.68) | (0.68) |
| N | 12,782 | 12,820 | 10,385 | 16,981 | 16,981 | 16,981 |
| r2 | 0.273 | 0.963 | 0.436 | 0.413 | 0.324 | 0.369 |

**Model B2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.03 | 0.02 | -2.14 | -4.01 | 1.70 |
| | (.) | (0.12) | (0.30) | (12.05) | (8.26) | (2.10) |
| $\text{I}_t(t \geq \text{2019-Q3})$ | 0.00 | 0.00 | 0.09 | -5.22 | 8.25 | -1.54 |
| | (.) | (0.12) | (0.30) | (12.02) | (8.24) | (2.10) |
| $\text{tariff}_p$ | -0.55*** | -0.03 | -0.10 | 28.19*** | 5.48** | -6.90*** |
| | (0.12) | (0.04) | (0.08) | (3.75) | (2.57) | (0.65) |
| N | 12,782 | 12,820 | 10,385 | 16,981 | 16,981 | 16,981 |
| r2 | 0.272 | 0.963 | 0.433 | 0.413 | 0.323 | 0.369 |

**Table 11: Wood & Wood Products**

**Model A1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.01 | 0.01*** | 0.12*** | -3.17*** | 1.18*** | 0.04 |
| | (0.03) | (0.00) | (0.01) | (0.40) | (0.20) | (0.16) |
| r2 | 0.350 | 0.970 | 0.423 | 0.460 | 0.245 | 0.444 |
| N | 38,794 | 41,852 | 34,623 | 53,577 | 53,577 | 53,577 |

**Model A2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.01 | -0.03 | -4.23*** | 1.67*** | 0.40 |
| | (.) | (0.01) | (0.02) | (0.89) | (0.44) | (0.36) |
| r2 | 0.350 | 0.970 | 0.420 | 0.460 | 0.245 | 0.444 |
| N | 38,794 | 41,852 | 34,623 | 53,577 | 53,577 | 53,577 |

**Model B1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.57*** | 0.01** | -0.04** | -0.29 | 0.74* | 0.75** |
| | (0.08) | (0.01) | (0.02) | (0.86) | (0.42) | (0.35) |
| $\text{I}_t(t \geq \text{2018-Q3})$ | -0.40*** | 0.00 | 0.18*** | -1.77** | 0.27 | -0.63** |
| | (0.07) | (0.01) | (0.02) | (0.76) | (0.38) | (0.31) |
| $\text{tariff}_p$ | -0.88*** | -0.01** | 0.01 | -4.78*** | 0.74*** | -0.54*** |
| | (0.03) | (0.00) | (0.01) | (0.50) | (0.24) | (0.20) |
| N | 38,794 | 41,852 | 34,623 | 53,577 | 53,577 | 53,577 |
| r2 | 0.367 | 0.970 | 0.425 | 0.461 | 0.245 | 0.444 |

**Model B2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.02* | -0.05 | -0.06 | 1.07* | 0.93* |
| | (.) | (0.01) | (0.03) | (1.28) | (0.63) | (0.52) |
| $\text{I}_t(t \geq \text{2019-Q3})$ | 0.00 | -0.02** | 0.09*** | -1.57 | 0.02 | -0.63 |
| | (.) | (0.01) | (0.03) | (1.14) | (0.56) | (0.46) |
| $\text{tariff}_p$ | -0.82*** | -0.01* | 0.01 | -4.88*** | 0.85*** | -0.42** |
| | (0.03) | (0.00) | (0.01) | (0.45) | (0.22) | (0.18) |
| N | 38,794 | 41,852 | 34,623 | 53,577 | 53,577 | 53,577 |
| r2 | 0.366 | 0.970 | 0.421 | 0.461 | 0.245 | 0.444 |

**Table 12: Textiles**

**Model A1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | -0.81*** | -0.01 | 0.08*** | -9.73*** | 2.55*** | 0.25** |
| | (0.03) | (0.00) | (0.01) | (0.56) | (0.42) | (0.12) |
| r2 | 0.301 | 0.975 | 0.452 | 0.305 | 0.197 | 0.216 |
| N | 98,478 | 93,718 | 76,294 | 121,268 | 121,268 | 121,268 |

**Model A2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.03** | -0.02 | -9.27*** | 2.29** | 0.06 |
| | (.) | (0.01) | (0.03) | (1.30) | (0.98) | (0.29) |
| r2 | 0.296 | 0.975 | 0.452 | 0.303 | 0.196 | 0.216 |
| N | 98,478 | 93,718 | 76,294 | 121,268 | 121,268 | 121,268 |

**Model B1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | -0.03 | -0.04*** | -0.03** | 2.58*** | -3.93*** | 0.11 |
| | (0.03) | (0.01) | (0.01) | (0.68) | (0.51) | (0.15) |
| $\text{I}_t(t \geq \text{2018-Q3})$ | 0.07*** | 0.03*** | 0.15*** | -2.86*** | 3.08*** | -0.08 |
| | (0.01) | (0.00) | (0.01) | (0.30) | (0.23) | (0.07) |
| $\text{tariff}_p$ | -1.39*** | 0.01*** | -0.00 | - 15.45*** | 6.34*** | 0.30*** |
| | (0.01) | (0.00) | (0.01) | (0.41) | (0.32) | (0.09) |
| N | 98,478 | 93,718 | 76,294 | 121,268 | 121,268 | 121,268 |
| r2 | 0.375 | 0.975 | 0.457 | 0.313 | 0.200 | 0.216 |

**Model B2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | -0.03*** | -0.07*** | 2.19** | -4.10*** | -0.12 |
| | (.) | (0.01) | (0.02) | (1.04) | (0.79) | (0.23) |
| $\text{I}_t(t \geq \text{2019-Q3})$ | 0.00 | 0.01*** | 0.12*** | -3.22*** | 4.53*** | -0.12 |
| | (.) | (0.00) | (0.01) | (0.46) | (0.35) | (0.10) |
| $\text{tariff}_p$ | -1.39*** | 0.00 | -0.01 | - 14.92*** | 5.61*** | 0.35*** |
| | (0.01) | (0.00) | (0.01) | (0.38) | (0.29) | (0.08) |
| N | 98,478 | 93,718 | 76,294 | 121,268 | 121,268 | 121,268 |
| r2 | 0.375 | 0.975 | 0.453 | 0.312 | 0.200 | 0.216 |

**Table 13: Stone and Glass**

**Model A1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.23*** | 0.02*** | 0.12*** | -3.72*** | 3.29*** | 0.53*** |
| | (0.06) | (0.00) | (0.01) | (0.51) | (0.28) | (0.17) |
| r2 | 0.270 | 0.964 | 0.419 | 0.426 | 0.288 | 0.304 |
| N | 27,787 | 32,663 | 27,421 | 41,094 | 41,094 | 41,094 |

**Model A2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.03*** | -0.08*** | -4.83*** | 3.76*** | 0.09 |
| | (.) | (0.01) | (0.02) | (1.14) | (0.64) | (0.38) |
| r2 | 0.270 | 0.964 | 0.416 | 0.426 | 0.286 | 0.304 |
| N | 27,787 | 32,663 | 27,421 | 41,094 | 41,094 | 41,094 |

**Model B1**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | -0.18* | 0.00 | -0.03* | -2.99*** | 1.38*** | 0.34 |
| | (0.10) | (0.01) | (0.02) | (0.90) | (0.50) | (0.30) |
| $\text{I}_t(t \geq \text{2018-Q3})$ | -0.00 | 0.02*** | 0.17*** | 2.11*** | -0.06 | 0.11 |
| | (0.08) | (0.01) | (0.02) | (0.75) | (0.42) | (0.25) |
| $\text{tariff}_p$ | 1.40*** | -0.00 | 0.01 | -8.21*** | 6.19*** | 0.27 |
| | (0.04) | (0.00) | (0.01) | (0.54) | (0.30) | (0.18) |
| N | 27,787 | 32,663 | 27,421 | 41,094 | 41,094 | 41,094 |
| r2 | 0.306 | 0.964 | 0.422 | 0.431 | 0.297 | 0.304 |

**Model B2**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.01 | -0.11*** | -4.27*** | 1.72** | 0.13 |
| | (.) | (0.01) | (0.03) | (1.38) | (0.77) | (0.46) |
| $\text{I}_t(t \geq \text{2019-Q3})$ | 0.00 | -0.00 | 0.12*** | 1.10 | 0.26 | 0.35 |
| | (.) | (0.01) | (0.03) | (1.15) | (0.64) | (0.39) |
| $\text{tariff}_p$ | 1.38*** | -0.00 | 0.01 | -8.64*** | 6.41*** | 0.35** |
| | (0.04) | (0.00) | (0.01) | (0.50) | (0.28) | (0.17) |
| N | 27,787 | 32,663 | 27,421 | 41,094 | 41,094 | 41,094 |
| r2 | 0.306 | 0.964 | 0.417 | 0.431 | 0.297 | 0.304 |

**Table 14: Metals**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| **Model A1** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq 2018\text{-Q3})$ | 0.32*** | 0.02*** | 0.10*** | 1.70*** | 1.30*** | 0.31*** |
| | (0.02) | (0.00) | (0.01) | (0.28) | (0.16) | (0.09) |
| r2 | 0.162 | 0.963 | 0.413 | 0.404 | 0.203 | 0.174 |
| N | 100,305 | 103,789 | 87,923 | 128,349 | 128,349 | 128,349 |
| **Model A2** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq 2019\text{-Q3})$ | 0.00 | 0.01* | -0.07*** | 0.41 | 1.71*** | 0.69*** |
| | (.) | (0.01) | (0.01) | (0.65) | (0.37) | (0.20) |
| r2 | 0.160 | 0.963 | 0.411 | 0.404 | 0.203 | 0.174 |
| N | 100,305 | 103,789 | 87,923 | 128,349 | 128,349 | 128,349 |
| **Model B1** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq 2018\text{-Q3})$ | -0.20*** | 0.01*** | -0.04*** | 0.14 | -0.12 | -0.09 |
| | (0.03) | (0.00) | (0.01) | (0.51) | (0.29) | (0.16) |
| $\text{I}_t(t \geq 2018\text{-Q3})$ | 0.19*** | 0.02*** | 0.16*** | 0.51 | 0.53** | 0.04 |
| | (0.03) | (0.00) | (0.01) | (0.42) | (0.24) | (0.13) |
| $\text{tariff}_p$ | 0.97*** | -0.01*** | 0.01* | 2.93*** | 2.50*** | 0.98*** |
| | (0.01) | (0.00) | (0.01) | (0.29) | (0.16) | (0.09) |
| N | 100,305 | 103,789 | 87,923 | 128,349 | 128,349 | 128,349 |
| r2 | 0.215 | 0.963 | 0.416 | 0.405 | 0.205 | 0.175 |
| **Model B2** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq 2019\text{-Q3})$ | 0.00 | -0.01 | -0.03** | -1.48* | 0.36 | 0.16 |
| | (.) | (0.01) | (0.02) | (0.79) | (0.45) | (0.24) |
| $\text{I}_t(t \geq 2019\text{-Q3})$ | 0.00 | 0.02*** | 0.03** | 1.07 | 0.44 | 0.16 |
| | (.) | (0.01) | (0.01) | (0.66) | (0.38) | (0.20) |
| $\text{tariff}_p$ | 0.94*** | -0.00 | 0.00 | 3.11*** | 2.43*** | 0.94*** |
| | (0.01) | (0.00) | (0.01) | (0.26) | (0.15) | (0.08) |
| N | 100,305 | 103,789 | 87,923 | 128,349 | 128,349 | 128,349 |
| r2 | 0.215 | 0.963 | 0.411 | 0.405 | 0.205 | 0.175 |

**Table 15: Machinery and Electrical**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| **Model A1** | | | | | | |
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.42*** | 0.04*** | 0.08*** | -0.85*** | 0.68*** | 0.34*** |
| | (0.02) | (0.00) | (0.00) | (0.17) | (0.07) | (0.05) |
| r2 | 0.138 | 0.950 | 0.421 | 0.337 | 0.128 | 0.118 |
| N | 209,717 | 265,977 | 223,344 | 323,081 | 323,081 | 323,081 |
| **Model A2** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.02*** | -0.14*** | -1.31*** | 1.33*** | 0.38*** |
| | (.) | (0.00) | (0.01) | (0.38) | (0.15) | (0.12) |
| r2 | 0.136 | 0.950 | 0.421 | 0.337 | 0.128 | 0.118 |
| N | 209,717 | 265,977 | 223,344 | 323,081 | 323,081 | 323,081 |
| **Model B1** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.22*** | 0.00 | -0.03*** | -1.18** | 0.22 | 0.15 |
| | (0.06) | (0.00) | (0.01) | (0.47) | (0.19) | (0.14) |
| $\text{I}_t(t \geq \text{2018-Q3})$ | 0.02 | 0.04*** | 0.12*** | 1.28*** | 0.30* | 0.14 |
| | (0.06) | (0.00) | (0.01) | (0.44) | (0.17) | (0.13) |
| $\text{tariff}_p$ | 1.12*** | -0.00 | 0.01* | -5.23*** | 1.09*** | 0.33*** |
| | (0.02) | (0.00) | (0.00) | (0.26) | (0.10) | (0.08) |
| N | 209,717 | 265,977 | 223,344 | 323,081 | 323,081 | 323,081 |
| r2 | 0.150 | 0.950 | 0.422 | 0.338 | 0.128 | 0.118 |
| **Model B2** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | -0.01 | -0.03** | -1.86** | 0.54* | 0.05 |
| | (.) | (0.01) | (0.01) | (0.72) | (0.29) | (0.22) |
| $\text{I}_t(t \geq \text{2019-Q3})$ | 0.00 | 0.03*** | -0.01 | 1.24* | 0.51* | 0.21 |
| | (.) | (0.01) | (0.01) | (0.68) | (0.27) | (0.21) |
| $\text{tariff}_p$ | 1.15*** | -0.00 | 0.00 | -5.39*** | 1.10*** | 0.37*** |
| | (0.02) | (0.00) | (0.00) | (0.23) | (0.09) | (0.07) |
| N | 209,717 | 265,977 | 223,344 | 323,081 | 323,081 | 323,081 |
| r2 | 0.150 | 0.950 | 0.420 | 0.338 | 0.128 | 0.118 |

**Table 16: Transportation**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| **Model A1** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.12** | 0.02*** | 0.09*** | -1.20*** | 1.07*** | 0.35** |
| | (0.05) | (0.00) | (0.01) | (0.42) | (0.20) | (0.17) |
| r2 | 0.274 | 0.958 | 0.435 | 0.477 | 0.252 | 0.258 |
| N | 31,588 | 34,114 | 28,876 | 41,446 | 41,446 | 41,446 |
| **Model A2** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.01 | -0.13*** | -2.55*** | 1.53*** | 0.11 |
| | (.) | (0.01) | (0.02) | (0.93) | (0.45) | (0.38) |
| r2 | 0.274 | 0.958 | 0.433 | 0.477 | 0.252 | 0.258 |
| N | 31,588 | 34,114 | 28,876 | 41,446 | 41,446 | 41,446 |
| **Model B1** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.38* | 0.00 | -0.03 | -0.63 | 0.91 | 0.66 |
| | (0.21) | (0.01) | (0.03) | (1.50) | (0.72) | (0.62) |
| $\text{I}_t(t \geq \text{2018-Q3})$ | -0.24 | 0.02* | 0.12*** | -0.70 | 0.15 | -0.40 |
| | (0.21) | (0.01) | (0.03) | (1.45) | (0.69) | (0.59) |
| $\text{tariff}_p$ | -0.27*** | 0.00 | 0.01 | 1.06 | 0.14 | 0.82** |
| | (0.08) | (0.01) | (0.02) | (0.87) | (0.42) | (0.36) |
| N | 31,588 | 34,114 | 28,876 | 41,446 | 41,446 | 41,446 |
| r2 | 0.275 | 0.958 | 0.435 | 0.477 | 0.252 | 0.258 |
| **Model B2** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | -0.02 | -0.05 | -0.14 | 0.16 | -0.90 |
| | (.) | (0.02) | (0.05) | (2.25) | (1.08) | (0.92) |
| $\text{I}_t(t \geq \text{2019-Q3})$ | 0.00 | 0.03 | 0.02 | -2.28 | 1.31 | 1.19 |
| | (.) | (0.02) | (0.05) | (2.18) | (1.04) | (0.89) |
| $\text{tariff}_p$ | -0.23*** | 0.00 | 0.01 | 0.87 | 0.40 | 1.11*** |
| | (0.08) | (0.01) | (0.02) | (0.79) | (0.38) | (0.32) |
| N | 31,588 | 34,114 | 28,876 | 41,446 | 41,446 | 41,446 |
| r2 | 0.274 | 0.958 | 0.432 | 0.477 | 0.252 | 0.258 |

**Table 17: Miscellaneous**

| | p | leadtime | roe | volchina | volindnam | volmexda |
|---|---|---|---|---|---|---|
| **Model A1** | | | | | | |
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 1.69*** | 0.02*** | 0.11*** | -3.31*** | 1.56*** | 0.07 |
| | (0.04) | (0.00) | (0.01) | (0.30) | (0.13) | (0.07) |
| r2 | 0.214 | 0.948 | 0.437 | 0.342 | 0.214 | 0.186 |
| N | 79,042 | 93,656 | 76,117 | 120,779 | 120,779 | 120,779 |
| **Model A2** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | 0.01* | -0.06*** | -4.88*** | 2.42*** | 0.04 |
| | (.) | (0.01) | (0.02) | (0.69) | (0.31) | (0.17) |
| r2 | 0.198 | 0.948 | 0.436 | 0.342 | 0.213 | 0.186 |
| N | 79,042 | 93,656 | 76,117 | 120,779 | 120,779 | 120,779 |
| **Model B1** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2018-Q3})$ | 0.79*** | -0.00 | 0.00 | -0.95** | 0.61*** | 0.13 |
| | (0.06) | (0.00) | (0.01) | (0.48) | (0.21) | (0.11) |
| $\text{I}_t(t \geq \text{2018-Q3})$ | -0.37*** | 0.03*** | 0.13*** | -0.66* | 0.47*** | -0.06 |
| | (0.04) | (0.00) | (0.01) | (0.37) | (0.17) | (0.09) |
| $\text{tariff}_p$ | 3.00*** | -0.00 | 0.00 | -4.21*** | 1.29*** | -0.00 |
| | (0.02) | (0.00) | (0.01) | (0.28) | (0.12) | (0.07) |
| N | 79,042 | 93,656 | 76,117 | 120,779 | 120,779 | 120,779 |
| r2 | 0.380 | 0.948 | 0.439 | 0.344 | 0.215 | 0.186 |
| **Model B2** | | | | | | |
| | p | leadtime | roe | volchina | volindnam | volmexda |
| $\text{tariff}_p \times I_t(t \geq \text{2019-Q3})$ | 0.00 | -0.00 | -0.03 | -1.26* | 1.14*** | 0.15 |
| | (.) | (0.01) | (0.02) | (0.74) | (0.33) | (0.18) |
| $\text{I}_t(t \geq \text{2019-Q3})$ | 0.00 | 0.01* | 0.05*** | -1.59*** | 0.36 | 0.01 |
| | (.) | (0.01) | (0.01) | (0.57) | (0.26) | (0.14) |
| $\text{tariff}_p$ | 3.10*** | -0.00 | 0.01 | -4.37*** | 1.36*** | 0.02 |
| | (0.02) | (0.00) | (0.01) | (0.25) | (0.11) | (0.06) |
| N | 79,042 | 93,656 | 76,117 | 120,779 | 120,779 | 120,779 |
| r2 | 0.378 | 0.948 | 0.436 | 0.344 | 0.214 | 0.186 |

# 6 Conclusion

We study how the US tariff imposed on China during 2018Q3 affected the operations of multinational US companies. We focus on 2018Q3 because it concentrates on a sharp rate increase over a brief period of time, which favors econometric evaluation. We used data between 2015 and 2019 to avoid the effect of the Covid-19 pandemic. We use transaction-level import data at the shipment level of imports to the United States. We find that companies have diversified their sources, reduced the share of imports from China, and increased the share of imports from other Asian countries, such as India and Vietnam, and North American countries, such as Canada and Mexico (similar to Alfaro and Chor, 2023). We also observe an increase in lead time in the operations of the company and a negative effect in the company's financial results. We test the causal effect of the tariff war on leadtime and diversification of sources. In both cases we find causal evidence. The increase on tariff produced an increase 1.5 more country sources, reduce the supply from the main country in a 0.3%, and finally increases the leadtime in the US supply chain importers of a 0.4%.

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