Anticipating Tariff Changes: Did American Importers Respond to Trump's 2016 Victory?

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Abstract

As the biggest U.S. presidential election upset in recent decades, Donald Trump's 2016 victory introduced new uncertainties in the trade environment, including the potential for additional prohibitive tariffs. While it is well-documented in the trade literature that firms anticipate and respond to scheduled tariff changes, it remains unclear whether this still holds when changes are uncertain and may happen at any moment, for example, following a contentious election. Focusing on the period between the 2016 election and the first round of China-specific tariffs in mid-2018, I empirically study if and how American importers reacted to potential tax hikes using U.S. Customs bills of lading data. By exploiting cross-product, origin, and time variations in tariff risks through a triple-difference approach, I find that importers facing higher risks stockpiled in response to Trump's election—increasing their quarterly imports by around 5% through larger order sizes rather than increased order frequency. However, there is no evidence that firms expanded their trade network, diversified their sourcing portfolio, or diverted away from China during this period. The stockpiling behavior was more pronounced among smaller importers, which can partially be explained by the downstream nature of their purchases rather than differences in post-election entry/exit rates or input storability.

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1 Introduction

1.1 Overview

In November 2017, more than 9,000 containers' worth of washers arrived in U.S. ports, a volume more than double that of November 2016 (Tangel, 2018). This happened just one month after the U.S. International Trade Commission (ITC) decided to side with Whirlpool Corporation in an investigation under Section 201 of the Trade Act of 1974 to safeguard American washers against imported competition. This spike in washing machine imports prior to a global safeguard is perhaps one of the most recent stories that exemplifies the anticipatory dynamics documented in the trade literature on tariff changes. When trade policy changes are announced before their implementations, firms will choose to buy in periods with lower prices, either stockpiling or delaying their purchases (Cavallo et al., 2021; Khan and Khederlarian, 2021). However, when changes are uncertain and the timing is not yet known, will firms still adjust their behaviors to prepare for what might come ahead?

To answer this question, I look into the 2016 U.S. presidential election and ask whether Donald Trump's victory caused American firms to change their import behaviors. Regarded as the biggest presidential election upset in recent decades, Trump's election introduced many uncertainties in the trade environment, including the potential for additional tariffs. Grounding his campaign on an "America First" agenda, Donald Trump and his administration signaled a return to protectionism in American trade policies, with China being the primary target. Nonetheless, right after the election, it was unclear whether the new president would follow through on his campaign promises and start a trade war with China. If additional tariffs were to be placed on Chinese goods, then questions remained over their timing, which products might be impacted, and how restrictive these new tariffs would be.

In reality, the trade war did not officially start until July 2018, when the U.S. implemented the first wave of tariffs on Chinese goods, known as List 1. Focusing on this gap between the 2016 election and the implementation of List 1, I use a rich set of transaction-level bills of lading data from the U.S. Customs to empirically examine whether American importers adjusted their purchases and supplier networks during this interim window in anticipation of potential tariff hikes. My identification strategy leverages the fact that firms buying different goods from different origins faced different risks after Trump was elected. This cross-product, origin, and time variation—coupled with the surprising election result—lends itself to a triple-difference (DDD) approach which I employ to estimate the causal effects of Trump's election on various import outcomes.

My findings indicate that American importers did in fact respond to the result of the 2016 election. Looking into import activities, I find that firms buying risky products from China stockpiled in the period between Trump's election and List 1 implementation.[1] Specifically, these firms increased their quarterly import volumes/weights by roughly 5%, mainly through buying more each time and not buying more frequently. The corresponding event studies further show that imports picked up immediately in the first quarter post-election and did not taper off until 2018Q2 at the end of the interim window. In addition to stockpiling, I also test whether at-risk firms decided to look for new partners or diversify their sourcing portfolio to divert away from China. However, I found no evidence of significant adjustments made to trade network outcomes. Together, these findings suggest that importers may still stockpile to prepare for unfavorable policy changes, even when the details about such changes are rather vague; however, making changes to the supplier network is not feasible in the short run.

Notably, this paper also shows that the stockpiling behavior is the most intensive for the smallest importers. During the same period, firms in the smallest size quintile increased their quarterly import volumes by about 15%, whereas those in the largest quintile only increased their import volumes by 3%. Thus, like most other trade outcomes, the baseline effects are heavily driven by the largest firms that dominate trade activities. To investigate why the election had the strongest impacts on the smallest firms, I test whether this heterogeneity can be explained by the upstreamness of imported goods, the storability of inputs, and the potentially differential entries and exits by firm size brackets post-election. I find that the baseline DDD coefficients are mainly driven by the imports of downstream goods, which were purchased more by the smallest firms compared to the rest. I do not find any evidence that the smallest firms bought more storable inputs which could enable stockpiling nor that there were significantly different entries and exits into this group.

1.2 Literature and Contributions

First and foremost, my paper complements the literature that examines the economic impacts of the U.S.-China trade war under the Trump administration. To empirically evaluate how tariffs on Chinese goods impact American welfare and prices, previous studies have typically relied on a difference-in-differences (DiD) approach, comparing tariff-affected goods to those unaffected. They document complete pass-through of the tariffs onto domestic prices (Amiti et al., 2020; Fajgelbaum et al., 2020; Cavallo et al., 2021), lower investment growth (Amiti et al., 2020), negative financial outcomes for firms more dependent on China (Huang et al., 2023), and substantial overall welfare loss (Amiti et al., 2019; Fajgelbaum and Khandelwal, 2022). In this paper, I instead focus on the period prior to the imposition of tariffs, a topic

[1] Risky products are characterized by the initial proposed List 1.

that receives relatively less attention but has important implications for current and future research on the consequences of the trade war. For the DiD approach to correctly estimate the causal effects of tariffs on economic outcomes, several key assumptions must be met, one of which being *no anticipation*. It is well-documented that firms anticipate and respond to scheduled policy changes (Cavallo et al., 2021; Khan and Khederlarian, 2021). The two-year gap between the 2016 election and the first wave of tariffs, as well as the smaller three-month window between the announcement and implementation of List 1, gave firms the opportunity to adjust their imports. Therefore, it is crucial to examine if firms did indeed react to Trump's election since the evidence of anticipation means that future studies on the effects of trade war tariffs need to take this into consideration. Ma and Meng (2023) accounts for this problem by using only the set of Chinese products initially included but eventually removed from the provisional tariff lists as a control group, finding some evidence of frontloading. My paper dives much deeper into this anticipatory response, asking not only *if* but also *how* importers changed their behaviors to counteract the potential for additional tariffs, and investigates not only trade flows but also trade network outcomes.

Secondly, my paper adds to the literature on anticipatory effects of policy changes. Outside of the trade literature, many studies have shown that economic agents are forward-looking and react to policy changes when there are lags in implementations. For example, consumers stock up on storable goods before sales tax hikes (Baker et al., 2021) or increase their purchase of gasoline before gasoline tax increases (Coglianese et al., 2017). Regarding trade policy changes, previous research has found some limited evidence of U.S. firms stockpiling in anticipation of the U.S.-China trade war tariffs (Cavallo et al., 2021; Ma and Meng, 2023) as well as peak-and-trough dynamics in trade flows surrounding NAFTA (Khan and Khederlarian, 2021) and China's WTO accession (Alessandria et al., 2024). In these papers, changes were scheduled and well-defined, allowing the economic agents to precisely react with complete information. I complement their findings by testing the anticipatory response in a much more uncertain environment to see if the economic agents—American importers in this case—still react when the details or even actualization of the policy change are unclear. While Donald Trump's election might have signaled incoming tighter trade policies, it was not yet known at the time if, when, and how the president would start making moves, especially against a large trade partner like China.

Last but not least, my paper contributes to the growing literature on trade policy uncertainty, in the sense that Donald Trump's election raised many questions about future trade policies and international relations in general. Alessandria et al. (2024) echoes this reasoning, finding that despite Trump's campaign rhetoric, the likelihood of the U.S. placing higher tariffs on China did not rise until the trade war actually began in 2018. Other works on trade policy uncertainty typically exploit either the formation of the WTO/China's accession to the WTO (Handley, 2014; Handley and Limão, 2017; Feng et al., 2017; Imbruno, 2019; Handley et al., 2020) or a text-based construct of uncertainty (Baker et al., 2016; Caldara et al., 2020; Sharma and Paramati, 2021). They find that a lower level of uncertainty leads to favorable macroeconomic outcomes such as higher trade flows and more traded varieties of higher quality, as well as positive financial outcomes for publicly traded firms. Complementing these studies, my paper brings up cyclical changes in politics as a source of uncertainty and offers novel evidence on the intricacies of importer's behavioral changes when faced with uncertain setbacks. Moreover, unlike papers that rely on earning calls which are only available for larger trading firms, my paper studies the impacts of uncertain risks on the near-universe of American importers captured by Customs data, thereby offering a glimpse into the way small and medium firms adjust to uncertainty compared to large corporations. Accounting for nearly two-thirds of net new private sector jobs in recent decades (Dilger, 2022) and 44% of the U.S. GDP in 2014 (Kobe and Schwinn, 2018), small and medium-sized enterprises play an important role in the U.S. economy, making it essential for policymakers to understand how these businesses respond to politically induced trade shocks.

The rest of the paper proceeds as follows: Section 2 summarizes key events surrounding the 2016 U.S. presidential election, Donald Trump's stance on trade, and the period leading up to the U.S.-China trade war. Section 3 then describes the datasets used in this paper and establishes three stylized facts about the trends and patterns in American imports around the election period to motivate the empirical analyses. Sections 4 and 5 estimate the effects of Trump's election on firms' import activities and trade networks. In Section 6, I break down the election effects by importer size to show that not all firms responded the same way and discuss some potential explanations for this heterogeneity. Section 7 shows the robustness of the main results to alternative specifications. Finally, Section 8 summarizes and concludes.

2 Institutional Background

On June 16, 2015, Donald Trump formally announced his candidacy for the 2016 United States presidential election. As part of his "Make America Great Again" campaign, Trump voiced his criticism of several international trade agreements, namely the North American Free Trade Agreement (NAFTA) and the Trans-Pacific Partnership (TPP), on the ground that these agreements undermined the American economy by moving jobs abroad and allowed foreign nations to take advantage of the United States. One particular nation heavily criticized was China, which was accused by the then-Republican candidate as a currency manipulator and operator of unfair trade practices against the United States. On November 8, 2016, Donald Trump defeated the Democratic candidate Hillary Clinton to become the 45th president of the United States, an event considered as one of the biggest political upsets in history by the media. Following President Trump's Memorandum of August 14, 2017, the U.S. Trade Representative (USTR) launched a Section 301 investigation into certain acts, policies, and practices of the Chinese government concerning technology transfer, intellectual property and innovation. This investigation resulted in the USTR releasing an initial list of 1,334 proposed products (worth US$50 billion) subject to a potential 25 percent tariff in April 2018, which was known as List 1 and eventually implemented on July 6, 2018 after some revisions. The implementation of List 1 marked the beginning of a trade war between the U.S. and China, which was characterized by tit-for-tat tariff hikes until January 2020 when the two countries signed a Phase One trade deal.

The election of Donald Trump, especially considering that it was largely unforeseen by major polls, naturally raised many questions about future trade policies. First and foremost, it was entirely unclear if or when the former president would follow through with his campaign promises. It took the administration about eight months to launch the Section 301 investigation, and the first wave of tariffs was implemented one and a half years into Trump's presidency. In other words, the timing of tariff hikes, if any, was uncertain right after the election. Second, it was not predetermined which industries from which countries would be impacted. Although a lot of Trump's rallying time was spent on manufacturing industries and China, the former president actually placed several tariffs on goods from other countries prior to the onset of the U.S.-China trade war. Specifically, Trump imposed safeguard tariffs on solar panels, washing machines, steel, and aluminum from most countries, including even America's traditionally close allies and major trade partners such as the European Union, Canada, and Mexico. Last but not least, the magnitudes of these prohibitive tariffs were not known, further compounding the uncertainties faced by American importers in this tumultuous period. In sum, the nature of the 2016 presidential election brings up many questions, one of which is how American importers weathered this period. This paper focuses on the period between Donald Trump's election and the implementation of the first China-specific tariff list to study if and how at-risk companies anticipated and reacted to changes in trade policies with China.

3 Data and Stylized Facts

3.1 Data

Bills of Lading Data I use the U.S. Customs bills of lading data for all containerized imports into the United States from January 2015 to October 2018 from Panjiva.[2] A bill of lading (BoL) is a legal document that contains the description of the goods being carried and serves as a record of the transportation of said goods. The raw data are transaction level; that is, each row is identified by a bill of lading. The bills of lading contain information on the shipper/consignor, the buyer/consignee, product description, shipment origin and destination (port/city/country), vessel, and weight. Based on the description of the product dimensions, Panjiva imputed the shipment volume, measured in twenty-foot equivalent units (TEU), which can be thought of as a regular cargo container. The company also assigns a Harmonized System (HS) code to each product based on the description.[3] For a more detailed discussion of this novel source of data, including its pros and cons as well as how closely it tracks data from the U.S. Census, refer to the Data Description section from this paper by Flaaen et al. (2021). I aggregate the data into a firm-product-origin by year-quarter panel running from 2015Q1 to 2018Q2, dropping Q3 and October of 2018 as List 1 went into effect in July 2018. I restricted my sample to this period to avoid price changes from China-specific tariffs, making it easier to tease out the effect of anticipation caused by Donald Trump's election. I also exclude logistic, wholesale, and retail firms from my sample, leaving a total of 954,664 firms.[4,5] Table 1 gives the definitions of the main variables and Table 2 shows the descriptive statistics for the overall sample.

Overall, the data is split quite evenly between the pre- and post-election periods. Roughly a third of the data contains imports from China, and imports of List 1 products make up for 17% of the observations. Exact details on import volumes and weights from China and List 1 products are described in Subsection 3.2 below. From 2015Q1 to 2018Q2, the average shipment into the U.S. takes up nearly six 20-foot-long cargo containers (5.8 TEUs) and weighs around 40 tons. For each input from a country, the average firm imports a bit less

[2]Panjiva was acquired by S&P Global in 2018. Similar data is used by Flaaen et al. (2021) to study supply chain disruptions.

[3]Sometimes the HS code is already included in the description of the good.

[4]Firms are identified by consignee names on bills of lading. Firms can request that the U.S. Customs and Border Protection redact their identity, in which case they cannot be identified. In the 2015-2018 period, approximately 11% of observations in the raw BoL data have missing consignee information.

[5]Logistic, wholesale, and retail firms are excluded to stay consistent with a theoretical model of firms buying intermediate inputs to produce an output. Moreover, I want to eliminate the difficulty of separating out indirect imports (firms buying from wholesalers) and quantifying trade activities/partners (logistic firms are transporting on behalf of other firms). All results are robust to the use of the full sample containing logistic, wholesale, and retail firms. See Section 7.

than 3 times per quarter, or about once a month. It is important to note that all of these statistics vary greatly for firms of different sizes, as shown in Table 3 below.[6]

Table 1: Definitions of Main Variables

Variable	**Definition**
Outcomes	
$Volume_{ikct}$	The volume of imports, measured in TEUs, of product k that firm i buys from country c in year-quarter t. Originally imputed by Panjiva.
$Weight_{ikct}$	The weight of imports, in kg, of product k that firm i buys from country c in year-quarter t. Recorded on the bills of lading.
$\#Shipments_{ikct}$	The total number of times firm i imports product k from country c in year-quarter t, i.e., the number of shipments per quarter. Constructed by counting the number of distinct bills for each i-k-c-t combination.
$\#Partners_{ikct}$	The total number of suppliers in country c that firm i buys product k from in year-quarter t.
HHI_{ikct}	The Herfindahl–Hirschman Index of sourcing portfolio concentration, constructed as following Equation 3. $0 \leq HHI \leq 1$, with 1 meaning that firm i only sources from one single supplier for k from c in t.
Regressors	
$AfterElection_t$	= 1 if after Trump's election ($t \geq$ 2016Q4), 0 if before.
$China_c$	= 1 if shipment comes from China, 0 if elsewhere.
$List1_k$	= 1 if product is on the initial List 1 tariffs, 0 otherwise.
$FirmSize_i$	Firm size quintile (1-5), assigned based on the average annual import volume, with 5 being the largest importers.

Notes: Firms are identified by consignee names on bills of lading. Products are coded as 6-digit Harmonized System (HS) codes by Panjiva. Initial List 1 refers to the proposed tariff action released on April 6, 2018.

Table 2: Summary Statistics of Main Variables

	N	Mean	SD	Med	Min	Max
AfterElection	5,674,724	0.46	0.50	0.00	0.00	1.00
China	5,674,724	0.32	0.47	0.00	0.00	1.00
List1	5,674,724	0.17	0.38	0.00	0.00	1.00
Volume (TEU)	5,674,724	5.80	98.77	1.00	0.00	39,997.64
Weight (kg)	5,674,724	41,667.97	592420.97	5,186.00	0.04	3.41e+08
#Shipments	5,674,724	2.70	11.48	1.00	1.00	4,467.00
#Partners	5,188,951	1.13	0.77	1.00	1.00	101.00
HHI	5,188,951	0.97	0.12	1.00	0.03	1.00

Notes: Observation unit is firm-product-origin country-year/quarter. Products are coded as 6-digit HS. The data run from 2015Q1 to 2018Q2. Logistic, wholesale, and retail firms are excluded. Total number of firms covered is 954,664.

[6] Larger firms also buy more inputs on average.

Table 3 breaks down the summary statistics in Table 2 by size quintiles. As expected, trade activities are heavily dominated by the largest firms (5$^{\text{th}}$ quintile) who make up almost 80% of the total number of observations.[7] On average per shipment, the biggest importers in the dataset buy roughly 180 times more in both volume and weight compared to the smallest importers, and there is much greater variation among these firms. Even though import volume and weight do not correlate with value perfectly, these statistics still demonstrate that firms of different sizes vary greatly in their trade activities; thus, it is natural to suspect that they might respond differently to the same event. If we look at the number of quarterly shipments, firms from quintile 1 to 4 buy around one time per quarter, whereas firms in the 5$^{\text{th}}$ quintile import around 3 times per quarter, or at least once a month.[8] However, for a particular input from a country, all firms appear to buy from a single supplier on average.

Table 3: Summary Statistics of Key Variables by Import Sizes

	Firm Size Quintile				
	1$^{\text{st}}$	2$^{\text{nd}}$	3$^{\text{rd}}$	4$^{\text{th}}$	5$^{\text{th}}$
Volume (TEU)	0.0403	0.149	0.550	0.978	7.346
	(0.0271)	(0.116)	(0.413)	(0.807)	(112.2)
Weight (kg)	285.4	878.2	2,758.1	5,193.1	53,042.3
	(700.9)	(1,183.6)	(4,068.0)	(7,088.8)	(672,745.0)
#Shipments	1.013	1.057	1.103	1.157	3.170
	(0.147)	(0.331)	(0.470)	(0.636)	(13.01)
#Partners	1.003	1.011	1.016	1.026	1.169
	(0.0685)	(0.157)	(0.189)	(0.242)	(0.873)
HHI	0.999	0.996	0.995	0.992	0.963
	(0.0238)	(0.0403)	(0.0479)	(0.0595)	(0.129)
Observations	239,644	302,627	338,879	398,687	4,394,887

Notes: Observation unit is firm-product-origin country-year/quarter. Products are coded as 6-digit HS. The data run from 2015Q1 to 2018Q2. Logistic, wholesale, and retail firms are excluded. Total number of firms covered is 954,664.

U.S. Census Bureau Data I complement the Bills of Lading data with official trade statistics from the U.S. Census Bureau, publicly available through USA Trade Online. The main advantage of the U.S. Census data over the BoL data comes from the availability of trade values in USD. However, this data does not allow me to investigate firm's level responses such as frequency of shipments, number of suppliers, sourcing diversity, among

[7]Note that there are roughly the same number of firms in each quintile by construction.

[8]This is one of the reasons why I aggregate the data to quarterly level. Another reason being the lumpiness of trade.

other outcomes. Therefore, all of my empirical analyses use BoL data from the U.S. Customs. Flaaen et al., 2021 has shown that aggregate BoL data closely track U.S. Census data of containerized imports (nominal values). I use U.S. Census data for CIF value of imports for consumption to plot Figure A.2, which corroborates Figure 1 shown in the main text.[9] I also use the most disaggregate imports—ten-digit HS product by district of entry and source country—to construct a measure of input storability as discussed in Section 6.2.2.

Table 4: Top 10 least and most upstream manufacturing industries

Industry	Upstreamness
Automobile manufacturing	1.0009
Light truck and utility vehicle manufacturing	1.0016
Motor home manufacturing	1.0041
Ophthalmic goods manufacturing	1.0186
Electronic computer manufacturing	1.0270
Clothing and clothing accessories stores	1.0296
Food and beverage stores	1.0318
Doll, toy, and game manufacturing	1.0353
Breakfast cereal manufacturing	1.0446
Primary battery manufacturing	1.0471
Other basic organic chemical manufacturing	3.8008
Copper rolling, drawing, extruding and alloying	3.9314
Carbon and graphite product manufacturing	3.9345
Fertilizer manufacturing	3.9450
Copper, nickel, lead, and zinc mining	4.0213
Forestry and logging	4.1153
Nonferrous metal smelting and refining	4.1452
Iron, gold, silver, and other metal ore mining	4.5148
Oilseed farming	4.5557
Petrochemical manufacturing	4.8161

Notes: BEA Input-Output Accounts Data (2012) and author's calculations.

BEA Input-Output Accounts Data The 2012 I-O use table (after redefinitions and valued in producers' prices), published by the Bureau of Economic Activities (BEA), is used to construct the industry-level measure of upstreamness à la Antràs et al. (2012). There are a total of 401 industries in the use table (not counting four that are never used as inputs/outputs). This construct of upstreamness characterizes the average distance from final use for each industry, with a minimum of 1 meaning all output goes directly to final uses and no theoretical maximum. An industry with a higher measure of upstreamness is thus further away from final consumption. In 2012, the measure of upstreamness ranges

[9] CIF stands for customs, insurance, and freight. Imports for consumption disregard imports for re-export purposes. Duties are excluded.

from a minimum of 1 (27 industries) to a maximum of 4.82 (Petrochemical Manufacturing). The top 10 most and least upstream manufacturing industries are shown in Table 4.

To assign upstreamness to products in the BoL data, I first convert HS6 codes to 2012 NAICS codes using the concordance table maintained by Liao et al. (2020), then from NAICS to BEA industry codes using the concordance table provided by the BEA. Table 5 shows the summary statistics for the measure of upstreamness for U.S. Imports in the BoL data. From 2015Q1 to 2018Q2, the average imported product belongs to an industry that is roughly one stage before final use, i.e., $Upstreamness \approx 2$.

Table 5: Upstreamness of U.S. Imports

Variable	N	Mean	SD	Med	Min	Max
Upstream	5,435,059	2.1085	0.8112	2.1021	1.0009	4.8161

Notes: Observation unit is firm-product-origin country-year/quarter. Products are coded as 6-digit HS. The data run from 2015Q1 to 2018Q2. Logistic, wholesale, and retail firms are excluded. Total number of firms covered is 954,664.

3.2 Stylized Facts

I now present three stylized facts that describe the trends in American imports surrounding Donald Trump's election, the sourcing patterns of American firms in the same period, and the relevancy of List 1 tariffs. These stylized facts serve as the motivation for my empirical research questions.

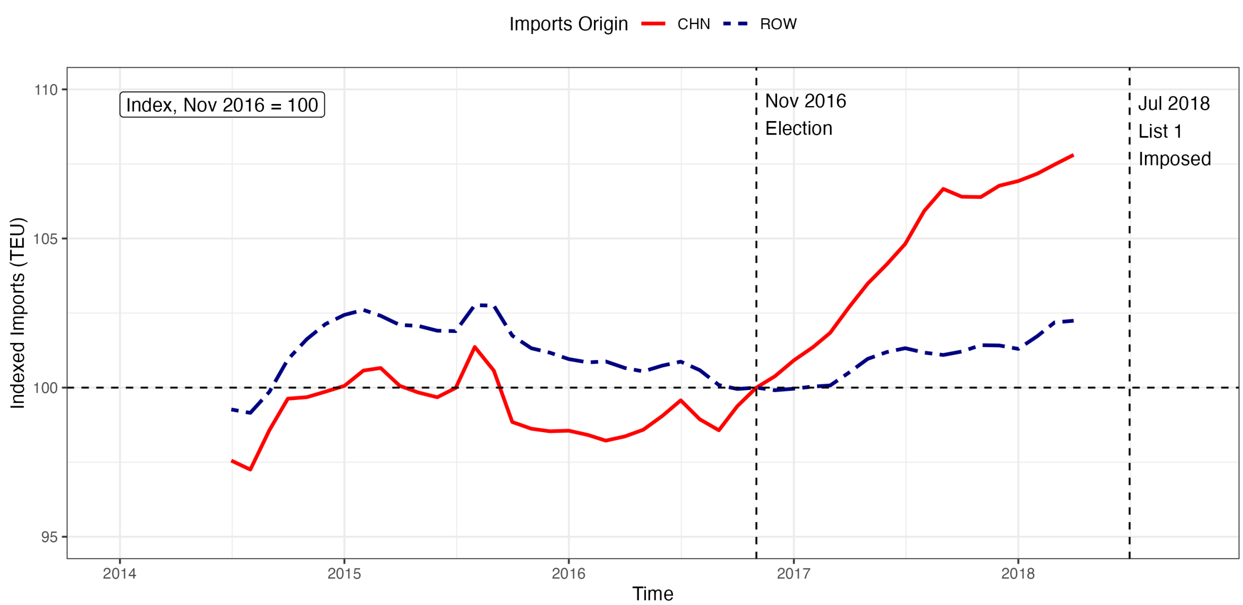
Stylized Fact 1 *In the period between Trump's election (November 2016) and the first implementation of Chinese tariffs (July 2018), U.S. imports from China followed a steeper upward trend compared to imports from the rest of the world (ROW).*

Figure 1 plots the trends in U.S. monthly imports, measured in TEUs, from China versus ROW in the period between January 2014 and July 2018 (when List 1 finally came into effect).[10] Between 2014 and the 2016 U.S. presidential election, quarterly U.S. imports from China and the rest of the world followed the same general pattern. However, in the period between Trump's election and the first wave of tariffs, imports from China saw a steep rise whereas imports from the ROW followed a largely stable trend. Compared to pre-election levels in November 2016 (indexed to equal 100), imports from China were about 8 percent

[10]The same trend lines can be observed using values of imports in USD instead of volumes, as shown in Figure A.2. I choose to present the plot with TEU volumes in the main text to stay consistent with my data availability from the bills of lading.

higher in April 2018, while imports from ROW were only about 2 percent higher.[11] Looking at the diverging trends in this transitioning period, it is natural to wonder whether American importers were rapidly responding to a new administration with new promises that could shock the trade environment in the coming years. Considering Donald Trump's presidential campaign and his frequent mentioning of China, perhaps the diverging trends suggest that Chinese good buyers were hedging by ramping up their purchases while no additional taxes were levied.

Figure 1: Trends in U.S. Imports, Indexed to November 2016



Notes: This plot shows the indexed monthly U.S. imports from China and ROW from 2014-2018 using U.S. Customs bills of lading data. I decompose the import time series into additive seasonal, trend, and error components using a symmetric 6-month moving average window with equal weights. The trend component, indexed to equal 100 in November 2016, is presented here. Component plots are shown in Figure A.1.

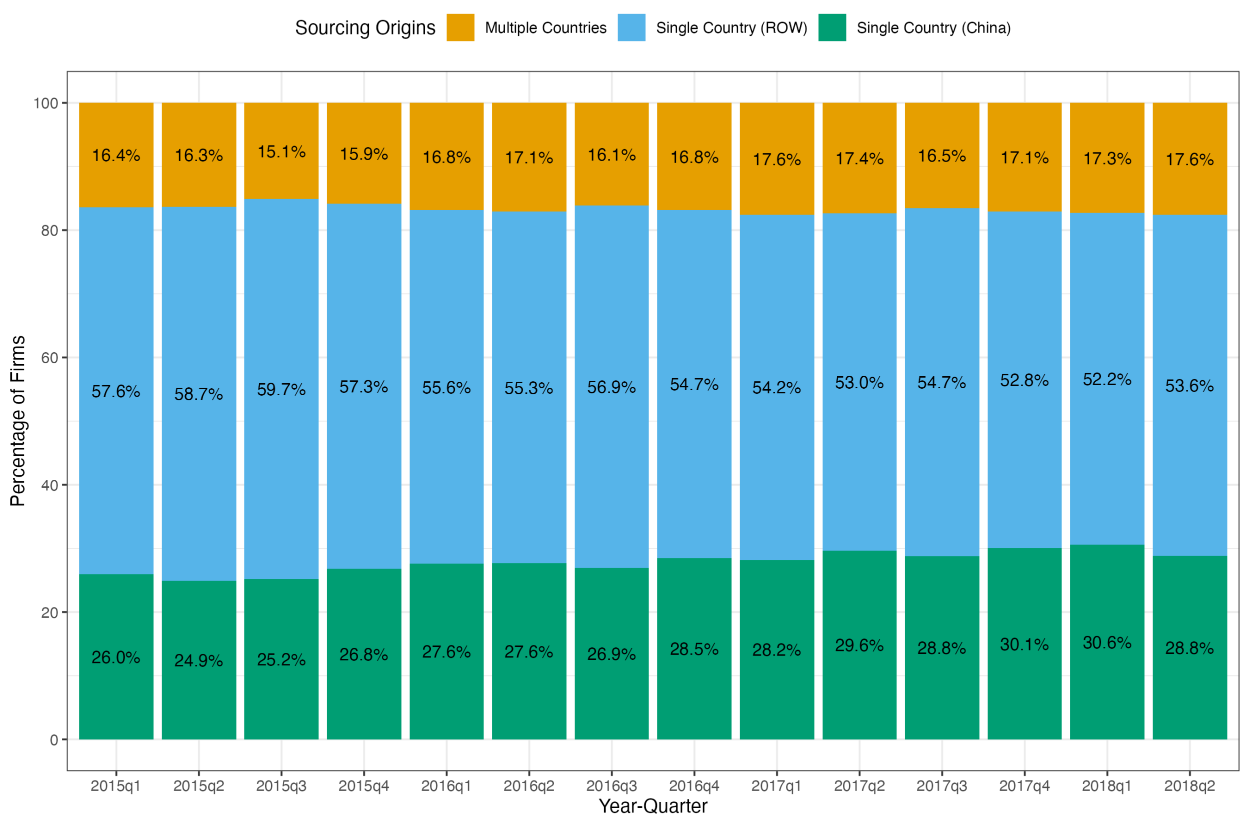
Stylized Fact 2 *The majority of American importers source from one country. Almost all of the smallest importers buy from a single country, while around 40% of the largest importers buy from multiple origins.*

Figure 2 breaks down the proportions of American importers in the dataset that buy from single and multiple countries for each quarter since 2015. In general, around 16-17% of all firms buy from multiple countries. Around half of the firms in the dataset buy from

[11]Immediately after List 1 came into effect, which marked the start of the U.S.-China trade war, U.S. imports from China declined sharply compared to imports from the rest of the world, which generally followed the same trend until the global pandemic (Bown, 2022).

one single country that is not China and about 30% only buy from Chinese exporters, which sums up to a bit more than 80% of firms that source from a single foreign market. There does not appear to be a change over time in the composition of firms by count of sourcing origins. Ceteris paribus, buying from multiple countries is safer than buying from one single nation as this type of sourcing is more resilient to exogenous, idiosyncratic shocks such as macroeconomic fluctuations, natural disasters, and bilateral relationship changes. In the context of this study, Donald Trump's surprising victory brought about new uncertainties and potential challenges for firms that source only or mostly from a country such as China. Colloquially speaking, in rocky times such as the period right after a political upset by an unconventional presidential candidate, firms that buy from only one country, especially if that country is China, might start to plan ahead because they are at a higher risk of input disruption due to prohibitive trade measures.

Figure 2: Firm Sourcing Origin Types over Time



Notes: This plot shows the percentage of firms that engage in multi-country and single-country sourcing over time using U.S. Custom bills of lading data. Single-country sourcing is divided into China and ROW.

However, it is not easy to source from multiple countries and so not all firms will have the capacity to do it, as shown by Figure 3. This graph plots separately the proportion of firms by number of sourcing origins for each importer size quintile. As mentioned previously, firms in the dataset are categorized into five quintiles based on their average annual import volume (as a proxy for size), with 1 being the smallest importers and 5 being the largest. Looking at this graph, we can first notice that a very small percentage of firms from quintiles 1 to 4 buy from multiple countries, but consistently around 40% of firms in the 5th quintile do so, a pattern not too surprising considering how trade is generally dominated by the right tail. If buying from a single country is riskier than buying from multiple countries, then smaller firms might have faced greater relative risks after Donald Trump got elected. Moreover, having China as the sole source makes up a smaller percentage of firms as importer size quintile goes up. That is to say, firms of different sizes face different levels of risk during this period, one reason being their sourcing origins. Thus, a question arises whether firms of different sizes reacted differently to November 2016.

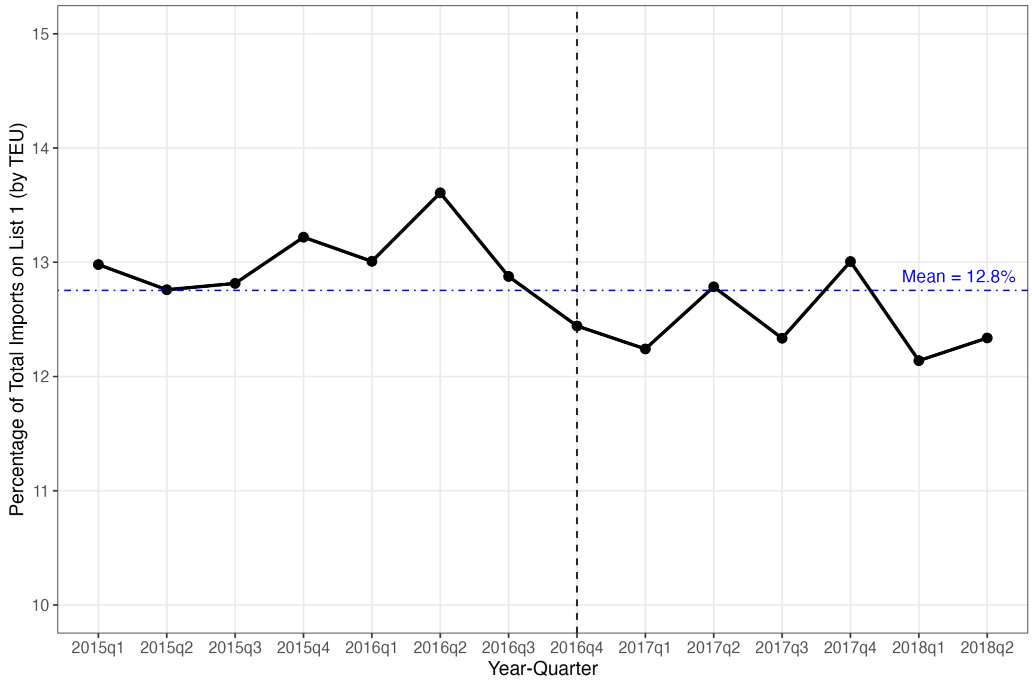
Figure 3: Firm Sourcing Origin Types over Time by Size Quintile

Notes: This plot shows the percentage of firms that engage in multi-country and single-country sourcing over time for each size quintile, using U.S. Custom bills of lading data. Single-country sourcing is divided into China and ROW. Importers are sorted into quintiles based on their size as proxied by the annual import volume. Bigger quintile indicates larger importers.

Stylized Fact 3 *Over the 2015-2018 period, List 1 products accounted for approximately 13% of total U.S. imports (in TEU). The average List 1 heading relied on China for nearly a quarter of its total imports in 2015, although the degree of China dependence varies among product headings.*

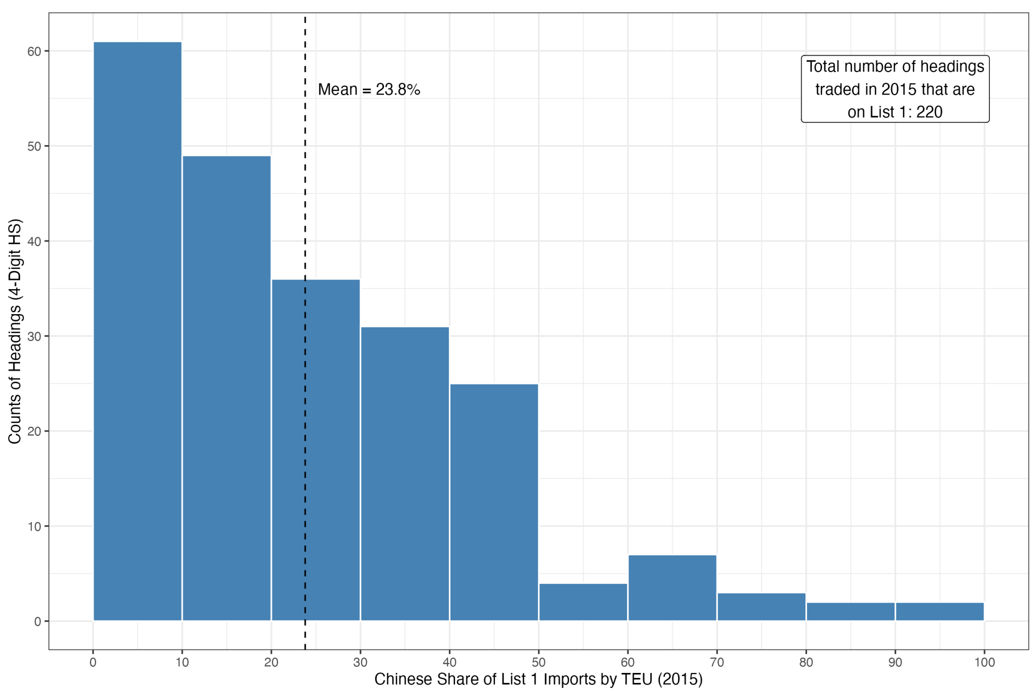
How relevant were List 1 tariffs? The proposed List 1 covered 50 billion USD worth of products, and the final List 1 covered 34 billion USD. Figure 4 further demonstrates the reach of the first wave of tariffs by plotting the percentage of total imports that belong to List 1, measured in TEUs, from 2015 to 2018. Over this period, List 1 products accounted for nearly 13% of total U.S. imports, with only a small difference before and after the 2016 election. These are goods that belong to the iron/steel, aluminum, machinery, and vehicles industries, among others, that were put at the forefront of Donald Trump's presidential campaign. Thus, after Trump was elected, if he were to pursue prohibitive tariffs on Chinese goods, then these industries would likely be first in line. Considering that these industries make up a non-trivial part of annual U.S. imports, it is plausible that the 2016 election had significant impacts on firms and trade. It is also important to point out that different products rely on imports from China in varying degrees. Figure 5 plots the distribution of Chinese shares of imports for all traded 4-digit HS headings on List 1 in 2015. The year before the election, 220 out of ∼1,200 traded HS4 product headings belonged to the initial List 1. On average, 23.8% of yearly imports for a heading came from China. However, there was a substantial spread across headings, showing that even among List 1 products, there could be sizeable differences in the levels of risk faced by importers after Trump's election. It is thus important to consider both the variation across origins and products when conducting empirical analyses.

Figure 4: Share of List 1 Products out of Total Imports



Notes: This plot shows the percentage of total U.S. imports accounted for by List 1 products over time, using U.S. Custom bills of lading data.

Figure 5: Chinese Share of List 1 Product Imports (2015)



Notes: This histogram shows the distribution of Chinese shares of imports for all traded 4-digit HS headings on List 1 in 2015. For example, the first column shows that ∼80 headings out of 220 headings on List 1 bought 0-10% from China in 2015.

4 Impacts on Import Activities

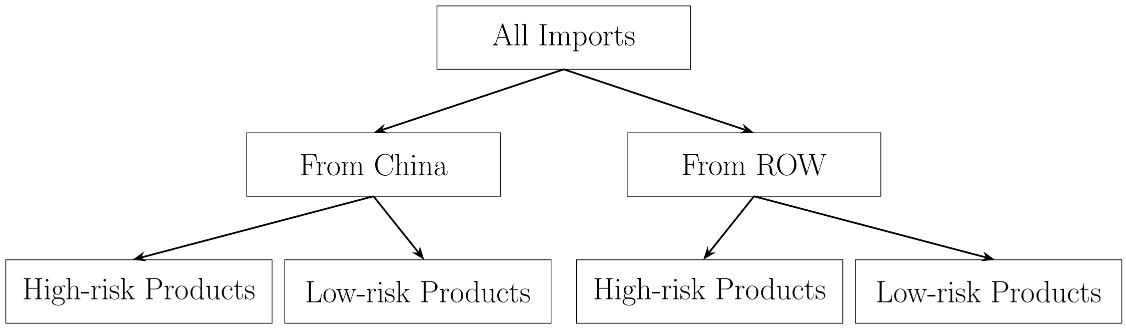
The primary goal of this paper is to empirically examine whether American importers reacted to Donald Trump's surprising victory in November 2016 due to the sudden actualization of potential additional tariffs after one night. Right after the election night, a hypothetical importer buying from China was faced with the following uncertain risks: (1) Whether Trump would actually follow through on his threats to start a trade war with China; (2) In the case that additional trade barriers were to be imposed, when; (3) Whether the products they were buying belonged to a high-risk industry; and (4) How restrictive the new barriers would be. If the firm is forward-looking and thinks that its imported inputs might get taxed, it can consider these actions in the period after Trump's election but before any imposition of tariffs: (1) Do nothing; (2) Stockpile, either by buying more each time or increasing shipment frequency; (3) Expand its network of suppliers away from China, and (4) Diversify its sourcing portfolio to help with current stockpiling and ease future transition to unaffected suppliers if Chinese tariffs hit.

This section touches on the most obvious strategy, *stockpiling* or *frontloading*, which has been documented in both the non-trade and trade literature.[12] Briefly speaking, at-risk firms did not choose the "do nothing" option in this interim period and instead decided to stockpile.

4.1 Estimation

Estimating the causal impacts of Trump's election, and the uncertain tariff threats it generated, on American imports comes with many challenges. As discussed in the Literature section, the usual difference-in-differences approach has several limitations when it comes to studying the impacts of *tariff imposition*, one of which is the failure of the "no anticipation" requirement. Since my focus is on the impacts of Trump's election, not of actual tariffs, I do not have to worry about anticipation of treatment since the 2016 victory for the Republican candidate was largely unforeseen. Nonetheless, I still have to deal with the usual identification challenges in trade, including the trends in import markets regardless of election outcome, other events during the same period that can contaminate the estimates, spillover effects, unparallel trends between control and treatment, and so on. To solve these challenges, I first realize that Trump's election generated different levels of risk for different products coming from different countries, based on my discussion in the Introduction (Section 1) and Stylized Facts (Section 3). More specifically, after Trump got elected, the set of all U.S. imports can broadly be broken down in the following manner:

[12] See subsection 1.2.



The argument here is that firms buying inputs from China incur a higher level of risk compared to firms buying from elsewhere after Trump got elected. Moreover, within each origin group, there are products that belong to industries more likely to get hit with tariffs than others (e.g., steel and aluminum products). Exploiting this fact, I propose a triple-difference (DDD) approach to estimate the impacts of Trump's election on American imports, comparing imports from China and ROW (first difference) across time (second difference) and between product groups (third difference). Under this identification strategy, the "treated group" is defined to be the set of imports that come from China and belong to industries more likely to be hit with additional tariffs. I use the provisional List 1 announced in April 2018 to characterize at-risk industries, as they comprise of those frequently mentioned by Trump's campaign rhetoric and would likely be the first to get taxed if the president decided to follow through on his promises. Before writing down the DDD specification and discussing the accompanying identification assumptions, I will briefly explain why a simpler difference-in-differences (DD) is inadequate in this context. Below are the possible DD approaches and why these comparisons might not be valid:

1. Compare imports by origins across time: It is unlikely that this approach satisfies the parallel trend assumption if products from different origins are subjected to different economic conditions which make them trend differently regardless of the election result. Another threat to the parallel trend assumption is the difference in import composition, i.e., types of products, from different origins.

2. Compare imports by risk groups across time: This approach suffers from limitations analogous to those listed in the first approach.

3. Compare imports of high-risk products and low-risk products coming only from China after the election: This will not be valid if there are within-origin spillovers from high-risk to low-risk products; for example, firms buying low-risk inputs from China might also get affected by Trump's threats towards other high-risk Chinese products.

4. Compare imports of high-risk products from China and high-risk products from ROW after the election: This suffers from the same limitations listed for approach #1, as high-risk products from China and ROW might be subjected to dissimilar economic conditions that lead to divergent trends.

The DDD approach addresses these identification threats and yields an average treatment effect on the treated (ATT) under fairly weak assumptions. First, there must be no anticipation of treatment, so in this case, no anticipation of Trump being elected. This assumption seems to be a given as few predicted Trump to defeat Clinton prior to the election night.[13] Second, the parallel (or common) trend assumption only requires the *relative* difference between high-risk and low-risk imports from China to trend in the same way as the relative difference between these two product groups from the ROW in the absence of treatment; that is, had Trump not won the 2016 election. This is a relatively weak assumption that likely holds, based on what we see in Figure 1. That said, if, for example, there exists some unobserved factor that causes the gap between high-risk and low-risk imports from China to widen over time while simultaneously narrowing this gap for imports from ROW, then the common trend assumption will fail. I attempt to limit this possibility through a rich set of additional fixed effects.

To see whether Trump's election had any effects on firm import activities, I estimate the following triple-difference equation:

$$\begin{aligned} y_{ikct} = \beta_0 &+ \beta_1 China + \beta_2 List1 + \beta_3 AfterElection \\ &+ \beta_4 China \times List1 + \beta_5 China \times AfterElection + \beta_6 List1 \times AfterElection \\ &+ \beta_7 China \times List1 \times AfterElection + \alpha_{c,year} + \theta_{industry,year} + \varepsilon_{ikct} \end{aligned} \tag{1}$$

where y_{ikct} is the outcome of interest for firm i buying HS-6 product k from origin country c in year-quarter t. Specifically, the outcomes in this section include (the natural log of) import volume (TEU), weight (kg), and number of shipments. $China$ is a binary variable that is equal to 1 if $c = China$. $List1$, a proxy for high-risk products, is equal to 1 if product k belongs to the List 1 tariffs initially announced in April of 2018. $AfterElection$ is a time dummy that equals 1 if $2016Q4 < t$. The sample excludes all logistic, wholesale, and retail firms.[14] The pre-period is 2015Q1-2016Q3 (seven quarters before the 2016 election) and the post-period is 2017Q1-2018Q2 (six quarters after the 2016 election). Although data are available through October 2018, I restrict the sample to the period before the implementation

[13] See "Who will win the presidency?" by FiveThirtyEight for a comprehensive summary of polls and forecast for the 2016 election. https://projects.fivethirtyeight.com/2016-election-forecast.

[14] The discussion for this decision is in 7. All baseline results are robust to the inclusion of logistic, wholesale, and retail firms.

of List 1 (July 2018) to avoid origin-specific price changes caused by tariffs on Chinese goods. 2016Q4 was dropped because the election happened in November, which is in the middle of Q4. β_7 is the DDD coefficient of interest, which can be interpreted as the causal effect (ATT) of Trump's election on high-risk Chinese imports under the assumptions listed in the previous paragraph. Origin country-year/quarter fixed effects are included to control for potential supply shocks and foreign macroeconomic conditions, whereas industry-year/quarter fixed effects are included to control for U.S. industrial demand shocks unrelated to the election.[15] Standard errors are robust to arbitrary heteroskedasticity using the standard robust Eicker-Hubert-White sandwich estimator. Results with clustered standard errors by origin and HS2 chapter are also presented.

4.2 Results

I first present the impacts of Trump's 2016 victory on import activities. As discussed previously, one way that firms can react to potential hikes in import taxes after the election is to stockpile in anticipation. If this is the case, then we should expect an increase in quarterly trade volumes and weights for firms whose imports face higher risks of additional taxes, meaning a positive average treatment effect reflected through a positive DDD coefficient. In the case that at-risk firms choose to stockpile, I further examine whether they do so by buying more each time or buying more frequently. I estimate equation 1 using as outcomes quarterly import volumes, weights, and numbers of shipments. Table 6 presents the results for these triple-differences analyses.

In Table 6, the odd columns display results from a traditional DDD specification with no added fixed effects, while the even columns control for year-specific origin and industry fixed effects for reasons described in Subsection 4.1. The average treatment effects on the treated, i.e., the impacts of Trump's election on at-risk firms, are in bold. Since the outcome variables are logged, the coefficients β can be interpreted roughly as $(100 * \beta)\%$ increases in the outcomes.

Overall, results from Table 6 indicate that in the period between the 2016 presidential election and the implementation of any China-specific tariffs, firms that import risky products from China display stocking-up behaviors. Specifically, these firms increase their quarterly import volumes by roughly 2.8-4.6%, and 4.4-4.8% in weight. From columns (5) and (6), we can infer that firms engage in stockpiling in this period by importing more

[15] These are fairly strict fixed effects on top of the triple-differencing. Origin and industry effects are allowed to vary arbitrarily across year-specific quarters. Industries are categorized by 4-digit HS headings which are quite narrow. For instance, HS Section II contains "Vegetable Products," Chapter 10 of this Section contains "Cereals," Heading 10.06 contains "Rice," and 6-digit subheading contains specific variations of rice and processing methods.

Table 6: Changes in Quarterly Import Activities

	(1) log(Volume)	(2) log(Volume)	(3) log(Weight)	(4) log(Weight)	(5) log(#Shipments)	(6) log(#Shipments)
AfterElection × China × List1	**0.0456*****	**0.0278*****	**0.0443*****	**0.0475*****	**-0.0211*****	**-0.0155*****
	(0.00988)	**(0.0101)**	**(0.00992)**	**(0.0101)**	**(0.00378)**	**(0.00387)**
China × List1	-0.0573***	-0.153***	0.164***	-0.0889***	0.0179***	-0.0117***
	(0.00692)	(0.00709)	(0.00696)	(0.00709)	(0.00265)	(0.00272)
AfterElection × List1	-0.0294***	-0.0231**	-0.0193***	-0.0309***	0.00564***	-0.00266
	(0.00549)	(0.0115)	(0.00571)	(0.0118)	(0.00209)	(0.00467)
AfterElection × China	-0.0618***	0	-0.0996***	0	-0.0179***	0
	(0.00404)	(.)	(0.00414)	(.)	(0.00158)	(.)
List1	-0.269***	0.00242	-0.403***	0.0336***	-0.0101***	0.0139***
	(0.00375)	(0.00802)	(0.00391)	(0.00823)	(0.00142)	(0.00324)
China	0.00710**	0	0.0706***	0	0.0273***	0
	(0.00286)	(.)	(0.00293)	(.)	(0.00111)	(.)
AfterElection	0.0697***	0	0.0796***	0	0.0219***	0
	(0.00227)	(.)	(0.00251)	(.)	(0.000894)	(.)
Observations	5,253,670	5,252,909	5,275,765	5,275,002	5,275,765	5,275,002
Fixed Effects						
Origin, Year-Quarter		X		X		X
Industry, Year-Quarter		X		X		X

Notes: This table shows the DDD estimation results from Equation 1 using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. The ATTs are the DDD coefficients in bold at the top of the table. Odd/Even columns are from DDD specifications without/with fixed effects. Volume is measured in TEUs and imputed by Panjiva. Weight is measured in kilograms and reported on the Customs bills of lading. Number of shipments is the count of distinct bills/shipments. Industry means HS 4-digit product headings. Robust standard errors in parentheses. See Table A.1 for clustered standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

each time, not by ordering more frequently. If anything, the number of quarterly shipments slightly decrease, although not by a practically significant magnitude in absolute terms.

4.3 Event Study Plots

In order to visualize the pretrends, if any, and examine how the impacts of Trump's election on American imports progress throughout this period, I estimate the dynamic effects on each outcome by running an event study specification of the following form:

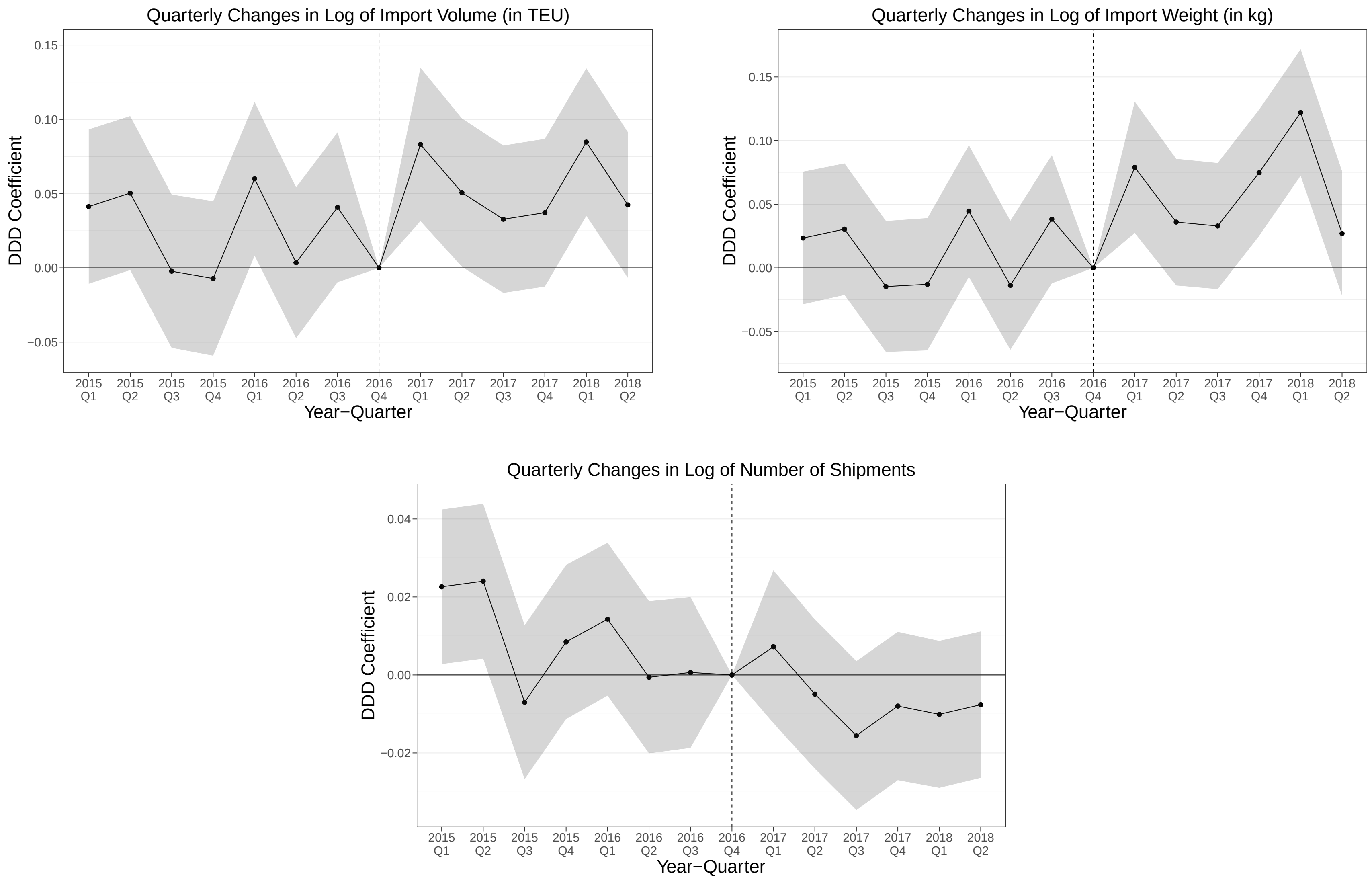
$$\begin{aligned} y_{ikct} = &\sum_{\substack{t=2015\text{Q1} \\ t\neq 2016\text{Q4}}}^{2018\text{Q2}} \mathbb{1}\{\text{time} = t\} \sum_j \beta_j (\text{DDD term} + \text{DD terms} + \text{linear terms}) \\ &+ \alpha_{c,t} + \theta_{\text{industry},t} + \varepsilon_{ikct} \end{aligned} \tag{2}$$

where the DDD, DD, and linear terms are the same as in Equation 1, abbreviated for conciseness. For each year-quarter, Equation 2 estimates a set of time-specific beta's, among which is the time-specific DDD coefficient of interest that represents the period treatment effect. In other words, this event study specification allows us to see how Trump's election affects import volumes, weights, and numbers of shipments over each quarter. Usually, in an event study setting, the first lead, i.e., the period before treatment adoption, is chosen as the reference period to be dropped to avoid perfect collinearity. In that case, the treatment coefficient in the adoption period is interpreted as the instantaneous treatment effect. However, I choose 2016Q4 (the quarter of the election) as the omitted reference period for two main reasons: (1) The election happened in November which sits squarely in the middle of the last quarter, which means there is one month before and after treatment, and (2) It is unlikely that the election had an immediate impact on imports given that firms need time to adjust and goods need to be shipped to the U.S., and so the instantaneous treatment coefficient is not of interest.

Figure 6 shows the event study results for quarterly import volumes, weights, and number of shipments, respectively. Overall, there does not seem to be a pretrend in import volumes or weights, i.e., firms do not adjust their import behaviors before the 2016 presidential election.[16] Considering that cargo shipping from China to the U.S. typically takes 15-30 days on average, depending on the exact route, transshipment, weather conditions, etc. (Artemus Group, 2024), we can take the 2017Q1 coefficients as the instantaneous impacts of Trump's election. Right after the election, both quarterly import volumes and weights of at-risk products from China jumped by about 8% and did not taper off until 2018Q2, the last quarter before the first round of Chinese tariffs came into effect. Overall, there is strong evidence that American importers did respond to Trump's election in anticipation of potential tariff hikes, and the respond happened rather quickly.

[16] There is arguably a downward trend in the quarterly numbers of shipments.

Figure 6: Event Studies: Changes in Quarterly Import Activities



Notes: This figure plots the dynamic DDD estimates from Equation 2 for trade activity outcomes using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. Shaded areas are 95% confidence intervals. Volume is measured in TEUs and imputed by Panjiva. Weight is measured in kilograms and reported on the Customs bills of lading. Number of shipments is the count of distinct bills/shipments.

5 Impacts on Firm's Trade Network

In addition to stockpiling, another strategy that firms buying risky products from China may adopt is to expand their trade networks and/or to diversify their sourcing portfolio. Moreover, it is interesting to see whether firms start to divert away from buying Chinese goods in this period. In the context of the U.S.-China trade war, Fajgelbaum et al. (2024) shows that the war led to a significant reduction in direct trade between the two countries and created new trade opportunities for "bystander" countries, who increased their exports to both the U.S. and China in products that became more expensive due to tariffs. On the other hand, Zeng and Zhang (2024) shows that industries and firms more heavily embedded in bilateral supply chain networks are less likely to reallocate production from China back to the U.S. due to pressure from the trade war. Since this paper looks at a relatively small window between the 2016 election and the onset of the trade war, I do not expect firms to make drastic decisions like backshoring or reallocating production to a new third country due to contractual commitments and high switch costs. However, it is conceivable that firms may start exploring alternative options from less risky sources, which would be reflected in their trade network and reliance on Chinese imports.

5.1 Estimation

I follow the same triple-difference approach as shown in equation 1. First, I examine whether at-risk firms decided to expand their trade networks and/or to diversify their sourcing portfolio during this period. To do so, I look at two variables: (i) The (natural log of) number of suppliers in country c from whom firm i buys HS6 good k in year-quarter t, and (ii) a measure of import concentration à la the Herfindahl–Hirschman Index (HHI). For each firm-product-country-time combination, the HHI measures how diverse the firm's sourcing portfolio is, or colloquially, whether the firm is buying mainly from a few suppliers or a bit from a lot of suppliers. It is constructed as follow:

$$0 \leq HHI_{ikct} = \sum_{j=1}^{J} (Share_{j,ickt})^2 = \sum_{j=1}^{J} \left(\frac{Import_{ijkct}}{Import_{ikct}} \right)^2 \leq 1 \tag{3}$$

where J is the set of suppliers. The HHI is the sum of squared supplier shares for each product k that firm i buys from country c in year-quarter t. If this index equals 1 for an i-k-c-t combination, it means that firm i only sources product k from one single supplier in country c at time t. The closer to 0 this measure is, the more sources that i is buying from, i.e., a more diverse sourcing portfolio. If firms buying risky products from China responded to the 2016 election by looking around for new partners, then we should expect the DDD coefficients to be positive for both the number of partners and HHI.

5.2 Results

Table 7 shows the DDD estimation results for the impacts of Trump's election on American importers' trade network outcomes during the period between the election and before any imposition of China-specific tariffs. Overall, there is no evidence that firms buying risky products from China, on average, expanded their trade network (i.e., number of partners/suppliers) or diversified their sourcing portfolio (i.e., buying from a wider set of suppliers) during this period, compared to other firms. The absolute magnitudes of the coefficients, which are all statistically insignificant, are also minute and arguably practically insignificant regardless.

Table 7: Quarterly Changes in Trade Network

	(1) log(#Partners)	(2) log(#Partners)	(3) HHI	(4) HHI
AfterElection × China × List1	**-0.00193**	**-0.00212**	**0.000346**	**0.000722**
	(0.00133)	**(0.00133)**	**(0.000582)**	**(0.000582)**
China × List1	-0.000935	-0.00297***	0.00159***	0.00286***
	(0.000933)	(0.000933)	(0.000408)	(0.000409)
AfterElection × List1	-0.00245***	-0.00229	0.00109***	0.00119*
	(0.000561)	(0.00140)	(0.000245)	(0.000611)
AfterElection × China	-0.00261***	0	0.000966***	0
	(0.000632)	(.)	(0.000281)	(.)
List1	-0.0189***	-0.00127	0.00919***	0.000170
	(0.000378)	(0.000974)	(0.000165)	(0.000425)
China	0.0476***	0	-0.0212***	0
	(0.000443)	(.)	(0.000197)	(.)
AfterElection	0.00313***	0	-0.00144***	0
	(0.000299)	(.)	(0.000132)	(.)
Observations	4,828,624	4,827,808	4,828,624	4,827,808
Fixed Effects				
Origin, Year-Quarter		X		X
Industry, Year-Quarter		X		X

Notes: This table shows the DDD estimation results from Equation 1 using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. The ATTs are the DDD coefficients in bold at the top of the table. Odd/Even columns are from DDD specifications without/with fixed effects. Number of partners is the count of total suppliers in country c from whom firm i buy HS6 good k in year-quarter t. HHI is calculated as Equation 3. Industry means HS 4-digit product headings. Robust standard errors in parentheses. See Table A.2 for clustered standard errors. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3 Event Study Plots

Similar to the previous section, for each trade network outcome variable, I also estimate an event study specification as stated by Equation 2. Figure 7 shows the event study estimates of how Trump's 2016 victory changed firms' number of trade partners as well as sourcing concentration (HHI). The event study estimates are consistent with the small and insignificant DDD coefficients presented in Subsection 5.2. Overall, in the period between the 2016 election and List 1 implementation, at-risk firms did not appear to seek out more partners or diversify their sourcing of inputs. This is to be expected given the relatively short window and high cost of establishing new trade relationships.

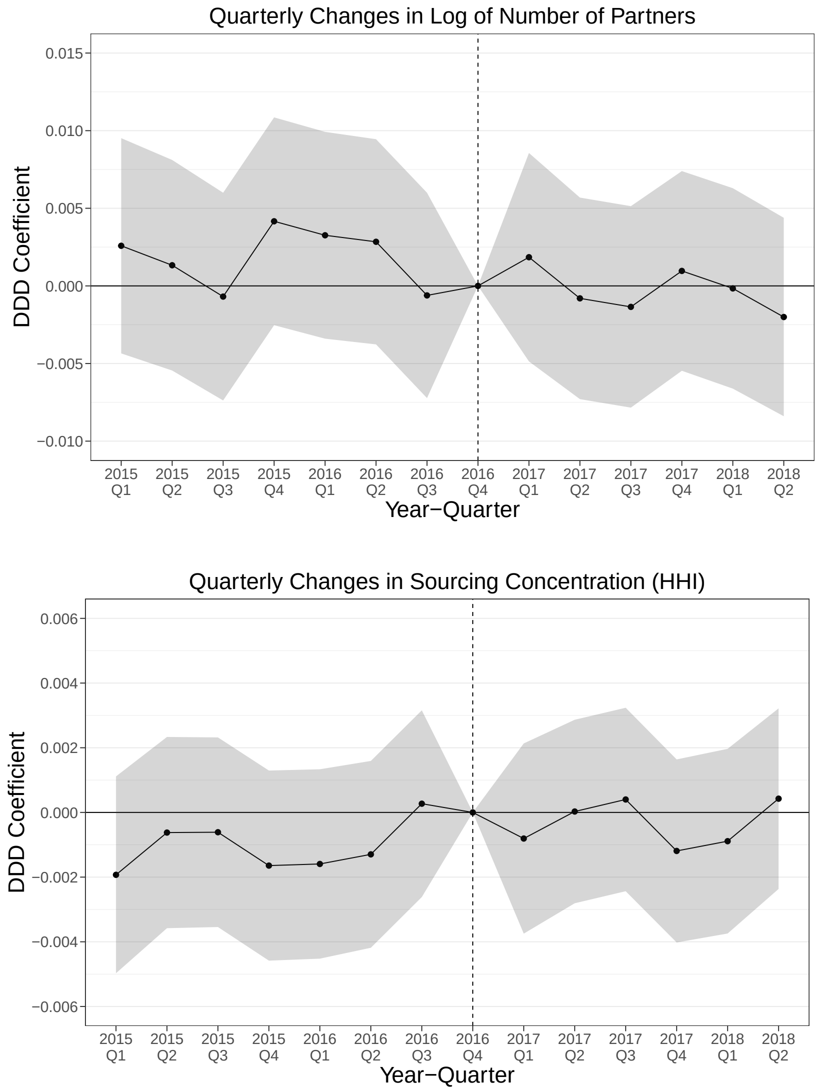
6 Heterogenous Impacts by Firm Size

In this section, I study whether importers of different sizes responded to the 2016 election in a similar manner. Firms in the dataset are divided into five quintiles based on their average annual import volumes, with 1 being the smallest and 5 the biggest. As shown by the summary statistics in Table 3, on average, there is a large discrepancy in trade activities between the smallest and largest importers, and a smaller difference regarding trade network variables. Moreover, stylized fact #2 and Figure 3 point out that almost all of the smallest importers buy from a single country, and around 30-40% of them import only from China in a given year. With the election of Donald Trump, it is arguable that the subset of firms that relied more heavily on Chinese goods faced a greater risk. Thus, it might be the case that they responded with greater intensity.

Apart from the differential levels of tariff risk, firms of different sizes also differ in other dimensions including the nature of their inputs, financial constraints, supplier relationships, internal structural barriers, and so on. Compared to large firms, small and medium enterprises have fewer financial resources and face tighter constraints due to asymmetric information in capital markets (Beck et al., 2006; Beck et al., 2008; Carreira and Silva, 2010; Kuntchev et al., 2013), which might limit their ability to engage in the stockpiling activity documented in Section 4, particularly in the short run. Additionally, the largest firms have more suppliers and well-established connections (Bernard et al., 2022), which can strengthen their ability to adapt to shocks (lower search frictions) but might also limit that ability in the short run (strict formal contracts versus relational contracts). It is also possible that responses from large firms are dampened in the short run due to their more complex internal structure (Sharma et al., 2020).

In short, there are numerous differences between firms of different sizes that merit further

Figure 7: Event Studies: Changes in Quarterly Trade Network



Notes: This figure plots the dynamic DDD estimates from Equation 2 for trade network outcomes using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. Shaded areas are 95% confidence intervals. Number of partners is the count of total suppliers in country c from whom firm i buy HS6 good k in year-quarter t. HHI is calculated as Equation 3.

investigation into how they responded to the additional tariff threats that came with Trump's 2016 election. In previous sections, I have found evidence of firms stockpiling in anticipation of potential price shocks but exhibiting no changes in their trade network. Here, I question whether this is more pronounced for a certain subset of firms. As briefly discussed above, there are multiple push and pull factors that might cause smaller or larger firms to react with greater intensity. After showing how firm responses vary by size categories, I will discuss several potential explanations and provide suggestive empirical evidence as the data allow.

6.1 Biggest Impacts on Smallest Importers

To explore the heterogeneity in treatment effect by firm size, I estimate the triple-difference Equation 1 separately for each size quintile. Figure 8 shows the heterogeneous ATT for import activity outcomes (analyzed in Section 4), whereas Figure 9 is for trade network outcomes (analyzed in Section 5).

Figure 8 shows a dampened effect on quarterly import volumes and weights for firms in larger size brackets. In other words, in the period after Trump's election but before any China-specific tariffs were imposed, smaller firms stockpiled more intensively compared to their larger counterparts. Specifically, the smallest firms increased their quarterly import volumes by about 15% and weights by 12%, whereas the largest firms only increased their quarterly import volumes and weights by around 3% in this period.[17] The smallest firms stockpiled *intensively*. If on average, a firm in the 1st quintile increased its post-election volumes by 15% per quarter, then over the whole treatment period (six quarters), that translates to almost an extra quarter of imports. As a reminder, the ATT for the whole sample is 4.6%, demonstrating how the largest firms generally dominate trade activities and thus exert a heavy weight on the overall treatment effect. Only when dissecting the DDD coefficients further by size can we observe that the smallest firms actually stockpiled more vigorously.[18] When it comes to the number of quarterly shipments, there is not a significant difference among size quintiles.

Figure 9 again demonstrates the same heterogeneous treatment effects, with the smallest firms responding the strongest. From Table 7, we know that overall, at-risk firms did not make significant changes to their trade network during this period. However, looking at this figure, we can see that unlike the rest, firms in the first size quintile statistically significantly diverted from China (0.5% decrease in the number of Chinese suppliers) while simultaneously focusing on buying from fewer Chinese suppliers (0.002 increase in HHI of sourcing portfolio).[19] However, these effects are negligible practically.

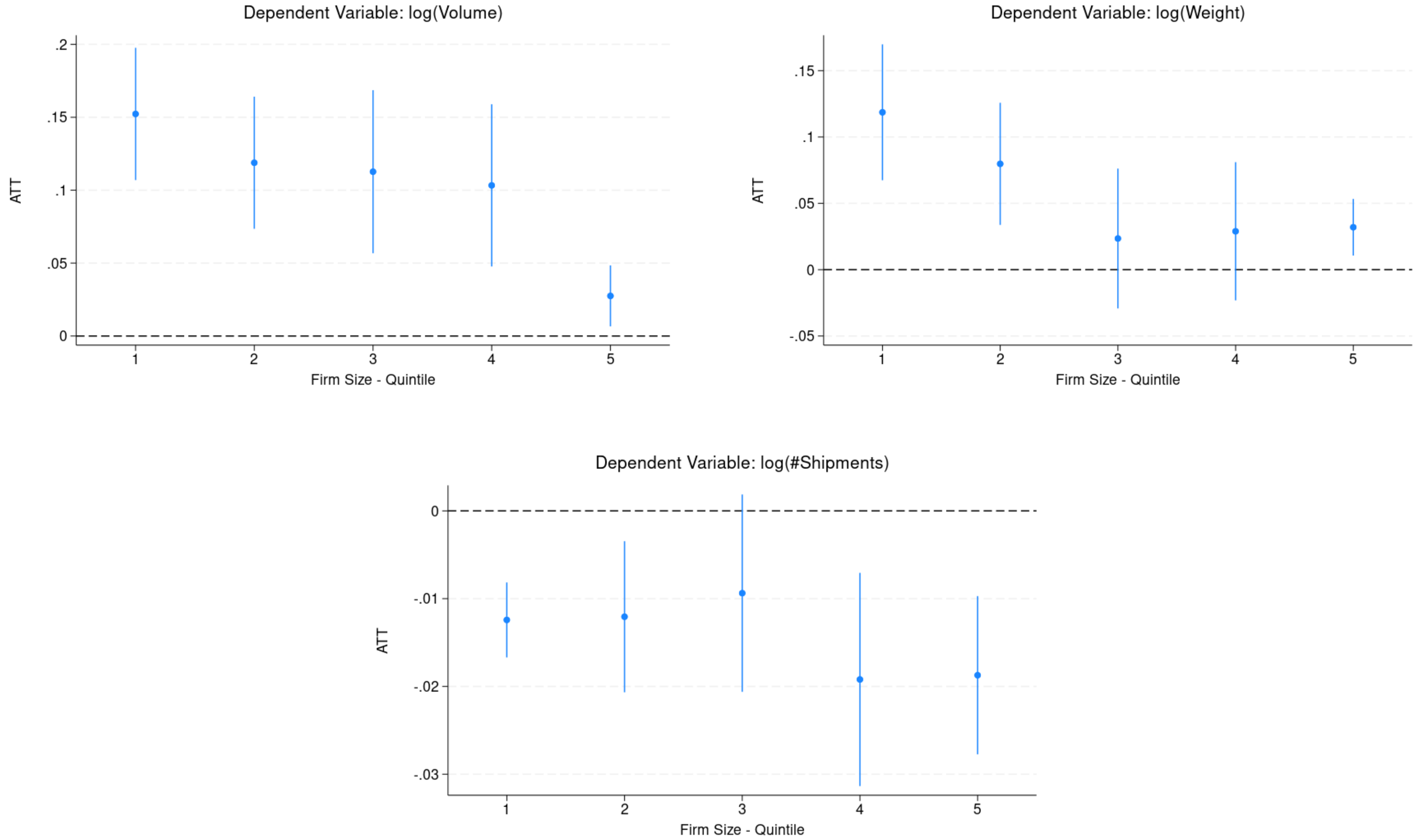
To summarize, Donald Trump's 2016 victory had the biggest impacts on the smallest importers, leading them to stockpile their inputs by the largest (relative) margin. However, the overall impacts are driven mostly by the largest firms that both dominate trade activities and exhibit smaller yet statistically significant changes.

[17] When controlling for origin-year/quarter and industry-year/quarter fixed effects, the smallest firms increased their quarterly import volumes by 5% and weights by 20%. These are still substantial changes. Also, note that volumes are imputed by Panjiva while weights are recorded on bills of lading.

[18] This conclusion still holds under a DDD specification with added fixed effects similar to the even columns in Table 6. The smallest firms still exhibited the strongest stockpiling behavior, although the estimates for the middle quintiles are noisier. See Figure A.3.

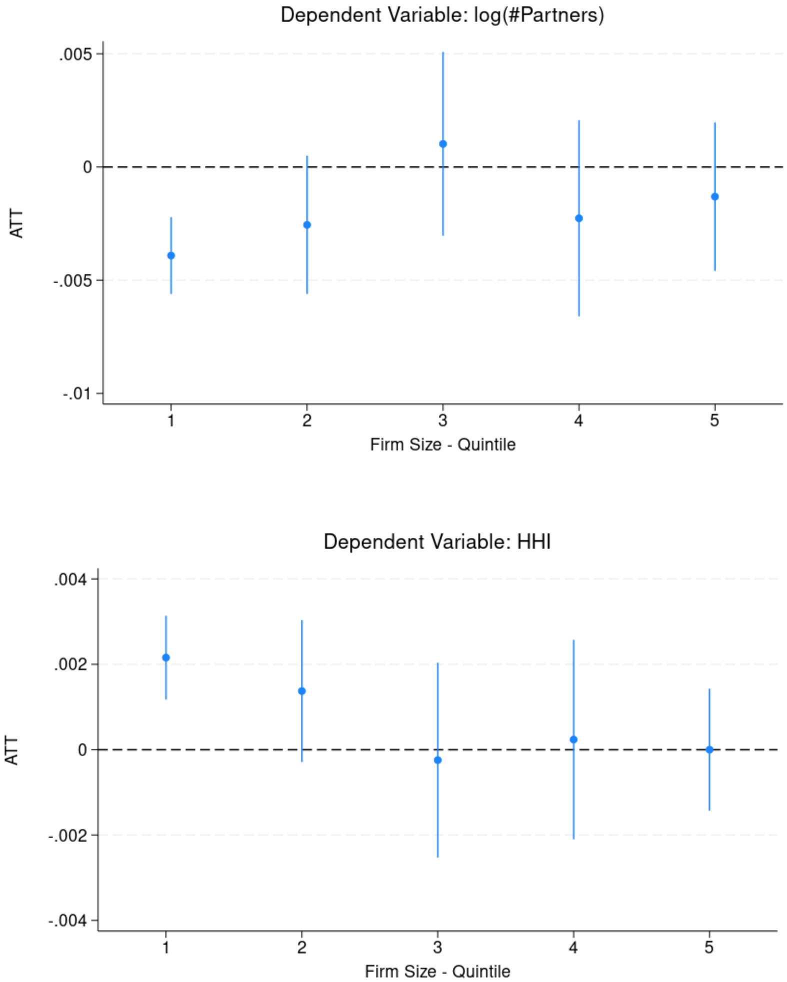
[19] The same conclusion holds under specifications with added fixed effects, and the absolute magnitudes of the DDD coefficients for the smallest firms are even larger. See Figure A.4.

Figure 8: Impacts of Trump's Election on Quarterly Import Activities by Firm Size



Notes: This figure plots the DDD estimates from Equation 1 for trade activity outcomes by size quintile, using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. Whiskers are 95% confidence intervals. Volume is measured in TEUs and imputed by Panjiva. Weight is measured in kilograms and reported on the Customs bills of lading. Number of shipments is the count of distinct bills/shipments. Importers are sorted into quintiles based on their size as proxied by the annual import volume. Bigger quintile indicates larger importers. See Figure A.3 for results with fixed effects.

Figure 9: Impacts of Trump's Election on Quarterly Trade Network by Firm Size



Notes: This figure plots the DDD estimates from Equation 1 for trade network outcomes by size quintile, using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. Whiskers are 95% confidence intervals. Number of partners is the count of total suppliers in country c from whom firm i buy HS6 good k in year-quarter t. HHI is calculated as Equation 3. Importers are sorted into quintiles based on their size as proxied by the annual import volume. Bigger quintile indicates larger importers. See Figure A.4 for results with fixed effects.

6.2 Potential Explanations for Heterogeneity by Firm Size

Having established that the smallest firms reacted to Trump's election more intensively than the largest firms, I now move on to examining the potential explanations for this heterogeneous treatment effect. I test three explanations: (1) The upstreamness of imported products, (2) The storability of imported products, and (3) The differential entries and exits by size. I also briefly discuss other potential explanations that I cannot test with my current data.

6.2.1 Upstreamness

Upstreamness characterizes how far an industry is from final consumption in the production chain. To calculate the upstreamness for each imported product, I follow the procedure laid out by Antràs et al. (2012) using the 2012 I-O use table by the Bureau of Economic Activity. The construction and summary statistics for this measure are discussed in Section 3 (Data). This construct of upstreamness measures the distance from final use for each industry to which the imported good belongs. For example, an industry with an upstreamness of exactly 1 has all of its output go directly to final consumption, whereas an upstreamness of 2 means that the industry's output feeds into another downstream industry before final use, on average. The larger the upstreamness measure, the earlier the industry enters into production processes, and thus further away from final consumption.

On average, smaller firms import products that belong to more downstream industries, i.e., closer to final use.[20] On the other hand, products in upstream industries are significantly less likely to be on List 1.[21] Therefore, it might be the case that the smallest set of firms were confronted with a larger threat of potential tariffs after Trump got elected due to the more downstream nature of their purchases. If the stockpiling behavior found in Section 4 can be shown to be driven largely by downstream goods, then this offers suggestive evidence linking upstreamness to why the smallest firms stockpiled the most (relative to their pre-election imports).

To understand how the treatment effects vary by the position of the imported good in the production chain, I estimate the following equation for each main outcome:

$$\begin{aligned} y_{ikct} = \beta_0 &+ \sum_{i=1}^{4} \beta_i \cdot (\text{4 Linear Terms}) + \sum_{i=5}^{10} \beta_i \cdot (\text{6 Double Interactions}) \\ &+ \sum_{i=11}^{14} \beta_i \cdot (\text{4 Triple Interactions}) \\ &+ \beta_{15} \cdot China \times List1 \times AfterElection \times Upstream \\ &+ \alpha_{c,year} + \theta_{industry,year} + \varepsilon_{ikct} \end{aligned} \tag{4}$$

[20]Using the same sample in the main specifications, I estimate the following linear equation and find that on average, the largest firms import products that belong to industries 0.2 stages more upstream compared to the smallest firms: $Upstreamness = \beta_1 + \sum_{j=2}^{5} \beta_j Size\_Quintile_j + \varepsilon$.

[21]I estimate the following linear probability model: $List1 = \alpha + \beta_2 Upstreamness + \varepsilon$ on a sample of all traded 6-digit HS products. I find that as upstreamness increases by 1, the probability that the corresponding HS6 good is on the initial List 1 is lower by 6.9pp (↓44.5%). Note that 875 out of 5,645 HS6 products in the data are on List 1, so a mean of 0.16.

where the outcome variable y_{ikct} includes: quarterly import volumes, weights, numbers of shipments, numbers of partners, and HHI. The coefficient on the interaction between DDD and Upstreamness, β_{15}, is the coefficient of interest.

Table 8 shows the results for import activity outcomes.[22] Looking at columns (1)-(4) on quarterly import volumes and weights, the coefficients on the interaction terms are (mostly) statistically significant and of the opposite signs to the DDD coefficients, suggesting that the DDD estimates in Table 6 are mainly driven by goods closer to final consumption (more downstream). In other words, the effects of Trump's victory on firm quarterly import activities (stockpiling) are "muted" by the upstreamness of the imported good. In sum, the heterogeneous ATT on trade activities by sizes can be partially linked to the fact that the smallest firms buy more downstream goods, and downstream goods largely drive the stockpiling behavior.[23]

6.2.2 Storability

Another potential explanation for why the smallest firms stockpiled more intensively in the period between Trump's election and the first wave of China tariffs might come from the storability of their inputs, i.e., these firms stockpiled more because what they buy is more storable. The literature on trade responses to anticipated tariff changes points out that the anticipatory dynamics are increasing in the degree of product storability. Khan and Khederlarian (2021) finds strong evidence that U.S. importers delayed their purchases from Mexico in advance of NAFTA's staged tariff reductions, and that this anticipatory response was strongest for more storable goods. Exploiting the annual China's Most Favored Nation (MFN) status renewal in the U.S. prior to joining the WTO, Alessandria et al. (2024) finds that trade between the two countries increases significantly in anticipation of uncertain future increases in tariffs and then drops after the uncertainty resolution, a peak-and-trough dynamics that is driven by goods that are relatively more storable. Therefore, I question whether the storability of inputs can partially explain the heterogeneous ATT by size.

Following Alessandria et al. (2010), Khan and Khederlarian (2021), and Alessandria et al. (2024), I proxy for a product's storability using the average lumpiness of its trade flows net of unrelated determinants. In essence, the measure of storability captures the average number of months in a year in which a good is ordered, which is calculated as the inverse of the

[22]See table A.3 for results related to trade network outcomes. Since there is no evidence of firm changing their trade network in this period, this table is left in the Appendix to keep the focus on stockpiling behavior in the main text.

[23]Admittedly, this is more of a mechanical explanation, but it nonetheless points towards the question why the impacts of Trump's election on trade activities are more pronounced for products in industries closer to final use. Unfortunately, the answer to that question is out of this paper's scope, so I leave that for future research.

Table 8: Changes in Quarterly Import Activities by Upstreamness

	(1) log(Volume)	(2) log(Volume)	(3) log(Weight)	(4) log(Weight)	(5) log(#Shipments)	(6) log(#Shipments)
DDD × Upstream	**-0.0609*****	**-0.0395*****	**-0.00541**	**-0.0234***	**0.0100****	**-0.00112**
	(0.0133)	**(0.0136)**	**(0.0137)**	**(0.0139)**	**(0.00510)**	**(0.00528)**
DDD	0.175***	0.117***	0.0601**	0.0916***	-0.0353***	-0.0119
	(0.0295)	(0.0306)	(0.0298)	(0.0307)	(0.0112)	(0.0116)
AfterElection × China × Upstr	0.00936*	0.00870*	-0.00257	0.00209	-0.00163	-0.00263
	(0.00509)	(0.00524)	(0.00523)	(0.00536)	(0.00202)	(0.00208)
AfterElection × List1 × Upstr	0.0532***	0.0320**	0.0167**	0.0343**	-0.00685**	0.0119**
	(0.00711)	(0.0129)	(0.00767)	(0.0134)	(0.00277)	(0.00517)
China × List1 × Upstr	0.259***	0.278***	0.124***	0.262***	-0.0429***	0.00189
	(0.00927)	(0.00951)	(0.00958)	(0.00975)	(0.00354)	(0.00367)
AfterElection × List1	-0.138***	-0.0946***	-0.0604***	-0.104***	0.0165***	-0.0300**
	(0.0150)	(0.0333)	(0.0159)	(0.0335)	(0.00575)	(0.0132)
China × List1	-0.554***	-0.746***	-0.0684***	-0.651***	0.116***	-0.0159**
	(0.0206)	(0.0214)	(0.0208)	(0.0216)	(0.00775)	(0.00809)
AfterElection × Upstr	-0.0210***	-0.0127	-0.0228***	-0.0234***	-0.00880***	-0.00758**
	(0.00276)	(0.00849)	(0.00303)	(0.00881)	(0.00112)	(0.00354)
China × Upstr	-0.203***	-0.213***	-0.213***	-0.241***	-0.0343***	-0.0400***
	(0.00360)	(0.00369)	(0.00370)	(0.00378)	(0.00142)	(0.00146)
List1 × Upstr	-0.200***	-0.0353***	-0.136***	-0.0767***	0.132***	0.0164***
	(0.00484)	(0.00900)	(0.00522)	(0.00931)	(0.00186)	(0.00358)
AfterElection × China	-0.0884***	0	-0.0914***	0	-0.0152***	0
	(0.0115)	(.)	(0.0116)	(.)	(0.00463)	(.)
List1	0.102***	0.0671***	-0.166***	0.194***	-0.299***	-0.0264***
	(0.0102)	(0.0233)	(0.0107)	(0.0235)	(0.00383)	(0.00918)
Upstr	0.0991***	0.0363***	0.311***	0.111***	-0.00177**	0.0191***
	(0.00193)	(0.00597)	(0.00211)	(0.00620)	(0.000769)	(0.00246)
China	0.399***	0	0.468***	0	0.0753***	0
	(0.00817)	(.)	(0.00821)	(.)	(0.00325)	(.)
AfterElection	0.116***	0	0.128***	0	0.0389***	0
	(0.00651)	(.)	(0.00700)	(.)	(0.00266)	(.)
Observations	5,031,709	5,031,010	5,052,484	5,051,783	5,052,484	5,051,783
Fixed Effects						
Origin, Year-Quarter		X		X		X
Industry, Year-Quarter		X		X		X

Notes: This table shows the estimation results from Equation 4 using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. Odd/Even columns are from specifications without/with fixed effects. Volume is measured in TEUs and imputed by Panjiva. Weight is measured in kilograms and reported on the Customs bills of lading. Number of shipments is the count of distinct bills/shipments. Industry means HS 4-digit product headings. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

annual HHI of monthly trade flows net of source-year fixed effects unrelated to storability. Details about the construction of this *Storability* variable are left in the Appendix and its distribution is shown by Figure A.5. $\textit{Storability} = 1/HHI$ ranges continuously from 1 to 12. When $\textit{Storability} = 1$, the product is imported in only one month of the year on average, and when $Storability = 12$, it is imported equally every month of the year. Goods ordered less frequently are assumed to be held as inventories for longer periods of time, hence more storable. Note that since I am using the inverse HHI, a **larger** value for $Storability$ (e.g., 12) means that a product is **less storable** as it is held as inventories for shorter periods of time. The distribution of my constructed $Storability$ is similar to others in the literature.

To see if storability drives the stockpiling behavior, I estimate the following equation:

$$\begin{aligned} y_{ikct} = \beta_0 &+ \sum_{i=1}^{4} \beta_i \cdot (\text{4 Linear Terms}) + \sum_{i=5}^{10} \beta_i \cdot (\text{6 Double Interactions}) \\ &+ \sum_{i=11}^{14} \beta_i \cdot (\text{4 Triple Interactions}) \\ &+ \beta_{15} \cdot China \times List1 \times AfterElection \times Storability \\ &+ \alpha_{c,year} + \theta_{industry,year} + \varepsilon_{ikct} \end{aligned} \tag{5}$$

The coefficient of interest is that of the interaction term between the DDD term and storability, β_{15}. From the literature, we should expect β_{15} to be negative and the DDD coefficient to be positive; that is, the stockpiling behavior is driven by more storable goods. Looking at columns (2)-(4) in Table 9, we can see that the interaction between storability and triple-difference term are mostly statistically insignificant at the 5% level, especially with added fixed effects. When it is statistically significant (column 1), the signs are opposite to my prior expectations and hard to explain. Nonetheless, there is insufficient evidence to support the heterogeneity of treatment effect by storability, and so it is not an appropriate explanation for why the smallest firms stockpiled the most.[24]

6.2.3 Differential Entries/Exits

Here, I investigate whether differential entries and exits cause the heterogeneity in treatment effects by size. First, it is possible that after the election, the set of smallest firms had a different survival rate compared to the rest. From the trade literature, we know that importing firms are more productive than non-importing firms (Amiti and Konings, 2007; Bernard et al., 2007; Kasahara and Rodrigue, 2008; Halpern et al., 2015).[25] Firms that drop out of importing are likely less productive. Therefore, if the smallest quintile saw a large dropout of the least productive firms, then the survivors would be more productive on average. Likewise, firms that start importing have higher productivity, which will raise the

[24] See Table A.4 for results related to trade network outcomes.

[25] In general, firms that engage in international trade are more productive than domestic firms, whether exporting or importing. See Bernard et al. (2007).

Table 9: Changes in Quarterly Import Activities by Storability

	(1) log(Volume)	(2) log(Volume)	(3) log(Weight)	(4) log(Weight)	(5) log(#Shipments)	(6) log(#Shipments)
DDD × Storability	0.0332***	0.0224*	-0.00745	0.00110	-0.000911	0.0107**
	(0.0116)	(0.0121)	(0.0114)	(0.0119)	(0.00422)	(0.00431)
DDD	-0.0954*	-0.0642	0.0871*	0.0511	-0.0134	-0.0604***
	(0.0513)	(0.0532)	(0.0505)	(0.0522)	(0.0182)	(0.0185)
AfterElection × China × Store	-0.00819*	-0.000602	-0.00893*	0.00511	-0.00538***	-0.00581***
	(0.00465)	(0.00484)	(0.00485)	(0.00500)	(0.00193)	(0.00198)
AfterElection × List1 × Store	0.00442	-0.00528	0.0518***	0.0112	0.0233***	0.00348
	(0.00488)	(0.00776)	(0.00505)	(0.00797)	(0.00190)	(0.00287)
China × List1 × Store	0.269***	0.265***	0.437***	0.343***	0.127***	0.0407***
	(0.00808)	(0.00844)	(0.00800)	(0.00833)	(0.00295)	(0.00301)
AfterElection × List1	-0.0471**	-0.00645	-0.249***	-0.0885**	-0.0953***	-0.0186
	(0.0224)	(0.0367)	(0.0230)	(0.0376)	(0.00836)	(0.0134)
China × List1	-1.267***	-1.303***	-1.836***	-1.579***	-0.542***	-0.185***
	(0.0359)	(0.0373)	(0.0354)	(0.0367)	(0.0128)	(0.0130)
AfterElection × Store	0.00408*	0.00900**	-0.00133	0.00290	-0.00422***	0.00230
	(0.00230)	(0.00372)	(0.00258)	(0.00399)	(0.00105)	(0.00156)
China × Store	-0.183***	-0.117***	-0.239***	-0.150***	-0.0629***	-0.0484***
	(0.00329)	(0.00342)	(0.00342)	(0.00353)	(0.00137)	(0.00139)
List1 × Store	-0.239***	-0.0998***	-0.548***	-0.119***	-0.0626***	-0.0101***
	(0.00325)	(0.00521)	(0.00337)	(0.00533)	(0.00124)	(0.00189)
AfterElection × China	-0.0273	0	-0.0584***	0	0.00381	0
	(0.0201)	(.)	(0.0208)	(.)	(0.00825)	(.)
List1	0.793***	0.422***	2.029***	0.535***	0.266***	0.0488***
	(0.0150)	(0.0247)	(0.0155)	(0.0252)	(0.00552)	(0.00887)
Store	0.242***	0.0932***	0.451***	0.117***	0.0797***	0.0514***
	(0.00160)	(0.00261)	(0.00179)	(0.00281)	(0.000729)	(0.00108)
China	0.845***	0	1.200***	0	0.308***	0
	(0.0142)	(.)	(0.0147)	(.)	(0.00582)	(.)
AfterElection	0.0504***	0	0.0799***	0	0.0390***	0
	(0.0103)	(.)	(0.0115)	(.)	(0.00454)	(.)
Observations	4,974,280	4,973,645	4,995,348	4,994,710	4,995,348	4,994,710
Fixed Effects						
Origin, Year-Quarter		X		X		X
Industry, Year-Quarter		X		X		X

Notes: This table shows the estimation results from Equation 4 using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. Odd/Even columns are from specifications without/with fixed effects. Higher values for storability mean less storable goods. Volume is measured in TEUs and imputed by Panjiva. Weight is measured in kilograms and reported on the Customs bills of lading. Number of shipments is the count of distinct bills/shipments. Industry means HS 4-digit product headings. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

average productivity of the group they are in. Either selective exits of the least productive firms or entries of the most productive firms or both into the smallest quintile can make this group relatively more productive, explaining the larger changes in trade activities for them after the 2016 election.

To characterize entries and exits, I track firms in my panel data and simply define an entry as the first time an importer appears in the dataset, and an exit as its last appearance.[26,27] Then, I aggregate the data across firms into a product-origin by year-quarter panel from 2015Q1 to 2018Q2, counting the total number of entries and exits in each quarter. To test whether different firm size quintiles have differential entries and exits in the period between Trump's election and China tariffs compared to the pre-election period, I estimate the following DDD equation for each size subsample:

$$
\begin{aligned}
y_{kct} = {} & \beta_0 + \beta_1 China + \beta_2 List1 + \beta_3 AfterElection \\
& + \beta_4 China \times List1 + \beta_5 China \times AfterElection + \beta_6 List1 \times AfterElection \\
& + \beta_7 China \times List1 \times AfterElection + \alpha_{c,year} + \theta_{industry,year} + \varepsilon_{ikct}
\end{aligned} \tag{6}
$$

where y_{kct} includes the natural log of total entries and total exits into a product-origin import market in a given year-quarter. Figure 10 shows the estimation results for each outcome variable by size quintile. First, we can see that the 2016 election did not induce many quarterly entries and exits for at-risk firms. Second, the point estimates across size quintiles do not differ significantly, offering no evidence to support differential entries/exits as a potential explanation for size-heterogeneous ATT.

6.2.4 Other Potential Explanations

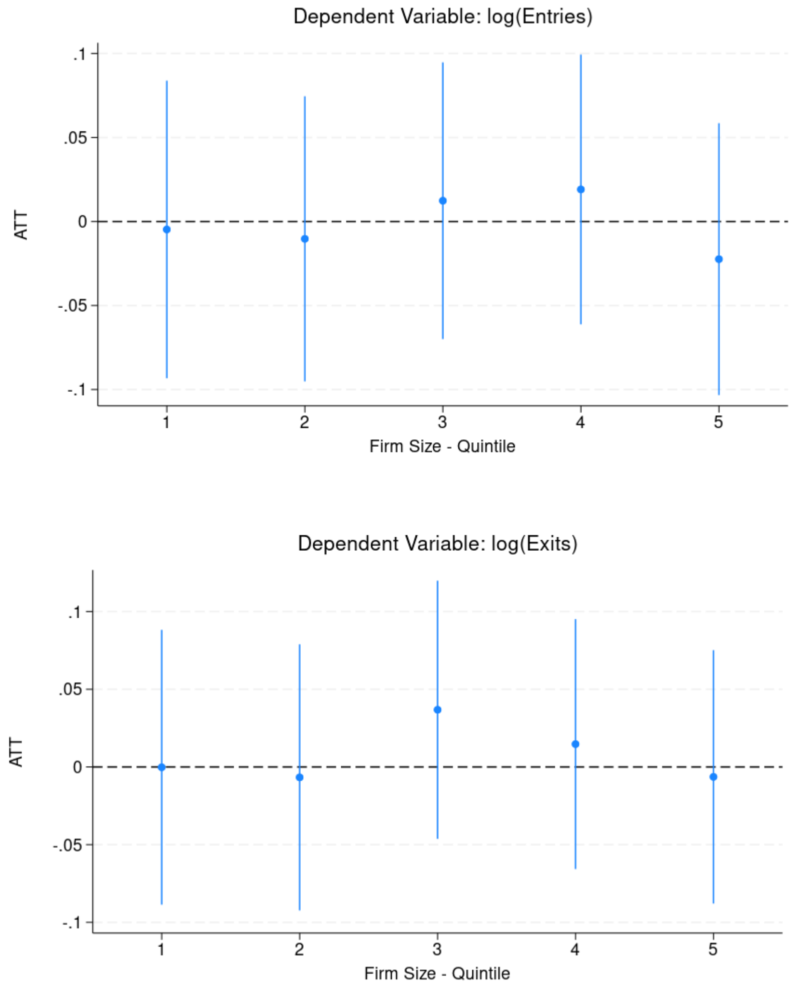
In the previous subsections, I investigate three possible explanations for why the smallest importers reacted the most to Trump's victory in 2016, namely the upstreamness of their purchases, the storability of their inputs, and differential entries and exits. I want to discuss a few other possible mechanisms behind this heterogeneity, which are unfortunately out of this paper's scope and/or data availability.

First, the smallest firms have simpler internal structures, which may allow them to better adjust their buying behaviors in the short run. As shown by the event study plots (Figure 6), quarterly imports picked up immediately after Trump was elected. Although the largest firms have more resources to absorb trade shocks in the longer run, it might be the case that they are more inert in the short term. Research in operations management have shown that structural complexity (vertical, horizontal, and spatial) may pose challenges to innovation

[26]From the summary statistics in Table 3, we know that the average firm in each size quintile imports at least once per quarter; therefore, if we do not observe any imports for a quarter, then it is likely that the firm has dropped out in their last trading quarter.

[27]Any definitions of entries and exits will suffer from the arbitrary span of the available data. Here, I have data outside of the analysis window to alleviate the mischaracterization of entries in the first quarter and exits in the last quarter.

Figure 10: Impacts on Entries and Exits by Size Quintile



Notes: This figure plots the DDD estimates from Equation 6 for counts of entries and exits by size quintile, using the aggregate product-origin-quarter panel from 2015Q1 to 2018Q2. Whiskers are 95% confidence intervals. An entry is defined as the first time an importer appears in the dataset, and an exit is its last appearance. Importers are sorted into quintiles based on their size as proxied by the annual import volume. Bigger quintile indicates larger importers.

after a certain point (Sharma et al., 2020) and complex sourcing relationships can worsen firm performance by imposing extra coordination burdens on organization units (Zhou and Wan, 2017). Therefore, it might be the case that the short-run costs outweighed the benefits of hedging against uncertain future risks, which might not even happen and could potentially last for four years, for the largest firms. Other than internal barriers, the largest firms may also face other factors that make them more rigid in the short term such as strict contracts and certain inventory model.

Second, the largest firm might have acquired more institutional information than the smallest firms, affecting both the first and second moments of the subjective tariff threats that they face. For example, these firms might have more accurate information about the potential timing of tariffs and affected products, thus lowering the uncertainty and dampening their reaction during this period. When List 1 was announced, the Trade Representative also established a process by which U.S. firms may request that particular products classified within a covered tariff subheading be excluded from the additional duties. The largest firms could have expected and prepared for this process. Of course, all of this is pure speculation that I cannot test. The USTR publishes data on exclusion requests from organizations and their status, perhaps future research can look further into this venue.

7 Robustness

The main results documented in Table 6 and Table 7 are robust to several alternative considerations. Here, I document the triple-difference estimates under alternative specifications, which include changing the post-period, placebo testing, and using a full sample that includes logistic, wholesale, and retail firms.

Alternative Post-Period. In all of my main specifications, the post-period is restricted to before the implementation of List 1 tariffs to exclude price effects. Even though List 1 was imposed starting July 1, 2018, the USTR had announced a proposed List 1 several months earlier on April 6, 2018. To make sure that the estimated anticipatory stockpiling behavior is due to the uncertain tariff threats posed by Trump's victory and not biased upwards due to firm learning and adjusting to the official announcement of List 1, I further restrict the post-period to the initial announcement of List 1 tariffs. That means the pre-period is 2015Q1-2016Q3 and the post-period is 2016Q4-2018Q1 (instead of 2018Q2). Table A.5 shows the DDD estimates for trade activity outcomes and Table A.6 shows the results for trade network variables. I get similar results, if not of slightly larger magnitudes, showing that the baseline main results are not biased by firms adapting to List 1 announcement.

Placebo: Alternative Event. To further corroborate that the triple difference approach isolates the impacts of Trump's election on American importers, I test a placebo specification where I replace the election with the implementation of List 1. In this placebo exercise, the pre-period is from the election to the implementation of List 1 tariffs (2017Q1-2018Q2) and the post-period is from the implementation to the end of my data (2018Q3-10/2018). The stockpiling behavior should go away and the DDD coefficients on trade activities should be negative to reflect the hikes in prices. Table A.7 and Table A.8 show the placebo DDD estimates for quarterly import activity and trade network outcomes, respectively. The results show no evidence of stockpiling as expected and limited evidence consistent with an increase in prices, probably due to the relatively short post-period.

Alternative Firm Sample. In all of my main analyses, I exclude logistic, wholesale, and retail firms from the sample to eliminate the difficulty of separating out indirect imports (firms buying from wholesalers) and quantifying trade activities/partners (logistic firms are transporting on behalf of other firms). Moreover, I want to ground the analyses in a framework of firms buying intermediate inputs to produce an output. Here, I re-estimate the baseline results using the full sample containing all firms. Tables A.9 and A.10 show the results, which are very similar to the baseline results. The stockpiling effect likely happened through both the direct and indirect channels.

8 Conclusion

Importers react to scheduled tariff changes through anticipatory dynamics. In this paper, I empirically explore if and how American importers anticipate and respond to a less well-defined, more uncertain kind of change: the unexpected victory of Donald Trump in the 2016 U.S. presidential election and the potential threats of additional tariffs that it brought. First, I establish that American firms did in fact respond to the election. In the period between the election and the first wave of China-specific tariffs, firms buying risky products from China stockpiled by increasing their quarterly import volumes and weights by roughly 5%, but not by increasing order frequency. Importantly, this stockpiling behavior was most pronounced among the smallest firms—a 15% increase in quarterly import volumes that translated to almost an extra quarter's worth of products over the post-treatment period (six quarters). This heterogeneity is partially due to the downstream nature of the smallest firms' imports instead of input storability or differential entries/exits. On the other hand, there is no evidence that firms made substantial adjustments to their trade network or diversified their sourcing portfolio to divert away from China during this period, indicating that importers prioritized (or were only capable of) inventory adjustments over supply chain shifts when confronted with an exogenous shock in the short run. The findings of this paper suggest that other empirical works in the future that study the impacts of the U.S.-China trade war and employ an identification strategy that requires no anticipation (such as difference-in-differences) need to account for this post-election anticipatory effects to tariff threats.

These findings also underline the potentially disruptive impacts that political shifts, among other shocks that generate trade uncertainty, can have on business operations, particularly inventory management. As such, policies aimed at enhancing trade predictability and timely communication of policy changes play a key role in stabilizing the import sector during transitionary periods. At the same time, it is crucial to support small businesses with financial access and business management since they are shown to stockpile intensively after the 2016 election. In broader terms, this paper demonstrates the need for greater trade stability through trade talks, especially at a time when protectionism is on the rise globally. Future studies could expand on this research by extending the results to the general U.S. election cycle, explaining why downstream industries drive the anticipatory effects, and linking the anticipatory dynamics to the resilience of the import sector.

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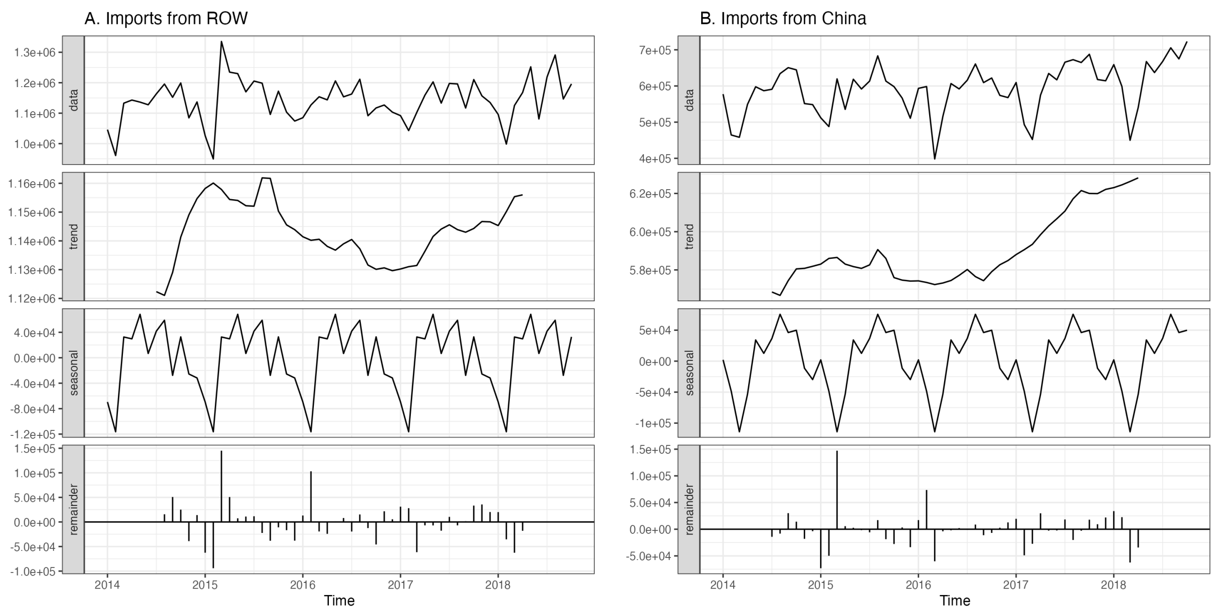
Appendix

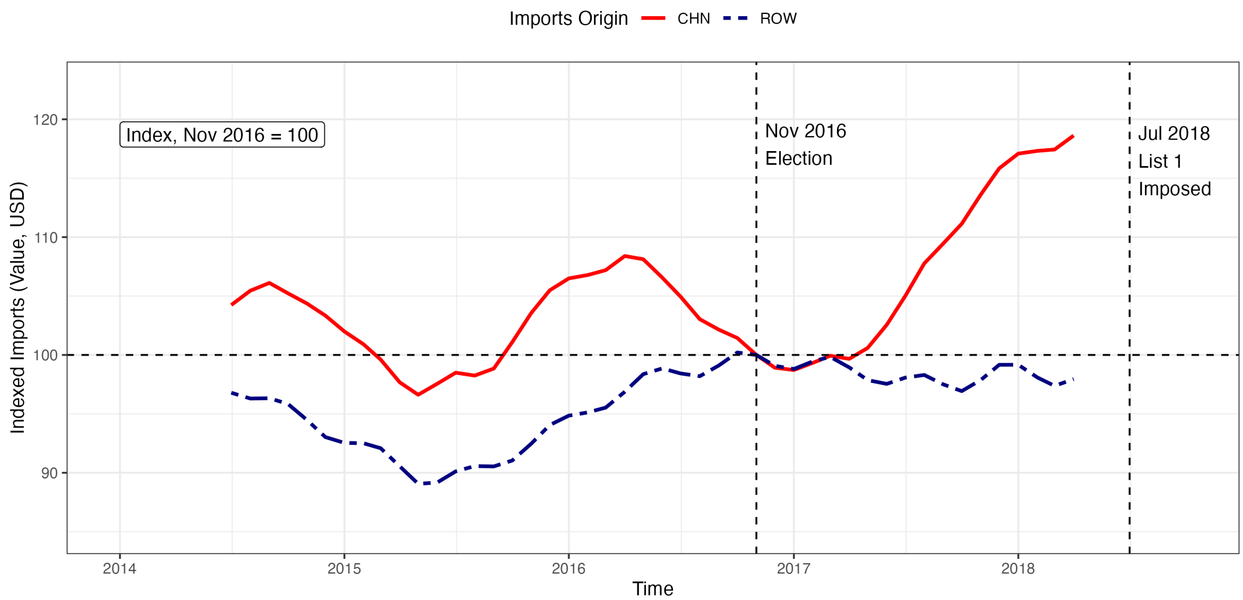
A Additional Tables and Figures

Figure A.1: Time-series Decomposition of Imports



Notes: This figure shows the time-series decomposition of imports from ROW and China from 2014-2018 using U.S. Customs bills of lading data. The first panel is the raw data. I use an additive model: $Y_t = T_t + S_t + \varepsilon_t$. The second panel plots the trend component using a moving average of symmetric 6-month window with equal weights. The additive seasonal component is in the third panel. The error component in the last panel is determined by removing trend and seasonality from the original time series.

Figure A.2: Trends in U.S. Imports (USD), Indexed to November 2016



Notes: This plot shows the indexed monthly U.S. imports, measured in USD, from China and ROW from 2014-2018 using U.S. Customs bills of lading data. I decompose the import time series into additive seasonal, trend, and error components using a symmetric 6-month moving average window with equal weights. The trend component, indexed to equal 100 in November 2016, is presented here.

Table A.1: Changes in Quarterly Import Activities

	(1) log(Volume)	(2) log(Volume)	(3) log(Weight)	(4) log(Weight)	(5) log(#Shipments)	(6) log(#Shipments)
AfterElection × China × List1	0.0456*	0.0278**	0.0443	0.0475***	-0.0211**	-0.0155***
	(0.0259)	(0.0132)	(0.0289)	(0.0156)	(0.0107)	(0.00573)
China × List1	-0.0573	-0.153**	0.164	-0.0889	0.0179	-0.0117
	(0.0883)	(0.0648)	(0.106)	(0.0644)	(0.0288)	(0.0148)
AfterElection × List1	-0.0294	-0.0231*	-0.0193	-0.0309**	0.00564	-0.00266
	(0.0208)	(0.0138)	(0.0248)	(0.0150)	(0.00825)	(0.00583)
AfterElection × China	-0.0618***	0	-0.0996***	0	-0.0179***	0
	(0.0157)	(.)	(0.0168)	(.)	(0.00555)	(.)
List1	-0.269***	0.00242	-0.403***	0.0336	-0.0101	0.0139
	(0.0542)	(0.0341)	(0.0613)	(0.0396)	(0.0181)	(0.0134)
China	0.00710	0	0.0706	0	0.0273	0
	(0.0789)	(.)	(0.0792)	(.)	(0.0190)	(.)
AfterElection	0.0697***	0	0.0796***	0	0.0219***	0
	(0.00872)	(.)	(0.0110)	(.)	(0.00266)	(.)
Observations	5,253,670	5,252,909	5,275,765	5,275,002	5,275,765	5,275,002
Fixed Effects						
Origin, Year-Quarter		X		X		X
Industry, Year-Quarter		X		X		X

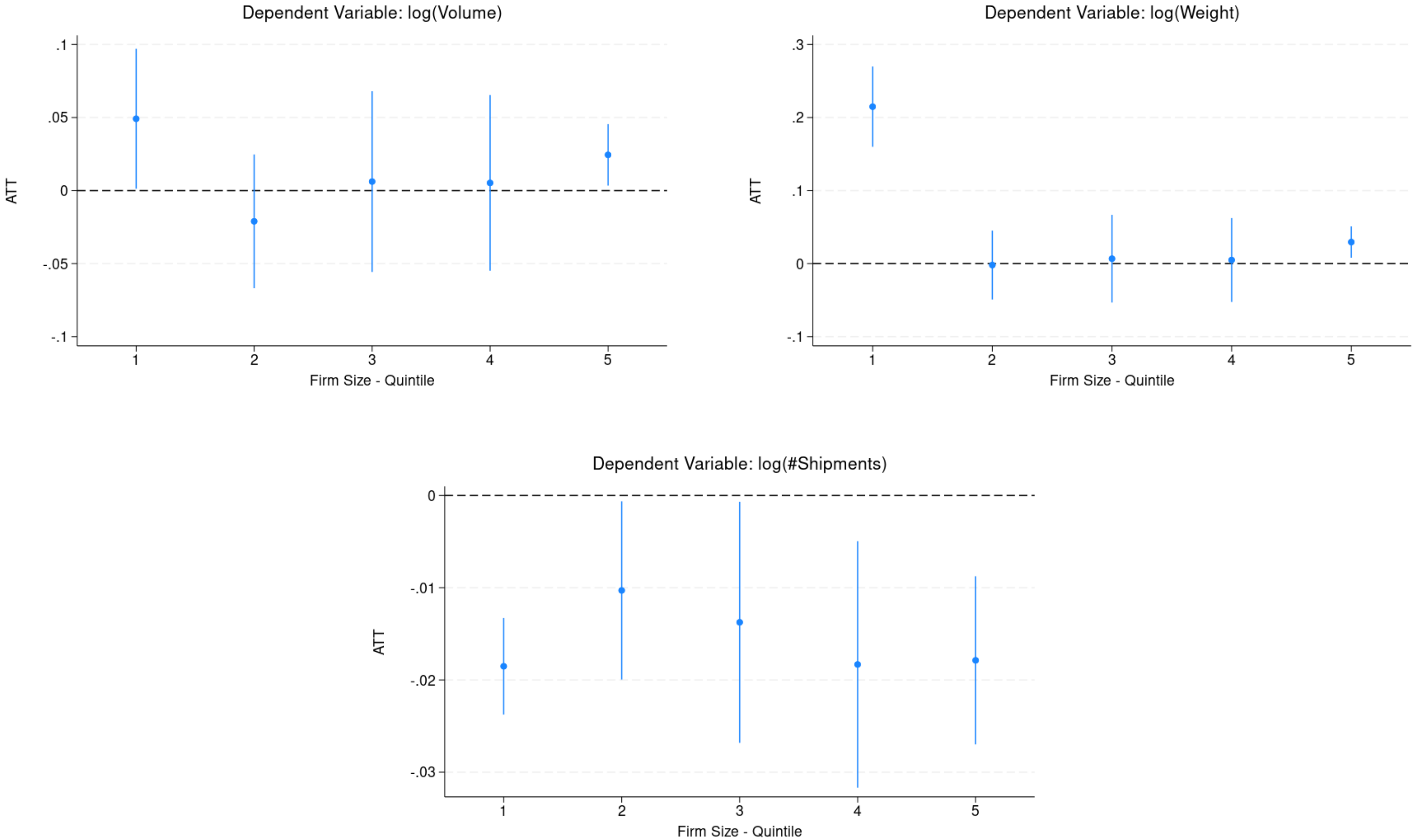
Notes: This table shows the DDD estimation results from Equation 1 using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. The ATTs are the DDD coefficients at the top of the table. Odd/Even columns are from DDD specifications without/with fixed effects. Volume is measured in TEUs and imputed by Panjiva. Weight is measured in kilograms and reported on the Customs bills of lading. Number of shipments is the count of distinct bills/shipments. Industry means HS 4-digit product headings. Standard errors are clustered by origin country and HS2 chapter. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Quarterly Changes in Trade Network

	(1) log(#Partners)	(2) log(#Partners)	(3) HHI	(4) HHI
AfterElection × China × List1	-0.00193	-0.00212	0.000346	0.000722
	(0.00257)	(0.00160)	(0.00112)	(0.000648)
China × List1	-0.000935	-0.00297	0.00159	0.00286**
	(0.00722)	(0.00333)	(0.00283)	(0.00136)
AfterElection × List1	-0.00245**	-0.00229	0.00109**	0.00119*
	(0.00112)	(0.00150)	(0.000514)	(0.000665)
AfterElection × China	-0.00261	0	0.000966	0
	(0.00213)	(.)	(0.000905)	(.)
List1	-0.0189***	-0.00127	0.00919***	0.000170
	(0.00365)	(0.00317)	(0.00139)	(0.00122)
China	0.0476***	0	-0.0212***	0
	(0.00690)	(.)	(0.00288)	(.)
AfterElection	0.00313***	0	-0.00144***	0
	(0.000786)	(.)	(0.000336)	(.)
Observations	4,828,624	4,827,808	4,828,624	4,827,808
Fixed Effects				
Origin, Year-Quarter		X		X
Industry, Year-Quarter		X		X

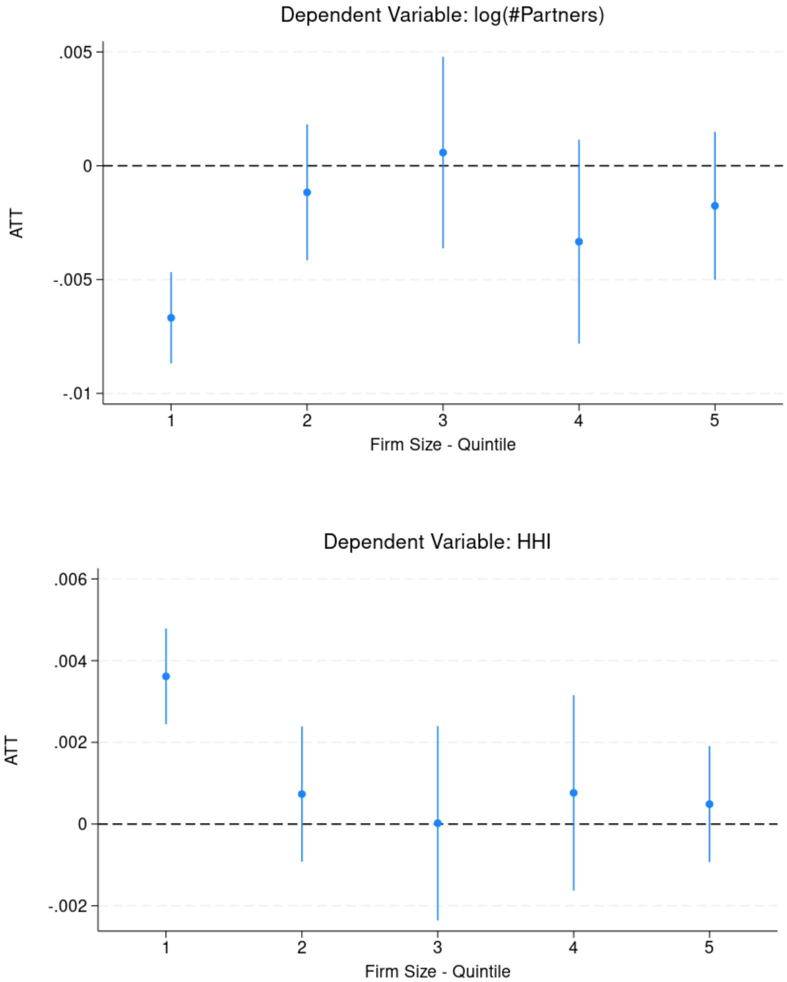
Notes: This table shows the DDD estimation results from Equation 1 using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. The ATTs are the DDD coefficients at the top of the table. Odd/Even columns are from DDD specifications without/with fixed effects. Number of partners is the count of total suppliers in country c from whom firm i buy HS6 good k in year-quarter t. HHI is calculated as Equation 3. Industry means HS 4-digit product headings. Standard errors are clustered by origin country and HS2 chapter. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.3: Impacts of Trump's Election on Quarterly Import Activities by Firm Size



Notes: This figure plots the DDD estimates from Equation 1 for trade activity outcomes by size quintile, using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. Whiskers are 95% confidence intervals. Volume is measured in TEUs and imputed by Panjiva. Weight is measured in kilograms and reported on the Customs bills of lading. Number of shipments is the count of distinct bills/shipments. Importers are sorted into quintiles based on their size as proxied by the annual import volume. Bigger quintile indicates larger importers. Origin country-year/quarter and industry-year/quarter fixed effects are included.

Figure A.4: Impacts of Trump's Election on Quarterly Trade Network by Firm Size



Notes: This figure plots the DDD estimates from Equation 1 for trade network outcomes by size quintile, using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. Whiskers are 95% confidence intervals. Number of partners is the count of total suppliers in country c from whom firm i buy HS6 good k in year-quarter t. HHI is calculated as Equation 3. Importers are sorted into quintiles based on their size as proxied by the annual import volume. Bigger quintile indicates larger importers.

Table A.3: Quarterly Changes in Trade Network by Upstreamness

	(1) log(#Partners)	(2) log(#Partners)	(3) HHI	(4) HHI
DDD × Upstream	**0.00117**	**0.000786**	**-0.000176**	**-0.000231**
	(0.00175)	**(0.00176)**	**(0.000785)**	**(0.000789)**
DDD	-0.00288	-0.00290	0.0000666	0.000785
	(0.00389)	(0.00392)	(0.00174)	(0.00175)
AfterElection × China × Upstr	-0.000247	-0.00157*	0.0000486	0.000624*
	(0.000800)	(0.000802)	(0.000358)	(0.000360)
AfterElection × List1 × Upstr	-0.000371	-0.00327**	-0.0000850	0.00133**
	(0.000717)	(0.00147)	(0.000319)	(0.000647)
China × List1 × Upstr	0.0115***	0.0170***	-0.00525***	-0.00760***
	(0.00123)	(0.00123)	(0.000549)	(0.000553)
AfterElection × List1	-0.00206	0.00534	0.00142**	-0.00187
	(0.00158)	(0.00377)	(0.000699)	(0.00165)
China × List1	-0.0212***	-0.0398***	0.0110***	0.0193***
	(0.00272)	(0.00274)	(0.00121)	(0.00122)
AfterElection × Upstr	-0.00231***	0.000317	0.000964***	-0.000294
	(0.000368)	(0.00113)	(0.000164)	(0.000500)
China × Upstr	-0.00762***	-0.00928***	0.00352***	0.00436***
	(0.000559)	(0.000560)	(0.000251)	(0.000252)
List1 × Upstr	0.0263***	-0.00248**	-0.0105***	0.00115**
	(0.000482)	(0.00103)	(0.000215)	(0.000450)
AfterElection × China	-0.00289	0	0.00125	0
	(0.00193)	(.)	(0.000853)	(.)
List1	-0.0779***	0.00388	0.0330***	-0.00224*
	(0.00105)	(0.00265)	(0.000466)	(0.00115)
Upstr	-0.0181***	-0.00106	0.00737***	0.000259
	(0.000248)	(0.000777)	(0.000111)	(0.000343)
China	0.0584***	0	-0.0264***	0
	(0.00135)	(.)	(0.000597)	(.)
AfterElection	0.00793***	0	-0.00346***	0
	(0.000950)	(.)	(0.000414)	(.)
Observations	4,615,705	4,614,942	4,615,705	4,614,942
Fixed Effects				
Origin, Year-Quarter		X		X
Industry, Year-Quarter		X		X

Notes: This table shows the estimation results from Equation 4 using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. Odd/Even columns are from specifications without/with fixed effects. Number of partners is the count of total suppliers in country c from whom firm i buy HS6 good k in year-quarter t. HHI is calculated as Equation 3. Industry means HS 4-digit product headings. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Construction of the *Storability* Measure

I calculate the degree of storability for each HS6 product following the procedure laid out by Alessandria et al. (2010), Khan and Khederlarian (2021), and Alessandria et al. (2024). The steps are as follow:

1. Using Census API, obtain imports data (CIF value of imports for consumption) at the 10-digit HS, district of entry, and source country level. This level of disaggregation is necessary to achieve variation in the HHI. I include U.S. imports from its main overseas trading partners (excluding China for endogeneity, Mexico and Canada for non-seaborne trade) between 2010 and 2015 (after the Great Recession but before the 2016 election to avoid bias). The countries included are 33 OECD countries and 10 ASEAN countries (members as of 2024). Let k denote a HS10-district combination (product), j the source country, m month, and t year.

2. Keep only products that are imported every year for each country to eliminate lumpiness due to product market entries and exits.

3. Calculate the annual HHI:

$$HHI_{jkt} = \sum_{m=1}^{12} \left(\frac{Import_{jkt,m}}{\sum_{m}^{12} Import_{jkt,m}} \right)^2 \in [1/12, 1] \tag{7}$$

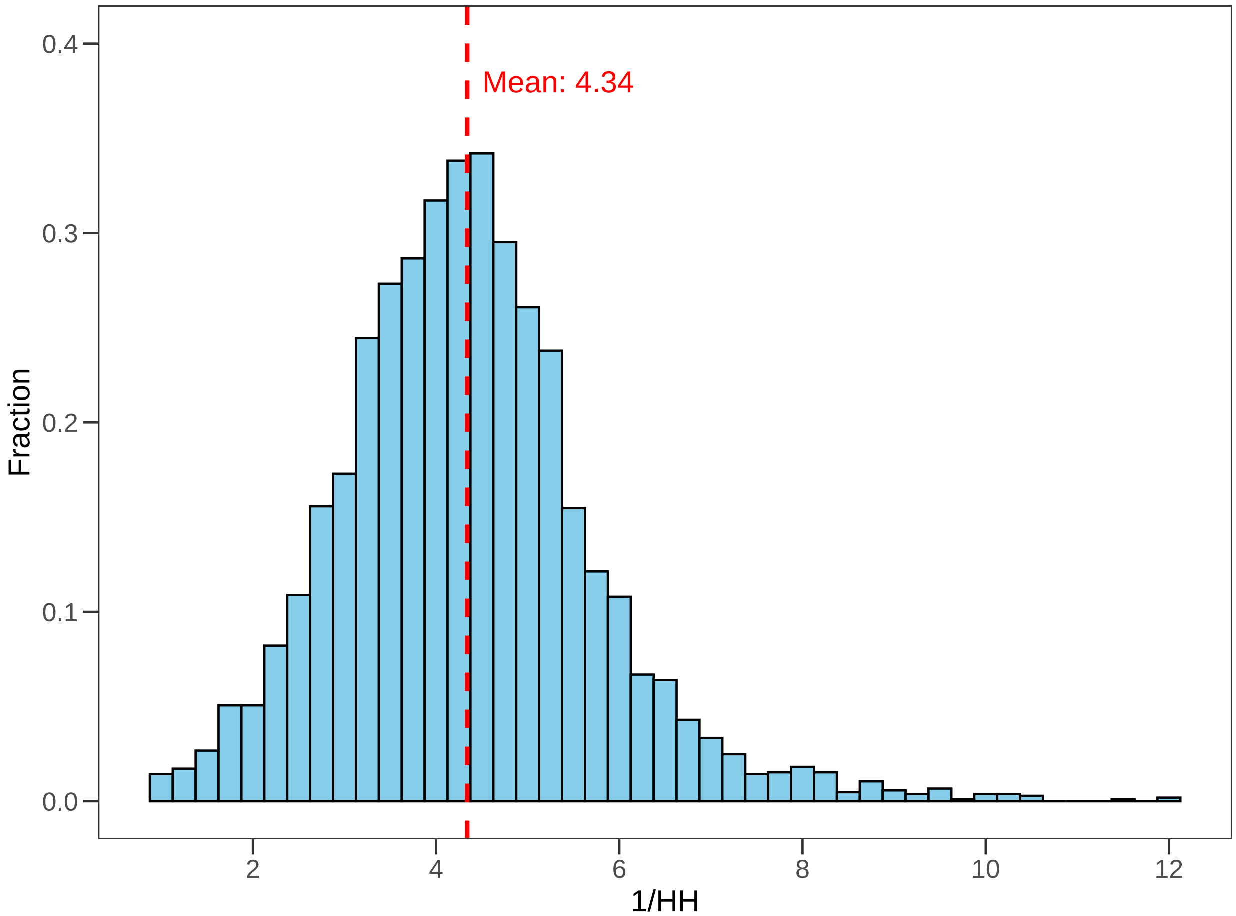
4. Estimate: $1/HHI_{jkt} = \beta_0 + \beta_k + \beta_{jt} + u_{jkt}$, and obtain the inverse HHI net of source-year fixed effects unrelated to storability, i.e., $\widehat{1/HHI}_k = \hat{\beta}_0 + \hat{\beta}_k$.

5. Average $\widehat{1/HHI}_k$ across districts for each HS10.

6. Average $\widehat{1/HHI}_k$ across HS10 for each HS6, obtaining the inverse HHI—or storability—for each HS6 product.

The distribution of the inverse HHI is reported in Figure A.5 below. It is comparable to the distributions in previous papers.

Figure A.5: Distribution of the Inverse HH Index for Storability



Notes: This is the distribution of the inverse HH index calculated for storability. Higher values of 1/HH means less storable goods. U.S. Census Data and author's calculations. See construction above.

Table A.4: Quarterly Changes in Trade Network by Storability

	(1) log(#Partners)	(2) log(#Partners)	(3) HHI	(4) HHI
DDD × Storability	0.00387***	0.00389***	-0.00181***	-0.00187***
	(0.00150)	(0.00148)	(0.000666)	(0.000661)
DDD	-0.0177***	-0.0179***	0.00770***	0.00827***
	(0.00635)	(0.00625)	(0.00285)	(0.00282)
AfterElection × China × Store	-0.00373***	-0.00341***	0.00164***	0.00159***
	(0.000754)	(0.000748)	(0.000341)	(0.000340)
AfterElection × List1 × Store	-0.000584	-0.00138*	0.000208	0.000610*
	(0.000514)	(0.000805)	(0.000233)	(0.000364)
China × List1 × Store	0.0311***	0.0187***	-0.0126***	-0.00747***
	(0.00104)	(0.00102)	(0.000466)	(0.000462)
AfterElection × List1	0.000209	0.00302	0.000125	-0.00123
	(0.00226)	(0.00370)	(0.00102)	(0.00169)
China × List1	-0.136***	-0.0829***	0.0565***	0.0347***
	(0.00442)	(0.00435)	(0.00200)	(0.00198)
AfterElection × Store	0.00197***	0.00205***	-0.000821***	-0.000767***
	(0.000346)	(0.000479)	(0.000154)	(0.000223)
China × Store	-0.0133***	-0.00990***	0.00573***	0.00388***
	(0.000528)	(0.000523)	(0.000240)	(0.000239)
List1 × Store	-0.00690***	-0.00755***	0.00295***	0.00358***
	(0.000333)	(0.000538)	(0.000153)	(0.000244)
AfterElection × China	0.0131***	0	-0.00595***	0
	(0.00325)	(.)	(0.00147)	(.)
List1	0.0121***	0.0302***	-0.00414***	-0.0148***
	(0.00147)	(0.00249)	(0.000676)	(0.00114)
Store	0.00885***	0.00972***	-0.00380***	-0.00409***
	(0.000232)	(0.000326)	(0.000103)	(0.000152)
China	0.105***	0	-0.0459***	0
	(0.00228)	(.)	(0.00103)	(.)
AfterElection	-0.00562***	0	0.00225***	0
	(0.00148)	(.)	(0.000665)	(.)
Observations	4,575,572	4,574,881	4,575,572	4,574,881
Fixed Effects				
Origin, Year-Quarter		X		X
Industry, Year-Quarter		X		X

Notes: This table shows the estimation results from Equation 4 using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. Odd/Even columns are from specifications without/with fixed effects. Higher values for storability mean less storable goods. Number of partners is the count of total suppliers in country c from whom firm i buy HS6 good k in year-quarter t. HHI is calculated as Equation 3. Industry means HS 4-digit product headings. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Robustness—Alternative Post-Period

Table A.5: Changes in Quarterly Import Activities

	(1) log(Volume)	(2) log(Volume)	(3) log(Weight)	(4) log(Weight)	(5) log(#Shipments)	(6) log(#Shipments)
AfterElection × China × List1	0.0476***	0.0304***	0.0507***	0.0551***	-0.0212***	-0.0153***
	(0.0104)	(0.0106)	(0.0105)	(0.0106)	(0.00398)	(0.00408)
China × List1	-0.0573***	-0.153***	0.164***	-0.0889***	0.0179***	-0.0117***
	(0.00692)	(0.00709)	(0.00696)	(0.00709)	(0.00265)	(0.00272)
AfterElection × List1	-0.0279***	-0.0217*	-0.0191***	-0.0295**	0.00606***	-0.00302
	(0.00580)	(0.0122)	(0.00603)	(0.0125)	(0.00221)	(0.00493)
AfterElection × China	-0.0631***	0	-0.102***	0	-0.0189***	0
	(0.00425)	(.)	(0.00436)	(.)	(0.00166)	(.)
List1	-0.269***	0.00242	-0.403***	0.0336***	-0.0101***	0.0139***
	(0.00375)	(0.00802)	(0.00391)	(0.00823)	(0.00142)	(0.00324)
China	0.00710**	0	0.0706***	0	0.0273***	0
	(0.00286)	(.)	(0.00293)	(.)	(0.00111)	(.)
AfterElection	0.0711***	0	0.0791***	0	0.0210***	0
	(0.00239)	(.)	(0.00265)	(.)	(0.000944)	(.)
Observations	4,788,748	4,788,038	4,809,013	4,808,301	4,809,013	4,808,301
Fixed Effects						
Origin, Year-Quarter		X		X		X
Industry, Year-Quarter		X		X		X

Notes: This table shows the DDD estimation results from Equation 1 using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. The post-period is further restricted to the initial announcement of List 1 tariffs, i.e., pre-period = 2015Q1-2016Q3 and post-period = 2016Q4-2018Q1 (instead of 2018Q2). The ATTs are the DDD coefficients at the top of the table. Odd/Even columns are from DDD specifications without/with fixed effects. Volume is measured in TEUs and imputed by Panjiva. Weight is measured in kilograms and reported on the Customs bills of lading. Number of shipments is the count of distinct bills/shipments. Industry means HS 4-digit product headings. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.6: Changes in Quarterly Trade Network

	(1) log(#Partners)	(2) log(#Partners)	(3) HHI	(4) HHI
AfterElection × China × List1	-0.00183	-0.00175	0.000298	0.000556
	(0.00140)	(0.00140)	(0.000613)	(0.000614)
China × List1	-0.000935	-0.00297***	0.00159***	0.00286***
	(0.000933)	(0.000933)	(0.000408)	(0.000409)
AfterElection × List1	-0.00221***	-0.00217	0.000955***	0.00116*
	(0.000595)	(0.00148)	(0.000260)	(0.000645)
AfterElection × China	-0.00308***	0	0.00117***	0
	(0.000665)	(.)	(0.000296)	(.)
List1	-0.0189***	-0.00127	0.00919***	0.000170
	(0.000378)	(0.000974)	(0.000165)	(0.000425)
China	0.0476***	0	-0.0212***	0
	(0.000443)	(.)	(0.000197)	(.)
AfterElection	0.00297***	0	-0.00137***	0
	(0.000316)	(.)	(0.000139)	(.)
Observations	4,407,352	4,406,588	4,407,352	4,406,588
Fixed Effects				
Origin, Year-Quarter		X		X
Industry, Year-Quarter		X		X

Notes: This table shows the DDD estimation results from Equation 1 using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. The post-period is further restricted to the initial announcement of List 1 tariffs, i.e., pre-period = 2015Q1-2016Q3 and post-period = 2016Q4-2018Q1 (instead of 2018Q2). The ATTs are the DDD coefficients at the top of the table. Odd/Even columns are from DDD specifications without/with fixed effects. Number of partners is the count of total suppliers in country c from whom firm i buy HS6 good k in year-quarter t. HHI is calculated as Equation 3. Industry means HS 4-digit product headings. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Robustness—Placebo: Alternative Event

Table A.7: Changes in Quarterly Import Activities

	(1) log(Volume)	(2) log(Volume)	(3) log(Weight)	(4) log(Weight)	(5) log(#Shipments)	(6) log(#Shipments)
AfterList1 × China × List1	-0.0305**	-0.0243	0.00667	0.00165	-0.00912	-0.00668
	(0.0153)	(0.0156)	(0.0154)	(0.0156)	(0.00565)	(0.00578)
China × List1	-0.0116*	-0.125***	0.209***	-0.0414***	-0.00317	-0.0272***
	(0.00705)	(0.00719)	(0.00707)	(0.00718)	(0.00270)	(0.00276)
AfterList1 × List1	-0.00182	0.0507***	0.00710	0.0483***	-0.00896***	0.0146**
	(0.00881)	(0.0180)	(0.00913)	(0.0185)	(0.00324)	(0.00698)
AfterList1 × China	0.0477***	0	0.00440	0	0.00411*	0
	(0.00607)	(.)	(0.00629)	(.)	(0.00235)	(.)
List1	-0.299***	-0.0207**	-0.423***	0.00266	-0.00443***	0.0112***
	(0.00400)	(0.00827)	(0.00416)	(0.00848)	(0.00154)	(0.00337)
China	-0.0547***	0	-0.0290***	0	0.00941***	0
	(0.00285)	(.)	(0.00293)	(.)	(0.00112)	(.)
AfterList1	0.0221***	0	0.0124***	0	-0.0282***	0
	(0.00351)	(.)	(0.00387)	(.)	(0.00137)	(.)
Observations	3,258,264	3,257,781	3,272,681	3,272,194	3,272,681	3,272,194
Fixed Effects						
Origin, Year-Quarter		X		X		X
Industry, Year-Quarter		X		X		X

Notes: This table shows the DDD estimation results from Equation 1 but instead of $AfterElection$, I use $AfterList1Implementation$, i.e., replacing the election with the implementation of List 1 as the event. I use the firm-product-origin-quarter dataset from 2017Q1 to 2018Q2, with the pre-period being 2017Q1-2018Q2 and post-period being 2018Q3-10/2018. The ATTs are the DDD coefficients at the top of the table. Odd/Even columns are from DDD specifications without/with fixed effects. Volume is measured in TEUs and imputed by Panjiva. Weight is measured in kilograms and reported on the Customs bills of lading. Number of shipments is the count of distinct bills/shipments. Industry means HS 4-digit product headings. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8: Changes in Quarterly Trade Network

	(1) log(#Partners)	(2) log(#Partners)	(3) HHI	(4) HHI
AfterList1 × China × List1	-0.00964***	-0.00813***	0.00474***	0.00387***
	(0.00204)	(0.00205)	(0.000904)	(0.000906)
China × List1	-0.00287***	-0.00509***	0.00194***	0.00359***
	(0.000943)	(0.000943)	(0.000415)	(0.000415)
AfterList1 × List1	-0.00136	0.000934	0.000268	-0.000950
	(0.000910)	(0.00219)	(0.000402)	(0.000962)
AfterList1 × China	0.00576***	0	-0.00277***	0
	(0.000994)	(.)	(0.000443)	(.)
List1	-0.0214***	-0.00356***	0.0103***	0.00136***
	(0.000415)	(0.00100)	(0.000181)	(0.000439)
China	0.0450***	0	-0.0202***	0
	(0.000452)	(.)	(0.000201)	(.)
AfterList1	0.00115**	0	-0.000561***	0
	(0.000488)	(.)	(0.000214)	(.)
Observations	2,943,742	2,943,216	2,943,742	2,943,216
Fixed Effects				
Origin, Year-Quarter		X		X
Industry, Year-Quarter		X		X

Notes: This table shows the DDD estimation results from Equation 1 but instead of $AfterElection$, I use $AfterList1Implementation$, i.e., replacing the election with the implementation of List 1 as the event. I use the firm-product-origin-quarter dataset from 2017Q1 to 2018Q2, with the pre-period being 2017Q1-2018Q2 and post-period being 2018Q3-10/2018. The ATTs are the DDD coefficients at the top of the table. Odd/Even columns are from DDD specifications without/with fixed effects. Number of partners is the count of total suppliers in country c from whom firm i buy HS6 good k in year-quarter t. HHI is calculated as Equation 3. Industry means HS 4-digit product headings. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Robustness—Full Firm Sample

Table A.9: Changes in Quarterly Import Activities and Trade Network—Full Sample

	(1) log(Volume)	(2) log(Volume)	(3) log(Weight)	(4) log(Weight)	(5) log(#Shipments)	(6) log(#Shipments)	(7) log(#Partners)	(8) log(#Partners)	(9) HHI	(10) HHI
AfterElection × China × List1	0.0385***	0.0282***	0.0374***	0.0382***	-0.00386	-0.00546*	0.00314***	0.00272**	-0.00144***	-0.00109**
	(0.00786)	(0.00794)	(0.00791)	(0.00795)	(0.00320)	(0.00324)	(0.00118)	(0.00117)	(0.000513)	(0.000510)
China × List1	-0.0631***	-0.191***	0.179***	-0.108***	-0.0197***	-0.0413***	-0.00990***	-0.0195***	0.00495***	0.00966***
	(0.00538)	(0.00544)	(0.00542)	(0.00545)	(0.00219)	(0.00223)	(0.000815)	(0.000808)	(0.000354)	(0.000352)
AfterElection × List1	0.00696	-0.00218	0.00680	-0.00414	0.0101***	0.00510	0.00223***	-0.0000478	-0.00104***	-0.000359
	(0.00443)	(0.00894)	(0.00461)	(0.00918)	(0.00181)	(0.00386)	(0.000521)	(0.00124)	(0.000225)	(0.000535)
AfterElection × China	-0.0704***	0	-0.0972***	0	-0.0122***	0	-0.00644***	0	0.00253***	0
	(0.00301)	(.)	(0.00309)	(.)	(0.00133)	(.)	(0.000594)	(.)	(0.000256)	(.)
List1	-0.394***	-0.0378***	-0.523***	-0.0173***	-0.0498***	-0.00534**	-0.0472***	-0.00485***	0.0214***	0.00194***
	(0.00299)	(0.00608)	(0.00311)	(0.00624)	(0.00122)	(0.00264)	(0.000350)	(0.000847)	(0.000151)	(0.000365)
China	0.0805***	0	0.0786***	0	0.0315***	0	0.0607***	0	-0.0266***	0
	(0.00206)	(.)	(0.00211)	(.)	(0.000917)	(.)	(0.000410)	(.)	(0.000177)	(.)
AfterElection	0.0339***	0	0.0476***	0	0.00217***	0	-0.00299***	0	0.00130***	0
	(0.00170)	(.)	(0.00187)	(.)	(0.000752)	(.)	(0.000295)	(.)	(0.000126)	(.)
Observations	9,183,904	9,183,345	9,217,596	9,217,039	9,217,596	9,217,039	8,291,719	8,291,068	8,291,719	8,291,068
Fixed Effects										
Origin, Year-Quarter		X		X		X		X		X
Industry, Year-Quarter		X		X		X		X		X

Notes: This table shows the DDD estimation results from Equation 1 using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. Logistic, wholesale, and retail firms are included. The ATTs are the DDD coefficients at the top of the table. Odd/Even columns are from DDD specifications without/with fixed effects. Volume is measured in TEUs and imputed by Panjiva. Weight is measured in kilograms and reported on the Customs bills of lading. Number of shipments is the count of distinct bills/shipments. Number of partners is the count of total suppliers in country c from whom firm i buy HS6 good k in year-quarter t. HHI is calculated as Equation 3. Industry means HS 4-digit product headings. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A.10: Changes in Quarterly Import Activities and Trade Network—Full Sample

	(1) log(Volume)	(2) log(Volume)	(3) log(Weight)	(4) log(Weight)	(5) log(#Shipments)	(6) log(#Shipments)	(7) log(#Partners)	(8) log(#Partners)	(9) HHI	(10) HHI
AfterElection × China × List1	0.0385**	0.0282**	0.0374*	0.0382***	-0.00386	-0.00546	0.00314	0.00272*	-0.00144	-0.00109*
	(0.0174)	(0.0115)	(0.0204)	(0.0136)	(0.00837)	(0.00501)	(0.00210)	(0.00163)	(0.000886)	(0.000626)
China × List1	-0.0631	-0.191***	0.179	-0.108*	-0.0197	-0.0413**	-0.00990	-0.0195***	0.00495	0.00966***
	(0.0995)	(0.0623)	(0.115)	(0.0600)	(0.0320)	(0.0165)	(0.0115)	(0.00586)	(0.00467)	(0.00240)
AfterElection × List1	0.00696	-0.00218	0.00680	-0.00414	0.0101	0.00510	0.00223*	-0.0000478	-0.00104**	-0.000359
	(0.0149)	(0.0118)	(0.0178)	(0.0130)	(0.00662)	(0.00435)	(0.00117)	(0.00144)	(0.000522)	(0.000641)
AfterElection × China	-0.0704***	0	-0.0972***	0	-0.0122***	0	-0.00644***	0	0.00253***	0
	(0.0103)	(.)	(0.0117)	(.)	(0.00377)	(.)	(0.00149)	(.)	(0.000627)	(.)
List1	-0.394***	-0.0378	-0.523***	-0.0173	-0.0498**	-0.00534	-0.0472***	-0.00485	0.0214***	0.00194
	(0.0530)	(0.0353)	(0.0549)	(0.0347)	(0.0201)	(0.0117)	(0.00546)	(0.00459)	(0.00222)	(0.00187)
China	0.0805	0	0.0786	0	0.0315	0	0.0607***	0	-0.0266***	0
	(0.0886)	(.)	(0.0820)	(.)	(0.0223)	(.)	(0.0112)	(.)	(0.00469)	(.)
AfterElection	0.0339***	0	0.0476***	0	0.00217	0	-0.00299***	0	0.00130***	0
	(0.00586)	(.)	(0.00706)	(.)	(0.00211)	(.)	(0.000924)	(.)	(0.000385)	(.)
Observations	9,183,904	9,183,345	9,217,596	9,217,039	9,217,596	9,217,039	8,291,719	8,291,068	8,291,719	8,291,068
Fixed Effects										
Origin, Year-Quarter		X		X		X		X		X
Industry, Year-Quarter		X		X		X		X		X

Notes: This table shows the DDD estimation results from Equation 1 using the firm-product-origin-quarter dataset from 2015Q1 to 2018Q2. Logistic, wholesale, and retail firms are included. The ATTs are the DDD coefficients at the top of the table. Odd/Even columns are from DDD specifications without/with fixed effects. Volume is measured in TEUs and imputed by Panjiva. Weight is measured in kilograms and reported on the Customs bills of lading. Number of shipments is the count of distinct bills/shipments. Number of partners is the count of total suppliers in country c from whom firm i buy HS6 good k in year-quarter t. HHI is calculated as Equation 3. Industry means HS 4-digit product headings. Standard errors are clustered by origin country and HS2 chapter. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.