Anxiety or Pain? The Impact of Tariffs and Uncertainty on Chinese Firms in the Trade War

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Abstract

Taking the 2018-2019 US-China trade war as an unexpected and exogenous event faced by Chinese firms, we study the impact of rising import and export tariffs on firm performance and show that an important mechanism has been a tariff-induced increase in trade policy uncertainty (TPU). Our analysis leverages a newly-constructed firm-level TPU measure based on a textual analysis of listed firms' annual reports, and a firm-level tariff-exposure measure built using custom transactions data. We estimate a difference-in-differences empirical specification based on variation across Chinese firms in exposure to trade war tariffs. We find that increases in U.S. tariffs and Chinese retaliatory tariffs both raised TPU for Chinese firms. The impact of tariffs on uncertainty is heterogeneous, and is larger among smaller and less capital-intensive firms. This impact is also smaller for exporters that are more diversified in terms of partner countries. Based on our estimates, a one standard deviation increase in TPU seen by Chinese firms during the trade war has led to a reduction in firm-level investment, R&D expenditures and profits by 1.4, 2.7 and 8.9 percent, respectively.

Keywords: Trade War, Tariffs, Trade Policy Uncertainty

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1 Introduction

The U.S. and China have been engaged in an unprecedented trade war involving broad rounds of tariffs imposed upon each other. Following an investigation on "China's laws, policies, practices, or actions that may be unreasonable or discriminatory and that may be harming American intellectual property rights, innovation, or technology development," the U.S. imposed, between July and September 2018 tariff rounds covering $74 billion of Chinese exports to the U.S. China retaliated immediately with tariffs targeting $31 billion of imports from the U.S.[1] In addition, this trade war, which breaks apart with decades of trade liberalization, has brought significant uncertainty to economic agents (IMF, 2018). Timely evidence on the overall consequences of the trade war is much needed to guide future policies towards either a deepening or a correction of the existing ones. In addition, this event provides a unique opportunity to understand the channels through which trade policy impacts the economy.

In this paper we provide the first account of the impact of the 2018-2019 trade war on Chinese firms. We assemble a unique and comprehensive dataset with firm-level measures of exposure to tariffs, firm-level measures of trade policy uncertainty and various real outcomes of listed firms. The tariff exposure measures are constructed using firm-level customs data and detailed data on product-level trade war and MFN tariffs. The firm-specific measures of trade policy uncertainty are based on a textual analysis of firms' annual reports. This data and a clean empirical strategy allows us to shed light on the mechanisms through which the trade war impacts firms.

We start by providing descriptive evidence showing that trade policy uncertainty (TPU) has spiked for most firms during the trade war period. We construct an aggregate index from the firm-level TPU measures and show it maps closely the evolution of economy-wide TPU measures based on newspaper articles constructed by Davis et al. (2019).

Next, we show that firms exposed to increases Chinese tariffs have faced increases in firm-level TPU. We estimate regressions of the change in firm TPU between 2017Q4 and 2018Q4 on changes in firm-specific tariff exposures. Note that US and Chinese tariffs affect firms differently. US tariffs reduce the demand for Chinese firms' exports, while Chinese tariffs make it difficult their access to imported inputs. We find that Chinese tariffs matter. A one percent increase in the Chinese tariff exposure measure is associated

[1] Both amounts targeted by these tariff rounds are based on the approximate value of 2017 US exports and imports in the product categories targeted by the tariffs. This convention is used throughout the paper. The amounts of Chinese (the US) exports to the US (China) affected by US (Chinese) tariff account for about 14.6% (23.8%) of total Chinese (US) exports to the US (China).

with 1.57 standard deviation increase in trade policy uncertainty. Our results are robust to including several controls such as region and industry fixed effects and lagged firm characteristics and we also rule out the existence of confounding pre-existing trends. This first key finding of our paper provides clear evidence that the trade war represents a *trade policy uncertainty shock* to exposed firms, and that this operates especially through tariffs raising the cost of imported inputs.

We also find that the effect of tariffs on firm-level TPU is heterogenous across firms. First, we allow for an interaction between tariffs and lagged firm revenue, as a measure of firm size, and find that the effect of US tariffs on TPU is larger among smaller firms. The impact of increase in US tariffs on trade policy uncertainty is 0.56 standard deviation lower as a firm's revenue doubles. Second, we also find that the impact of both US and Chinese tariffs on firm-level TPU are larger among less capital intensive firms. As a firm's capital stock doubles, the impact of increase in US tariff (resp. Chinese tariff) on trade policy uncertainty is 0.45 standard deviation (resp. 0.87 standard deviation) lower. Finally, we ask whether firms with more destinations and products for their exports, or more source countries and variety of imports, respond less to tariffs. We find this to be the case indeed especially for exporting. One additional country in a firm's export basket reduces the impact of US tariffs on firm-level TPU by 0.031 standard deviation. We argue this reveals a *real hedging* channel. Diversification of destination countries reduces the impact of shocks.[2] Overall, these patterns provide novel evidence on the impact of external trade policy shocks on firm-level uncertainty.

In the second part of our paper, we analyze whether increases in TPU affect firm-level real activities. We find that firms that increases in firm-level TPU reduce firm-level investment, R&D expenditures, and profits. A one standard deviation increase in TPU induces a decline in investment by 1.4 percent. After 3 quarters, the magnitude of the TPU shock on firm-level investment amplified to 2.0 percent. A one standard deviation increase in TPU induces a decline in R&D expenditures by 2.7 percent. Lastly, a one standard deviation increase in TPU is associated with a decline in profits by 8.4 million Chinese yuan after two quarters and 11.0 million Chinese yuan after two quarters.

An important contribution of our paper is the dataset we assemble to decompose the underlying mechanisms. We measure outcomes based on quarterly and up-to-date data on Chinese listed firms. A key advantage from focusing on listed firms is timeliness. More representative data produced by the Chinese government becomes available with a

[2]The *real hedging* channel is consistent with previous work by Macedoni and Xu (2018) and Kramarz et al. (2020). Kramarz et al. (2020) find that most exporters' volatility is directly due to the lack of diversification in their portfolio of customers; using theory and empirical evidence, Macedoni and Xu (2018) show that trade elasticity is smaller for firms with more products.

lag of several years.[3] In addition we have compiled detailed product level data on most-favored-nation and additional trade war tariffs imposed by the U.S. and China on each other. We are able to assign exact measures of tariff exposure to each firm based not only on their broad industry but also based on customs transactions data.[4]

The most novel aspect of our dataset is the firm-level measure of trade policy uncertainty based on a textual analysis of firms' annual reports. We follow very recent work using the same approach to capture international firms' exposure and responses to Brexit (Hassan et al., 2020), and U.S. firms' exposure to political risk (Hassan et al., 2020, 2019) and the 2018-2019 trade war (Caldara et al., 2019).

The rest of the paper is organized as follows. Section 1.1 discusses the contribution of this paper to the existing literature. Section 2 summarizes the events in the ongoing trade war. Section 3 describes the various data sources employed. Section 4 analyzes the impact of trade war tariffs on firm-level trade policy uncertainty. Section 5 then studies the effect of firm-level TPU on economic outcomes. Section 6 concludes.

1.1 Contribution to the Literature

This paper joins a nascent literature evaluating the consequences of the U.S.-China trade war, and is, to the best of our knowledge, the first to examine the impact on real economic outcomes of Chinese firms in particular or the Chinese economy in general. The literature so far has focused on the U.S. economy. Specifically, Fajgelbaum et al. (2019) and Amiti et al. (2019) quantify the effect of the tariffs applied by the U.S. on China and other trade partners, and these countries' retaliatory tariffs, and using different methods establish a similar aggregate welfare loss for the U.S. equal to about 0.04% of GDP. Huang et al. (2018) study the response of both U.S. and Chinese firms' stock market prices to the March 2018 announcement of the investigation that led to the first round of U.S. tariffs on China, finding that Chinese firms that export to the U.S. have lower stock market returns around

[3]A second advantage from data on listed firms is its reliability. Chen et al. (2019) explain how local governments adjust data reported in official firm-level surveys (which underlie GDP calculations) to meet the goals imposed by the central government. Data reported on listed firms should be much more reliable as these firms face more scrutiny. The main limitation of the sample is its coverage. Listed firms are just a fraction of all firms, are larger on average, and are not representative of the entire firm distribution. Given the concentration of economic activity, however, these firms account for a large share of macroeconomic aggregates. We argue that sacrificing coverage in favor of timeliness is worthwhile, especially in the current context of very limited available empirical work on the impact of these previously unseen policies. Previous work studying the effects of trade policies or trade shocks using data on listed firms includes Bloom et al., 2019; Hombert and Matray, 2018; Guadalupe and Wulf, 2010; Autor et al., n.d.; Keller and Yeaple, 2009 and Benguria, 2019 among others.

[4]The most recent customs data available is from 2016, so we are not able at this point to analyze firm-level trade flows as outcomes.

the announcement date.

This paper also adds to a literature that has used novel empirical methods to measure the impact of uncertainty on firms. Pioneering work by Hassan et al. (2019) analyzes earnings call reports to construct measures of politically-related risk as a count of the share of space in earnings calls reports devoted to discussing political risk. Closer to our paper, Caldara et al. (2019) analyze the effect of trade policy uncertainty on investment by U.S. listed firms. They construct firm-level trade policy uncertainty measures based on earnings calls reports by counting the share of instances in which trade-policy related words appear together with uncertainty related terms. Using this measure, they document a negative impact of firm-level TPU on investment over the 2015Q1-2018Q4 period. In addition, they show that firms in industries facing new US import tariffs during the trade war further reduce their investment. The comments by Steinberg (2019b) on Caldara et al. (2019) suggest new exercises that we implement. Specifically, we use firm-level measures of tariff exposure and link them to firm-level TPU, thereby unpacking the sources of firm-level TPU.[5]

Our work complements a broader literature on the economic consequences of trade policy uncertainty (or economic uncertainty in general). A set of papers has used the uncertainty surrouding U.S. tariff preferences towards China around China's W.T.O. entry (Handley and Limão, 2017; Pierce and Schott, 2016; Feng et al., 2017). An alternative approach to capture the consequences of trade policy uncertainty has relied on estimating structural models (Steinberg, 2019a).[6]

This paper also contributes to a literature that has studied the impact of various trade policies or trade shocks on Chinese firms. Brandt et al. (2017) dissects the channels through which China's entry into the W.T.O. led to productivity improvements among Chinese firms, while Lu and Yu (2015) document that this episode led to a reduction in markup dispersion across firms and Khandelwal et al. (2013) study the response of exporters in the textile and apparel sector to the removal of quotas in destination markets and how this response is mediated by the allocation of quotas.

[5]Handley and Li (2018) construct time-varying measure of firm-specific idiosyncratic uncertainty from analyzing the text of company reports filed with the U.S. Securities and Exchange Commission. However, our focus is the trade policy uncertainty that is in line with Caldara et al. (2019).

[6]Additional work in this literature includes Handley (2014); Handley and Limao (2015); Handley and Limão (2017); Carballo et al. (2018); Graziano et al. (2018).

2 The US-China Trade War

The current U.S. administration has implemented trade policies that contrast with a long overall trend towards freer trade, applying tariffs towards several trading partners under various justifications. The first trade barriers imposed early in the Trump administration were global safeguard tariffs on imports of washing machines and solar panels in January 2018 and tariffs on steel and aluminum imports in March 2018, which were justified by a national security threat. These tariffs were focused on a few industries, were not specific to China, and led to retaliatory tariffs from several trading partners.

The trade war between the U.S. and China is at the center of the current adminstration's trade policies and is a first order concern for the global economy. Following an investigation on China's laws or actions that could result discriminatory towards intellectual property rights of U.S. companies disclosed in March 2018, the U.S. has imposed broad rounds of tariffs on Chinese products, leading to immediate retaliatory tariffs applied by China. U.S. tariffs towards China largely dominate in economic significance the earlier policies. In total, U.S. tariffs on Chinese products cover a list representing $250 billion (in terms of their 2017 value), which is about half the imports from China in 2017. Chinese tariffs apply to a list of products representing about 85% of U.S. exports to China in 2017. Here we briefly describe the main, broad tariff rounds imposed by the U.S. and China upon each other.[7]

The first tariff round by the U.S. covering $50 billion in imports was imposed in a $34 billion July 2018 wave targeting 818 HS 8-digit products and an August 2018 wave targeting 279 HS 8-digit products, both with 25% rates. China's retaliatory first round also covers $50 billion in imports and was also implemented in July and August waves covering $34 billion and $16 billion and targeting 545 and 333 HS 8-digit products respectively with a 25% rate.[8] The second U.S. round imposed in September 2018 applies a 10% rate to 6056 HS 8-digit covering $200 billion in imports. China's second round was imposed simultaneously in September 2018, applying 5% and 10% rates on 5207 HS 8-digit level products covering $60 billion in imports.[9]

The initial announcement of the U.S. $200 billion round included a future increase to a 25% rate on the same list of products and China also announced a rate increase. In December 2018, following a meeting between the U.S. and Chinese presidents agree to

[7] Bown and Kolb (2019) provide a detailed timeline to the U.S. - China trade war.

[8] Note that earlier, in April 2018, China had imposed tariffs on a small set of products covering $2.4 billion in imports from the U.S. in response to the U.S. steel and aluminum tariffs. This tariff round applies 15% and 25% ad-valorem rates targeting 91 HS 6-digit (104 HS 8-digit) products.

[9] This second Chinese round was announced as a $60 billion round but in practice covered $52 billion in imports from the U.S.

a truce that postpones the increase in the rates on the products targeted by the U.S. $200 billion round and China's retaliatory round. In January 2019, China eliminated retaliatory tariffs on cars and car parts and reduced MFN tariffs.

Finally, in May 2019, the US did raise the ad-valorem rates on the product list of the $200 billion round from 10% to 25% in June 2019 China raises rates on a product list already targeted in September 2018, covering $36 billion.

As Amiti et al. (2019) argue, the U.S.-China trade war was a surprising, unanticipated event for firms given that Trump's election was not predicted by the polls. In additon, while there was a discussion on revising trade policy during the presidential campaign, there were no early announcements on which industries would be targeted by tariffs.

3 Data Sources and Firm-level Measurement

3.1 Firm-level Data

We use firm-level data from three sources. The first is the China Customs Dataset (2013-2016), which provides export and import values at the firm-product-destination-year level for all international transactions from China. We define a product as a Harmonized System (HS) eight-digit code.

Second, to construct the firm-level uncertainty measure, we use transcripts of the annual reports released by Chinese firms that are listed in Shanghai and Shenzhen Stock Exchange's domestic A share markets in all years between 2008 and 2018. The reports are scraped from *East Money Information* (i.e., a financial data provider in China) in PDF format, and we convert them into text.[10]

Third, to better understand the effects of US-China trade war on firm performance, we use firm-level data reported by COMPUSTAT Global that tracks firm performance for 2,312 Chinese firms on a quarterly basis. This data is limited to firms listed on the stock market. Focusing on listed firms has the advantage of timeliness; other firm-level data sources are released with a lag of several years. We use data from 2016Q1 to 2019Q3. But, to link the COMPUSTAT Global to firm-level uncertainty measure, we use two data points (i.e., 2017Q4 and 2018Q4) for our benchmark analysis. The variables used are revenue, capital stock, profits, and liquidity. We supplement this with R&D expenditure which is only available annually.

[10] An annual report documents a public company's activity, which includes the names of key staff, what they did and why in a financial year, the main financial data, the operational performance, and future ventures and plans. The Accounting Standard for Business Enterprise promulgated by the Ministry of Finance of China requires that all Chinese firms use December 31 as the same end date of the financial year.

3.2 Tariff Data

We compile a detailed dataset of US tariffs imposed upon China and Chinese retaliatory tariffs on the US. We complement this with US and Chinese MFN tariffs. We follow Fajgelbaum et al. (2019) in the construction of our dataset, extending it forward in time.

The data sources for US trade war tariffs are official communications by the U.S. Trade Representative, Fajgelbaum et al. (2019) and the Li (2018) trade war tariff dataset. We obtain U.S. MFN tariffs from the WTO (World Trade Organization) *Tariff Download Facility* database.

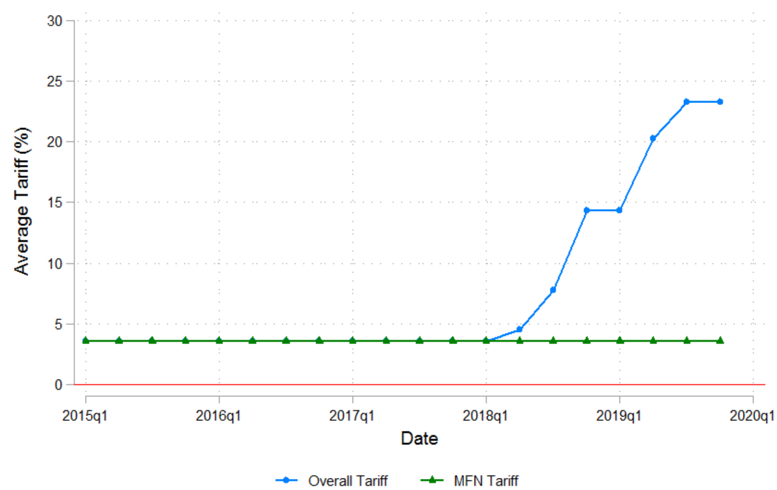
The data sources for Chinese trade war tariffs are Fajgelbaum et al. (2019), the Li (2018) trade war tariff dataset and Bown and Kolb (2019). Note that Chinese MFN tariffs from the WTO *Tariff Download Facility* database are complemented by Bown and Kolb (2019) who compiles recent and frequent changes in Chinese tariffs observed during 2018 and 2019 from official Chinese government communicaitons.

Figure 1 displays the evolution pattern of tariff imposed by the US (panel (a)) and China (panel (b)), respectively, where each dot denotes the average tariff computed as the simple mean of tariffs across all HS 6-digit sectors.[11] As shown in the Figure, the average tariff faced by China in the US was essentially constant up to the second quarter of 2018, at about 4.1%. Starting from the third quarter of the same year, the US tariff on Chinese goods increases from 7% to 20.3% in the fourth quarter of 2019. For comparison, we display the average MFN tariff with the green color in the same graph, which remain unchanged at its low level of 3.6% through the periods. The increase in Chinese tariffs on US exports reflect the very small April 2018 round in retaliation for US steel and aluminum tariffs, and then starting on the third quarter of 2018 the $50 billion followed by the $60 billion rounds occurring between July and September that year. The figure also reflects the removal of retaliatory tariffs on cars and car parts in January 2019 and the extension in tariff rates on some of the products in the earlier $60 billion round occuring in June 2019.

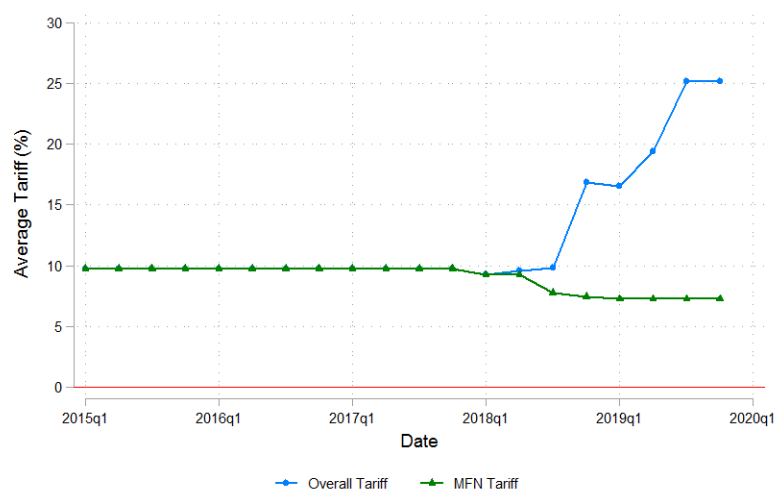
Similar tariff change is found for the tariff imposed by China; that is, the tariff remain at its low level of 9.0% up to the third quarter of 2018, after which the tariff increases from 15.3% in the third quarter of 2018 to 22.0% in the fourth quarter of 2019. The figure reflects the imposition of tariffs on steel and aluminum in the first quarter of 2018, followed by broad tariff rounds (covering $50 and $200 billions in imports) between July and September 2019. In addition, it shows the increase in tariff rates in the products covered by the $200 billion round in May 2019.

[11] The detailed numbers are provided in Table A.2 in the appendix.

Figure 1: The Average U.S. and Chinese Tariff



(a) US Tariff on Chinese Goods



(b) Chinese Tariff on the US Goods

Notes: The average tariff is the simple arithmetic average of HS 10-digit tariffs. The green line denotes the MFN tariffs for both countries, and the blue line is for the overall tariff (MFN tariff plus trade war tariff).

To relate firm performance to trade policy uncertainty and the tariff exposure measures, we first translate names of firm in COMPUSTAT Global into Chinese, according to which we refine the sample to listed firms in Shanghai and Shenzhen Stock Exchange's domestic A share markets (for which we have annual reports). Then we use firm names to exactly match the firms in COMPUSTAT Global to those in China customs to track their previous activities in the global market.[12] Table 1 reports the summary statistics on average exports and imports for the matched Chinese listed firms in COMPUSTAT Global. Table A.1 reports the similar statistics for matched Chinese listed firms by year. Figure 2 displays the variation in the number of firms across Chinese cities, and we use darker colors to denote a greater number of firms. According to the map, the matched sample is geographically representative overall, covering large geographic areas within China with coastal regions hosting more firms than other areas.

Table 1: Summary Statistics: Matched Chinese Firms in COMPUSTAT Global

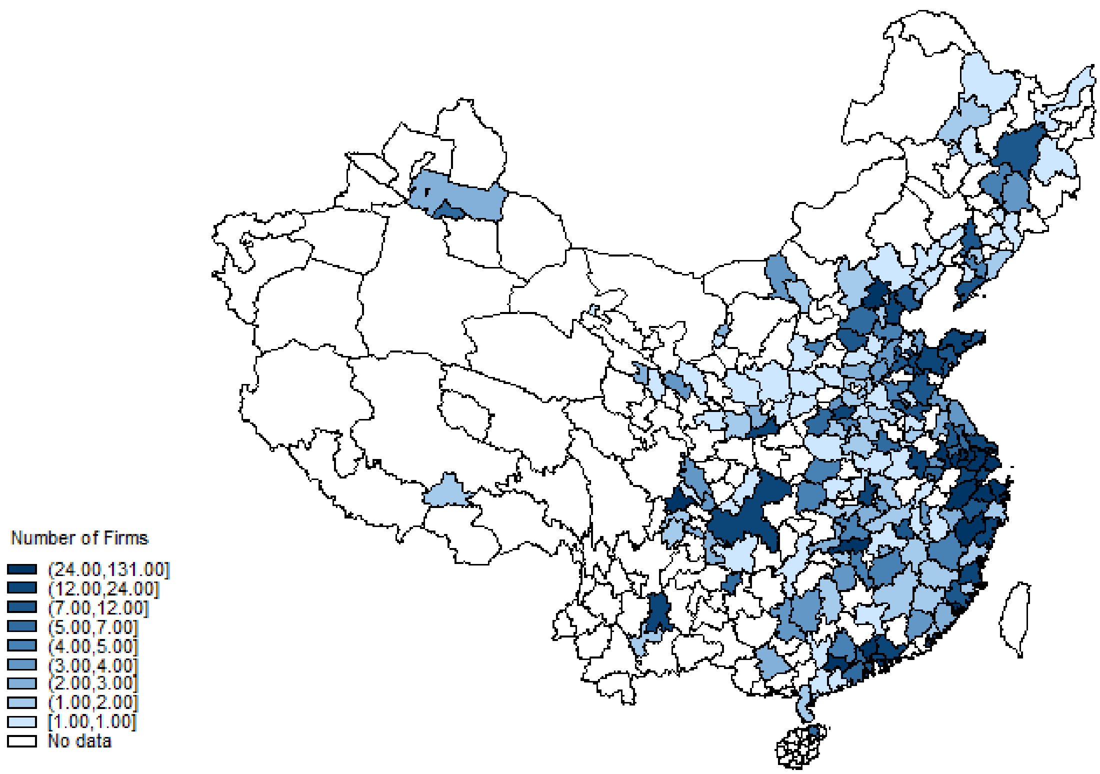
Variable	Mean	Standard Deviation
Average Firm Exports (2013-2016)		
Number of Unique Matched Firms	1,601	-
Number of Observations	5,127	-
Number of Products	22.400	61.601
Number of Countries	24.988	26.121
Exports (million USD)	60.148	213.655
Share of Exports to the US	12.22 %	21.43 %
Average Firm Imports (2013-2016)		
Number of Unique Matched Firms	1,611	-
Number of Observations	4,925	-
Number of Products	20.972	37.877
Number of Countries	7.195	7.164
Imports (million USD)	39.914	223.874
Share of Imports from the US	13.22 %	25.87 %

Notes: The table summarizes firm-year-level exports and imports for the matched listed enterprise during 2013 and 2016 (pooling firms together). Each product is defined by the unique HS 8-digit code.

Figure 3 reports some patterns on firm exports and imports in the pre-period. As displayed in panel (a), we observe that firms with bigger total exports are also associated with a larger share of sales to the US market, which is robust to pooling samples together

[12] Specifically, we first identify the firms whose names are identical in both samples. For the unmatched firms in COMPUSTAT Global, we employ the fuzzy match technique powered by Stata: for each of the unmatched firm in COMPUSTAT Global, we use the code "*matchit*" and set the cutoff similarity score as 0.65 to find out a wide range of possible firm names in customs; we then manually exclude false matches.

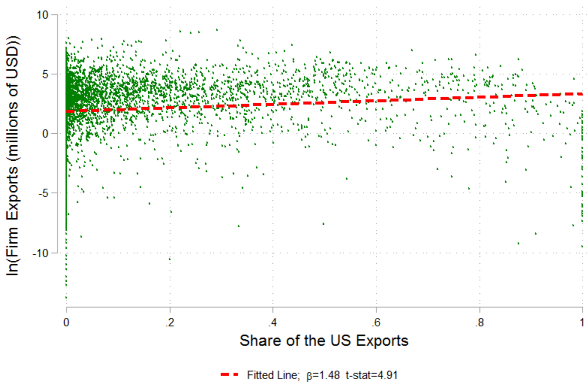
Figure 2: Geographic Distribution of the Matched Firms



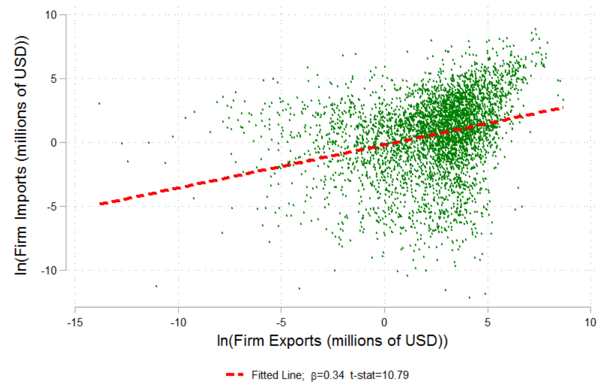
Notes: The information on city location of matched firms is from China custom data, where a city defined by a unique 4-digit region code.

or using the average between 2013 and 2016.[13] While firm selling more in the global market are also likely to import larger amount of goods (panel (b) of Figure 3), there is no systematic pattern suggesting that firm exports positively depends on its imports from the United States, as the coefficient remain insignificant in panel (c). Figure 3 shows that firms that are more likely to export to the U.S. are usually bigger in scale.

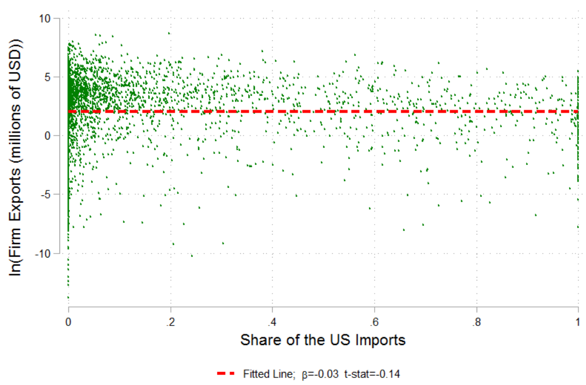
Figure 3: Firm Exports, Imports and the US Shares for the Matched Listed Firms



(a) Exports and the U.S. Export Share



(b) Exports and Imports



(c) Exports and the U.S. Import Share

Notes: the scatter plot use custom data of the matched firms for years between 2014 and 2016. Panel (a) displays the correlation between firm total exports and the share of exports that goes to the United States; panel (b) reports the correlation between firm imports and exports; panel (c) plot the firm exports and the share of imports that are from the United States.

[13] For instance, the t-statistics for the share coefficient that is obtained by regressing ln(Firm Exports) on the share of exports to the US is 4.91 in the pooling sample, and it shows strong significance. In contrast, imports display the opposite pattern: firms that import more have a smaller share of from the United States, as displayed in Figure A.2 in appendix.

3.3 Firm-level Tariff Exposure Measures

Provided with tariffs and customs data, we are able to create time-varying measures of a given firm's import and export tariff exposures. We denote $\text{Tariff}_{it}^{\text{US}}$ as the U.S. tariff exposure of a Chinese firm i in time t (i.e., quarter), which is constructed as follows,

$$\text{Tariff}_{it}^{\text{US}} = \sum_{j \in J_i^e} \left[\frac{X_{ij0}^{\text{US}}}{\sum_{s \in J_i^e} X_{is0}^{\text{US}}} \tau_{jt}^{\text{US}} \right] \tag{1}$$

where τ_{jt}^{US} is good j's *ad valorem* tariff (i.e., MFN tariff plus trade war tariff) imposed by the U.S. in time t, X_{ij0}^{US} is average exports of good j to the US by firm i during 2013 and 2016, and J_i^e is the set of goods produced by firm i. Following Topalova and Khandelwal (2011) and Rodriguez-Lopez and Yu (2017), we let exports of each good fixed at the initial period to avoid potential reverse causality in firm's exports with respect to the US tariff. The ratio $X_{ij0}^{\text{US}} / \sum_{s \in J_i^e} X_{is0}^{\text{US}}$ captures the relative importance of τ_{jt}^{US} in affecting firm i's exports. Likewise, based on China's retaliation tariffs on the U.S. goods and imports data, we construct firm i's Chinese tariff exposure in time t as follows:

$$\text{Tariff}_{it}^{\text{CHN}} = \sum_{j \in J_i^m} \left[\frac{M_{ij0}^{\text{US}}}{\sum_{s \in J_i^m} M_{is0}^{\text{US}}} \tau_{jt}^{\text{CHN}} \right] \tag{2}$$

where τ_{jt}^{CHN} is good j's tariff imposed by China on the US goods in time t, M_{ij0}^{US} is average imports of good j from the US by firm i during 2013 and 2016, and J_i^m is the set of goods imported by firm i. We use time-invariant weights to avoid an endogeneity issue to to the negative correlation between imports and tariff across products.

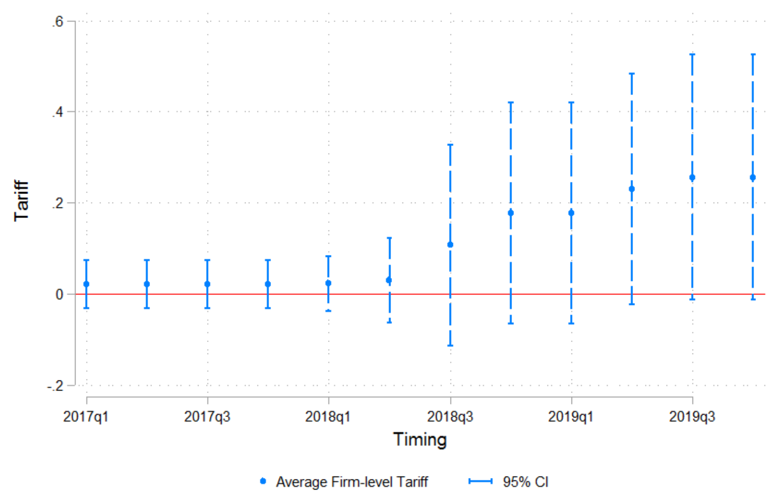
Figure 4 displays the mean and standard deviation per quarter of the firm-level export and import tariff exposures. Panel (a) corresponds to the tariff imposed by US on Chinese goods ($\text{Tariff}_{it}^{\text{US}}$). While the average firm-level export tariff exposure starts to increase after the second quarter of 2018 (from 2.3 percent in 2018-Q1 to 3.0 percent), substantial increase took place in the third quarter of 2018, which also exhibits large heterogeneity across the listed firms. Panel (b) report the firm-level import tariff exposure based on Chinese retaliatory tariff over US goods ($\text{Tariff}_{it}^{\text{CHN}}$). The average import tariff exposure starts to increase in the third quarter of 2018, a quarter later than the export tariff change (from 6 percent in 2018-Q3 to 12.7 percent in 2018-Q4).[14]

Table 2 reports the most affected SIC 3-digit industries according to the two tariff ex-

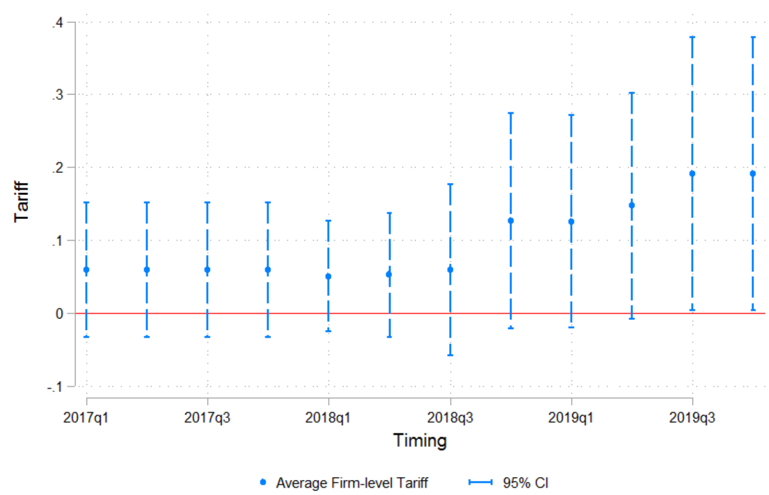
[14] Table A.3 reports the detailed statistics. We also report the change in the export and import tariff exposure measures for Chinese firms in Figure A.3 in appendix, which shows a similar pattern as observed in Figure 4.

posure for Chinese listed firms. According to panel (I), the US tariff targets heavily on China's sectors related to industrial and commercial machinery & computer equipment, electronic equipment, and transportation equipment, for which the average firm-level $\text{Tariff}_{it}^{\text{US}}$ increases by above 30% compared with that in period 2013 to 2016. In contrast, in panel (II), China's retaliatory tariff targets on light-manufacturing sectors such as food & kindred products, furniture, and fabricated metal products. The average increase of $\text{Tariff}_{it}^{\text{CHN}}$ is above 20% by the end of 2019.

Figure 4: Import and Export Tariff Exposures of Chinese Listed Firms



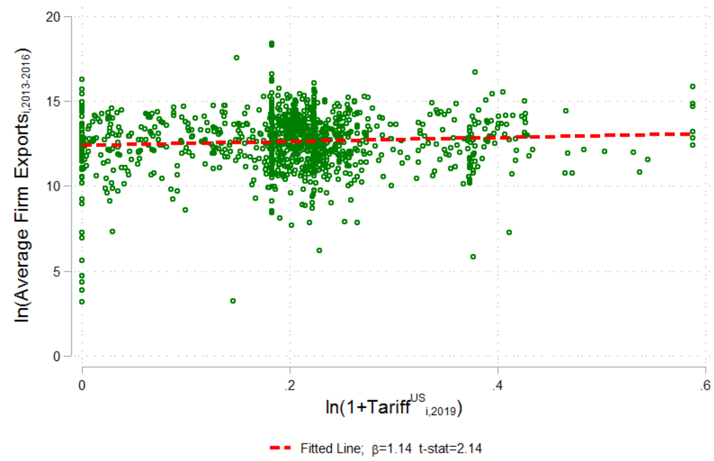
(a) US Tariff on Chinese Goods



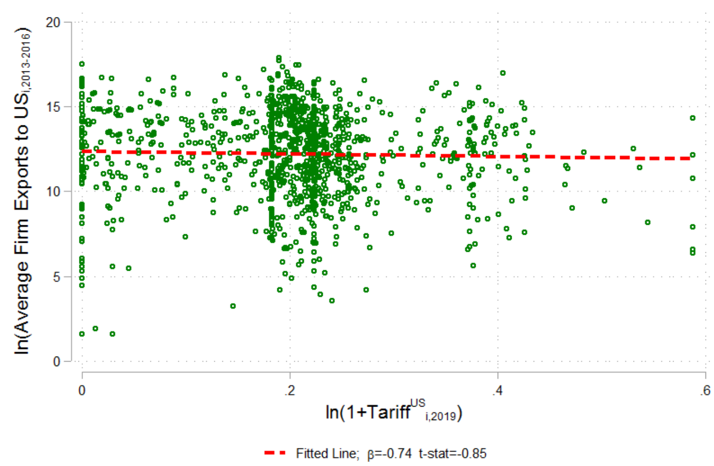
(b) Chinese Tariff on US Goods

In Figure 5 we show how firm-level tariff exposures depend on a firm's exports and

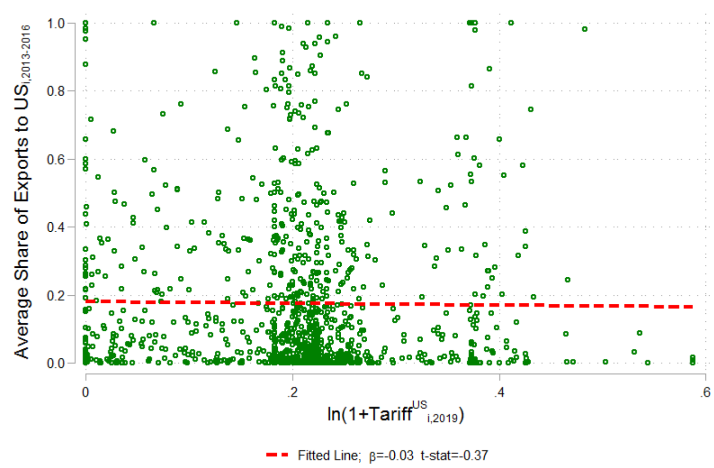
Figure 5: Pre-period Exports and Export Tariff Exposure Measure Tariff^{US}_{it}



(a) Average Firm Exports

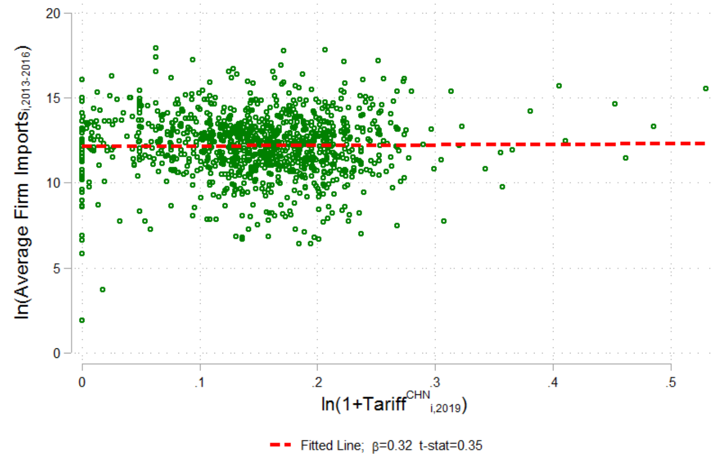


(b) Average Firm Exports to the United States

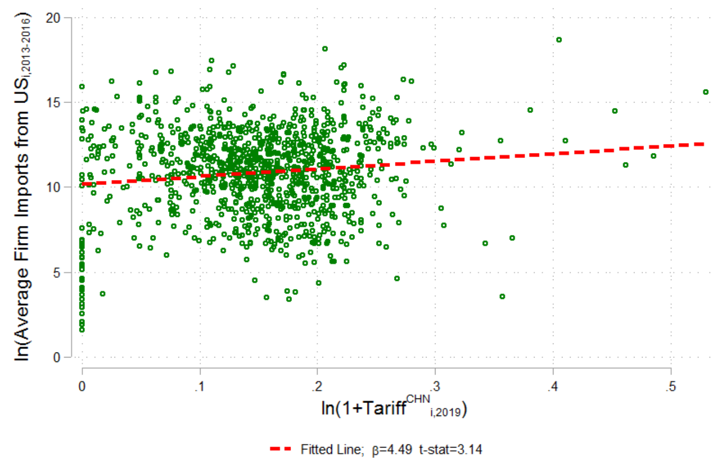


(c) Share of Exports to the United States

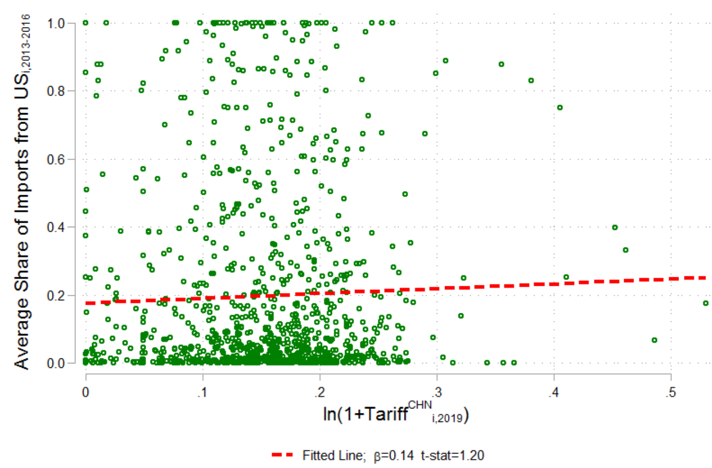
Figure 6: Pre-period Import and Import Tariff Exposure Measure $\text{Tariff}_{it}^{\text{CHN}}$



(a) Average Firm Imports



(b) Average Firm Imports from the United States



(c) Share of Imports from the United States imports activities in the pre-period (2013-2016). In panel (a), firms with bigger total exports are more likely to have higher value of $\text{Tariff}_{it}^{\text{US}}$. However, we do not find a systematic pattern between U.S. exports or export reliance on the US market (i.e., the share of exports to the US) and $\text{Tariff}_{it}^{\text{US}}$, as displayed in panel (b) and (c), respectively. On the import side (Figure 6), $\text{Tariff}_{it}^{\text{CHN}}$ is not correlated to firm overall imports. Instead, as displayed in panel (b), a firm's imports from the US is positively related to $\text{Tariff}_{it}^{\text{CHN}}$, though the positive correlation becomes weaker when we look at import reliance on the US market in panel (c).

Table 2: Top Ten Most Affected SIC 3-digit Industries (Firm Tariff Exposure Measures)

		(I) US Tariff on Chinese Goods	
Rank	SIC 3-digit	Description	$\Delta\text{Tariff}_{it}^{\text{US}}$
1	360	Electronic & Other Electrical Equipment	0.441
2	362	Electrical Industrial Apparatus	0.405
3	351	Engines and Turbines	0.403
4	321	Flat Glass	0.389
5	361	Electric Distribution Equipment	0.374
6	350	Industrial Machinery & Equipment	0.344
7	373	Aircraft and Parts	0.343
8	356	General Industrial Machinery	0.339
9	359	Industrial Machinery, Nec	0.329
10	374	Railroad Equipment	0.310
		(II) Chinese Tariff on US Goods	
Rank	SIC 3-digit	Description	$\Delta\text{Tariff}_{it}^{\text{CHN}}$
1	203	Preserved Fruits and Vegetables	0.287
2	243	Millwork, Plywood and Structural Members	0.250
3	263	Household Appliances	0.241
4	339	Misc. Primary Metal Products	0.239
5	204	Grain Mill Products	0.234
6	314	Footwear, Exc Rubber	0.230
7	342	Cutlery, Hand Tools and Hardware	0.216
8	341	Metal Cans and Shipping Containers	0.214
9	301	Tires and Inner Tubes	0.211
10	334	Secondary Nonferrous Metals	0.203

Notes: The table lists the top ten industries that have highest tariff exposure measures. For each type of tariff exposure measure, its change is calculated as the difference between its average industry-level exposure in 2019-Q4 and that during 2013 and 2016.

The summary figures and tables in this part imply that firm's export to the United States is correlated to firm size. The selection of firms into the US market may lead to an endogeneity issue when we aim to estimate the impact of tariff exposure on firm-level trade policy uncertainty and other firm-level outcomes, and we will address this issue by checking pre-existing trends in the empirical analysis that follows.

3.4 Firm-level Trade Policy Uncertainty Measure

To construct a firm-level time-varying measure of trade policy uncertainty (TPU), we employ a textual analysis of transcripts of annual reports released by Chinese listed firms for each year between 2008 and 2018, following the method in Caldara et al. (2019). We collect all reports of companies listed in the Shanghai and Shenzhen Stock Exchange's domestic A share markets. An annual report documents a public company's activity, which includes the names of key staff, what the companies did and why in a financial year, the main financial indicators, the operational performance, and future ventures and plans.[15]

The reports data are scraped from the *East Money Information* (a financial data provider in China) in PDF format, and we convert them into text. Then we translate the English firm names (as reported in COMPUSTAT Global) to Chinese, and we manually match them to the listed firms which have annual reports. Table 3 summarizes the number of firms in COMPUSTAT Global that are matched to their annual reports. As annual reports are only for the listed firm in China (i.e., Shanghai and Shenzhen Stock A share markets only), we are not able to find reports for firms that are listed in other regions such as Taiwan, Singapore or the US. In the end, we are able to match about 2400 Chinese Compustat firms (out of 2505).[16]

Table 3: Number of Compustat Firms Matched with Annual Reports

Year	Number of Firms
2008	929
2009	1,042
2010	1,261
2011	1,516
2012	1,620
2013	1,650
2014	1,738
2015	1,878
2016	2,088
2017	2,368
2018	2,274
Total number of obs	18,364

[15] The Accounting Standard for Business Enterprise promulgated by the Ministry of Finance of China requires that all Chinese firms use December 31 as the same end date of the financial year.

[16] Figure A.4 in appendix displays an example annual report for *Angang Steel Company* (which has a COMPUSTAT GVKEY 205808). The picture only exhibits the initial page of the 2018 report. The total number of pages in that firm's annual report (in the original PDF format) is 195.

Background: Rules on Information Disclosure

Chinese accounting standard has been revolutionized several times. Four increasingly refined sets of accounting standards were introduced in 1992, 1998, 2002 and 2006, receptively (Peng and Smith (2010); Liu et al. (2011)). It has been widely noted in the accounting literature (Xiang (1998); IASB (2005, 2006); Peng et al. (2008); Chen and Zhang (2010)) and by the International Accounting Standards Board (IASB) that impressive progress has been made towards the convergence of Chinese accounting standards with International Financial Reporting Standards (IFRS), which suggests the higher financial reporting quality and the efficient capital market.[17] Compared with IFRS or US Generally Accepted Accounting Principles (GAAP), Chinese accounting standards are more rules-based and rigid, and this leaves much less room for firms to manage earnings via discretionary accruals (Chen et al. (2008)).

To promote transparency and to increase the ability of investors, stake holders and the state authority to monitor the activities of listed firms, China Securities Regulatory Commission's (CRSC) has adopted a set of regulations and standards similar to those in the US and Europe (Fan et al. (2011)).[18] According to the current exchange rules of the Shanghai and Shenzhen Stock Exchanges and the CSRC regulations, all listed Chinese firms are required to make periodic disclosure of reports to the public (CSRC (2008)).[19] These regulations require all China's listed firms to prepare and disclose the "annual report" within 4 months subsequent to the end of financial year. The listed firms are also required to make the "interim report" (i.e., the half-year report) available within 2 months following the end of the first half of each fiscal year, and "quarterly reports" within one month subsequent to the end of the first three and nine months in each fiscal year. Particularly, CSRC also requires the annual report of each listed firm to be audited by a qualified CPA firm.[20]

[17]It is a consensus in the literature that adopting IFRS significantly improves financial reporting quality and efficiency in capital market. For detailed reference, see Ball (2006); Jermakowicz et al. (2007); Barth et al. (2008); Daske et al. (2008). Street and Gray (2002) find that Chinese listed firms exhibit greater compliance with IFRS than companies in other countries in Europe.

[18]A detailed background information on China's financial reporting practices and information environment of Chinese listed firms can refer to Fan et al. (2011).

[19]In addition, the listed Chinese firms are also required to release any *Prospectus* (2-5 days prior to the offering period) and *Offering Circular* (3 days before IPO) on time.

[20]The "quarterly reports" are exempt from such requirement while the "half-year report" should also be audited if the company has plans such as to distribute profit, or transfer reserves into share capital (see Fan et al. (2011) for detailed information).

Construction Method

Our annual firm-level trade policy uncertainty measures are constructed using a textual analysis of the transcript of yearly reports of publicly listed companies in China. The construction method is similar to Caldara et al. (2019), and consists of three steps.[21]

Table 4: The List of Keywords

Keywords Type	Keywords
Trade policy	**international trade** (mao4yi4, jing1mao4, zi4mao4, shi4mao4), **export** (chu1kou3), **import** (jin4kou3), **tariff** (guan1shui4), **barriers** (bi4lei3), **anti-dumping** (fan3qing1xiao1), **outsourcing** (wai4bao1), **protectionism** (bao3hu4zhu3yi4), **unilateralism** (dan1bian1zhu3yi4)
Uncertainty	**uncertainty** (bu4que4ding4, bu4ming4que4), **unclear** (bu4ming4lang3, wei4ming2), **unexpected** (nan2liao4, nan2yi3gu1ji4, nan2yi3yu4ji4, nan2yi3yu4ce4, nan2yi3yu4liao4), **risks** (feng1xian3, wei1xian3), **crisis** (wei1ji1), **threat** (wei1xie2), **unknown** (wei4zhi1)

Notes: Chinese pinyin for each keyword is displayed in the bracket.

In the first step, we import annual reports with each line of transcript stored as an observation (see Figure A.4 for example). In the second step, in each line we search for the keywords related to uncertainty or future risk (regardless of whether they are related to trade policy), such as *uncertainty* and *risk*. Then we count their frequency in each line. Third, to isolate the uncertainty-related words that are also related to trade policy, in each line we search nearby if there are trade policy related keywords such as *tariff*, *import duty*, *export tariff*, *protectionism*, *unilateralism*, *trade barriers*, and *anti-dumping*.[22] Lastly, we set the uncertainty counting variable as zero if they are not trade policy related keywords. The firm-year specific number of keywords on TPU are calculated by summing the frequency of TPU in each line. Table 4 reports the keywords for uncertainty and trade policy as used in practice.

Formally, the firm-level TPU for firm i in year t is provided by the following expres-

[21]The reason we use annual reports while Caldara et al. (2019) construct quarterly measures is that the quarterly or the half-year reports of Chinese listed firms provide little information. In most cases, the information disclosed in the quarterly or the half-year reports will be reiterated in the annual reports.

[22]Figure A.5 provides an example to demonstrate the procedure, where the risk-related keywords marked by blue are not considered as trade policy uncertainty as there are no trade policy related keywords nearby. In contrast, the uncertainty keywords marked in red are classified as TPU because we also observe trade related keywords ahead of these uncertainty keywords (i.e., *protectionism* and *unilateralism*).

sion:[23]

$$TPU_{it} = \frac{1}{R_{it}} \sum_{w=1}^{R_{it}} \{1\Big[w \in \text{Keywords}^{\text{Uncertainty}}\Big] \times 1\Big[|w-t| < \text{One Line}\Big]\} \tag{3}$$

where $w = 0, 1, ..., R_{it}$ are the words contained in the annual report of firm f in year t; the length of report R_{it} is measured as the total number of Chinese characters; t is the position of the nearest synonym of trade policy keywords (i.e., $t \in \text{Keywords}^{\text{Trade policy}}$). In practice, we condition on a neighborhood of roughly 15 words before and after the appearance of uncertainty keywords.[24]

To corroborate that our constructed TPU measures capture firm-level variation in the global corporate exposure to US-China trade tension, we compare our TPU indexes to those created by Davis et al. (2019) who base the China TPU on the information of two mainland Chinese newspapers.[25] As the proposed TPU measures are able to track the uncertainty exposure (resulting from China-US trade tension) at the firm level across time, our method is superior to that in Davis et al. (2019) who is only able to capture the national trend of uncertainty change. For comparison, we average firm-level TPU to the yearly level and scatter plot the two TPUs in Figure 7, where we compute TPU_{it} using the total number of TPU keywords appearing in annual report in panel (a), and using the percentage of TPU keywords in panel (b). In both panel, we mark our TPU index in red and that of Davis et al. (2019) in blue.[26] In both panels, the two TPU measures are remarkably highly correlated, which remain stagnant before 2016. After Trump were elected to the presidency in November 2016, the TPU index based on annual reports increased by above 300% in 2018.[27]

In Table 5, we report the top ten most affected SIC 3-digit industries according to the

[23]In addition to measuring TPU as the percentage of report containing TPU keywords, we also experiment with the TPU measure based on the total number of keywords (i.e., $TPU_{it} = \sum_{w=1}^{R_{it}} \{1\Big[w \in \text{Keywords}^{\text{Uncertainty}}\Big] \times 1\Big[|w-t| < \text{One Line}\Big]\}$). Results remain similar.

[24]That is, trade policy and uncertainty keywords are in the same line. We also use a loose criteria: we require that the trade related words are in one line above or below the place where there is uncertainty related words.

[25]The two newspaper is Renmin Daily and Guangming Daily. Their construction method follows Baker et al. (2016) who construct newspaper-based indices of economic policy uncertainty. The data is downloaded from https://www.policyuncertainty.com/trade_cimpr.html.

[26]The TPU measure in Figure 7 is constructed following the rule that trade policy and uncertainty keywords are in the same line. In Figure A.6, the TPU measure is based on a loose criteria: the trade related words are in one line above or below the place where there is uncertainty related words. Our proposed TPU measure remains close to that of Davis et al. (2019).

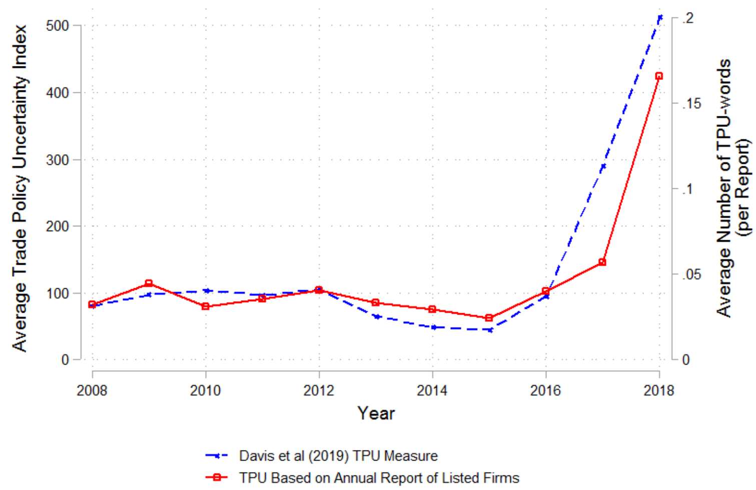
[27]Similar pattern is observed in Figure 7 in appendix. The detailed summary statistics is provided in Table A.4 in the appendix.

mean TPU measure based on the number of keywords per report for China's listed firms. The mean industry level measure is computed by averaging all firm in a particular industry. In panel (I), a TPU keyword require that trade policy and uncertainty related words are in the same line, and we release this criteria in panel (II). The most affected sectors are the ones related to textile and apparel manufacturing, fabricated metal products, and tel-communication & transportation.

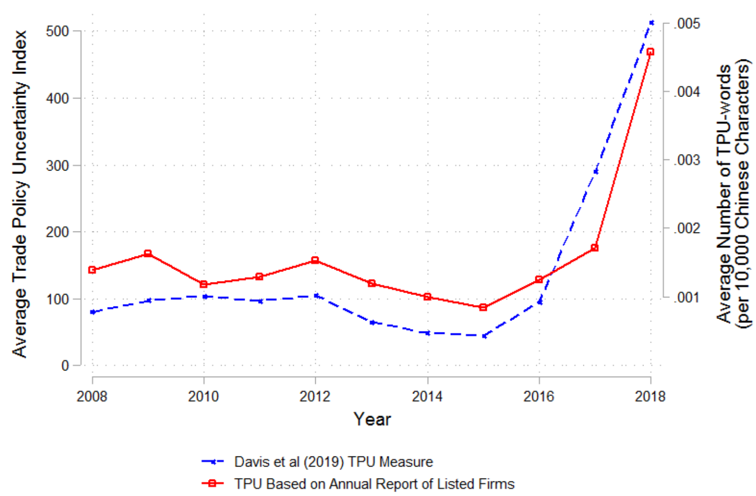
How trade policy uncertainty depends on a firm's previous exports and imports activities? In Figure 8 we plots the average firm-level TPU measure against firm average exports in the pre-period (2013-2016) in panel (a). The slope coefficient is positive significant indicating that firms exporting more previously are associated with greater TPU exposure during 2017 and 2018. Firms with larger exports to the US are also exposed to greater TPU. In contrast, we do not observe that firm with a bigger share of exports to the US are likely to have greater TPU exposure. We repeat the same exercise for firm imports, as displayed in Figure 9. We find a similar pattern that the scale of imports in the pre-period is associated with a firm's exposure to trade policy uncertainty, while the share of imports from the U.S. is not correlated TPU.

In Figure 10, we present the correlation between firm-level TPU_{it} and tariff exposure. In panel (a), we display firm average TPU by the percentile of exposure to the US tariff ($\text{Tariff}_{it}^{\text{US}}$), where each dot stands for the average TPU of firms in that group, and the dashed interval for the standard deviation. It is clear that TPU is strongly correlated to the firm exposure to the US tariffs on Chinese products, but still there there are substantial differences in TPU for firms with high ($\text{Tariff}_{it}^{\text{US}}$). In contrast, the pattern become less clear in panel (b) where we relate TPU to the import tariff exposure $\text{Tariff}_{it}^{\text{CHN}}$ (i.e., the tariff imposed by China on the U.S. products).

Figure 7: TPU Based on Annual Report of Listed Firms and TPU in Davis et al. (2019)



(a) Number of TPU Related Words Per Report



(b) Number of TPU Related Words Per 10,000 Chinese Characters

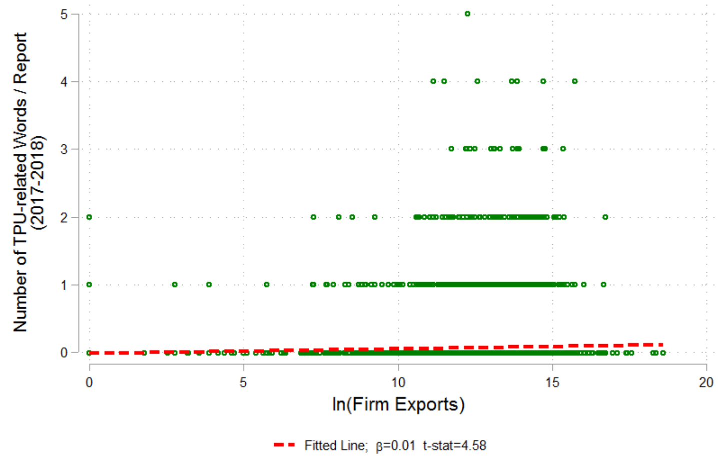
Notes: A TPU keyword is identified if the trade related words are in the same line with the uncertainty related words. In panel (a), TPU is measured as the number of TPU related keywords per report; we also measure TPU using the number of TPU keywords per 10,000 Chinese characters as shown in panel (b).

Table 5: Top Ten Most Affected SIC 3-digit Industries (Firm TPU Measures)

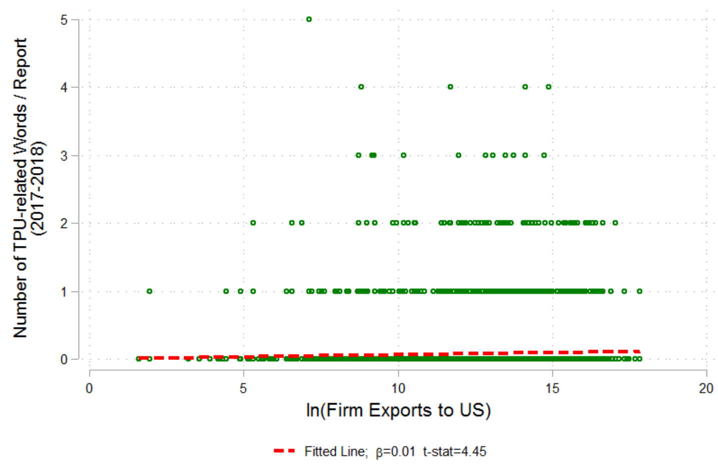
		(I) Appearance in Range of $+/-$ 1 Lines		
Rank	SIC 3-digit	Description	Keywords Number	Keywords Share
1	481	Telephone Communication	3.00	0.313
2	379	Misc. Transportation Equipmen	3.00	0.283
3	225	Knitting Mills	2.00	0.239
4	341	Metal Cans and Shipping Containers	2.00	0.084
5	234	Women's and Children's Undergarments	2.00	0.205
6	221	Broadwoven Fabric Mills, Cotton	2.00	0.215
7	306	Fabricated Rubber Products, Nec	1.67	0.133
8	347	Metal Services, Nec	1.50	0.151
9	396	Costume Jewelry and Notions	1.33	0.145
10	373	Ship and Boat Building and Repairing	1.00	0.071
		(II) Appearance in the Same Line		
Rank	SIC 3-digit	Description	Keywords Number	Keywords Share
1	379	Misc. Transportation Equipmen	2.00	0.189
2	221	Broadwoven Fabric Mills, Cotton	2.00	0.215
3	225	Knitting Mills	2.00	0.239
4	341	Metal Cans and Shipping Containers	1.60	0.058
5	347	Metal Services, Nec	1.50	0.151
6	306	Fabricated Rubber Products, Nec	1.33	0.110
7	345	Screw Machine Products, Bolts, etc	1.00	0.100
8	234	Women's and Children's Undergarments	1.00	0.103
9	222	Broadwoven Fabric Mills, Manmade	1.00	0.090
10	233	Women's, Misses', and Juniors' Outerwear	1.00	0.095

Notes: The table lists the top ten industries that have highest TPU measure for years between 2017 and 2018 using two criteria. In panel (I), a TPU keyword is identified if the trade related words are in one line above or below the place where there is uncertainty related words. In panel (II), we require that the trade related words are in the same line with uncertainty words. In column of "Keywords Number", TPU is measured as the number of TPU related keywords per report; we also measure TPU using the number of TPU keywords per 10,000 Chinese characters as shown in the column "Keywords Share".

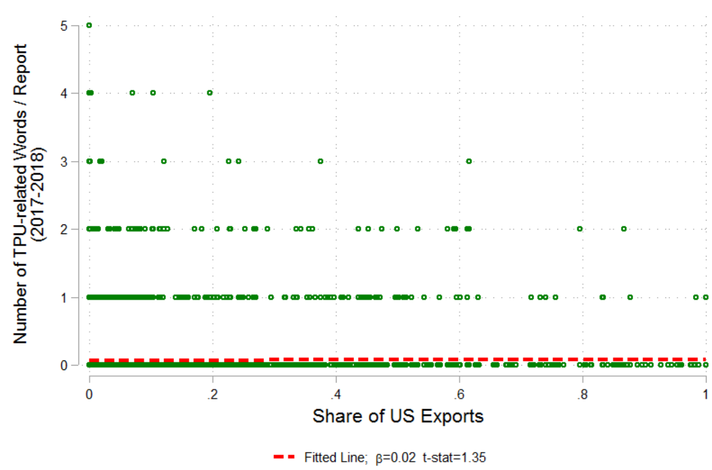
Figure 8: TPU Measure (2017 and 2018) and Pre-period Exports



(a) Firm Exports

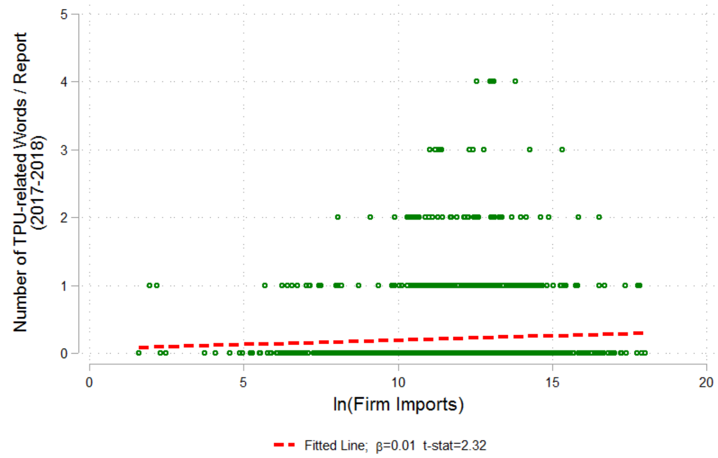


(b) Firm Exports to the United States

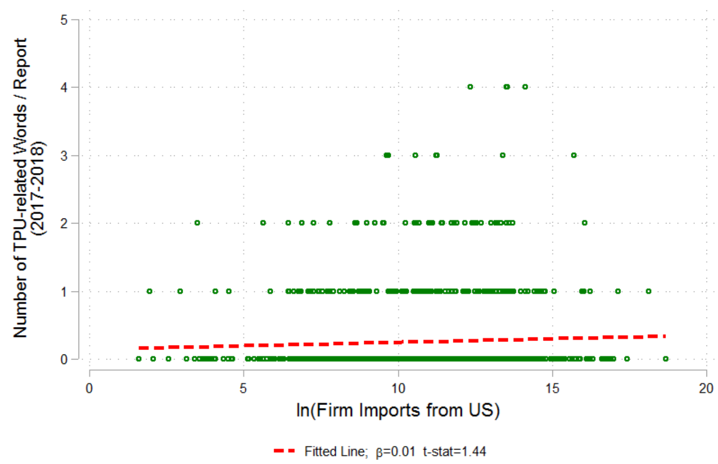


(c) Share of Exports to the United States

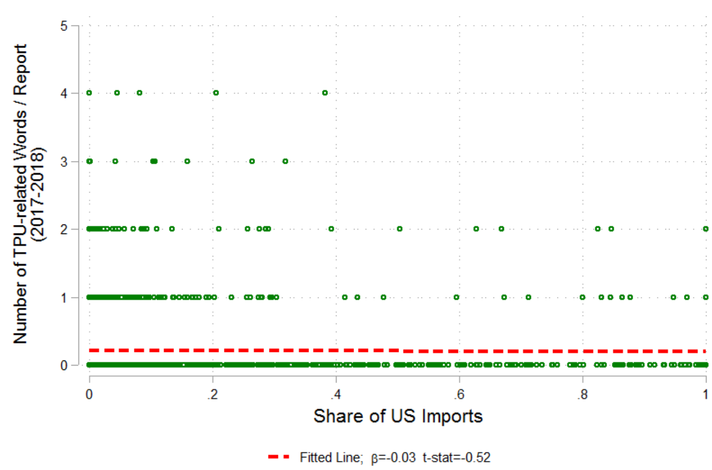
Figure 9: TPU Measure (2017 and 2018) and Pre-period Imports



(a) Firm Imports

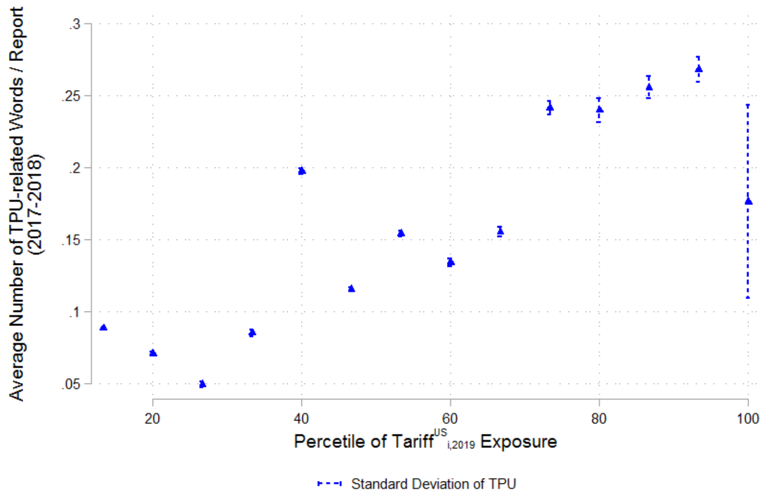


(b) Firm Imports from the United States

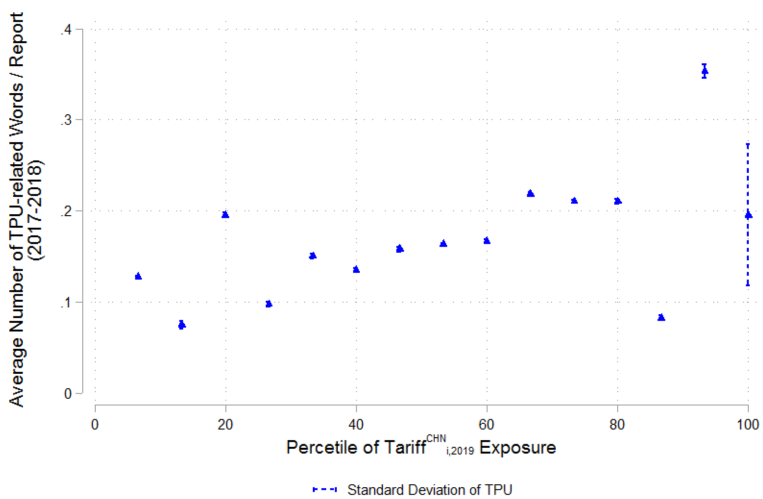


(c) Share of Imports from the United States

Figure 10: TPU Measure and Firm-level Tariff Exposure Measures (2017-2018)



(a) US Tariff on Chinese Goods ($\text{Tariff}_{it}^{\text{US}}$)



(b) Chinese Tariff on US Goods ($\text{Tariff}_{it}^{\text{CHN}}$)

4 The Firm-Level Impacts of Trade War on TPU

In the previous section we have shown a positive correlation between the newly-constructed firm-level TPU measure and both U.S. and Chinese tariff exposure measures.

We now formally investigate the impact of trade war tariffs on firm-level trade policy uncertainty using the following first-difference estimation strategy:

$$\Delta\text{TPU}_i = \alpha + \beta\Delta\text{log}(1 + \text{Tariff}_i^{\text{US}}) + \gamma\Delta\text{log}(1 + \text{Tariff}_i^{\text{CHN}}) + \delta X_i + \psi_{REG} + \psi_{IND} + \Delta\varepsilon_i$$

where Δ denotes the change between 2017Q4 and 2018Q4.[28] The dependent variable, ΔTPU_i, measures the change in firm i's trade policy uncertainty measure between 2017Q4 and 2018Q4. $\text{Tariff}_i^{\text{US}}$ is firm i's U.S. tariff exposure (i.e. firm i's exposure to US tariffs on Chinese imports).[29] $\Delta\text{log}(1 + \text{Tariff}_i^{\text{US}})$ denotes a percent change in $\text{Tariff}_i^{\text{US}}$ between 2017Q4 and 2018Q4. $\text{Tariff}_i^{\text{CHN}}$ is a measure of firm i's exposure to Chinese tariffs on imports from the U.S.[30] $\Delta\text{log}(1 + \text{Tariff}_i^{\text{CHN}})$ denotes a percent change in $\text{Tariff}_i^{\text{CHN}}$ between 2017Q4 and 2018Q4. X_i is a firm-level control vector that includes revenue and capital in 2017Q4. ψ_{REG} denotes region fixed effects, which can capture region-level unobserved heterogeneity.[31] ψ_{IND} are industry fixed effects, which can capture industry-level unobserved heterogeneity.[32]

Table 6 shows the estimation results. In column (1), we report the impact of U.S. tariffs on firm-level TPU without including control variables. The coefficient is positive and statistically significant, implying that US tariffs, which act as a barrier on Chinese exports to the US, increase TPU. Quantitatively, the coefficient of 0.31 indicates that one percent increase in the US tariff exposure measure is associated to a 0.31 point (0.74 standard deviation) increase in TPU. In column (2), we report the impact of Chinese tariffs, which limit Chinese firms imports from the US, on TPU, again without yet including control variables. We also find a positive and statistically significant relationship. The coefficient of 0.70 indicates that one percent increase in the Chinese tariff exposure measure is associated to a 0.70 point (1.65 standard deviation) increase in TPU. In column (3) we include US and Chinese tariffs simultaneously. The coefficients are fairly similar and still statistically significant.

[28] The most recent firm-level TPU measure available corresponds to 2018. Also, the trade war tariff increases started in 2018Q3. Hence, we use two data points, i.e., 2017Q4 and 2018Q4, to study the impact of firm-level tariff shocks on firm-level TPU. Note also that when $T = 2$, the first-difference estimator and fixed effects estimator are equivalent.

[29] Recall this is a weighted average across all of firm i's products exported to the U.S.

[30] Recall this is a weighted average across all of firm i's products imported to the U.S.

[31] The number of regions in the sample is 32.

[32] Industry is defined at the SIC-3-digit level and the number of industries in the sample is 112.

One might argue that the selection of the set of products targeted by tariffs can result from governments' strategic decisions. For example, the Trump administration imposed higher tariffs on Chinese goods in IT or high-tech-related industries. Hence, unobserved industry characteristics might simultaneously increase trade policy uncertainty and tariffs. However, we focus on firm-level variation in tariffs (instead of industry-level variation in tariffs), which appear to be orthogonal to the government's choice of tariffs. Alternatively, to reduce the concern about the endogeneity of tariffs, we add region and SIC-3-digit level industry fixed effects in column (4) of Table 6. The coefficient of US tariff exposure is positive, but it becomes statistically insignificant. The coefficient of Chinese tariff exposure is still positive and statistically significant. In column (4), coefficients can be interpreted as between-firm variations of tariffs on firm-level trade policy uncertainty, controlling for region and industry fixed effects. Finally, in column (5), we control for observable lagged firm-level characteristics such as size and capital intensity. This specification alleviates a concern that larger firms and/or more capital-intensive firms have seen an increase in both firm-level tariffs and trade policy uncertainty. The results change little when including these controls. Quantitatively, one percent increase in the Chinese tariff exposure measure is associated to a 0.67 point (1.57 standard deviation) increase in TPU.

4.1 Pre-Existing Trends

In addition to estimating the contemporaneous impact of tariff changes on trade policy uncertainty, we check for preexisting-trends in firm-level trade policy uncertainty. We regress the change in firm i's trade policy uncertainty between 2016Q4 and 2017Q4 against the change in firm i's tariff exposure measures between 2017Q4 and 2018Q4 as follows:

$$\begin{aligned}\Delta_{16Q4-17Q4}\text{TPU}_i = \alpha + \beta\Delta_{17Q4-18Q4}\log(1+\text{Tariff}_i^{\text{US}}) + \gamma\Delta_{17Q4-18Q4}\log(1+\text{Tariff}_i^{\text{CHN}}) \\ + \delta X_i + \psi_{REG} + \psi_{IND} + \Delta\varepsilon_i\end{aligned}$$

where $\Delta_{16Q4-17Q4}$ denotes the change between 2016Q4 and 2017Q4 and $\Delta_{17Q4-18Q4}$ denotes the change between 2017Q4 and 2018Q4.

Table 7 reports the pre-trend tests for trade policy uncertainty. Across all specifications, we do not find any statistically significant relationship between pre-period trade policy uncertainty and tariff changes.

Table 6: Trade Policy Uncertainty and Tariffs: 2017Q4–2018Q4

	Dependent Variable: ΔTrade Policy Uncertainty				
	(1)	(2)	(3)	(4)	(5)
Δlog(1+Tariff^{US})	0.314***		0.245*	0.131	0.124
	(0.121)		(0.125)	(0.128)	(0.130)
Δlog(1+Tariff^{CHN})		0.701**	0.569*	0.722**	0.668**
		(0.296)	(0.307)	(0.303)	(0.310)
log(Revenue)					-0.006
					(0.014)
log(Capital)					0.017
					(0.014)
Region FE	No	No	No	Yes	Yes
Industry FE	No	No	No	Yes	Yes
Observations	2,180	2,180	2,180	2,168	2,135
R-squared	0.003	0.003	0.005	0.078	0.080

Notes: The dependent variable is change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. Tariff^{US} denotes a firm-level measure of exposure to US tariffs on imports from China, computed as a weighted average across each firm's set of products exported to the U.S. Tariff^{CHN} denotes a firm-level measure of tariff to Chinese tariffs on imports from the US, computed as a weighted average across each firm's set of products imported from the U.S. Δlog(1+Tariff^{US}) and Δlog(1+Tariff^{CHN}) are percent changes in Tariff^{US} and Tariff^{CHN} between 2017Q4 and 2018Q4. Firm revenue and capital are both measured in 2017Q4. Industries are defined according to the 3-digit Standard Industrial Classification (SIC). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Tests for Pre-Existing Trends

	Dependent Variable: $\Delta_{16Q4-17Q4}$Trade Policy Uncertainty				
	(1)	(2)	(3)	(4)	(5)
$\Delta_{17Q4-18Q4}$log(1+Tariff^{US})	0.011		0.009	-0.024	-0.004
	(0.082)		(0.085)	(0.093)	(0.095)
$\Delta_{17Q4-18Q4}$log(1+Tariff^{CHN})		0.022	0.017	-0.031	-0.001
		(0.214)	(0.222)	(0.225)	(0.228)
log(Revenue)					0.007
					(0.017)
log(Capital)					-0.012
					(0.022)
Region FE	No	No	No	Yes	Yes
Industry FE	No	No	No	Yes	Yes
Observations	2,028	2,028	2,028	2,017	1,984
R-squared	0.000	0.000	0.000	0.081	0.083

Notes: The dependent variable is the change in firm-level trade policy uncertainty between 2016Q4 and 2017Q4. Tariff^{US} denotes a firm-level measure of exposure to US tariffs on imports from China, computed as a weighted average across each firm's set of products exported to the U.S. Tariff^{CHN} denotes a firm-level measure of tariff to Chinese tariffs on imports from the US, computed as a weighted average across each firm's set of products imported from the U.S. Δlog(1+Tariff^{US}) and Δlog(1+Tariff^{CHN}) are percent changes in Tariff^{US} and Tariff^{CHN} between 2017Q4 and 2018Q4. Firm revenue and capital are both measured in 2017Q4. Industries are defined according to the 3-digit Standard Industrial Classification (SIC). Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.2 Heterogeneity in TPU Response

Capital-Intensity

Next, we explore whether the trade war tariffs have had a differential impact on trade policy uncertainty for firms of different sizes. To this end, we augment our baseline equation with two interaction terms as follows:

$$\begin{aligned}\Delta\text{TPU}_i = \alpha &+ \beta_1 \Delta\log(1+\text{Tariff}_i^{\text{US}}) + \beta_2 \Delta\log(1+\text{Tariff}_i^{\text{US}}) \times \log(\text{Revenue}_i) \\ &+ \gamma_1 \Delta\log(1+\text{Tariff}_i^{\text{CHN}}) + \gamma_2 \Delta\log(1+\text{Tariff}_i^{\text{CHN}}) \times \log(\text{Revenue}_i) \\ &+ \delta X_i + \psi_{REG} + \psi_{IND} + \Delta\varepsilon_i\end{aligned}$$

The β_2 coefficient captures the differential impact of firm-level exposure to U.S. tariffs on trade policy uncertainty for firms of different sizes, while γ_2 captures the differential impact of firm-level exposure to Chinese tariffs.

In column (1) of Table 8, we start by estimating the equation with firm-level US tariff exposure and its interaction term with log revenue, which is our measure of firm size. The coefficient β_2 is negative and statistically significant. In column (2), we relate trade policy uncertainty to firm-level Chinese tariff exposure and its interaction term with log revenue. We find that γ_2 is negative and statistically significant. In columns (3), we then estimate the full equation above and find that the coefficient β_2 is -0.24 (and statistically significant at the 5 percent level) and that the coefficient γ_2 is -0.23 and statistically insignificant. Hence, we conclude that only the impact of US tariff exposure on trade policy uncertainty differs across firms of different sizes. Quantitatively, the impact of US tariffs on trade policy uncertainty is 0.24 points (0.56 standard deviations) lower as a firm's revenue doubles.

We then turn our attention to differences across firms in terms of capital stocks. We thus replace the log revenue by log capital in the equation above. Then, we repeat the analysis from columns (4) to (6) in Table 8. In column (6), when both US and Chinese tariffs are considered β_2 and γ_2 are negative and statistically significant. This implies that the impact of US tariffs and/or Chinese tariff exposure on trade policy uncertainty is mitigated as firms' capital stock increases. Quantitatively, as a firm's capital stocks double, the impact US tariffs on trade policy uncertainty is 0.19 points (0.45 standard deviations) lower, while the impact of Chinese tariffs on trade policy uncertainty is 0.37 points (0.87 standard deviations) lower, while the impact of Chinese tariffs on trade policy uncertainty is 0.37 points (0.87 standard deviation) lower.

Table 8: Trade Policy Uncertainty, Tariffs, and Size: 2017Q4–2018Q4

	Dependent Variable: ΔTrade Policy Uncertainty					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\log(1+\text{Tariff}^{US})$	1.838***		1.600***	1.715***		1.355**
	(0.597)		(0.615)	(0.598)		(0.611)
$\Delta\log(1+\text{Tariff}^{US})$ $\times$ log(Revenue)	-0.262***		-0.237**			
	(0.096)		(0.099)			
$\Delta\log(1+\text{Tariff}^{US})$ $\times$ log(Capital)				-0.235**		-0.192**
				(0.095)		(0.097)
$\Delta\log(1+\text{Tariff}^{CHN})$		3.349**	2.239		4.104***	3.208**
		(1.387)	(1.411)		(1.341)	(1.353)
$\Delta\log(1+\text{Tariff}^{CHN})$ $\times$ log(Revenue)		-0.397*	-0.234			
		(0.215)	(0.219)			
$\Delta\log(1+\text{Tariff}^{CHN})$ $\times$ log(Capital)					-0.497***	-0.370*
					(0.193)	(0.194)
log(Revenue)	0.009	0.002	0.012	-0.004	-0.006	-0.004
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)
log(Capital)	0.019	0.017	0.017	0.029**	0.027*	0.033**
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,135	2,135	2,135	2,135	2,135	2,135
R-squared	0.081	0.082	0.085	0.081	0.083	0.086

Notes: The dependent variable is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. Tariff^{US} denotes a firm-level measure of exposure to US tariffs on imports from China, computed as a weighted average across each firm's set of products exported to the U.S. Tariff^{CHN} denotes a firm-level measure of tariff to Chinese tariffs on imports from the US, computed as a weighted average across each firm's set of products imported from the U.S. $\Delta\log(1+\text{Tariff}^{US})$ and $\Delta\log(1+\text{Tariff}^{CHN})$ are percent changes in Tariff^{US} and Tariff^{CHN} between 2017Q4 and 2018Q4. Firm revenue and capital are both measured in 2017Q4. Industries are defined according to the 3-digit Standard Industrial Classification (SIC). Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Trade Diversification

We further explore how trade war tariffs have affected Chinese firms' perceived trade policy uncertainty by investigating heterogeneous impacts across firms that differ in terms of their product and market diversification. If the actual tariff shock can be alleviated by reweighting or switching markets and product baskets, then Chinese firms that initially export to or import from multiple countries and/or many products are less likely to see an increase in TPU during the trade war. Using detailed firm-product-country-level Chinese customs data, we calculate the numbers of exported products and destination markets (and the number of imported products and source countries) between 2013 and 2016 at the firm-level. Then, we incorporate them into our baseline equation as follows:

$$\begin{aligned}\Delta \text{TPU}_i = \alpha &+ \beta_1 \Delta \log(1 + \text{Tariff}_i^{\text{US}}) + \beta_2 \Delta \log(1 + \text{Tariff}_i^{\text{US}}) \times N_i^{exp,prod} \\ &+ \gamma_1 \Delta \log(1 + \text{Tariff}_i^{\text{CHN}}) + \gamma_2 \Delta \log(1 + \text{Tariff}_i^{\text{CHN}}) \times N_i^{imp,prod} \\ &+ N_i^{exp,prod} + N_i^{imp,prod} + \delta X_i + \psi_{REG} + \psi_{IND} + \Delta \varepsilon_i\end{aligned}$$

where $N_i^{exp,prod}$ and $N_i^{imp,prod}$ are the number of exported and imported products for firm i from 2013 to 2016. The β_2 coefficient captures the differential impact of firm-level exposure to U.S. tariffs on trade policy uncertainty across firms with different numbers of exported products, while γ_2 captures the differential impact of firm-level exposure to Chinese tariffs across firms with different numbers of imported products.

Columns 1 through 3 in Table 9 display the results. Across all specifications, the interaction terms are statistically insignificant. These results imply that more diverse product baskets have not played a role in reducing Chinese firms' perceived trade policy uncertainty.

Next, we replace the number of products by the number of countries a firm exports to or imports from ($N_i^{exp,ctry}$ and $N_i^{imp,ctry}$, respectively), and report results in columns 4 through 6. In column (6), including both US and Chinese tariffs we find that for firms that export to more countries the impact of US tariffs on firm-level TPU is smaller. One additional country in a firm's export basket reduces the impact of US tariffs on firm-level TPU by 0.013 points (0.031 standard deviation). However, we do not find any evidence of importing from more countries can mitigate the impact of Chinese tariffs on TPU. All in all, multi-country exporters perceive less uncertainty as a consequence of tariffs, presumably due to their ability to reroute trade.

Table 9: Trade Policy Uncertainty, Tariffs, and Diversification: 2017Q4–2018Q4

	Dependent Variable: ΔTrade Policy Uncertainty					
	(1)	(2)	(3)	(4)	(5)	(6)
Δlog(1+Tariff^{US})	0.270*		0.174	0.578***		0.400**
	(0.151)		(0.152)	(0.193)		(0.194)
Δlog(1+Tariff^{US}) $\times N_i^{exp,prod}$	-0.003		-0.003			
	(0.002)		(0.002)			
Δlog(1+Tariff^{US}) $\times N_i^{exp,ctry}$				-0.016***		-0.013**
				(0.005)		(0.005)
Δlog(1+Tariff^{CHN})		0.781**	0.748**		0.580	0.571
		(0.380)	(0.373)		(0.460)	(0.471)
Δlog(1+Tariff^{CHN}) $\times N_i^{imp,prod}$		-0.006	-0.006			
		(0.010)	(0.009)			
Δlog(1+Tariff^{CHN}) $\times N_i^{imp,ctry}$					-0.019	-0.019
					(0.035)	(0.035)
$N_i^{exp,prod}$	0.000		0.000			
	(0.000)		(0.000)			
$N_i^{imp,prod}$		0.001	0.001			
		(0.001)	(0.001)			
$N_i^{exp,ctry}$				0.002***		0.000
				(0.001)		(0.001)
$N_i^{imp,ctry}$					0.005**	0.006**
					(0.002)	(0.003)
Firm Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,135	2,135	2,135	2,135	2,135	2,135
R-squared	0.080	0.081	0.083	0.082	0.083	0.087

Notes: The dependent variable is change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. Tariff^{US} denotes a firm-level measure of exposure to US tariffs on imports from China, computed as a weighted average across each firm's set of products exported to the U.S. Tariff^{CHN} denotes a firm-level measure of tariff to Chinese tariffs on imports from the US, computed as a weighted average across each firm's set of products imported from the U.S. Δlog(1+Tariff^{US}) and Δlog(1+Tariff^{CHN}) are percent changes in Tariff^{US} and Tariff^{CHN} between 2017Q4 and 2018Q4. Firm revenue and capital are both measured in 2017Q4. Both measures are included in the regressions, but are not displayed in the above table. Industries are defined according to the 3-digit Standard Industrial Classification (SIC). Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5 The Firm-Level Impacts of TPU on Economic Outcomes

5.1 Investment

Next, we analyze whether heightened firm-level trade policy uncertainty affects firm-level outcomes.[33] We estimate the following regression equation:

$$\log(\mathrm{K}_{i,t+k}) - \log(\mathrm{K}_{i,t}) = \alpha + \beta \Delta \mathrm{TPU}_i + \gamma X_i + \psi_{REG} + \psi_{IND} + \Delta \varepsilon_i. \tag{4}$$

The dependent variable, $\log(\mathrm{K}_{i,t+k}) - \log(\mathrm{K}_{i,t})$, measures the percent change in capital stocks for firm i from 2017Q4 to $t+k$ where $t+k$ denotes a quarter after 2018Q4 (i.e., $t+k = \{18Q4, 19Q1, 19Q2, 19Q3\}$). In this way we capture the dynamic response of capital stocks to TPU. $\Delta\mathrm{TPU}_i$ measures the change in firm i's trade policy uncertainty between 2017Q4 and 2018Q4. X_i is a firm-level control vector that includes profit, revenue and capital in 2017Q4. ψ_{REG} and ψ_{IND} denote region and industry fixed effects. Both fixed effects are the same as in Section 4.

Table 10: Investment and Trade Policy Uncertainty

	Dependent Variable: ΔCapital			
	(1)	(2)	(3)	(4)
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
ΔTrade Policy Uncertainty (17Q4-18Q4)	-0.034**	-0.034*	-0.040**	-0.048**
	(0.017)	(0.019)	(0.020)	(0.024)
Profit_{17Q4}	0.000*	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
$\log(\text{Revenue})_{17Q4}$	0.058***	0.062***	0.079***	0.086***
	(0.022)	(0.022)	(0.023)	(0.024)
$\log(\text{Capital})_{17Q4}$	-0.060***	-0.072***	-0.087***	-0.099***
	(0.016)	(0.017)	(0.018)	(0.020)
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,134	2,135	2,131	2,121
R-squared	0.109	0.113	0.111	0.113

Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. Firm profit, revenue and capital are measured in 2017Q4. Industries are defined according to the 3-digit Standard Industrial Classification (SIC). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10 shows estimation results. The coefficent in column (1) reflects the contemporaneous impact of changes in trade policy uncertainty on changes in capital stock during 2017Q4 - 2018Q4. The coefficient is negative and statistically significant, and its mag-

[33] Caldara et al. (2019) find that increases in firm-level TPU reduce business investment in the US during the period 2015Q1 and 2018Q4.

nitude implies that one point increase in trade policy uncertainty is associated with 3.4 percent decrease in firm-level capital stocks.[34]

In columns (2), (3) and (4), we report the responses of capital stocks at 5, 6 and 7 quarter horizons. In general, the (negative) magnitudes become larger as time goes by. After 3 quarters, the coefficient of β is -0.048.[35] This finding is consistent with Caldara et al. (2019), who find that the negative impact of trade policy on business investment in the U.S. is statistically significant after two quarters. Likewise, heightened trade policy uncertainty, which originated from the 2018-2019 trade war, discourages firm-level investment and its impact becomes larger over longer time horizons in China.

5.2 R&D Expenditures

We also explore whether trade policy uncertainty effects firm-level R&D expenditures. Since the firm-level R&D expenditure variable is only available yearly, we use the percent change in R&D between 2017 and 2018 as a dependent variable as follows:

$$\Delta \text{RD}_i = \alpha + \beta \Delta \text{TPU}_i + \gamma X_i + \psi_{REG} + \psi_{IND} + \Delta \varepsilon_i. \tag{5}$$

where ΔTPU_i is the change in trade policy uncertainty between 2017Q4 and 2018Q4.

Table 11 shows the estimation results. In columns (1) to (3), we include region fixed effects. In column (1), we start by relating the percent change in R&D expenditure to the change in trade policy uncertainty and found that the coefficient is negative but statistically insignificant. Then, we add pre-period R&D expenditure in column (2) and pre-period R&D expenditure, profit, log of revenue, and log of capital in column (3). In column (3), we found that the coefficient is negative with statistical significance. Then, we add both region and industry fixed effects into the regression in column (4) and (6). In column (6), the coefficient is -0.063 with statistical significance. Quantitatively, one point increase in TPU is associated with 6.3 percent decrease in R&D expenditure.[36]

[34] Alternatively, a one standard deviation increase in trade policy uncertainty is associated with 1.4 percent decrease in firm-level capital stocks.

[35] After 3 quarters, a one standard deviation increase in trade policy uncertainty is associated with 2.0 percent decrease in firm-level capital stocks.

[36] Alternatively, a one standard deviation increase in trade policy uncertainty is associated with 2.7 percent decrease in R&D expenditure.

Table 11: R&D Expenditures and Trade Policy Uncertainty

	Dependent Variable: ΔR&D (2017-2018)					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTrade Policy Uncertainty	-0.039	-0.034	-0.048*	-0.052*	-0.049*	-0.063**
(17Q4-18Q4)	(0.028)	(0.027)	(0.025)	(0.030)	(0.028)	(0.025)
R&D$_{2017}$		-0.130***	-0.254***		-0.150***	-0.326***
		(0.030)	(0.053)		(0.033)	(0.058)
Profit$_{17Q4}$			0.000**			0.000*
			(0.000)			(0.000)
log(Revenue)$_{17Q4}$			0.140***			0.188***
			(0.045)			(0.048)
log(Capital)$_{17Q4}$			0.043**			0.073***
			(0.020)			(0.022)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes
Observations	2,032	2,032	2,004	2,019	2,019	1,993
R-squared	0.019	0.083	0.160	0.069	0.145	0.260

Notes: ΔR&D (2017-2018) is the log change in firm-level R&D expenditure between 2017 and 2018. ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. Firm profit, revenue and capital are measured in 2017Q4. Industries are defined according to the 3-digit Standard Industrial Classification (SIC). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.3 Profits

We then turn our attention to firm-level profits and analyze whether heightened firm-level trade policy uncertainty affects firm-level profits. We specify the following regression equation:

$$\Pi_{i,t+k} - \Pi_{i,t} = \alpha + \beta \Delta \text{TPU}_i + \gamma X_i + \psi_{REG} + \psi_{IND} + \Delta\varepsilon_i.$$

where the dependent variable, $\Pi_{i,t+k} - \Pi_{i,t}$, measures the change in profit for firm i from 2017Q4 to $t+k$ where $t+k$ denotes a quarter after 2018Q4 (i.e., $t+k = \{18Q4, 19Q1, 19Q2, 19Q3\}$).[37]

Table 12 shows estimation results. In columns (1) and (2), the coefficients are negative but statistically insignificant in both Panels. However, in both columns (3) and (4), the coefficients are negative with statistical significance. After two quarters, the heightened trade policy decreases firm-level profits. The coefficient is -19.8 (column 3) and -25.9 (column 4). Quantitatively, one point increase in trade policy uncertainty is associated with 19.8 and 25.9 million Chinese yuan decrease in firm-level quarterly profits.[38]

[37]Note that we use the level of profits, i.e., millions of Chinese yuan, instaed of the log of profits to allow for negative values.

[38]Alternatively, a one standard deviation increase in trade policy uncertainty is associated with 8.4 and 11.0 million Chinese yuan decrease in firm-level quarterly profits.

5.4 Robustness Check

We further assess the impact of trade policy uncertainty on investment and profits estimating the following equations:

$$\log(\mathrm{K}_{it}) = \alpha + \beta \mathrm{TPU}_{it} + \psi_i + \psi_t + \varepsilon_i,$$
$$\Pi_{it} = \alpha + \beta \mathrm{TPU}_{it} + \psi_i + \psi_t + \varepsilon_i$$

where ψ_i are firm fixed effects and ψ_t are time fixed effects. We cluster standard errors at the firm-level. The sample coverage is between 2016Q1 and 2019Q3 with firm-level quarterly observations. Since $\mathrm{TPU}_{i,t}$ variable is observed yearly, we use yearly level of TPU to impute quarterly levels of TPU. Also, TPU observations are not available for the year 2019 and we use 2018 TPU levels.

Table 12: Profits and Trade Policy Uncertainty

	Dependent Variable: ΔProfit			
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
	(1)	(2)	(3)	(4)
ΔTrade Policy Uncertainty	-24.571	-9.609	-19.786*	-25.915*
(17Q4-18Q4)	(16.381)	(11.278)	(10.503)	(13.598)
Profit_{17Q4}	-0.210**	-0.339***	-0.293**	-0.334***
	(0.103)	(0.121)	(0.148)	(0.117)
$\log(\text{Revenue})_{17Q4}$	-33.014*	17.109	14.116	22.009*
	(17.187)	(11.776)	(14.313)	(12.550)
$\log(\text{Capital})_{17Q4}$	8.943	21.893**	49.745***	25.470***
	(16.591)	(9.152)	(15.536)	(8.988)
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,135	2,135	2,131	2,121
R-squared	0.142	0.269	0.191	0.251

Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. Firm profit, revenue and capital are measured in 2017Q4. Industries are defined according to the 3-digit Standard Industrial Classification (SIC). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 13 presents estimation results. In columns (1) through (3), the dependent variable is capital stocks; in column (4) through (6), the dependent variable is profits. We use slightly different fixed effects across specifications. Reassuringly, the impacts of trade policy uncertainty on capital and profit are negative and statistically significant.

Table 13: Robustness Check: Investment, Profits and Trade Policy Uncertainty

	Dependent Variable:					
		Capital			Profit	
	(1)	(2)	(3)	(4)	(5)	(6)
TPU	-0.062**	-0.060**	-0.065**	-14.254*	-13.653*	-17.279**
	(0.031)	(0.028)	(0.030)	(8.315)	(7.835)	(8.377)
Fixed Effects:						
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Time	Yes	No	No	Yes	No	No
Region-Time	No	Yes	Yes	No	Yes	Yes
Industry-Time	No	No	Yes	No	No	Yes
Observations	32,509	32,509	32,339	32,954	32,954	32,793
R-squared	0.950	0.952	0.954	0.648	0.652	0.685

Notes: The sample period is from 20161Q to 2019Q3. Standard errors are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

5.5 The Direct Impacts of Tariffs on Economic Outcomes

We have uncovered a new channel that heightened firm-level trade policy due to the trade war leads to a reduction in firm-level investment, R&D expenditures and profits for Chinese listed firms. However, rising US tariffs and Chinese retaliatory tariffs could also have negatively affected Chinese firms through the standard terms-of-trade channel, i.e., the direct impacts of tariffs. If so, the previous estimates of the trade policy uncertainty channel might be compounded with the direct impacts of tariffs. To alleviate this concern, we augment our baseline equations (4) and (5) with U.S. and Chinese tariff exposure measures as follows:

$$\begin{aligned}
\log(\mathrm{K}_{i,t+k}) - \log(\mathrm{K}_{i,t}) &= \alpha + \beta_1 \Delta\mathrm{TPU}_i + \beta_2 \Delta\log(1 + \mathrm{Tariff}_i^{\mathrm{US}}) + \beta_3 \Delta\log(1 + \mathrm{Tariff}_i^{\mathrm{CHN}}) \\
&\quad + \gamma X_i + \psi_{REG} + \psi_{IND} + \Delta\varepsilon_i, \\
\Pi_{i,t+k} - \Pi_{i,t} &= \alpha + \beta_1 \Delta\mathrm{TPU}_i + \beta_2 \Delta\log(1 + \mathrm{Tariff}_i^{\mathrm{US}}) + \beta_3 \Delta\log(1 + \mathrm{Tariff}_i^{\mathrm{CHN}}) \\
&\quad + \gamma X_i + \psi_{REG} + \psi_{IND} + \Delta\varepsilon_i,
\end{aligned}$$

where β_1 measures the trade policy uncertainty effect. The coefficients, β_2 and β_3, denote the direct impacts of tariffs.

Tables 14 and 15 report the estimation results. Reassuringly, the sign and significance of the coefficients of the trade policy uncertainty effect on investment and profits remain unchanged, even after controlling for the direct impact. Interestingly, the direct impacts of U.S. and Chinese tariff exposure measures on both investment and profit are statistically insignificant.

Table 14: Investment, Trade Policy Uncertainty, and Tariffs

	Dependent Variable: ΔCapital			
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
	(1)	(2)	(3)	(4)
ΔTrade Policy Uncertainty	-0.036**	-0.035*	-0.042**	-0.050**
(17Q4-18Q4)	(0.017)	(0.019)	(0.020)	(0.025)
$\Delta\log(1+\text{Tariff}^{US})$	0.090	0.054	0.111	0.163
(17Q4-18Q4)	(0.086)	(0.093)	(0.100)	(0.114)
$\Delta\log(1+\text{Tariff}^{CHN})$	0.176	0.161	0.196	0.237
(17Q4-18Q4)	(0.163)	(0.175)	(0.190)	(0.208)
Firm Characteristics	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,134	2,135	2,131	2,121
R-squared	0.110	0.113	0.112	0.115

Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. Firm profit, revenue and capital are measured in 2017Q4. Three measures are included in the regressions, but are not displayed in the above table. Industries are defined according to the 3-digit Standard Industrial Classification (SIC). Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Discussion

There might be several mechanisms explaining why we found no direct impacts of tariffs. First, the average ratio of exports to the U.S. to total sales for Chinese listed firms in the sample is about 1.7 percent in 2016 according to custom data. The low ratio suggests that the output loss resulting from rising US tariffs would be quite limited even if US tariffs at the industry have risen substantially. Correspondingly, reactions in investment and profits would be small for these firms.[39]

Second, the re-routing channel may have alleviated negative impacts on Chinese firms. Liu and Shi (2019) find that trade re-routing has been used by Chinese firms in the past to

[39]Firm shares of imports from US are also small, leading to the insignificant effect of rising retaliatory tariffs. In appendix B, we investigate by adding the US export share and the US import share along with their interaction with tariffs. The exercise seeks to explore whether the direct impacts of US and Chinese tariff exposures have especially stronger for firms that export to and/or import from the U.S. more. Results are reported in Tables A.5 and A.6. The coefficients of interaction terms between US tariff and US export share are still insignificant; while the coefficients of interaction terms between Chinese tariff and US import share are negative and statistically significant. Although the overall direct impacts of Chinese retaliatory tariffs are insignificant, Chinese firms that especially import from the U.S. suffer from the trade war.

Table 15: Profit, Trade Policy Uncertainty, and Tariffs

	Dependent Variable: ΔProfit			
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
	(1)	(2)	(3)	(4)
ΔTrade Policy Uncertainty	-26.079	-8.624	-18.182*	-25.154*
(17Q4-18Q4)	(16.391)	(11.352)	(10.597)	(13.807)
$\Delta\log(1+\text{Tariff}^{US})$	102.150	-38.250	-93.622	-4.881
(17Q4-18Q4)	(122.952)	(79.449)	(86.981)	(79.447)
$\Delta\log(1+\text{Tariff}^{CHN})$	194.837	-159.796	-221.017	-145.197
(17Q4-18Q4)	(211.802)	(147.866)	(188.854)	(158.522)
Firm Characteristics	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,135	2,135	2,131	2,121
R-squared	0.143	0.270	0.191	0.252

Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. Firm profit, revenue and capital are measured in 2017Q4. Three measures are included in the regressions, but are not displayed in the above table. Industries are defined according to the 3-digit Standard Industrial Classification (SIC). Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

avoid antidumping duties in the context of trade tariffs.[40] Though we cannot formally test firm re-routing behaviours because of data limitation, the recent news report by Chau and Boudreau (2019) suggests that there is a high possibility that re-routing took place during the US-China trade tension. According to the report, exports from Vietnam to the US have grown much in 2019 and many products such as plywood are claimed to be produced in China but shipped to the US with 'Made in Vietnam' labels.

Thirdly, trade diversification can help mitigate the negative impacts of tariffs. For instance, if Chinese firms could easily switch buyers, then the direct negative impacts of tariffs on firm-level investment and profits were reduced.[41] In fact, Chinese government have implemented policies to help affected Chinese producers to switch to other partners.[42]

[40] Trade re-routing means firms send their products to a third country where US tariffs are not applicable. After that, goods are reissued certificates of origin and sent to the final destination country without being subject to the US tariffs.

[41] Our previous analysis has uncovered the real hedging channel where Chinese exporters that are more diversified in terms of destination markets see a lower increase in trade policy uncertainty.

[42] According to the report by CNBC, Chinese government has taken mainly four ways to bolster business during the trade tension, which includes increasing government support, opening channels to other international markets through programs such as free trade zones and the Belt and Road Initiative, improve the environment for state-owned and foreign enterprises and implementing policies such as tax and fee cuts. See https://www.cnbc.com/2019/08/26/trade-war-what-it-means-for-china-firms-as-trumps-calls-us-firms-to-go.html

Lastly, endogenous price adjustments taken by different parties may have effectively absorbed the increase in both tariffs, contributing to the null impact on Chinese firms. For instance, using micro data, Cavallo et al. (2019) find that US tariffs placed on imports from China were almost fully passed through to the total prices paid by importers, while the rising import prices are mainly absorbed by lowering retail margins in the US.[43] In contrast, Cavallo et al. (2019) also find that US exporters lowered their prices on goods subjected to China's retaliatory tariffs. Both price adjustments on the US side tend to mitigate tariff-induced change in export and import prices for Chinese enterprises.

6 Conclusions

We construct a new measure of firm-level trade policy uncertainty for Chinese listed firms. Using this measure combined with the 2018-2019 US-China trade war episode, we unpack sources of trade policy uncertainty shocks. The firm-level trade policy uncertainty responds to exogenous firm-level exposures to US imposed tariff and Chinese retaliatory tariff shocks, both of which were unlikely to be anticipated. To the best of our knowledge, this paper is the first study to investigate the determinants of trade policy uncertainty shock using an almost natural experiment setting. In this regard, our empirical results can be used as a strong complement to supporting the validity of the economic policy uncertainty measures based on textual analysis such as Baker et al. (2016) and Hassan et al. (2019). We then investigate whether heightened firm-level trade policy uncertainty harmed firm-level economic outcomes and find that it did reduce firm-level investment, R&D expenditures and profits.

Recent studies such as Fajgelbaum et al. (2019) and Amiti et al. (2019) have focused on the impact of the 2018-2019 US-China trade war on the US economy through the standard price and quantity adjustment channel (i.e., terms-of-trade effects) along with general equilibrium effects. In this paper, we provide a new angel on the impact of the 2018-2019 US-China trade war thorough the lens of trade policy uncertainty channel. The trade war heightened firm-level uncertainty that also reduced firm-level economic activities. While we have not analyzed the aggregate impacts of the trade war on Chinese economy, which are the beyond the scope of this study, our empirical results shed light on the trade policy uncertainty channel that has rarely been investigated in this research arena.

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for details.

[43] Cavallo et al. (2019) also find that imports of US retailers increased after the initial announcement of possible tariffs, but before the full implementation of tariffs. Therefore, by completing sales/purchase beforehand, tariff's impact on firm sales for Chinese firms can be very limited overall.

Future research could take several further steps. First, it would be essential to study the aggregate impact of trade policy uncertainty on Chinese economy. Second, it would be interesting to analyze the long-run dynamic impacts of trade policy uncertainty beyond 2019Q3. Third, using our newly-constructed firm-level trade policy uncertainty measure, one can study the relationship between this measure and other economic outcomes.

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Appendix

Appendix A: Tables

Table A.1: Summary Statistics by Year

Year	Number of Exporters	Export (million USD)		Share of Exports to the US	
		Mean	Standard Deviation	Mean	Standard Deviation
2013	1189	74.746	252.612	12.61%	22.57%
2014	1222	60.190	206.606	11.69%	20.95%
2015	1216	58.330	217.279	11.91%	20.55%
2016	1500	50.016	179.491	12.60%	21.61%
Year	Number of Importers	Import (million USD)		Share of Imports from the US	
		Mean	Standard Deviation	Mean	Standard Deviation
2013	1163	49.614	306.218	13.67%	26.39%
2014	1192	41.512	221.539	14.15%	27.09%
2015	1151	38.029	188.600	13.04%	25.36%
2016	1419	32.151	164.276	12.22%	24.77%

Notes: The table summarizes firm-level exports and imports for the matched listed enterprise during 2013 and 2016, respectively. Each product is defined by the unique HS 8-digit code.

Table A.2: Summary of Import Tariff by Quarter

Time	US		China	
	Mean	Standard Deviation	Mean	Standard Deviation
2015-Q1	0.033	0.057	0.091	0.060
2015-Q2	0.033	0.057	0.091	0.060
2015-Q3	0.033	0.057	0.091	0.060
2015-Q4	0.033	0.057	0.091	0.060
2016-Q1	0.033	0.057	0.091	0.061
2016-Q2	0.033	0.057	0.091	0.061
2016-Q3	0.033	0.057	0.091	0.061
2016-Q4	0.033	0.057	0.091	0.061
2017-Q1	0.033	0.057	0.091	0.061
2017-Q2	0.033	0.057	0.091	0.061
2017-Q3	0.033	0.057	0.091	0.061
2017-Q4	0.033	0.057	0.091	0.061
2018-Q1	0.033	0.057	0.086	0.059
2018-Q2	0.041	0.067	0.089	0.064
2018-Q3	0.070	0.091	0.090	0.082
2018-Q4	0.130	0.087	0.153	0.077
2019-Q1	0.130	0.087	0.150	0.076
2019-Q2	0.180	0.096	0.174	0.078
2019-Q3	0.203	0.106	0.220	0.091
2019-Q4	0.203	0.106	0.220	0.091

Notes: The table summarizes tariff imposed by China and the US, respectively. For each country, the mean value of tariff is calculated as the simple average across sector-level tariff $\ln(1 + \text{Tariff})$ across HS 6-digit code.

Table A.3: Summary of Firm-level Tariff by Quarter

Time	Tariff^{US}_{it}		$\Delta\text{Tariff}^{US}_{it}$		Tariff^{CHN}_{it}		$\Delta\text{Tariff}^{CHN}_{it}$	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
2017-Q1	0.022	0.027	0.000	0.002	0.059	0.047	0.000	0.006
2017-Q2	0.022	0.027	0.000	0.002	0.059	0.047	0.000	0.006
2017-Q3	0.022	0.027	0.000	0.002	0.059	0.047	0.000	0.006
2017-Q4	0.022	0.027	0.000	0.002	0.059	0.047	0.000	0.006
2018-Q1	0.023	0.031	0.001	0.016	0.051	0.039	-0.006	0.031
2018-Q2	0.030	0.047	0.008	0.041	0.052	0.044	-0.005	0.035
2018-Q3	0.108	0.112	0.086	0.115	0.060	0.060	0.003	0.041
2018-Q4	0.177	0.124	0.155	0.126	0.127	0.075	0.070	0.060
2019-Q1	0.177	0.124	0.155	0.126	0.126	0.074	0.068	0.060
2019-Q2	0.230	0.129	0.208	0.130	0.147	0.079	0.090	0.064
2019-Q3	0.256	0.137	0.234	0.138	0.191	0.095	0.134	0.082
2019-Q4	0.256	0.137	0.234	0.138	0.191	0.095	0.134	0.082

Notes: The table summarizes firm-level tariff imposed by China and the US, respectively. For each country, the mean value of tariff is calculated as the simple average across firms. The tariff change is relatiev to the average firm-level tariff between 2013 and 2016.

Table A.4: Summary of Firm-level TPU Measure by Year

Year	(I) Appearance in Range of +/− 1 Lines				(II) Appearance in the Same Line			
	Keywords Number		Keywords Share		Keywords Number		Keywords Share	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
2008	0.111	0.377	0.014	0.047	0.039	0.204	0.005	0.028
2009	0.145	0.487	0.017	0.059	0.052	0.246	0.006	0.029
2010	0.076	0.315	0.009	0.039	0.033	0.195	0.004	0.024
2011	0.098	0.373	0.011	0.044	0.036	0.213	0.004	0.025
2012	0.099	0.403	0.012	0.047	0.048	0.278	0.006	0.033
2013	0.070	0.332	0.008	0.038	0.035	0.230	0.004	0.026
2014	0.068	0.314	0.007	0.033	0.031	0.218	0.003	0.023
2015	0.069	0.312	0.007	0.032	0.028	0.187	0.003	0.020
2016	0.112	0.430	0.011	0.041	0.042	0.241	0.004	0.023
2017	0.132	0.461	0.012	0.044	0.063	0.298	0.006	0.029
2018	0.303	0.733	0.026	0.063	0.182	0.536	0.015	0.045

Notes: The table summarizes firm-level TPU measure by year. In each year, the mean value of firm-level TPU is calculated as the simple average across firms. In panel (I), a TPU keyword is identified if the trade related words are in one line above or below the place where there is uncertainty related words. In panel (II), we require that the trade related words are in the same line with uncertainty words. In column of "Keywords Number", TPU is measured as the number of TPU related keywords per report; we also measure TPU using the number of TPU keywords per 10,000 Chinese characters as shown in the column "Keywords Share".

Appendix B: Tariff Effect and Dependence on the US Market

The exercise seeks to explore whether the direct impacts of US and Chinese tariff exposures have especially stronger for firms that export to and/or import from the U.S. more. Results are reported in Tables A.5 and A.6. The coefficients of interaction terms between US tariff and US export share are still insignificant; while the coefficients of interaction terms between Chinese tariff and US import share are negative and statistically significant. Although the overall direct impacts of Chinese retaliatory tariffs are insignificant, Chinese firms that especially import from the U.S. suffer from the trade war.

$$
\begin{aligned}
\log(\mathrm{K}_{i,t+k}) - \log(\mathrm{K}_{i,t}) = \alpha &+ \beta_1 \Delta \mathrm{TPU}_i \\
&+ \beta_2 \Delta \log(1 + \mathrm{Tariff}_i^{\mathrm{US}}) + \beta_3 \Delta \log(1 + \mathrm{Tariff}_i^{\mathrm{US}}) \times \text{US export share}_i \\
&+ \beta_4 \Delta \log(1 + \mathrm{Tariff}_i^{\mathrm{CHN}}) + \beta_5 \Delta \log(1 + \mathrm{Tariff}_i^{\mathrm{CHN}}) \times \text{US import share}_i \\
&+ \gamma_1 X_i + \gamma_2 \text{US export share}_i + \gamma_3 \text{US import share}_i + \psi_{REG} + \psi_{IND} + \Delta \varepsilon_i, \\
\Pi_{i,t+k} - \Pi_{i,t} = \alpha &+ \beta_1 \Delta \mathrm{TPU}_i \\
&+ \beta_2 \Delta \log(1 + \mathrm{Tariff}_i^{\mathrm{US}}) + \beta_3 \Delta \log(1 + \mathrm{Tariff}_i^{\mathrm{US}}) \times \text{US export share}_i \\
&+ \beta_4 \Delta \log(1 + \mathrm{Tariff}_i^{\mathrm{CHN}}) + \beta_5 \Delta \log(1 + \mathrm{Tariff}_i^{\mathrm{CHN}}) \times \text{US import share}_i \\
&+ \gamma_1 X_i + \gamma_2 \text{US export share}_i + \gamma_3 \text{US import share}_i + \psi_{REG} + \psi_{IND} + \Delta \varepsilon_i.
\end{aligned}
$$

Tables A.5 and A.6 report the estimation results. The coefficients of interaction terms between US tariff and US export share are still insignificant; while the coefficients of interaction terms between Chinese tariff and US import share are negative and statistically significant. Although the overall direct impacts of Chinese retaliatory tariffs are insignificant, Chinese firms that especially import from the U.S. suffer from the trade war.

Table A.5: Investment, Trade Policy Uncertainty, Tariffs, and US share

	Dependent Variable: ΔCapital			
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
	(1)	(2)	(3)	(4)
ΔTrade Policy Uncertainty	-0.037**	-0.036*	-0.043**	-0.051**
	(0.017)	(0.019)	(0.020)	(0.025)
$\Delta\log(1+\text{Tariff}^{\text{US}})$	0.036	-0.005	0.063	0.115
	(0.098)	(0.107)	(0.115)	(0.132)
$\Delta\log(1+\text{Tariff}^{\text{US}})$	0.112	0.171	0.049	0.040
$\times$ US Export Share	(0.337)	(0.363)	(0.402)	(0.440)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$	0.282	0.281	0.324	0.405
	(0.197)	(0.214)	(0.233)	(0.261)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$	-0.932	-1.080	-1.292*	-1.640*
$\times$ US Import Share	(0.638)	(0.692)	(0.733)	(0.838)
Firm Characteristics	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,134	2,135	2,131	2,121
R-squared	0.111	0.114	0.113	0.116

Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. Firm profit, revenue and capital are measured in 2017Q4. Three measures are included in the regressions, but are not displayed in the above table. US export share is defined as the ratio of export to the US to total export during 2013-2016. US import share is defined as the ratio of import to the US to total import during 2013-2016. Both measures are included in the regressions, but are not displayed in the above table. Industries are defined according to the 3-digit Standard Industrial Classification (SIC). Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

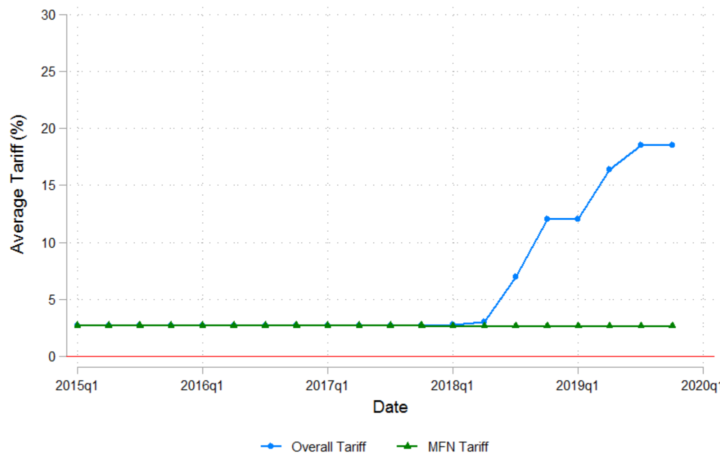
Table A.6: Profit, Trade Policy Uncertainty, Tariffs, and US share

	Dependent Variable: ΔProfit			
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
	(1)	(2)	(3)	(4)
ΔTrade Policy Uncertainty	-26.799	-9.290	-19.090*	-26.016*
	(16.393)	(11.453)	(10.632)	(13.883)
$\Delta\log(1+\text{Tariff}^{\text{US}})$	118.260	-58.207	-163.163	-35.907
	(142.664)	(94.274)	(110.799)	(92.957)
$\Delta\log(1+\text{Tariff}^{\text{US}})$	-480.103	-109.867	261.758	-114.716
× US Export Share	(429.584)	(315.478)	(314.658)	(298.636)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$	320.008	40.911	26.310	-14.222
	(292.551)	(191.517)	(208.923)	(206.705)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$	-969.356	-1,965.529*	-2,555.229	-1,506.623*
× US Import Share	(833.736)	(1,007.963)	(1,799.834)	(866.491)
Firm Characteristics	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,135	2,135	2,131	2,121
R-squared	0.143	0.273	0.196	0.254

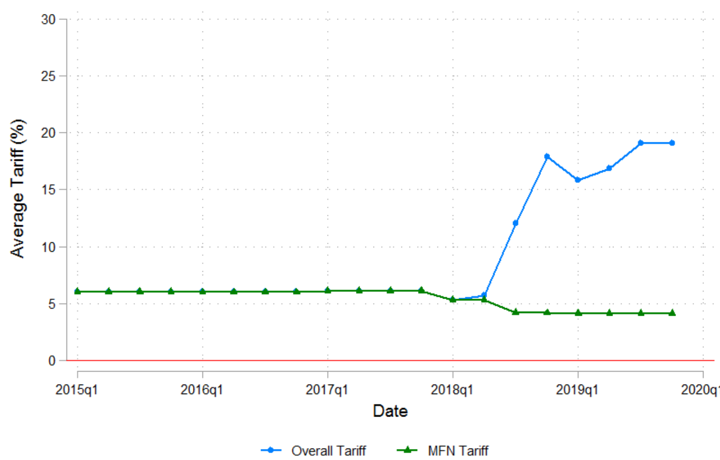
Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. Firm profit, revenue and capital are measured in 2017Q4. Three measures are included in the regressions, but are not displayed in the above table. US export share is defined as the ratio of export to the US to total export during 2013-2016. US import share is defined as the ratio of import to the US to total import during 2013-2016. Both measures are included in the regressions, but are not displayed in the above table. Industries are defined according to the 3-digit Standard Industrial Classification (SIC). Robust standard errors are in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Appendix C: Figure

Figure A.1: The Weighted Average U.S. and Chinese Tariff



(a) US Tariff on Chinese Goods

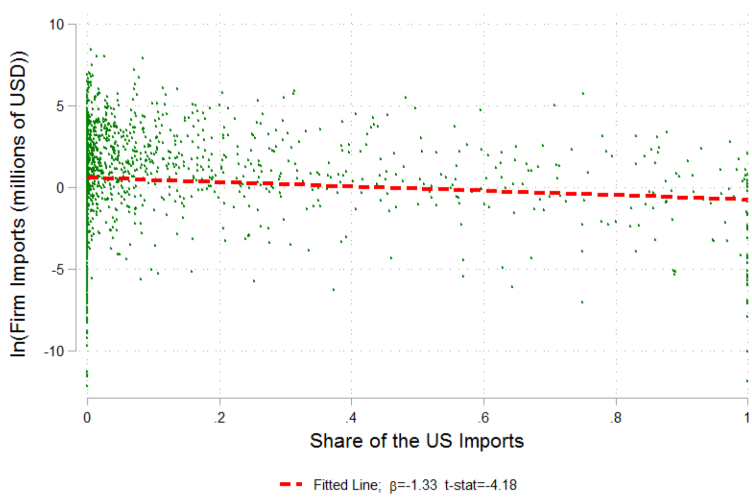


(b) Chinese Tariff on the US Goods

Notes: The average tariff is the weighted arithmetic average of HS 10-digit code tariffs, where the weights are total exports (or imports) at the HS 10-digit level. The green line denotes the MFN tariffs for both countries, and the blue line is for the overall tariff (MFN tariff plus trade war tariff).

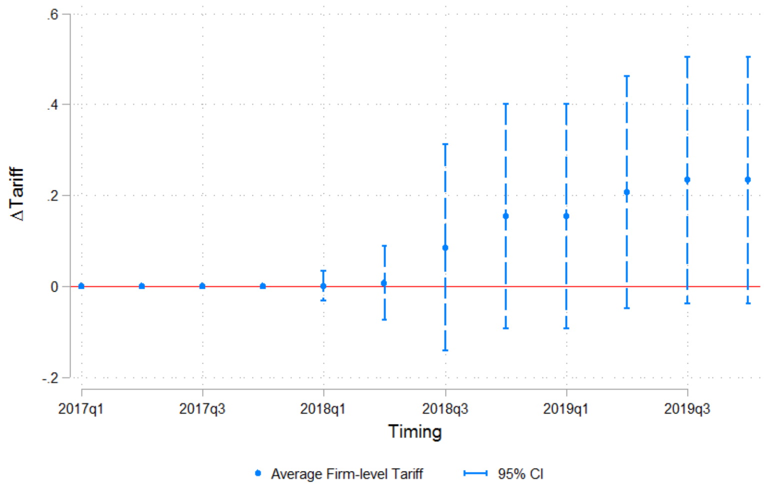
Figure A.2: Total Imports and Imports from the U.S. by Matched Listed Firms

(a) Pooling Sample (2013-2016)

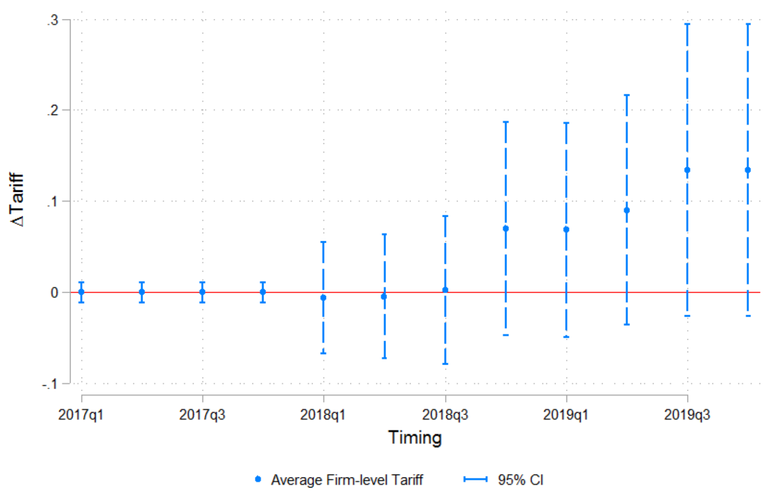


(b) Average Imports and the U.S. Shares (2013-2016)

Figure A.3: The Change in Import and Export Tariff Exposures of Chinese Listed Firms



(a) US Tariff on Chinese Goods



(b) Chinese Tariff on US Goods

Figure A.4: Example: the Beginning Page of Annual Report

(Angang Steel Company - GVKEY 205808)

1
鞍钢股份有限公司
Angang Steel Company Limited
二零一八年度报告
A n n u a l R e p o r t 2 0 1 8

2
第一节　重要提示、目录和释义
重 要 提 示
本公司董事会、监事会及董事、监事、高级管理人员保证本报告内容的真实、
准确、完整，不存在任何虚假记载、误导性陈述或者重大遗漏，并承担个别和连带的
法律责任。
本公司负责人董事长王义栋先生、主管会计工作负责人马连勇先生及会计机构
负责人郭武女士保证本报告中财务报告的真实、准确、完整。
风险提示：公司已在本年度报告中详细描述公司将面临的风险，敬请投资者予
以关注，详见本年度报告"管理层讨论与分析"等有关章节中关于公司面临风险的描
述。
经公司董事会审议通过的 2018 年度利润分配预案为：董事会建议，以现有总股
本 7,234,807,847 股为基数，向公司全体股东每 10 股派发现金红利人民币 2.2 元（含
税），共计分配利润人民币 1,591,657,726.34 元；同时，以资本公积金向全体股东转股
每 10 股转增 3 股。若截至 2018 年度分红派息股权登记日公司总股本发生变化，将按
照现金分配利润总额不变的原则，以分红派息股权登记日公司总股本为基数，调整每
股现金分红。此项预案尚须提交 2018 年度股东大会审议。

3
目　　录

4
释　　义
本公司、公司、鞍钢股份 指 鞍钢股份有限公司
本集团 指 鞍钢股份有限公司及其下属子公司
鞍山钢铁 指 鞍山钢铁集团有限公司，本公司的控股股
东。
鞍山钢铁集团 指 鞍山钢铁及其持股 30%以上的公司（不包
含本集团）
鞍钢新钢铁公司 指 鞍钢集团新钢铁有限责任公司，原为鞍山
钢铁的全资子公司。2006 年 1 月，本公司
收购了鞍山钢铁持有的该公司 100%股权，
并注销了该公司的工商登记。
鞍钢 指 鞍钢集团有限公司，本公司的最终控股股
东。
鞍钢集团 指 鞍钢及其持股 30%以上的公司（不包含本
集团）。
鞍钢财务公司 指 鞍钢集团财务有限责任公司
卡拉拉 指 卡拉拉矿业有限公司
攀钢钒钛 指 攀钢集团钒钛资源股份有限公司
攀钢钒钛集团 指 攀钢钒钛及其下属子公司
鞍蒂大连 指 鞍钢蒂森克虏伯汽车钢有限公司
《 原 材 料 和 服 务 供 应 协 议
（2016-2018 年度）》
指 2015 年 10 月 12 日，本公司 2015 年第二
次临时股东大会审议批准的本公司与鞍钢
集团公司签署的《原材料和服务供应协议
（2016-2018 年度）》。

Figure A.5: Example: Trade Policy Related Keywords in the Annual Report

(Angang Steel Company - GVKEY 205808)

5. 可能面对的风险
2019 年是全面建成小康社会关键之年，是贯彻落实新发展理念，推动高质量发展的重要时期。为更好适应内外部形势变化，有效防范重大风险事件发生，确保生产经营目标的实现，公司开展了 2019 年度风险评估工作，并研究制定风险应对措施。根据评估情况，公司 2019 年度可能会面对以下重大风险：

（1）环保风险
① 风险描述
新《环保法》、新污染物排放标准等相关法律实行，政府监管和执法愈发严格，对企业环保监管力度和标准提高，社会民众环保意识增强，对企业环保要求进一步提高，钢铁企业面临着巨大的环保压力。
② 风险管理解决方案
从管理体系方面，全方位与先进企业对标，查找差距、改进不足，高起点编制生态环境保护规划。对现有环保设施运行现状进行全面评估，实施环保设施运行月评价

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制度，做到“一点，一措，一责任人”，全方位控制污染。对新、改、扩建项目，严把项目竣工验收关，确保“三同时”执行率 100%。
推进固体废物综合利用及规范化管理工作，推进森林式绿色生态厂区建设；全面实施环保技术改造项目，巩固现有扬尘治理成果，加强环保改造项目管理，加快项目实施步伐，实现“天常蓝、水常青、草常绿、固废零出厂”。

（2）营销风险 Risks in sales
① 风险描述
钢铁产能过剩基本面没有根本改变，国内供需矛盾仍突出，市场竞争激烈。新经济增长点对钢材需求强度明显减弱，传统用钢行业对钢铁产品需求由品种、数量的增长转向质量和品质的提升，对钢铁行业提出了更高要求。钢铁行业原燃材料价格上涨、环保运行成本上升，给钢铁企业带来的成本压力不断增加。
随着世界经济深刻调整，保护主义、单边主义抬头，经济全球化遭遇波折，不稳定不确定因数较大，钢铁企业将面临越来越多的国际贸易争端，给钢材出口带来诸多不利影响。

Protectionism, unilateralism　Uncertainty increases

② 风险管理解决方案
完善“1+4+N”营销模式，发挥营销体系统筹管理作用。对内，强化调品指数、预期制造、客户服务、销量价格等方面对标；对外，以推进汽车钢一体化协同、中厚板事业部制为突破口，统筹协调华东、华南、华北三大区域重点客户。
拓宽营销渠道，深耕细作东北市场；加大重点工程项目投标力度；响应“一带一路”倡议，拓展海外营销渠道，积极开拓东南亚、印度等新兴市场。
延伸产业链，积极开展深加工处理配送、配套、期现结合等业务；按照产业链融资管理方案，推进实施下游客户金融服务，在增加客户粘性、提高市场占有率的同时增加公司效益。
建立完善以客户体验为导向的科研、质量和营销管理机制，解决客户痛点，增强客户粘结性，不断提高盈利能力。发挥销售龙头带动作用，将市场信息和客户需求反馈给研发、质量、生产部门，提高自身产品质量，提高竞争力。

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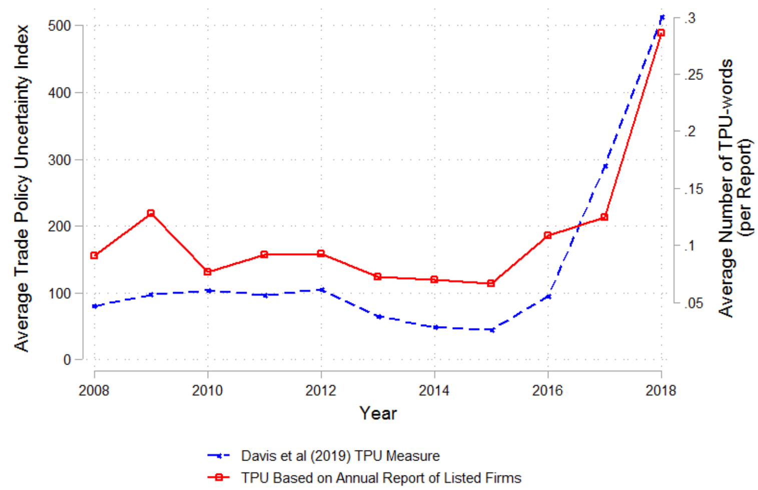
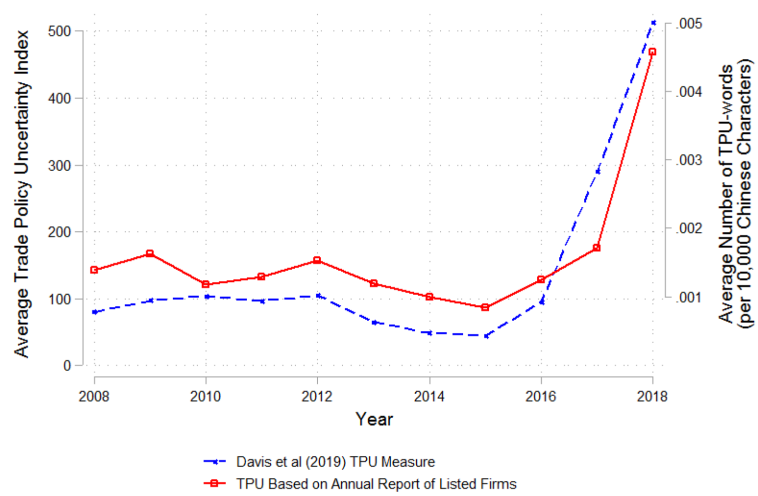
（3）投资风险
① 风险描述
国内外经济形势复杂多变，给公司投资决策及实施带来较大不确定性。投资项目尽职调查和可行性论证如果不全面、不深入、不充分，可能导致投资决策质量不高或项目受阻中止、或违规受罚。 智能制造涉及技术领域多、开发难度大，如果项目实施方案论证不充分，管理手段不完善，可能导致项目不能实现预期建设目标。

Figure A.6: TPU Based on Annual Report of Listed Firms and TPU in Davis et al. (2019)



(a) Number of TPU Related Words Per Report



(b) Number of TPU Related Words Per 10,000 Chinese Characters

Notes: As TPU keyword is identified if the trade related words are in one line above or below the place where there is uncertainty related words. In panel (a), TPU is measured as the number of TPU-related keywords per report; we also measure TPU using the number of TPU keywords per 10,000 Chinese characters as shown in panel (b).