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

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Abstract

The unexpected outbreak of the U.S.-China trade war led to dramatic increases in the import and export tariffs confronting Chinese firms, and ushered in an era of unprecedented trade policy uncertainty (TPU). To assess the effects of this development on the operations of Chinese firms we adopt a new textual analysis approach to listed firms' annual reports that allows us to create measures of TPU that vary over firms and time. Linking our new TPU measures to firm-level trade war exposure shows that increases in U.S. tariffs and Chinese retaliatory tariffs elevated firm-level TPU. The effects of Chinese firm-level tariff changes on firm TPU are heterogeneous: smaller firms experienced the most pronounced increases while firms that were more diversified in terms of partner countries were more insulated. Importantly, connecting firm-level increases in TPU during the trade war with subsequent firm performance reveals notable impairment of firm operations. Our estimates indicate that Chinese firms hit by a one standard deviation increase in TPU during the trade war reduced firm-level investment, R&D expenditures, and profits by 2.3, 2.3, and 11.5 percent, respectively.

Keywords: Trade War, Tariffs, Trade Policy Uncertainty, Firm-level Analysis
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1 Introduction

Tariff escalation during the U.S.-China trade war triggered high levels of trade policy uncertainty as firms were forced to re-evaluate their sourcing, production and sales strategies. As noted by Amiti et al. (2019), these changes in trade policies were particularly disruptive since Trump's 2016 election victory was not predicted by the polls, and therefore was an unanticipated event in the eyes of firms. Though the cycle of retaliatory trade actions paused in December 2019 when the U.S. and China agreed to a Phase One deal, the trade war tariffs remain in place and the most challenging trade war arguments have yet to be resolved. Thus, by rupturing and reversing decades of progress towards trade liberalization and by setting tariffs in a fashion that violated the rules and norms of past WTO practice, the U.S.-China trade war dramatically raised economic uncertainty for trading firms (IMF, 2018). For this reason, timely evidence on the overall consequences of the trade war is greatly needed to understand the impacts on firms and to guide future trade policy decisions.

To accomplish these goals we assemble a unique and comprehensive dataset that links firm-level measures of tariff exposure and trade policy uncertainty with a number of real outcomes for listed firms. As a result, our paper provides the first detailed account of the economic impacts of the trade war on Chinese firms. The core of the analysis is tied to our creation of firm-specific measures of trade policy uncertainty that are created through a textual analysis of firms' annual reports. Notably, when we aggregate our new measures, our composite closely tracks the evolution of the economy-wide TPU index created by Davis et al. (2019). By combining our new TPU measures with firm-level trade war tariff measures that combine firm-level customs product data with product-level trade war and MFN tariffs and implementing a clean empirical strategy, we shed light on the mechanisms by which the trade war impacted firms.

The first part of our project examines the connection between firm exposure to trade war tariffs and firm TPU during the trade war. Note that U.S. and Chinese tariffs affect firms differently: U.S. tariffs reduce the demand for Chinese firms' exports, while Chinese tariffs make access to imported inputs more costly. We find that Chinese import tariffs elevated TPU: a ten percentage points increase in the Chinese tariff exposure measure is associated with a 0.153 standard deviations increase in trade policy uncertainty. Our results are robust to controlling for region and industry fixed effects and the inclusion of lagged firm characteristics. Thus, the first key finding of our paper provides clear evidence that firms exposed to trade war tariffs experienced a *trade policy uncertainty shock* which operated particularly through tariffs that raised the cost of imported inputs.

We also examine how heterogeneity in the association between tariffs and firm-level

TPU across firms is related to firm characteristics and activities. First, we allow for an interaction between tariffs and lagged firm revenue, as a measure of firm size, and find that the effect of U.S. tariffs on TPU is larger among smaller firms.[1] The impact of an increase in U.S. tariffs on TPU is 0.561 standard deviations lower as a firm's revenue doubles. Second, we ask whether firms with a wider range of export destinations and more extensive product variety, or more source countries and variety of imported products, exhibited smaller responses to rising tariffs. We find this to be the case generally, and particularly for exports. One additional country in a firm's export basket reduces the impact of U.S. tariffs on firm-level TPU by 0.031 standard deviations. We argue this reveals a *real hedging* channel since the diversification of export destinations reduces the impact of tariff shocks.[2] Finally, we further investigate whether the ability to hedge in export markets could be hampered when firms have too much dependence on U.S. sales, given the fixed costs of locating and entering new markets. We find that the impact of U.S. tariffs on firm-level TPU is 1.277 standard deviations higher for U.S. dependent exporters compared to non-U.S. dependent exporters. Overall, these patterns provide novel evidence on how external trade policy shocks affect firm-level uncertainty.

In the second part of our paper, we analyze how increases in TPU affected firm-level performance at different horizons. We find that increases in firm-level TPU reduce firm-level investment, R&D expenditures, and profits, and lead to a short–run increase in inventories. A one standard deviation increase in TPU leads to a 1.58 percent decrease in investment contemporaneously. Compared with the initial period of 2017Q4, the effect of the 2017Q4 - 2018Q4 TPU shock on firm-level investment cumulatively amounts to a 2.26 percent decline by 2019Q3. In addition, a one standard deviation increase in TPU induces a decline in R&D expenditures by 2.27 percent contemporaneously. While we do not detect a significant impact of the 2017Q4 - 2018Q4 TPU change on firm profits at the same time horizon, we find that a one standard deviation increase in 2017Q4 - 2018Q4 TPU is associated with an overall decline in profits by 8.7 and 11.5 percent later on in 2019Q2 and Q3, suggesting that it takes time for profits to erode and give way to losses brought by rising trade policy uncertainty. Note that while our trade policy uncertainty measure captures a second–moment effect, we show, following the literature (Hassan et al., 2020, 2019), that these results are robust to controlling for a measure of *trade policy sentiment*,

[1] We find the same result using lagged firm capital as a measure of size.

[2] The *real hedging* channel is consistent with previous work by Macedoni and Xu (2018), Caselli et al. (2020), and Kramarz et al. (2020). Caselli et al. (2020) note that international trade can lower economic volatility by allowing countries to diversify the sources of demand and supply across countries. 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.

which captures the first moment effect.[3] In fact, we find it is only the uncertainty measure that has a significant impact on firm–level outcomes, which is consistent with the findings of Hassan et al. (2020) in the context of Brexit.

A key contribution of our paper is linking a measure of firm–level trade policy uncertainty to firm–level measures of trade exposures and the quarterly and up–to–date outcomes of Chinese listed firms.[4] This enables us to analyze how trade exposure affects TPU, and how TPU in turn shapes the dynamic response of firm–level outcomes. Our textual analysis used to measure TPU follows very recent work studying international firms' exposure and responses to Brexit (Hassan et al., 2020), and U.S. firms' exposure to political risk (Hassan et al., 2019) and to 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 of the trade war on real economic outcomes for Chinese firms in particular and the Chinese economy in general.[5] The literature to date has made strides quantifying the effects on the U.S. economy. Specifically, Fajgelbaum et al. (2020) and Amiti et al. (2019) quantify the combined effect of the tariffs applied by the U.S. on China and other trade partners, and these countries' retaliatory tariffs; the results indicate that the U.S. has suffered a welfare loss

[3]The trade policy sentiment measure is based on a count of instances in which trade policy–related words are surrounded by positive– and negative–tone words.

[4]We focus on listed firms for the following reasons. First, only these firms are required to publish the annual reports used to construct the TPU measure. In addition, this allows us to analyze the impact of the trade war on Chinese firms in a timely manner, given that more representative data produced by the Chinese government becomes available with a lag of several years. Another advantage of using data of listed firms is its reliability. Chen et al. (2019) explain how local governments adjust data reported in official firm-level surveys (which underlies 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 a fraction of all Chinese firms, and they are larger in size and are not representative of the entire firm population. 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. (2020); Keller and Yeaple (2009).

[5]See Fajgelbaum and Khandelwal (2021) for a recent survey of this literature.

equal to about 0.04% of GDP. Subsequent work by Amiti et al. (2020) demonstrates the investment consequences for U.S. listed firms. Turning to evidence from financial markets, analysis of U.S. and Chinese firm stock price reactions by Huang et al. (2018) finds that the March 2018 announcement of the investigation that led to the first round of U.S. tariffs on China led to a substantial drop in stock market returns for Chinese exporters around the announcement date.

This paper also adds to a new strand of work in the literature which leverages 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 time in earnings calls reports devoted to discussion of political risk. Closer to our paper, Caldara et al. (2019) analyze the effect of trade policy uncertainty on investment by U.S. listed firms. Their measure of firm-level trade policy uncertainty, which is based on earnings calls reports, is constructed 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 U.S. import tariffs during the trade war further reduce their investment. Steinberg (2020)'s comment on Caldara et al. (2019) suggests new exercises that we implement in this paper. Specifically, we use firm-level measures of tariff exposure and link them to firm-level TPU, thereby unpacking the sources of firm-level TPU.[6]

Our work complements a broader literature on the economic consequences of trade policy uncertainty. A set of papers have used the uncertainty surrounding U.S. tariff preferences towards China around China's W.T.O. entry (Handley and Limão, 2017; Pierce and Schott, 2016; Alessandria et al., 2019; Feng et al., 2017; Handley et al., 2020). Other work has studied the consequences of uncertainty generated by the Brexit referendum (Steinberg, 2019; Graziano et al., 2021).[7] Our empirical findings provide new insights that speak to a literature that uses models to estimate the the aggregate effects of trade policy uncertainty (Handley and Limão, 2017; Caldara et al., 2019; Steinberg, 2019). A first message is that we find that smaller and less diversified firms face a larger increase in TPU due to trade war tariffs.[8] Given how much exports and imports are concentrated among

[6]Other related work includes Handley and Li (2018), who construct time-varying measures 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 on trade policy uncertainty, in line with Caldara et al. (2019).

[7]Additional work in this literature includes Handley (2014), Handley and Limao (2015) and Carballo et al. (2018). In the context of the U.S.–China trade war, our findings are consistent with Benguria and Saffie (2019) who study U.S. exports to China during the trade war and find support for a trade policy uncertainty channel— the aggregate exports fall relatively more in sectors facing a larger risk of tariff increases.

[8]It is important to take into account that the size distribution of listed firms is shifted to the right relative to the entire firm size distribution, as we document in Appendix A.

the largest and more diversified firms in the economy (Bernard et al., 2009), incorporating this fact into these models could potentially lead to a lower estimate of the aggregate effects of TPU. A second message comes from our finding that the largest and most robust impact of tariffs on TPU is driven by Chinese tariffs that make imports more costly.[9] This second finding could raise the magnitude of the aggregate effects of TPU computed using models only considering tariffs on firms' exports.

Finally, this paper also contributes to a literature that has studied the impact of trade policies or trade shocks on Chinese firms. Brandt et al. (2017) dissects the channels through which China's entry into the WTO led to productivity improvements among Chinese firms, while Lu and Yu (2015) document how this episode led to a reduction in markup dispersion across firms. Khandelwal et al. (2013) study the response of Chinese 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.

2 The U.S.-China Trade War

To quantify the degree of tariff changes that firms faced, we review the tariff changes implemented under the Trump administration up to the point where the trade war was put on pause by a Phase one agreement.

Immediately after taking office, the Trump administration dramatically reversed the longstanding U.S. course towards freer trade by launching numerous actions which imposed new tariffs on named partners. The initial Trump tariffs, which were rationalized by argued threats to national security led to U.S. global safeguard tariffs on imports of washing machines and solar panels in January 2018, and tariffs on steel and aluminum imports in March 2018. The initial tariffs were focused on a few products and applied to all trading partners (with a few exceptions), and eventually led to retaliatory tariff action by some countries including China, Canada, Mexico, and the European Union.

In March 2018 Trump's trade policy turned its focus to Chinese trade following the completion of a Section 301 investigation into "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". On April 3, 2018 the U.S. government used this report to justify levying 25% tariffs on $50 billion of its imports from China. The very next day, China released its plan to retaliate against these U.S. tariffs by setting 25% tariffs of its own on $50 billion of its imports from the U.S. As these threats were converted into action, the U.S. and China engaged in further rounds

[9] This is consistent with Handley et al. (2020) who show that the reduction in uncertainty about tariffs following China's WTO entry had an effect on firms' sourcing decisions.

of protection and retaliation.[10] The first round of tariff penalties imposed by the U.S. on $50 billion in imports was rolled out in two rounds which levied new 25% tariffs on all covered products. The first wave launched in July 2018 covered 818 HS 8-digit products which were tied to $34 billion of U.S. imports, while the second tariff wave in August 2018 targeted 279 HS 8-digit products involving $16 billion in U.S. imports. China's first round of retaliatory tariffs also covered $50 billion in imports from the U.S. Paralleling U.S. actions, China's new 25% tariffs were implemented in July and August waves covering $34 billion and $16 billion of imports, as 545 and 333 HS 8-digit products were targeted in the respective rounds.[11]

The second U.S. tariff round, imposed in September 2018, applied a 10% tariff to 6,056 HS 8-digit products covering $200 billion in imports. China unleashed its second round of tariffs in tandem with the U.S. actions, imposing new 5% and 10% rates in September 2018 on 5,207 HS 8-digit products comprising $60 billion of China's imports.[12]

In December 2018 the U.S. announced its intention to levy further tariffs on the $200 billion product list. This new round included a future elevation of tariffs to 25% on the products the U.S. had just set 10% tariffs against. As before, China responded immediately with its intention to also increase its tariff charges. However, the December 2018 meeting of the U.S. and Chinese presidents culminated in a truce that postponed 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 unilaterally reduced some of its MFN tariffs.

In May 2019, the U.S. decided to raise its ad-valorem tariff rates on the product list for the $200 billion round from 10% to 25%. In June 2019, in response to this tariff hike, China also raised its tariff rates on the product list that was already targeted in September 2018, covering $36 billion. Finally, in September 2019 the U.S. imposed tariffs on $112 billion of imports from China. This was the first part of a larger $300 billion round, the second part of which was later suspended. China immediately retaliated announcing tariffs covering $75 billion to be imposed in September and December 2019, with the December list being later cancelled. Although tariffs have not been rescinded by the U.S. or China, the tit-for-tat escalation ended in December 2019 when the U.S. and China entered into a Phase One agreement. In total, at this point U.S. tariffs on Chinese products cover a list representing

[10]The value of U.S.-China trade affected by these actions is based on the approximate value of 2017 U.S exports and imports in the product categories targeted by the tariffs. This convention is used throughout the paper.

[11]In April 2018, China also 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 applied 15% and 25% ad-valorem rates against 91 HS 6-digit (104 HS 8-digit) products.

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

$362 billion (in terms of their 2017 value), which represents roughly 72% of the imports from China in 2017. Chinese tariffs apply to a list of products representing about 97% of U.S. exports to China in 2017.[13] Even with a truce, continued uncertainty about the prospects for future trade actions remained.

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-country-year level for all international transactions associated with China. We define a product as a Harmonized System (HS) 8-digit code. Importantly, by combining firm-level trade engagement with data on tariffs, we are able to create time-varying, firm-level measures of tariff exposure. The magnitude of the tariff changes, and the variation across firms and time demonstrate the dramatic burden placed on many Chinese firms.

Second, to measure firm-level changes in trade policy uncertainty over time, we construct a new measure that is based on the 2008 to 2018 transcripts of the annual reports released by Chinese firms that were listed in the Shanghai and Shenzhen Stock Exchange's domestic A share markets. The reports were scraped from *East Money Information* (i.e., a financial data provider in China) in PDF format, and converted into text.[14] Through this approach our paper is the first to provide this form of textual analysis for Chinese firms that allows us to quantify the increase in trade policy uncertainty during the trade war.

Third, to better understand the effects of the U.S.-China trade war on firm performance, we use firm-level data reported by COMPUSTAT Global which tracks firm performance for 2,312 Chinese firms on a quarterly basis. These data are limited to firms listed on the stock market.[15] Focusing on listed firms provides the advantage of timeliness; other firm-level data sources are released with a lag of several years. The data we use from this source run from 2016Q1 to 2019Q3. However, when we link the COMPUSTAT Global data with our annual firm-level uncertainty measure, we use two data

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

[14] The annual reports document each public company's activities, including the names of key staff, and what they did and why in the financial year. These reports disclose each firm's main financial data, information on operational performance, as well as 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 end date for the financial year.

[15] In Appendix A we compare the distribution of listed firms in our sample to the distributions of all exporting or all importing firms in China. While listed firms are on average larger, in both cases we see similarly shaped distributions.

points (i.e., 2017Q4 and 2018Q4) for our benchmark analysis and three more data points (i.e., 2019Q1, 2019Q2, and 2019Q3) for additional dynamic analysis. The COMPUSTAT variables we use are quarterly measures of firm revenue, capital stock, profits and inventories. We also utilize the data on R&D expenditure which is only available on an annual basis.

To relate firm performance to trade policy uncertainty and the tariff exposure measures, we first translate firm names in COMPUSTAT Global into Chinese, and refine the sample to listed firms from the 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 Chinese customs, to track their pre–trade war trade activities in the global market.[16] Table 1 reports the summary statistics on average exports and imports for the matched Chinese listed firms in COMPUSTAT Global.[17, 18]

Appendix Figure C.2 displays the pattern of firm exports and imports in the period before the outbreak of the U.S.–China trade war. As shown in panel (a), firms with larger exports also had larger shares of sales to the U.S. market. This association emerges whether we pool the samples or use the firm-level average between 2013 and 2016.[19] While firms selling more in the global market are also likely to import larger amount of goods (panel (b)), there is no systematic pattern suggesting that firm exports positively depend on firm imports from the United States, as the coefficient remains insignificant in panel (c).

3.2 Tariff Data

Our detailed tariff dataset includes the U.S. trade war tariffs imposed on China and Chinese retaliatory tariffs levied on U.S. exports, as well as the standard U.S. and Chinese MFN tariffs. We follow Fajgelbaum et al. (2020) as we prepare the tariff data for analysis and extend it forward in time. The data sources for Chinese trade war tariffs are Fajgelbaum et al. (2020), Li (2018)'s trade war tariff dataset, and Bown and Kolb (2019).

[16] 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 identify a wide range of possible firm names in customs; we then manually exclude false matches.

[17] Appendix Table B.1 reports similar statistics for matched Chinese listed firms by year.

[18] Our sample provides variation that allows us to identify the impact of tariffs on TPU and on other outcomes for a wide range of firms. For example, Appendix Figure C.1 illustrates its geographic coverage. The geographic spread of firms across Chinese cities aligns with the overall distribution of Chinese firms; while it spans many areas across China, it is relatively concentrated in coastal areas.

[19] For example, the t-statistics for the coefficient obtained by regressing $\ln(\text{Firm Exports})$ on the share of exports to the U.S. is 4.91 in the pooled sample, and is strongly significant. In contrast, as displayed in Appendix Figure C.3, imports display the opposite pattern: firms that import more had a smaller share of imports from the U.S.

Note that Chinese MFN tariffs from the WTO *Tariff Download Facility* database are complemented by Bown and Kolb (2019), who compile the recent and frequent changes in Chinese tariffs observed during 2018 and 2019 according to official Chinese government communications.

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

Variable	Mean	Standard Deviation
(A) 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 U.S.	12.22%	21.43%
(B) 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 U.S.	13.22%	25.87%

Notes: This table summarizes the exports and imports for the matched firms in our sample. In both panels, each observation is at the firm-year level. Averages pool all firm-year observations together during 2013–2016. Products are defined at the HS 8–digit level.

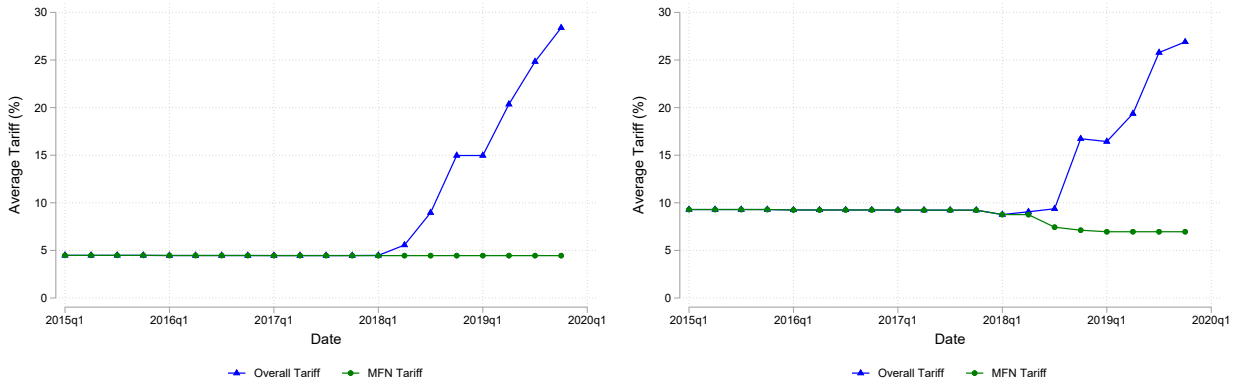
Figure 1 displays the evolution of tariffs imposed by the U.S. (panel (a)) and China (panel (b)), respectively, where each dot denotes the average tariff computed as the simple mean of tariffs across all HS 10-digit sectors.[20] As shown in Figure 1, the average U.S. tariff on imports from China remained essentially constant, at roughly 4.5%, up to the first quarter of 2018. In stark contrast, by the fourth quarter of 2019 the average U.S. tariff hit 28.4%, more than six times larger than the original tariff.[21] For comparison, the average MFN tariff (in green in the same graph) the U.S. applied to other trade partners remained constant at roughly 4.5% over the same time interval.

Over this time period, China imposed similarly dramatic tariff increases on products imported from the U.S. Starting from a low level of 9.2% and without much change up to

[20]The detailed numbers are provided in Appendix Table B.2. Numerical values of weighted average tariffs for the U.S. and China can be found in Appendix Figure C.4.

[21]The U.S. average tariff on China includes the imposition of tariffs on steel and aluminum in late March of 2018, the U.S. trade war tariff rounds on China covering $50 billion and $200 billion in imports between July and September 2018, the tariff rate increase that hit products covered by the $200 billion round in May 2019 and the $112 billion round (i.e. the first part of the $300 billion round) in September 2019.

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



(a) U.S. Tariff on Chinese Goods

(b) Chinese Tariff on U.S. Goods

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

the third quarter of 2018, China's tariffs rose to 16.7% by the fourth quarter of 2018 and 26.9% by the fourth quarter of 2019.[22]

3.3 Firm-level Tariff Exposure Measures

We combine tariff rate and firm-level customs data to create time-varying measures of individual firm import and export tariff exposure. $\text{Tariff}_{it}^{\text{U.S.}}$, which measures the U.S. tariff exposure of Chinese firm i at time t (i.e., quarter), is constructed as follows:

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

where $\tau_{jt}^{\text{U.S.}}$ is good j's *ad valorem* tariff (i.e., MFN tariff plus trade war tariff) imposed by the U.S. at time t, $X_{ij0}^{\text{U.S.}}$ is average exports of good j to the U.S. by firm i during 2013-2016, and J_i^e is the set of goods exported by firm i.[23] Following Topalova and Khandelwal

[22] The figure illustrating China's tariffs on the U.S. include its April 2018 retaliation against U.S. steel and aluminum tariffs, as well as its 2018 trade war tariff rounds covering $50 billion in July-August 2018 and $60 billion in September 2018. The figure also reflects the removal of retaliatory tariffs on cars and car parts in January 2019, the increase in tariff rates on some of the products in the earlier $60 billion round occurring in June 2019, and finally the September 2019 retaliation (i.e. part of the announced $75 billion round).

[23] In this expression, j corresponds to an HS6 product. Product–level tariffs $\tau_{jt}^{\text{U.S.}}$ are the sum of MFN and additional trade war tariffs. As in Fajgelbaum et al. (2020), MFN tariffs are obtained from the WTO and are reported at the HS6 level. To construct HS6-level trade war tariffs for U.S. imports from China we take a weighted average of the tariffs originally reported at the 8–digit level of the U.S. version of the Harmonized System, with weights equal to U.S. imports from China in 2017. The result is almost identical (the correlation is greater than 0.99) to using an unweighted average of HS8 tariffs, since there is almost no

(2011) and Rodriguez-Lopez and Yu (2017), we hold export value weights for each good fixed at the initial period value to avoid potential reverse causality in firm's exports with respect to U.S. tariffs. Ad-valorem tariffs are weighted by the share of each product in each firm's total exports. Likewise, based on China's retaliatory tariffs on U.S. goods and firm import data, we construct firm i's Chinese tariff exposure at time t as follows:

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

where τ_{jt}^{CHN} is good j's tariff imposed by China on U.S. goods at time t, $M_{ij0}^{\text{U.S.}}$ is the average import value of good j from the U.S. by firm i during 2013-2016, and J_i^m is the set of goods imported by firm i.[24] Here too, we use time-invariant weights computed in the initial period to avoid potential changes in weights driven by tariff changes.

Figure 2 displays the mean and standard deviation for the firm-level export and import tariff measures for each quarter. Panel (a) displays the tariff imposed by the U.S. on Chinese goods ($\text{Tariff}_{it}^{\text{U.S.}}$). Notably, while the average firm-level export tariff exposure started to increase in the second quarter of 2018, the substantial increase in the third quarter of 2018 involved dramatic heterogeneity across firms. Panel (b) reports the firm-level import tariff exposure based on Chinese retaliatory tariffs on U.S. goods ($\text{Tariff}_{it}^{\text{CHN}}$), also showing substantial heterogeneity across firms.[25] Appendix Table B.3 provides more details about the most affected SIC 3-digit industries as indicated by the two tariff exposure measures for Chinese listed firms. According to panel (a), U.S. trade war tariffs most heavily affected China's sectors related to industrial and commercial machinery & computer equipment, electronic equipment, and transportation equipment. In contrast, in panel (b), tariff exposure due to China's retaliatory tariffs had the strongest effects in light-manufacturing sectors such as food & kindred products, furniture, and fabricated metal products.

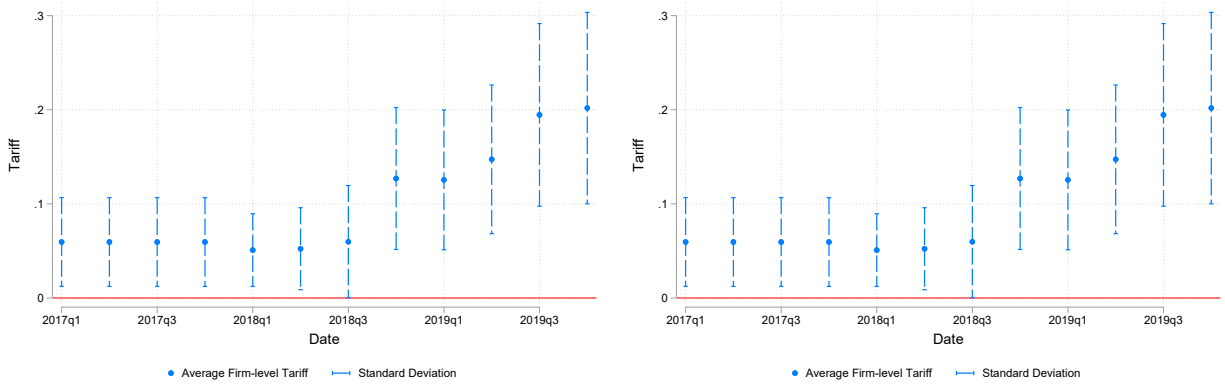
In Figure 3 we show how firms' initial export outcomes correlate with tariff increases during the trade war. We do not find a statistically significant correlation between total exports, exports to the U.S. or the share of exports to the U.S. and changes in tariffs. On the import side, as shown in Figure 3, we see that firms facing the largest increases in Chinese tariffs were those with the largest total imports, largest imports from the U.S., and a largest share of imports from the U.S.

variation in tariff rates within HS6.

[24] To construct HS6–level trade war tariffs for Chinese imports from the U.S., we take a weighted average of the tariffs originally reported at the 8-digit level of the Chinese version of the Harmonized System, with weights equal to Chinese imports from the U.S. in 2017. The result is nearly identical to using an unweighted average of 8-digit tariffs.

[25] Appendix Table B.4 provides more detailed statistics on the time pattern of tariff exposure changes.

Figure 2: Export and Import Tariff Exposure of Chinese Listed Firms



(a) U.S. Tariff on Chinese Goods

(b) Chinese Tariff on U.S. Goods

Notes: These figures plot the evolution of the mean and standard deviation of the firm-level measures of exposure to U.S. tariffs on Chinese goods (panel a)) and Chinese tariffs on U.S. goods (panel B)).

Overall, these summary statistics demonstrate that higher exposure to trade war tariffs was correlated with baseline firm characteristics, such as size. For this reason, our regression analysis will control for firm characteristics and rule out pre–existing trends.

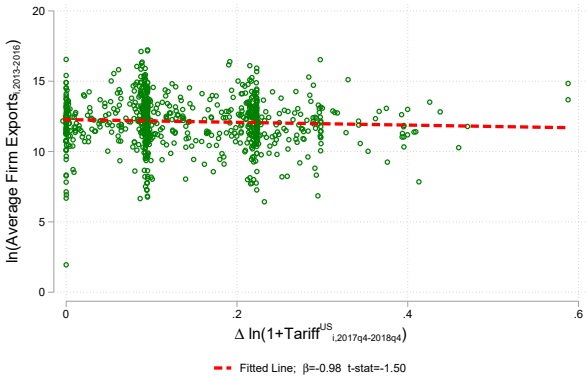
3.4 Firm-level Trade Policy Uncertainty Measure

To construct a firm-level time-varying measure of trade policy uncertainty, we employ Caldara et al. (2019)'s method of textual analysis. We collect all reports filed by companies listed in the Shanghai and Shenzhen Stock Exchange's domestic A share markets, and apply the technique to the transcripts of annual reports released by Chinese listed firms for each year between 2008 and 2018. These annual reports document public companies' activities, including the names of key staff, what the companies did and why in each financial year, main financial indicators and operational performance measures, as well as information about future ventures and plans.[26]

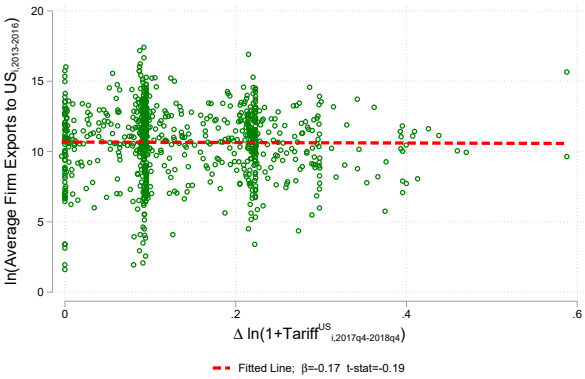
The reports are scraped from *East Money Information* (a financial data provider in China) in PDF format. We then convert the reports to text and translate the firm names from English (as reported in COMPUSTAT Global) into Chinese, so we can manually match them to the listed firms which have annual reports. Appendix Table B.5 summarizes the number of firms in COMPUSTAT Global that are matched to their annual

[26]The Accounting Standard for Business Enterprises promulgated by the Ministry of Finance of China requires that all Chinese firms use December 31 as the end date for the financial year. Detailed information on Chinese accounting standards and rules on information disclosure are provided in Appendix D.

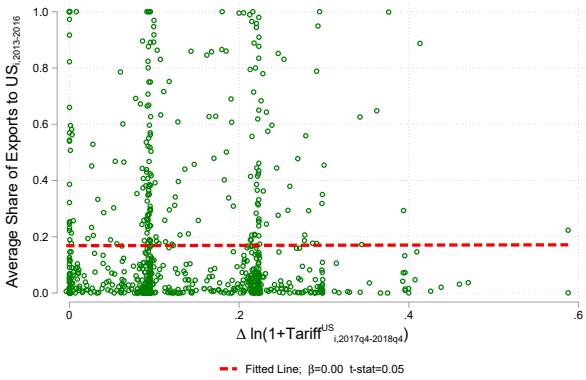
Figure 3: Initial Exports and Exposure to U.S. Tariffs



(a) Total Exports



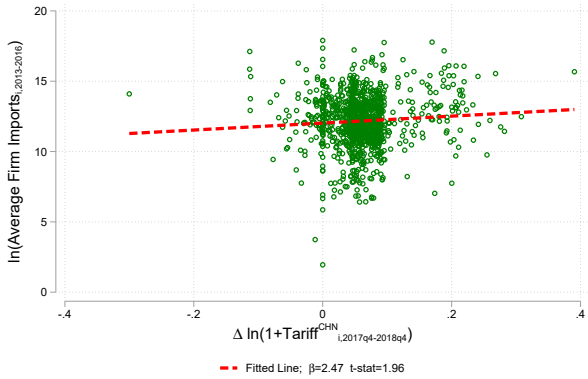
(b) Exports to the U.S.



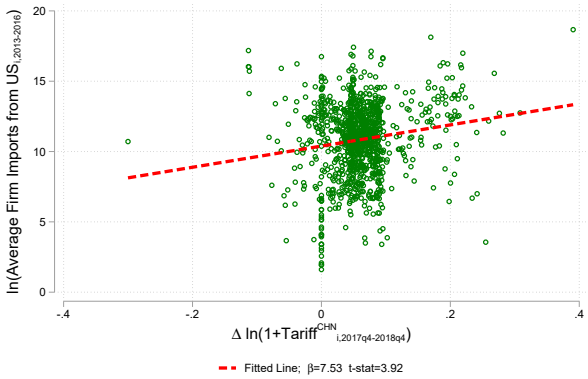
(c) Share of Exports to the U.S.

Notes: This figure shows the relationship between initial (pre–trade war) firm level export outcomes (averaged over 2013-2016) and the change in the firm–level measure of exposure to U.S. tariffs between 2017Q4 and 2018Q4, which is the period used in our regression analysis.

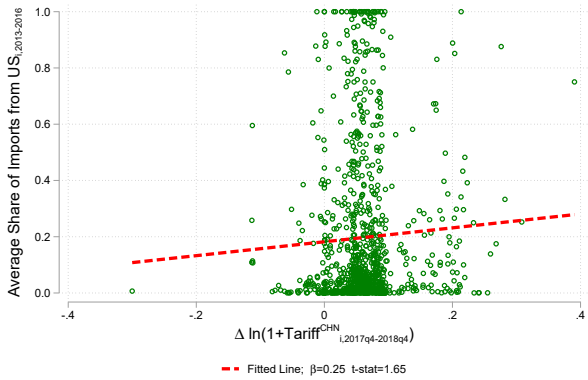
Figure 4: Initial Imports and Exposure to Chinese Tariffs



(a) Total Imports



(b) Imports from the U.S.



(c) Share of Imports from the U.S.

Notes: This figure shows the relationship between initial (pre–trade war) firm level import outcomes (averaged over 2013-2016) and the change in the firm–level measure of exposure to Chinese tariffs between 2017Q4 and 2018Q4, which is the period used in our regression analysis.

reports. As annual reports are only available for listed firms 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 U.S. Through this process we are able to match about 2,400 Chinese COMPUSTAT firms (out of 2,505).[27]

Construction Method Our annual firm-level trade policy uncertainty measures are constructed using a textual analysis of the transcripts of yearly reports of publicly listed companies in China. Our measure counts instances in which trade policy–related words (tariff, protectionism, anti-dumping, etc.) are found in close proximity (in the same line or one line above or below) uncertainty–related words (uncertainty, threat, risks, etc.). We create annual counts of TPU-related instances for each firm. We use annual reports rather than following Caldara et al. (2019) construction of quarterly measures given the lack of sufficient information in quarterly or half-year reports.[28] Hence, a limitation of our approach is missing high–frequency variation in TPU, yet we still are able to estimate large impacts of TPU on firm outcomes, of the same order of magnitude as those found by Caldara et al. (2019) for the U.S. This evidence is particularly important for the understanding of the impacts of the trade war on firms and for the guidance of future trade policy decisions. The construction method is similar to Caldara et al. (2019), and consists of three steps.

Table 2: 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 Appendix Figure C.5 for instance). In the second step, we search each line for the keywords related to uncertainty or future risk (regardless of whether they are related to trade policy), such as *uncertainty* and *risk*. Third, we isolate the uncertainty-related words that are also related to trade policy. We search each line for trade policy

[27] Appendix Figure C.5 displays an example of an annual report for *Angang Steel Company* (which has a COMPUSTAT GVKEY 205808). The figure 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.

[28] Most quarterly or half-year reports provide limited information, and the content from these reports is reiterated in the annual reports.

related keywords such as *tariff*, *import duty*, *export tariff*, *protectionism*, *unilateralism*, *trade barriers*, and *anti-dumping*. Figure 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*). Finally, our measure of trade policy uncertainty counts the number of cases in which we find uncertainty-related words and trade policy-related words in the same line or one line above or below. This count is then normalized by the length of the report. Table 2 reports the keywords associated with uncertainty and trade policy used. The choice of trade policy and uncertainty–related words follows the textual analysis in Caldara et al. (2019) closely. Small differences between both papers in this regard, are due to the difference in writing between the Chinese and English languages.[29]

Formally, the firm-level TPU measure for firm i in year t is computed according to the following expression:[30]

$$TPU_{it} = \frac{1}{R_{it}} \sum_{w=1}^{R_{it}} \left\{ \mathbb{1}\left[w \in \text{Keywords}^{\text{Trade Policy}} \right] \times \mathbb{1}\left[|w - r| \leq \text{One line} \right] \right\} \ , \tag{3}$$

where $w = 1, ..., R_{it}$ are the words contained in the annual report of firm i in year t; the length of report R_{it} is measured as the total number of words; and r is the position of the nearest uncertainty–related keyword (i.e., $r \in \text{Keywords}^{\text{Uncertainty}}$). According to equation (3), our TPU measure counts cases in which trade policy-related words are contained in the same line or one line above or below uncertainty-related words.[31]

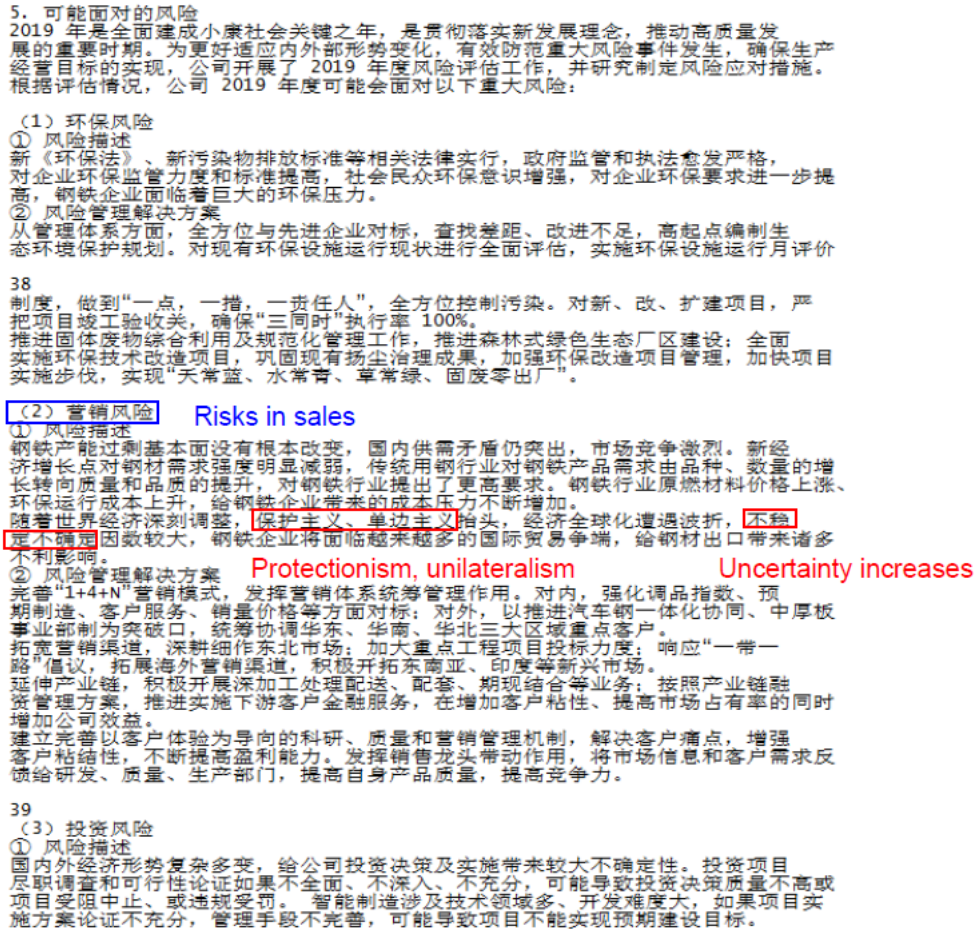
To confirm that our newly constructed firm-level TPU measures reflect exposure to the

[29]For example, Chinese characters tend to have a larger number of different meanings and compounds than English words (Pasquarella et al. (2011); Deng et al. (2014)). For instance, "*tari**", "*import dut**", and "*import tax**" could be expressed with Chinese charaters "*guan1shui4*". Another example is that "*worr**", "*concern**", and "*fear**" have very similar meanings in Chinese, and could be expressed with "*dan1xin1*". A second difference comes from the fact that some abbreviations like "*GATT*" and "*MTA*" are not widely used in writing. Instead, they are more frequently expressed as "**xie2ding4*". An asterisk indicates a search wild card. Third, we avoid some keywords in Caldara et al. (2019) for which the translated Chinese phrase could have multiple meanings and a wide number of applications in the Chinese context, making them quite different from the neutral meaning intended by the English words. For example, the Chinese meaning of the translated word for "*potential*" is not quite related to uncertainty because it is usually used with positive– and negative–tone words.

[30]In addition to measuring TPU as the number of TPU counts normalized by the length of a report, we also experiment with the TPU measure based on the total number of TPU counts (i.e., $TPU_{it} = \sum_{w=1}^{R_{it}} \left\{ \mathbb{1}\left[w \in \text{Keywords}^{\text{Trade Policy}} \right] \times \mathbb{1}\left[|w - r| \leq \text{One line} \right] \right\}$). Results remain similar.

[31]Note that a line consists of about thirty Chinese characters on average. For robustness, we also use a more strict criteria – we require that the trade-related words are in the same line with the uncertainty-related words. Appendix Table B.6 summarizes the firm-level exposure to TPU by year.

Figure 5: Example: Trade Policy and Uncertainty Keywords in the Annual Report of 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，不稳定不确定因素较大，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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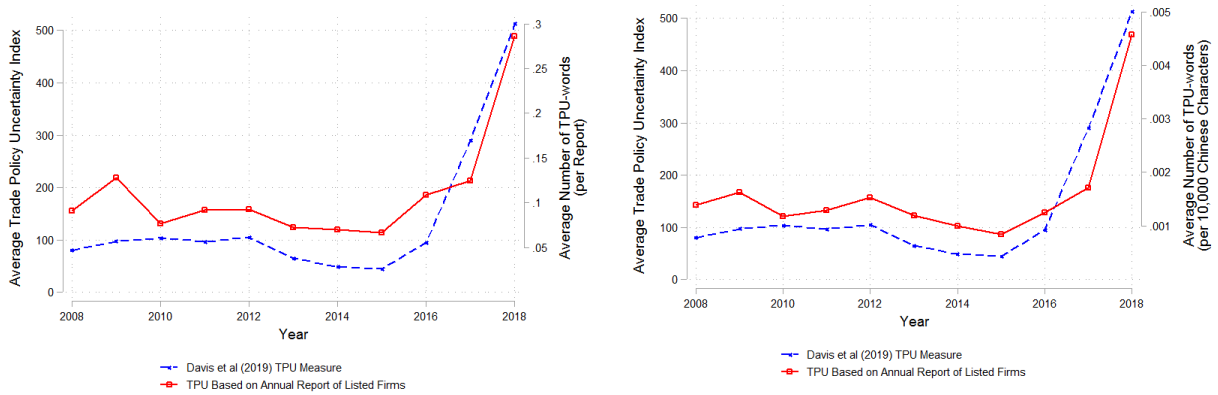
（3）投资风险
① 风险描述
国内外经济形势复杂多变，给公司投资决策及实施带来较大不确定性。投资项目尽职调查和可行性论证如果不全面、不深入、不充分，可能导致投资决策质量不高或项目受阻中止、或违规受罚。 智能制造涉及技术领域多、开发难度大，如果项目实施方案论证不充分，管理手段不完善，可能导致项目不能实现预期建设目标。

Notes: This example consists of one page of the annual report of Angang Steel Company in year 2018. Marked in red are words associated with trade policy which appear in the same line as words associated with uncertainty, adding one unit to the TPU measure. Marked in blue are uncertainty–related words that are not counted, as there are no words related to trade policy in the same line or in the lines immediately above or below.

Figure 6: Aggregate TPU Based on Annual Reports of Listed Firms and by Davis et al. (2019)



(a) Number of TPU Related Words Per Report

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

Notes: In this figure, the TPU measure counts cases in which trade policy-related words are contained in the same line or one line above or below uncertainty-related words. In panel (a), TPU is measured as the number of TPU counts per report; we also measure TPU using the number of TPU counts per 10,000 Chinese characters as shown in panel (b).

U.S.-China trade war, we compare our new measures with the indices created by Davis et al. (2019) based on two mainland Chinese newspapers.[32] To facilitate comparison we aggregate our firm-level series to create a national index and compare it with Davis et al. (2019). We plot both series in Figure 6.[33] Notably, the two series evolve closely, both when we create our index based on the total number of TPU counts per report (panel (a)) or the number of TPU counts normalized by the length of each report (panel (b)). Both series are fairly flat prior to 2016. In contrast, following Trump's election in November 2016, our TPU index based on annual reports increased by more than 300% between 2016 and 2018.[34] In Appendix Table B.7, we list ten 3-digit SIC industries facing the largest degree of trade policy uncertainty in 2018. The mean industry-level measure is computed by averaging all firms in a particular industry. In panel (I), our TPU measure counts cases in which trade policy–related words are contained in the same line or one line above or below uncertainty–related words. In panel (II), we require that the trade policy–related

[32]The two newspapers are 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.

[33]The TPU measure in Figure 6 is constructed following the rule that trade policy and uncertainty keywords are found in the same line or one line above or below. A similar pattern is observed in Appendix Figure C.6, which has a TPU measure based on a more strict criterion: that trade policy and uncertainty keywords are found in the same line.

[34]In Appendix E we show that during the trade war, there was also an important increase in economic uncertainty, captured by stock market price volatility in China.

words and the uncertainty words are both contained in the same line. Regardless of the measure chosen, we find that sectoral TPU reached higher levels for the textile and apparel manufacturing, fabricated metal products, and telephone communication & transportation equipment industries. In sum, our new TPU measures for Chinese firms during the trade war match the aggregate trends contained in Davis et al. (2019), while providing the first granular measures that document the firm-level evolution of Chinese TPU during the trade war.

How does trade policy uncertainty relate to each firm's previous export and import activities? In Appendix Figure C.7 (panel (a)) we plot the 2017–2018 change in firm-level TPU against firm average exports in the period prior to the trade war (2013-2016). The slope coefficient is positive and significant, indicating that firms exporting more in the period before the trade war experience greater TPU exposure during 2017 and 2018. We also see a positive relationship between initial exports to the U.S. (or the share of exports to the U.S.) and the increase in TPU during the trade war. We repeat the same exercise for firm imports, as displayed in Appendix Figure C.8, but do not find statistically significant associations between initial import outcomes and TPU changes.

Controlling for Trade Policy Sentiment Our trade policy uncertainty measure captures a second moment effect. Following Hassan et al. (2020) and Hassan et al. (2019), we also construct a measure of trade policy sentiment (TPS), which captures the first moment effect. This is an important control variable in our analysis, given the possibility that risk and sentiment measures may be correlated. Following these papers, the TPS measure is based on a count of instances in which trade policy–related words are surrounded by positive– and negative–tone words. Appendix F provides further details of its construction.

4 Firm-level Impact of the 2018-2019 Trade War on TPU

As the previous section documents, there is a positive correlation between our newly-constructed firm-level TPU measure and a number of facets of firm-level trade engagement. To formally investigate the relationship between firm-level trade war tariffs and TPU we implement the following first-differences regression:

$$\Delta\text{TPU}_i = \alpha + \beta\Delta\log(1 + \text{Tariff}_i^{\text{U.S.}}) + \gamma\Delta\log(1 + \text{Tariff}_i^{\text{CHN}}) + \delta X_i + \psi_{\text{REG}} + \psi_{\text{IND}} + \varepsilon_i \quad (4)$$

where Δ denotes changes between 2017Q4 and 2018Q4.[35] The dependent variable, ΔTPU_i, measures the change in firm i's trade policy uncertainty measure between 2017Q4 and 2018Q4.[36] The independent variable $\Delta\log(1 + \text{Tariff}_i^{\text{U.S.}})$ denotes the change in $\text{Tariff}_i^{\text{U.S.}}$ between 2017Q4 and 2018Q4, where $\text{Tariff}_i^{\text{U.S.}}$ is firm i's exposure to U.S. tariffs on Chinese imports. Likewise, $\Delta\log(1 + \text{Tariff}_i^{\text{CHN}})$ denotes the change in $\text{Tariff}_i^{\text{CHN}}$ between 2017Q4 and 2018Q4, where $\text{Tariff}_i^{\text{CHN}}$ is a measure of firm i's exposure to Chinese tariffs on its imports from the U.S. We also control for firm characteristics, X_i, which includes revenue, capital and profits in 2017Q4. We control for region- (ψ_{REG}) and industry- (ψ_{IND}) specific trends with fixed effects.[37] The TPU measure might capture many factors, beyond tariffs, that elevate trade uncertainty: concerns range from the implications of currency movements or demand shocks, to the implications of local policy efforts and/or factor cost changes that promote or inhibit trade opportunities, to the emergence of new competitors. The controls are meant to capture many of the sources of TPU heterogeneity across firms, as they relate to firms' industries, regions, or characteristics.

Table 3 reports the first set of results. In column (1), we report the impact of U.S. tariffs on firm-level TPU in the absence of control variables. The coefficient is positive and statistically significant, implying that U.S. tariffs, which act as a barrier on Chinese exports to the U.S., increase TPU. The coefficient of 0.314 indicates that a ten percentage point increase in the U.S. tariff exposure measure is associated with 0.074 standard deviations increase in TPU. In column (2), we report the impact of Chinese tariffs on TPU, again in the absence control variables. Here too, we find a positive and statistically significant relationship. The coefficient of 0.701 indicates that a ten percentage point increase in the Chinese tariff exposure measure is associated with 0.165 standard deviations increase in

[35] Since annual reports are issued on a yearly basis, there is a single firm-level TPU measure per year. The most recent measure available for our project corresponds to 2018. The trade war tariff increases started in early 2018. 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.

[36] Specifically, we follow equation (3) to define the measure TPU as the number of TPU counts normalized by the length of a report. Here, our measure counts cases in which trade policy–related words are in the same line or one line above or below uncertainty–related words; the denominator is the total number of Chinese characters in the report. Because the mean and standard deviation of TPU are very small numbers, without loss of generality, we multiply this measure by 100,000. The mean and standard deviation of adjusted TPU are 0.117 and 0.425, respectively, in the year 2017.

[37] The administrative units are currently based on China's three-level method of classification. The country is first divided into provincial units, including provinces (e.g., Jiangsu Province), autonomous regions (e.g., Tibet), and municipalities directly under the central government (e.g., Beijing, Shanghai, Chongqing, and Tianjin). Prefecture-level divisions are the second level of the administrative structure, and most provincial units except municipalities are divided into only prefecture-level cities without any other units. In this paper, each region refers to the unit in the first level of the administrative structure – autonomous regions, province municipal city (i.e., municipality) and province. For details, see http://xzqh.mca.gov.cn/statistics/2018.html. Industry is defined at the SIC-3-digit level as reported in COMPUSTAT and the number of industries in the sample is 112.

Table 3: Trade Policy Uncertainty and Tariffs: 2017Q4–2018Q4

	Dependent Variable: ΔTrade Policy Uncertainty					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})$	0.314***		0.247**	0.151	0.147	0.117
	(0.122)		(0.126)	(0.131)	(0.133)	(0.141)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$		0.690**	0.558*	0.705**	0.652**	0.556*
		(0.297)	(0.308)	(0.303)	(0.310)	(0.325)
Firm Characteristics	No	No	No	No	Yes	Yes
'Decoupling' Controls	No	No	No	No	No	Yes
Region FE	No	No	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes
Observations	2,160	2,160	2,160	2,148	2,116	2,116
R-squared	0.003	0.003	0.005	0.078	0.080	0.082

Notes: The dependent variable is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. $\text{Tariff}^{\text{U.S.}}$ denotes the firm-level measure of exposure to U.S. tariffs on imports from China, computed as a weighted average across each firm's set of products exported to the U.S. $\text{Tariff}^{\text{CHN}}$ denotes the firm-level measure of exposure to Chinese tariffs on imports from the U.S., computed as a weighted average across each firm's set of products imported from the U.S. $\Delta\log(1+\text{Tariff}^{\text{U.S.}})$ and $\Delta\log(1+\text{Tariff}^{\text{CHN}})$ are percent changes in $\text{Tariff}^{\text{U.S.}}$ and $\text{Tariff}^{\text{CHN}}$ between 2017Q4 and 2018Q4. Firm characteristics in columns 5 and 6 include profit, revenue and capital and are measured in 2017Q4. Additional firm characteristics in column 6 include a dummy variable for multinational affiliates, a dummy variable for firms engaged in processing trade and measures of the share of intermediate inputs in firms' exports and imports. 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.

TPU. In column (3) when we include U.S. and Chinese tariffs together, the coefficients remain similar in magnitude and remain statistically significant.

It is possible that industries targeted by tariffs had a different trend in TPU. The set of products targeted by tariffs were probably not chosen randomly; for example the Trump administration targeted Chinese goods in IT or high–tech industries. Alternatively, unobserved industry shocks might be correlated with changes in TPU. For this reason, in column 4 in Table 3 we add industry (by 3-digit SIC codes) and region fixed effects, which absorb industry– and region–specific trends. The coefficient on U.S. tariff exposure remains positive, but is no longer statistically significant. The coefficient for Chinese tariff exposure, in contrast, remains positive and statistically significant.

Next, in column (5), we control for observable lagged firm-level characteristics such as revenue, capital and profit. This specification addresses the potential concern that larger firms may have experienced increases in both firm-level tariffs and trade policy uncertainty. The results change little when these controls are added to the estimating equation. Quantitatively, a ten percentage point increase in the Chinese tariff exposure

measure is associated with 0.153 standard deviations increase in TPU.

It is possible that beyond the effect of tariffs, the trade war might imply a decoupling of the U.S. and Chinese economies. To the extent that this potential trend is common to all firms, or to all firms within each industry, it would be absorbed by the intercept or by the industry fixed effects. However, it might be the case that it could have a differential effect based on firms' multinational status, or based on the participation of firms in global value chains. This could generate an omitted variable bias. For that reason, in column (6) we control for firm exposure to US-China decoupling via i) a dummy variable for multinational affiliates, ii) a dummy variable for firms engaged in processing trade and iii) measures of the share of intermediate inputs in firms' exports and imports.[38] Notably, the estimated coefficients remain similar with the previous column estimates.

A number of factors may explain why tariffs on Chinese imports were more directly connected to firm-level TPU increases than were tariffs on Chinese exports. First, export diversification may have created a natural hedge against negative export demand shocks.[39] Second, this result suggests the absence of a hedging effect on the import side, and it may imply that trade policy supply shocks are more difficult to hedge against. If the U.S. was a source of customized parts, diversification opportunities were probably more limited. Third, recent evidence in the U.S. shows that the pass-through of import tariffs to final prices is nearly complete (Amiti et al. (2019)); that is, the U.S. importers bear nearly all tariff burden. Recently, using the most up-to-date customs data, Ma et al. (2021) also find that the pass-through of China's retaliatory tariffs is almost complete, which is in line with the fact that the perception of TPU of Chinese importers is more sensitive to import tariff changes.

4.1 Pre-Existing Trends

Another potential concern is that tariffs may have targeted particular firms (e.g., large Chinese exporters within an industry) and that those firms also had pre-existing trends in TPU (i.e., those firms were already exhibiting a steeper increase in TPU than other firms within their industry). In order to alleviate this concern, we check for pre-existing trends in firm-level trade policy uncertainty. We regress the change in firm i's trade policy

[38] Multinational affiliate are defined as foreign owned firms based on China's *Firm Administrative Registration Database*, which is maintained by China's State Administration for Industry and Commerce (SAIC) and covers the universe of firms in China. Firms engaged in processing trade are defined based on the customs data identifiers. Measures of the share of intermediate inputs in firms' imports and exports are constructed using customs data for year 2016.

[39] However, as we show below, this hedging was not without limit. It appears that firms with excessive dependence on U.S. sales were less insulated, possibly due to the fixed costs of quickly locating and entering new markets as U.S. sales declined.

uncertainty between 2016Q4 and 2017Q4 against the change in firm i's tariff exposure measures between 2017Q4 and 2018Q4 as follows:

$$\Delta_{16Q4-17Q4}\text{TPU}_i = \alpha + \beta\Delta_{17Q4-18Q4}\log(1+\text{Tariff}_i^{\text{U.S.}}) + \gamma\Delta_{17Q4-18Q4}\log(1+\text{Tariff}_i^{\text{CHN}}) + \delta X_i + \psi_{\text{REG}} + \psi_{\text{IND}} + \varepsilon_i \ , \tag{5}$$

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

Table 4: Tests for Pre-Existing Trends

	Dependent Variable: $\Delta_{16Q4-17Q4}$Trade Policy Uncertainty					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta_{17Q4-18Q4}$log(1+Tariff$^{\text{U.S.}}$)	0.010		0.008	-0.030	-0.010	-0.019
	(0.082)		(0.085)	(0.094)	(0.095)	(0.100)
$\Delta_{17Q4-18Q4}$log(1+Tariff^{CHN})		0.020	0.016	-0.046	-0.016	0.032
		(0.215)	(0.223)	(0.226)	(0.230)	(0.239)
Firm Characteristics	No	No	No	No	Yes	Yes
'Decoupling' Controls	No	No	No	No	No	Yes
Region FE	No	No	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes
Observations	2,007	2,007	2,007	1,996	1,963	1,963
R-squared	0.000	0.000	0.000	0.083	0.085	0.087

Notes: The dependent variable is the change in firm-level trade policy uncertainty between 2016Q4 and 2017Q4. Tariff$^{\text{U.S.}}$ denotes a firm-level measure of exposure to U.S. 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 exposure to Chinese tariffs on imports from the U.S., computed as a weighted average across each firm's set of products imported from the U.S. Δlog(1+Tariff$^{\text{U.S.}}$) and Δlog(1+Tariff^{CHN}) are percent changes in Tariff$^{\text{U.S.}}$ and Tariff^{CHN} between 2017Q4 and 2018Q4. Firm characteristics in column 5 include profit, revenue and capital and are measured in 2017Q4. Additional firm characteristics in column 6 include a dummy variable for multinational affiliates, a dummy variable for firms engaged in processing trade and measures of the share of intermediate inputs in firms' exports and imports. 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 4 reports these pre-trend tests for trade policy uncertainty. Across all specifications, we do not find any statistically significant relationship between pre-period changes in trade policy uncertainty and tariff changes.

4.2 Heterogeneity in TPU Response

Firm Size Next, we explore whether the trade war tariffs differentially impacted firm trade policy uncertainty depending on firm size. To this end, we augment our baseline equation with two interaction terms as follows:

$$\begin{aligned}\Delta\text{TPU}_i = \alpha &+ \beta_1 \Delta\text{log}(1+\text{Tariff}_i^{\text{U.S.}}) + \beta_2 \Delta\text{log}(1+\text{Tariff}_i^{\text{U.S.}}) \times \text{log}(\text{Revenue}_i) \\ &+ \gamma_1 \Delta\text{log}(1+\text{Tariff}_i^{\text{CHN}}) + \gamma_2 \Delta\text{log}(1+\text{Tariff}_i^{\text{CHN}}) \times \text{log}(\text{Revenue}_i) \\ &+ \delta X_i + \psi_{\text{REG}} + \psi_{\text{IND}} + \varepsilon_i \ , \end{aligned} \tag{6}$$

where 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 5, we start by estimating the equation with firm-level U.S. tariff exposure and its interaction term with log revenue, which is our baseline 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 with log revenue. We find that γ_2 is negative and statistically significant. In column (3), we then estimate the full equation above and find that the coefficient β_2 is -0.239 and statistically significant at the 5 percent level. The coefficient γ_2 is -0.234 and statistically insignificant. Hence, we conclude that only the impact of U.S. tariff exposure on trade policy uncertainty differs across firms of different sizes. As the estimated effect of the U.S. tariffs on TPU is $1.635 - 0.239 \times log(Revenue_i)$, the effect on TPU would be zero when $log(Revenue_i) = 6.84$ which is positioned at the 73rd percentile of $log(Revenue_i)$.[40]

We next turn our attention to differential responses across firms as related to differences in firms' size as measured by capital stocks. We thus replace the log revenue interaction terms with new interaction terms that use log capital. Then, we repeat the analysis from columns (4) to (6) in Table 5. In column (6) when both U.S. and Chinese tariffs are considered, β_2 and γ_2 are negative and statistically significant. This implies that the impact of U.S. tariffs and/or Chinese tariff exposure on trade policy uncertainty is mitigated as firms' capital stock increases. As the estimated effect of the U.S. tariffs on TPU is $1.392 - 0.194 \times log(Capital_i)$, the effect on TPU would be zero when $log(Capital_i) = 7.18$ which is positioned at the 72nd percentile of the $log(Capital_i)$.[41]

[40] The impact of U.S. tariffs on trade policy uncertainty is 0.561 standard deviations lower as a firm's revenue doubles.

[41] Quantitatively, as a firm's capital stocks double, the impact of U.S. tariffs on trade policy uncertainty is 0.455 standard deviations lower, while the impact of Chinese tariffs on trade policy uncertainty is 0.847 standard deviations lower.

Table 5: Trade Policy Uncertainty, Tariffs, and Size: 2017Q4–2018Q4

	Dependent Variable: ΔTrade Policy Uncertainty					
	Interaction with Revenue			Interaction with Capital		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})$	1.872***		1.635***	1.740***		1.392**
	(0.590)		(0.609)	(0.594)		(0.611)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$		3.352**	2.227		4.044***	3.136**
		(1.376)	(1.407)		(1.324)	(1.346)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})\times\log(\text{Revenue})$	-0.264***		-0.239**			
	(0.095)		(0.098)			
$\Delta\log(1+\text{Tariff}^{\text{CHN}})\times\log(\text{Revenue})$		-0.398*	-0.234			
		(0.213)	(0.219)			
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})\times\log(\text{Capital})$				-0.235**		-0.194**
				(0.094)		(0.097)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})\times\log(\text{Capital})$					-0.489**	-0.361*
					(0.190)	(0.193)
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	2,116	2,116	2,116	2,116	2,116	2,116
R-squared	0.082	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. $\text{Tariff}^{\text{U.S.}}$ denotes the firm-level measure of exposure to U.S. tariffs on imports from China, computed as a weighted average across each firm's set of products exported to the U.S. $\text{Tariff}^{\text{CHN}}$ denotes the firm-level measure of exposure to Chinese tariffs on imports from the U.S., computed as a weighted average across each firm's set of products imported from the U.S. $\Delta\log(1+\text{Tariff}^{\text{U.S.}})$ and $\Delta\log(1+\text{Tariff}^{\text{CHN}})$ are percent changes in $\text{Tariff}^{\text{U.S.}}$ and $\text{Tariff}^{\text{CHN}}$ between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue and capital and 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.

In both cases (i.e., revenue and capital), the results suggest that the increased tariffs elevated TPU for the smallest two thirds of firms. One explanation could be that these firms might have benefited most from using U.S. sourcing to improve the quality of their products, which previously was facilitated by trade liberalization. Consequently, if Chinese firms were sourcing optimally before the trade war, the reversal of opportunities due to the trade war implies that the damage would be greatest for these firms which are likely to be characterized by small revenue and low productivity (Fan, Li and Yeaple, 2018).[42]

Trade Diversification In addition to the quality channel, the effect of tariffs on TPU could also depend on firms' product and market diversification patterns. Firm-level diversification will matter if the detrimental economic impacts of tariff shocks could be mitigated by strategically switching markets or by re-allocating sales across products. This

[42] Fan, Li and Yeaple (2018) find that, around the time of China's WTO accession, lower productivity firms benefited more from the accession due to the quality upgrading that was facilitated by trade liberalization.

implies that the adverse effects of firm-level TPU increases should have been smaller for more internationally diversified firms as measured by the number of partner countries and the number of products.

To operationalize the idea of diversification, we exploit the transactions data from Chinese customs at the firm-product-country level. We compute the number of exported and imported products, and the number of destination and source markets between 2013 and 2016 at the firm-level. Then, we incorporate these variables in our baseline equation as follows:

$$\begin{aligned}\Delta\text{TPU}_i = \alpha &+ \beta_1 \Delta\text{log}(1+\text{Tariff}_i^{\text{U.S.}}) + \beta_2 \Delta\text{log}(1+\text{Tariff}_i^{\text{U.S.}}) \times N_i^{exp,prod} \\ &+ \gamma_1 \Delta\text{log}(1+\text{Tariff}_i^{\text{CHN}}) + \gamma_2 \Delta\text{log}(1+\text{Tariff}_i^{\text{CHN}}) \times N_i^{imp,prod} \\ &+ N_i^{exp,prod} + N_i^{imp,prod} + \delta X_i + \psi_{\text{REG}} + \psi_{\text{IND}} + \varepsilon_i \ , \end{aligned} \tag{7}$$

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

Columns (1) through (3) in Table 6 display the results. Across all specifications, the interaction terms are statistically insignificant, suggesting that more diverse product import or export scope did not reduce Chinese firms' perceived trade policy uncertainty. Next, we replace the total number of products with the total number of countries a firm exports to ($N_i^{exp,ctry}$) or imports from ($N_i^{imp,ctry}$), and report results in columns (4) through (6). According to column (6), faced with an increase in U.S. tariffs of the same magnitude, firms exporting to more countries registered smaller increases in TPU. One additional country in a firm's export basket reduces the impact of U.S. tariffs on firm-level TPU by 0.031 standard deviations. However, we do not uncover any evidence which suggests that importing from more countries mitigated the impact of Chinese tariffs on TPU. These results are also consistent with our previous result that the TPU increase was less pronounced for larger firms measured by revenue or capital, which were also more diversified across trade partners and traded products.[43]

In sum, multi-country exporters registered less evidence of uncertainty increases following an increase in their tariffs, presumably due to their ability to re-route trade (see Kramarz et al., 2020; Caselli et al., 2020). In addition, the result may suggest an element

[43]However, we are agnostic on the effect of TPU on product mix changes, which may be an avenue of future research on the mechanisms behind TPU effects.

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

	Dependent Variable: ΔTrade Policy Uncertainty					
	Number of Products			Number of Partner Countries		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})$	0.289*		0.193	0.595***		0.415**
	(0.151)		(0.152)	(0.193)		(0.193)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})\times N_i^{exp,prod}$	-0.003		-0.003			
	(0.002)		(0.002)			
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})\times N_i^{exp,ctry}$				-0.016***		-0.013**
				(0.005)		(0.005)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$		0.760**	0.718*		0.570	0.555
		(0.374)	(0.367)		(0.461)	(0.472)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})\times N_i^{imp,prod}$		-0.006	-0.006			
		(0.010)	(0.009)			
$\Delta\log(1+\text{Tariff}^{\text{CHN}})\times N_i^{imp,ctry}$					-0.020	-0.020
					(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)
$N_i^{imp,ctry}$					0.006**	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	2,116	2,116	2,116	2,116	2,116	2,116
R-squared	0.080	0.081	0.083	0.082	0.084	0.087

Notes: The dependent variable is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. $\text{Tariff}^{\text{U.S.}}$ denotes the firm-level measure of exposure to U.S. tariffs on imports from China, computed as a weighted average across each firm's set of products exported to the U.S. $\text{Tariff}^{\text{CHN}}$ denotes the firm-level measure of exposure to Chinese tariffs on imports from the U.S., computed as a weighted average across each firm's set of products imported from the U.S. $\Delta\log(1+\text{Tariff}^{\text{U.S.}})$ and $\Delta\log(1+\text{Tariff}^{\text{CHN}})$ are percent changes in $\text{Tariff}^{\text{U.S.}}$ and $\text{Tariff}^{\text{CHN}}$ between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue and capital and 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.

of sunk costs in Chinese firms' exporting. If there are sunk costs of searching for trade partners, or fixed investments that are placed as new export destinations are created, the existence of alternative established trade partners may help explain the diversification effects.

U.S. Dependence Although the majority of firms had sales and/or sourcing in a number of countries, for many the U.S. was their dominant connection. Due to the fixed costs of locating and entering new markets, firms that had the heaviest reliance on U.S. sales may have had less ability to hedge their U.S. export challenges by quickly expanding elsewhere. To test this hypothesis, we construct measures of U.S. reliance based on firm trade prior to the trade war. Specifically, let $D_i^{\text{exp, U.S.-dominant}}$ ($D_i^{\text{imp, U.S.-dominant}}$) be a dummy variable that equals one if the firm's U.S. exports (imports) as a share of its total exports (imports) exceeded a critical value. The new U.S. dependence variables are then incorporated into our baseline regression in the form of interactions with the tariff exposure variables.

Table 7: Trade Policy Uncertainty, Tariffs, and U.S. Dependence: 2017Q4–2018Q4

	Dependent Variable: ΔTrade Policy Uncertainty				
	(1)	(2)	(3)	(4)	(5)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})$	-0.259	0.044	0.116	0.125	0.195
	(0.211)	(0.244)	(0.238)	(0.232)	(0.232)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$	0.243	0.110	0.053	0.870	0.794
	(1.858)	(1.849)	(1.129)	(1.116)	(1.104)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})\times N_i^{exp,ctry}$		-0.009**	-0.009**	-0.009**	-0.009**
		(0.004)	(0.004)	(0.004)	(0.004)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})\times N_i^{imp,ctry}$		0.014	0.015	0.016	0.016
		(0.028)	(0.028)	(0.028)	(0.028)
U.S. Dependence Threshold:	5%	5%	10%	15%	20%
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})$	0.544**	0.561**	0.501**	0.511**	0.404*
$\times D_i^{\text{exp, U.S.-dominant}}$	(0.249)	(0.248)	(0.243)	(0.238)	(0.239)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$	0.376	0.354	0.408	-0.483	-0.394
$\times D_i^{\text{imp, U.S.-dominant}}$	(1.882)	(1.840)	(1.128)	(1.117)	(1.103)
Firm Characteristics	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	2,116	2,116	2,116	2,116	2,116
R-squared	0.083	0.086	0.085	0.086	0.085

Notes: The dependent variable is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. $\text{Tariff}^{\text{U.S.}}$ denotes the firm-level measure of exposure to U.S. tariffs on imports from China, computed as a weighted average across each firm's set of products exported to the U.S. $\text{Tariff}^{\text{CHN}}$ denotes the firm-level measure of exposure to Chinese tariffs on imports from the U.S., computed as a weighted average across each firm's set of products imported from the U.S. $\Delta\log(1+\text{Tariff}^{\text{U.S.}})$ and $\Delta\log(1+\text{Tariff}^{\text{CHN}})$ are percent changes in $\text{Tariff}^{\text{U.S.}}$ and $\text{Tariff}^{\text{CHN}}$ between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue and capital and 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.

As reported in column (1) of Table 7, the impact of U.S. tariffs on firm-level TPU is 1.277 standard deviations higher for U.S. dependent exporters compared to non-U.S. dependent exporters. However, we do not find any heterogeneous impacts of U.S. dependent importers relative to non-U.S. dependent importers. In column (2) of the same table, we add interaction terms for the number of countries a firm exports to or imports from, and the estimation results remain almost unchanged. From columns from (3) to (5), we changed the threshold from 5% to 10%, 15%, and 20%, respectively. Reassuringly, our core results stand. In sum, our findings indicate that the ability to hedge in export markets (row 3) may be diminished when firms have a high level of dependence on U.S. sales (row 5) given the fixed costs of locating and entering new markets.

Aggregate Implications Our reduced-form empirical approach is unable to capture the aggregate impact of increased TPU, as it is not possible to capture the trade war effects that were common to all firms, or any general equilibrium spillovers. In exchange, our approach reveals new findings that can guide model-based computations of the aggregate effects of TPU (Handley and Limão, 2017; Caldara et al., 2019; Steinberg, 2019). First, we find that smaller firms face a larger increase in TPU due to trade war tariffs. Given the well–established fact that exports and imports are highly concentrated among larger and more diversified firms, incorporating this fact into these models could potentially lead to a lower estimate of the aggregate effects of TPU on trade flows. In addition, we establish that TPU affects both exporters and importers. In fact, we find the stronger response of TPU is associated with Chinese tariffs on these firms' imports.[44] This second finding could lead to an upward adjustment of the aggregate effects of TPU relative to computations that only consider tariffs on firms' exports.

4.3 Extensions and Robustness Checks

Firm Orientation To the extent that some Chinese firms focus on serving the domestic market, while others are more heavily involved in exporting, we explore whether our main results change based on firm orientation. For this purpose, we focus on subsets of firms based on indicator variables $\mathbb{1}$(Persistent Exporter) ($\mathbb{1}$(Persistent Importer)) that equal one if the firm exported (imported) in all years between 2013 and 2016. Alternatively, orientation can be defined via the measure of exports-to-revenue or imports-to-cost ratio. Appendix Table G.1 reports the result under both specifications. However, the impact of tariffs on firm TPU remain consistent with the original results reported in Ta-

[44]This is consistent with Handley et al. (2020) who show that the reduction in uncertainty about tariffs following China's WTO entry had an effect on firms' sourcing decisions.

ble 3 for both groups. Next, we include firm orientation variables in our regressions that investigates the role of trade diversification, and provide the results in Appendix Table G.2. As before, we find that firms exporting to a larger number of destination countries experienced smaller increases in TPU.

State–Owned Firms A key institutional feature of the Chinese economy is the presence of state–owned firms. In Appendix H, we explore whether changes in TPU in response to trade war tariffs differed for these firms. To this end we augment equation (4) with the interactions between a dummy variable for state–owned firms and each tariff measure. We do not find a statistically significant coefficient on these interaction terms (see Table H.1).

Firm Financial Positions As suggested in Table 6, firms with a more diversified set of trade relationships experienced smaller increases in TPU. However, this outcome might also be shaped by differences in firms' financial strength. That is, if more diversified firms had better access to financial resources, it is possible that the access to funds rather than diversification explains how diversified firms adapted to the changing environment. To address this concern, we follow Manova and Yu (2016) and construct firm-level financial measures as follows:

$$\text{Liquidity} = \frac{\text{Current assets-Current liabilities}}{\text{Total assets}}, \qquad \text{Leverage} = \frac{\text{Current liabilities}}{\text{Current assets}}.$$

We interact the financial terms with tariffs in our new regression specification. This allows us to determine whether firms that were in a better financial position experienced lower increases in TPU in response to increases in tariffs. However, in Appendix Table G.3 both interaction terms are statistically insignificant. Thus, the results confirm that firm liquidity and leverage were not responsible for mediating the impact of tariffs on TPU during the trade war.

5 Firm-level Impact of TPU on Economic Outcomes

In this section we analyze the detrimental effects of heightened firm-level TPU on three aspects of firm operations: investment, profits and research and development. We also examine the response of inventory dynamics. In each case, our analysis documents the large economic magnitude of these effects that were associated with firm-level TPU changes.

5.1 Investment

To examine the effects of firm-level TPU changes on investment, we estimate the following regression:

$$\log(\mathrm{K}_{i,t+k}) - \log(\mathrm{K}_{i,t}) = \alpha + \beta_1 \Delta\mathrm{TPU}_i + \beta_2 \Delta\mathrm{TPS}_i + \gamma X_i + \psi_{\mathrm{REG}} + \psi_{\mathrm{IND}} + \varepsilon_i \ . \tag{8}$$

The dependent variable, $\log(\mathrm{K}_{i,t+k}) - \log(\mathrm{K}_{i,t})$, measures the percentage change in capital stocks for firm i from t = 2017Q4 to $t+k$, where $t+k = \{18Q4, 19Q1, 19Q2, 19Q3\}$. In this way we capture the dynamic response of capital stocks to TPU developments. The variable $\Delta\mathrm{TPU}_i$ measures the change in firm i's trade policy uncertainty between 2017Q4 and 2018Q4, while $\Delta\mathrm{TPS}_i$ measures the change in firm i's trade policy sentiment during the same period. Recall that the measure of trade policy sentiment (TPS) captures the first moment effect, and is based on a count of instances in which trade policy–related words are surrounded by positive– and negative–tone words.[45] We also control for firm characteristics including profit, revenue and capital in 2017Q4 (X_i), region (ψ_{REG}) and industry (ψ_{IND}) fixed effects, as we did in Section 4.

Table 8: Investment and Trade Policy Uncertainty

	Dependent Variable: Δlog(Capital)			
	(1)	(2)	(3)	(4)
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
ΔTrade Policy Uncertainty (17Q4-18Q4)	-0.037**	-0.038**	-0.044**	-0.053**
	(0.017)	(0.018)	(0.020)	(0.024)
ΔTrade Policy Sentiment (17Q4-18Q4)	0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Firm Characteristics	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,116	2,115	2,108	2,110
R-squared	0.110	0.113	0.111	0.115

Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. ΔTrade Policy Sentiment (2017Q4-2018Q4) is the change in firm-level trade policy sentiment between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue and capital and 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.

The estimation results are reported in Table 8. The coefficient in column (1) reflects the contemporaneous impact of changes in trade policy uncertainty on changes in firm capital stocks between 2017Q4 and 2018Q4. In the second column, the coefficient of -0.038 is negative and statistically significant, and its magnitude implies that a one standard

[45] The trade policy sentiment (TPS) measure is defined in Appendix F.

deviation increase in 2017Q4 - 2018Q4 trade policy uncertainty was associated with a cumulative 1.62 percent decrease in firm-level capital stocks in 2019Q1 compared with 2017Q4. We also report the overall effect of 2017Q4 - 2018Q4 TPU change on capital in 2019Q2 and Q3 in columns (3) and (4). In general, the (negative) magnitudes become larger over time. In 2019Q3, the coefficient β_1 is -0.053 (i.e., a one standard deviation increase in trade policy uncertainty is associated with a 2.26 percent decrease in a firm's capital stock in 2019Q3). 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 stemming from the 2018-2019 trade war immediately discouraged Chinese firm-level investment and led to adverse impacts that grew over time. To compare the magnitudes, note that Caldara et al. (2019) find that at a four quarter horizon, an increase in TPU equal to the median value of TPU among firms with non-zero TPU is associated with a 2 percent decline in a firm's capital stock. With an equivalent computation, we find a 2.62 percent decline in firm capital.[46]

In Appendix Table H.2 we ask whether the impact of TPU on investment differed for state–owned firms. To this end, we interact the TPU measure with a state–owned dummy variable. However, we do not find any statistically significant differences between state–owned firms and the other firms in our sample.

5.2 R&D Expenditures

We also explore the connection between firm-level TPU changes and firm R&D efforts. Since firm R&D expenditures are only recorded annually, the dependent variable for this analysis is the percentage change in R&D between 2017 and 2018. In this specification:

$$\Delta\log(\text{R\&D})_i = \alpha + \beta_1 \Delta\text{TPU}_i + \beta_2 \Delta\text{TPS}_i + \gamma X_i + \psi_{\text{REG}} + \psi_{\text{IND}} + \varepsilon_i \tag{9}$$

ΔTPU_i and ΔTPS_i are the changes in trade policy uncertainty and trade policy sentiment between 2017Q4 and 2018Q4.

In this analysis, our preferred specification, displayed in columns (3) and (6) in Table 9, controls for past firm R&D expenditures as well as firm characteristics and a number of fixed effects. Both illustrate substantial changes in research efforts related to firm-level changes in TPU. For example, the column (6) coefficient of -0.053 implies that a one standard deviation increase in trade policy uncertainty was associated with 2.27 percent

[46]The median value of TPU among firms with non-zero TPU in our sample is equivalent to 1.66 standard deviations in TPU. Given that a one standard deviation increase in TPU is associated to a 1.58 decline in capital stock at a four quarter horizon, we compute 1.66 $\times$ 1.58 = 2.62.

Table 9: R&D Expenditures and Trade Policy Uncertainty

	Dependent Variable: Δlog(R&D) (2017-2018)					
	(1)	(2)	(3)	(4)	(5)	(6)
ΔTrade Policy Uncertainty	-0.030	-0.025	-0.040	-0.043	-0.040	-0.053**
(17Q4-18Q4)	(0.028)	(0.027)	(0.025)	(0.030)	(0.028)	(0.025)
ΔTrade Policy Sentiment	0.002	0.002	0.002	0.001	0.002	0.003
(17Q4-18Q4)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\log(\text{R\&D})_{2017}$		-0.126***	-0.252***		-0.146***	-0.326***
		(0.030)	(0.054)		(0.034)	(0.060)
Firm Characteristics	No	No	Yes	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes
Observations	2,015	2,015	1,988	2,002	2,002	1,977
R-squared	0.020	0.082	0.160	0.069	0.144	0.263

Notes: Δlog(R&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. ΔTrade Policy Sentiment (2017Q4-2018Q4) is the change in firm-level trade policy sentiment between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue and capital and 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.

decrease in R&D expenditure.

5.3 Profits

Next, to test whether heightened firm-level TPU depressed firm profits we estimate the following regression:

$$\Pi_{i,t+k} - \Pi_{i,t} = \alpha + \beta_1 \Delta\text{TPU}_i + \beta_2 \Delta\text{TPS}_i + \gamma X_i + \psi_{\text{REG}} + \psi_{\text{IND}} + \varepsilon_i \ , \tag{10}$$

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 $t+k = \{18Q4, 19Q1, 19Q2, 19Q3\}$). Note that we use the level of profits, i.e., millions of Chinese yuan, instead of the log of profits, to allow for the inclusion of negative values.

Table 10 shows how changes in firm-level TPU affected firm profits over increasingly long intervals of time. Though short-run changes in firm profits displayed in columns (1) and (2) are negative, the coefficients are statistically insignificant. However, when we study firm profit changes over a longer period of time, the negative impact of TPU increases and attains statistical significance, as displayed in columns (3) and (4). According to the estimates, a one standard deviation increase in 2017Q4 - 2018Q4 TPU was associated with 8.7 and 11.5 percent decreases in profits, by 2019Q2 and 2019Q3 respectively.

The dynamic pattern of profit erosion suggests that the adverse impacts of firm-level TPU grew over time.[47]

Table 10: Profits and Trade Policy Uncertainty

	Dependent Variable: ΔProfit			
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
	(1)	(2)	(3)	(4)
ΔTrade Policy Uncertainty	-22.144	-9.935	-19.209*	-25.415*
	(16.387)	(11.286)	(10.420)	(13.405)
ΔTrade Policy Sentiment	1.346	1.576**	1.286**	1.479**
	(0.996)	(0.656)	(0.618)	(0.652)
Firm Characteristics	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,116	2,116	2,112	2,111
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. ΔTrade Policy Sentiment (2017Q4-2018Q4) is the change in firm-level trade policy sentiment between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue and capital and 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.

5.4 Inventories

We also explore the behavior of firms' inventories in response to the uncertainty shock. We define quarterly firm–level inventory intensity as the ratio of inventory to revenue, and modify equation (8) such that the dependent variable is the growth in the inventories to revenue ratio at different horizons.

The results are shown in Appendix Table I.1. We find that the contemporaneous impacts of changes in trade policy uncertainty on changes in inventory intensity are positive, though the coefficients become statistically insignificant as time passes. This is consistent with the inventory dynamics noted by Alessandria et al. (2019), who analyze the adjustment of inventories to TPU. Notably, Alessandria et al. (2019) predict that importers facing an uncertainty shock will initially accumulate inventories. Similarly, we have documented in our earlier tables, how the main impact of tariffs on TPU is driven by Chinese tariffs which affect Chinese firms' imports.

[47]The percent changes are calculated based on the relative magnitude as compared with listed firms' average profit, 94.24 million Chinese yuan, in 2017Q4.

5.5 The Direct Impacts of Tariffs on Economic Outcomes

We have shown how the trade tension increases firm-level trade policy uncertainty, which in turn leads to reductions in firm-level investment, R&D expenditures and profits, and a short–runt increase in inventories, for Chinese listed firms. However, to ensure that our results are based on the effects of trade policy uncertainty, rather than the underlying changes in tariffs, we add the firm-level tariff changes to our specifications as a control for the direct effects of the tariffs, driven by reduced demand for Chinese exports or by increasing costs of imported inputs. To implement this exercise, we augment our baseline equations (8) and (9) which yields new specifications:

$$\begin{aligned}\log(\mathrm{K}_{i,t+k}) - \log(\mathrm{K}_{i,t}) = \alpha + \beta_1 \Delta\mathrm{TPU}_i + \beta_2 \Delta\mathrm{TPS}_i + \beta_3 \Delta\log(1 + \mathrm{Tariff}_i^{\mathrm{U.S.}}) \\ + \beta_4 \Delta\log(1 + \mathrm{Tariff}_i^{\mathrm{CHN}}) + \gamma X_i + \psi_{\mathrm{REG}} + \psi_{\mathrm{IND}} + \varepsilon_i \ , \end{aligned} \tag{11}$$

and

$$\begin{aligned}\Pi_{i,t+k} - \Pi_{i,t} = \alpha + \beta_1 \Delta\mathrm{TPU}_i + \beta_2 \Delta\mathrm{TPS}_i + \beta_3 \Delta\log(1 + \mathrm{Tariff}_i^{\mathrm{U.S.}}) \\ + \beta_4 \Delta\log(1 + \mathrm{Tariff}_i^{\mathrm{CHN}}) + \gamma X_i + \psi_{\mathrm{REG}} + \psi_{\mathrm{IND}} + \varepsilon_i, \end{aligned} \tag{12}$$

where β_1 measures the trade policy uncertainty effect, β_2 captures the impact of trade policy sentiment, and the coefficients β_3 and β_4 capture the direct impacts of U.S. and Chinese tariffs.

Tables 11 and 12 report the estimation results. Reassuringly, the estimated effects of firm-level trade policy uncertainty remain unchanged, even after controlling for the direct impact of tariffs. Notably, in these augmented regressions the direct impacts of U.S. and Chinese tariff exposure measures on investment and profit are statistically insignificant.

Discussion There may be several factors that could explain the absence of direct tariff impacts in these new results. First, the average ratio of exports to the U.S. to total sales for Chinese firms in the sample was roughly 1.7 percent in 2016 according to Chinese customs data and COMPUSTAT Global data.[48] The low ratio suggests that the output loss resulting from rising U.S. tariffs would be quite limited even if U.S. tariffs in a firm's industry rose substantially. Similarly, this would explain the negligible investment and

[48]The calculation is based on the COMPUSTAT sample restricted to manufacturing sectors. The average ratio of exports to the U.S. is computed as U.S. exports relative to total revenues including domestic sales. As not all manufacturing firms are exporters, we set exports of the non-exporting firms as zero in the above calculation.

Table 11: Investment, Trade Policy Uncertainty, and Tariffs

	Dependent Variable: Δlog(Capital)			
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
	(1)	(2)	(3)	(4)
ΔTrade Policy Uncertainty	-0.039**	-0.039**	-0.046**	-0.055**
	(0.017)	(0.019)	(0.020)	(0.024)
ΔTrade Policy Sentiment	0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})$	0.092	0.058	0.116	0.165
	(0.086)	(0.093)	(0.100)	(0.115)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$	0.190	0.183	0.214	0.244
	(0.164)	(0.176)	(0.191)	(0.207)
Firm Characteristics	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,116	2,115	2,108	2,110
R-squared	0.111	0.114	0.112	0.116

Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. ΔTrade Policy Sentiment (2017Q4-2018Q4) is the change in firm-level trade policy sentiment between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue and capital and 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.

profit changes associated with tariff changes.[49]

The absence of a connection between trade war tariffs and firm operational outcomes could also arise if Chinese firms mananaged to avoid trade war tariffs by re-routing their exports through third countries. Liu and Shi (2019) find that trade re-routing has been used by Chinese firms in the past to avoid antidumping duties.[50] Though data limitations prevent us from examining firm re-routing responses, evidence from Chau and Boudreau (2019) suggests that some re-routing took place during the trade war. According to their report, exports from Vietnam to the U.S. have grown strongly in 2019 and many products,

[49]U.S. import shares for firms in our sample are also small, possibly leading to the absence of effects related to China's rising retaliatory tariffs. In Appendix J, we further investigate the robustness these findings. By adding interaction terms our additional exercises seek to explore whether the direct impact of U.S. and Chinese tariff exposure was stronger for firms that had larger export to and/or import from the U.S. As reported in Appendix Tables J.1 and J.2 coefficients on the interaction of U.S. tariffs and U.S. export shares are insignificant, while the interaction between Chinese tariffs and U.S. import shares are negative and significant, though only for the longest estimation window. This suggests that Chinese retaliatory tariffs were harmful to the subset of Chinese firms that sourced the most heavily from the U.S. while they were of little consequence to most firms. This implies that import sourcing was probably less flexible for critical parts embedded in the ongoing relationship between Chinese firms and U.S. exporters.

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

Table 12: Profit, Trade Policy Uncertainty, and Tariffs

	Dependent Variable: ΔProfit			
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
	(1)	(2)	(3)	(4)
ΔTrade Policy Uncertainty	-23.472	-9.023	-17.657*	-24.787*
	(16.431)	(11.376)	(10.546)	(13.625)
ΔTrade Policy Sentiment	1.367	1.560**	1.264**	1.467**
	(1.001)	(0.662)	(0.624)	(0.657)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})$	75.113	-39.889	-100.345	-7.947
	(122.037)	(78.956)	(87.298)	(78.804)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$	183.242	-140.604	-194.060	-121.363
	(213.160)	(148.747)	(185.897)	(157.629)
Firm Characteristics	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,116	2,116	2,112	2,111
R-squared	0.142	0.269	0.192	0.251

Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. ΔTrade Policy Sentiment (2017Q4-2018Q4) is the change in firm-level trade policy sentiment between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue and capital and 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.

such as plywood produced in China, may be shipped to the U.S. with 'Made in Vietnam' labels.

Third, the negative operational effects of trade war tariffs may be mitigated by trade diversification. For instance, if Chinese firms easily switched buyers, then the direct negative impacts of tariffs on firm-level investment and profits would be diminished.[51] Indeed, the Chinese government implemented policies to help Chinese producers to switch to other partners.[52]

Since the firms in the analysis are relatively large, the majority engage in a wide range of business activities. For this reason, a final margin for mitigating the impacts of trade

[51] Our TPU analysis uncovers a real hedging channel by which Chinese exporters that are more diversified in terms of destination markets experience smaller increases in trade policy uncertainty.

[52] According to a report by CNBC, the Chinese government has taken four approaches to support its firms during the trade war: 1) increasing government support, 2) opening channels to other international markets through programs such as free trade zones and the Belt and Road Initiative, 3) improving the environment for state-owned and foreign enterprises and 4) 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 for details). Another adjustment margin is noted by Cavallo et al. (2021) which notes how U.S. retailer imports increased after the initial tariff announcements, but in advance of tariff implementation. Thus, by completing sales/purchases in advance, Chinese firms may have succeeded in reducing the direct effect of tariffs on firm operations.

war tariffs was to re-focus firm operations away from trade-oriented activities and towards non-trade business opportunities, thereby sustaining firm-level revenues. In contrast, since rising TPU inherently interferes with firm planning, the rises in TPU rationalize why firms had an interest in reducing, or at least postponing, new investments, as we find in our analysis.[53]

6 Conclusions

In this paper, we explore the sources and consequences of trade-policy uncertainty during the ongoing U.S.-China trade war. Our analysis is based on a novel measure of firm-level TPU constructed from a textual analysis of firm-level statements, and firm-specific measures of exposure to trade war tariffs based on customs data and tariff lines. The firm-level TPU measure accurately tracks existing aggregate indices of TPU in China, and reveals the dramatic rise in firm-level TPU during the trade war.

Our first contribution is to open the TPU black box. While it has been generally acknowledged that TPU must have played a role in the trade war (IMF, 2018), there is little understanding of how the process works, the magnitude of this channel, and which firms were most exposed to its effects. We move in this direction by taking advantage of firm-level variation across Chinese firms in their exposure to the trade war. We show that firm-level increases in TPU experienced during this period were systematically associated with firm-level exposure to both U.S. tariffs (which lowered U.S. demand for Chinese exports) and Chinese tariffs (which raised the cost of imported inputs for Chinese firms). We further show that the impact of tariffs on TPU was heterogeneous across firms, as the tariff effect on TPU was largest for smaller and less diversified firms.

The second contribution of our paper is to document the negative consequences of the TPU spike on firm-level investment, R&D expenditures and profits, along with firm-level short–run increases in inventories. Our work allows us to identify the timing of TPU effects, including the changes over the short- to medium-run. Notably, TPU effects on firms' operational results are quantitatively important, even after controlling for the direct impact of tariffs. The estimates imply that a one standard deviation increase in firm-level TPU was associated with investment, R&D expenditures, and profit declines of 2.3, 2.3, and 11.5%, respectively. We show that these effects of firm-level TPU, which capture second–moment effects, are robust to controlling for the first moment effects measured by changes in firm-level trade policy sentiment.

[53] By modeling firms' dynamic sourcing decisions, Handley et al. (2020) show that firms tend to postpone making investment decisions in the presence of trade policy uncertainty.

Overall, our work highlights the economic importance of *trade policy uncertainty* during the ongoing U.S.-China trade war. The paper also illustrates the benefits of new measures of firm-level uncertainty based on textual analysis of firm statements (Hassan et al., 2020, 2019; Caldara et al., 2019). The stylized facts established by these responses to the US-China trade war, will be useful for shaping future models in which firms respond endogenously to developements in trade policy uncertainty.

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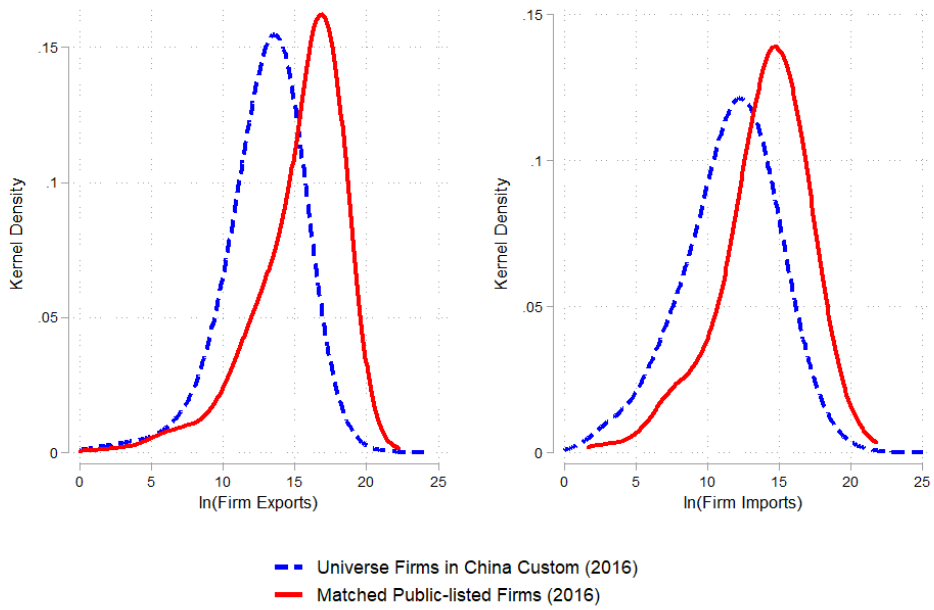
Appendix

Appendix A: Comparison of our Sample to All Trading Firms

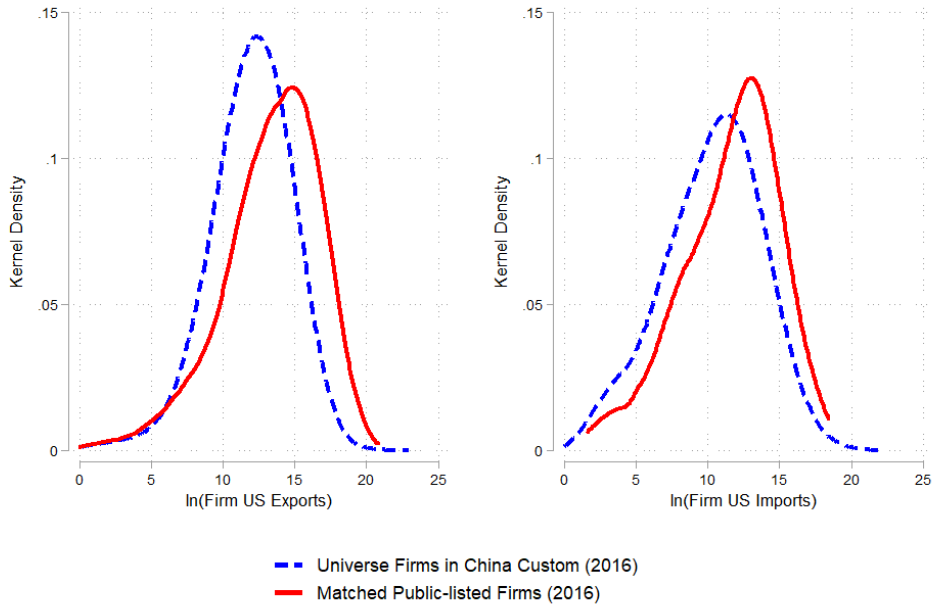
In this section we compare the sample of listed firms used in the paper to the universe of exporting and importing firms in China.

Appendix Figure A.1 illustrates the distribution of firms' total exports, total imports, exports to the U.S., and imports from the U.S. in 2016. The red solid lines correspond to firms in our sample (listed firms in COMPUSTAT). The blue dashed lines correspond to all firms in Chinese customs data. As expected, listed firms are on average larger. However, in both cases we see similarly shaped distributions.

Figure A.1: Comparison of our sample to all trading firms



(a) Total exports and imports



(b) U.S. exports and imports

Notes: Exports and imports are measured in 2016 based on Chinese customs data. The bandwidth of the kernel density estimate is one in all cases.

Appendix B: Descriptive Statistics

Table B.1: Summary Statistics of Firm-level Exports and Imports by Year

Year	Number of Exporters	Exports (million USD)		Share of Exports to the U.S.	
		Mean	Standard Deviation	Mean	Standard Deviation
2013	1,189	74.746	252.612	12.61%	22.57%
2014	1,222	60.190	206.606	11.69%	20.95%
2015	1,216	58.330	217.279	11.91%	20.55%
2016	1,500	50.016	179.491	12.60%	21.61%
Year	Number of Importers	Imports (million USD)		Share of Imports from the U.S.	
		Mean	Standard Deviation	Mean	Standard Deviation
2013	1,163	49.614	306.218	13.67%	26.39%
2014	1,192	41.512	221.539	14.15%	27.09%
2015	1,151	38.029	188.600	13.04%	25.36%
2016	1,419	32.151	164.276	12.22%	24.77%

Notes: This table summarizes firm-level exports and imports for our sample of listed firms during 2013 and 2016, respectively.

Table B.2: Summary Statistics of Tariffs by Quarter

Quarter	U.S.		China	
	Mean	Standard Deviation	Mean	Standard Deviation
2015q1	4.5	7.4	9.3	7.1
2015q2	4.5	7.4	9.3	7.1
2015q3	4.5	7.4	9.3	7.1
2015q4	4.5	7.4	9.3	7.1
2016q1	4.5	7.4	9.2	7.1
2016q2	4.5	7.4	9.2	7.1
2016q3	4.5	7.4	9.2	7.1
2016q4	4.5	7.4	9.2	7.1
2017q1	4.5	7.4	9.2	7.1
2017q2	4.5	7.4	9.2	7.1
2017q3	4.5	7.4	9.2	7.1
2017q4	4.5	7.4	9.2	7.1
2018q1	4.5	7.5	8.8	6.9
2018q2	5.6	8.5	9.1	7.5
2018q3	9.0	10.9	9.4	10.1
2018q4	15.0	11.2	16.7	9.9
2019q1	15.0	11.2	16.4	9.7
2019q2	20.4	12.5	19.4	9.8
2019q3	24.8	12.9	25.8	11.4
2019q4	28.4	12.4	26.9	12.0

Notes: This table summarizes the tariffs imposed by China and the U.S. on each other. We compute the mean and standard deviation of tariff rates (in %) across HS 10-digit codes.

Table B.3: SIC 3-digit Industries with Largest Tariff Increases

Panel (a): U.S. Tariff on Chinese Goods			
Rank	SIC 3-digit	Description	$\Delta\text{Tariff}_{it}^{\text{U.S.}}$
1	362	Electrical Industrial Apparatus	0.330
2	351	Engines and Turbines	0.329
3	360	Electronic & Other Electrical Equipment	0.319
4	359	Industrial Machinery, Nec	0.286
5	350	Industrial Machinery & Equipment	0.280
6	361	Electric Distribution Equipment	0.280
7	321	Flat Glass	0.278
8	356	General Industrial Machinery	0.273
9	374	Railroad Equipment	0.258
10	353	Construction and Mining Machinery and Equip.	0.256

Panel (b): Chinese Tariff on U.S. Goods			
Rank	SIC 3-digit	Description	$\Delta\text{Tariff}_{it}^{\text{CHN}}$
1	203	Preserved Fruits and Vegetables	0.243
2	263	Household Appliances	0.241
3	204	Grain Mill Products	0.203
4	339	Misc. Primary Metal Products	0.188
5	301	Tires and Inner Tubes	0.167
6	201	Meat Products	0.148
7	209	Miscellaneous Food Preparations	0.135
8	342	Cutlery, Hand Tools and Hardware	0.134
9	262	Paper Mills	0.131
10	260	Paper and Allied Products	0.131

Notes: This 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 between the 2013–2016 average and 2018Q4, which is the period used in our regression analysis.

Table B.4: Summary Statistics of Firm-level Tariff Exposure by Quarter

Time	$\text{Tariff}_{it}^{\text{U.S.}}$		$\Delta\text{Tariff}_{it}^{\text{U.S.}}$		$\text{Tariff}_{it}^{\text{CHN}}$		$\Delta\text{Tariff}_{it}^{\text{CHN}}$	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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	0.266	0.135	0.244	0.135	0.195	0.097	0.137	0.083
2019-Q4	0.286	0.138	0.263	0.137	0.202	0.102	0.145	0.088

Notes: Columns 1 and 2 report the mean and standard deviation of the firm–level measures of exposure to U.S. tariffs. Columns 3 and 4 report the mean and standard deviation of the change in the firm–level measures of exposure to U.S. tariffs between each date listed and the 2013-2016 average. Columns 5 and 6 report the mean and standard deviation of the firm–level measures of exposure to Chinese tariffs. Columns 7 and 8 report the mean and standard deviation of the change in the firm–level measures of exposure to Chinese tariffs between each date listed and the 2013-2016 average.

Table B.5: Number of Firms in COMPUSTAT Matched to 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

Table B.6: Summary of the Firm-level TPU Measure by Year

Year	(I) Appearance in Range of $+/-$ 1 Lines				(II) Appearance in the Same Line			
	Total Count		Normalized Count		Total Count		Normalized Count	
	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: This table summarizes the 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), we add one to the TPU count if the trade policy–related words are within one line above or below the location of uncertainty–related words. In panel (II), we require that the trade policy–related words are in the same line with uncertainty–related words. In the columns labeled "Total Count", TPU is measured as the number of TPU instances per report; we also measure TPU using the number of TPU instances per 10,000 Chinese characters as shown in the columns labelled "Normalized Count".

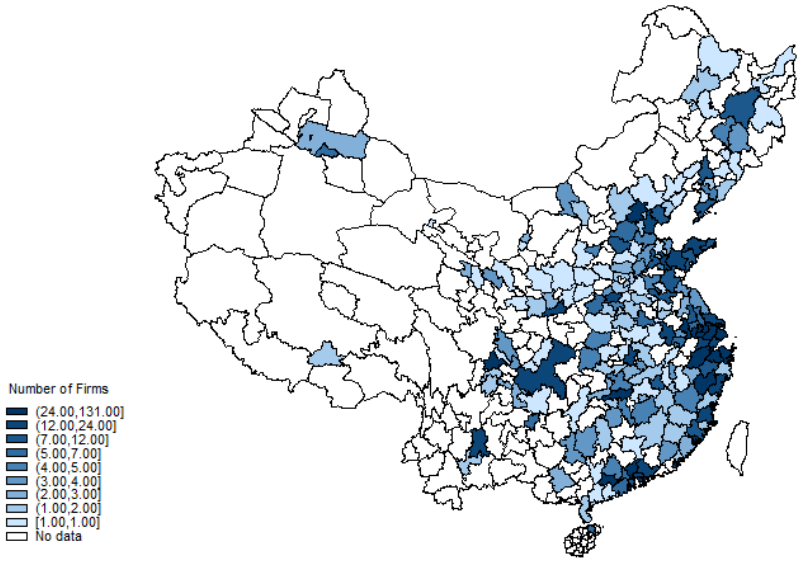
Table B.7: 3-digit SIC Industries with Highest TPU in 2018

(I) Appearance in Range of $+/-$ 1 Lines				
Rank	SIC 3-digit	Description	Total Count	Normalized Count
1	481	Telephone Communication	3.00	0.313
2	379	Misc. Transportation Equipment	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	Total Count	Normalized Count
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: This table lists the ten industries that had highest TPU measure values in 2018 based on two criteria. In panel (I), we add one to the TPU count if the trade–policy related words are within one line above or below the location of uncertainty related words. In panel (II), we require that the trade–policy related words are in the same line with uncertainty related words. In the columns labeled "Total Count", TPU is measured as the number of TPU instances per report; we also measure TPU using the number of TPU instances per 10,000 Chinese characters as shown in the columns "Normalized Count".

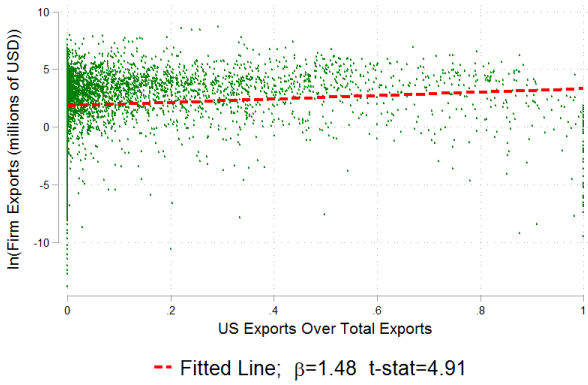
Appendix C: Additional Figures

Figure C.1: Geographic Distribution of the Matched Firms

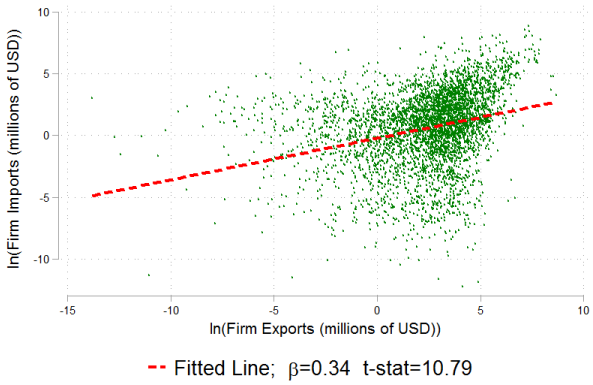


Notes: Darker colors denote areas with a larger numbers of firms in our sample. The information on the city location of each firm is collected from Chinese customs data, where a city is defined by a unique 4-digit region code.

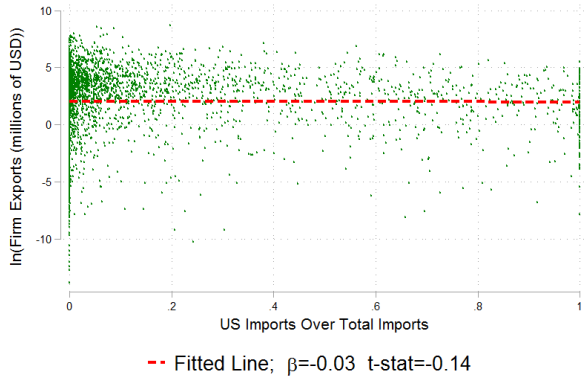
Figure C.2: Total Exports, Total Imports and U.S. Export and Import Shares



(a) Total exports and U.S. export share



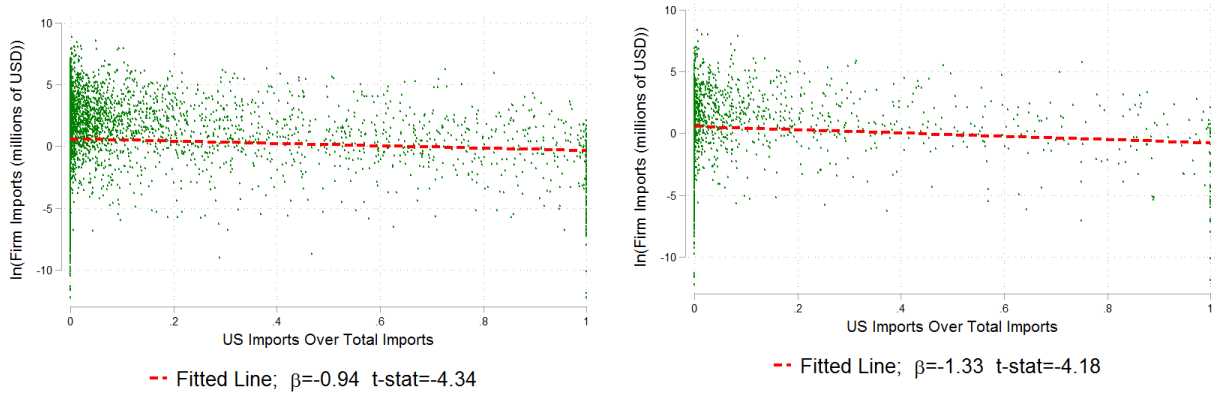
(b) Total exports and total imports



(c) Total exports and U.S. import share

Notes: These scatter plots are constructed using customs data for the firms in our sample for all years between 2013 and 2016. Panel (a) plots firms' total exports against the share of exports to the United States. Panel (b) plots firms' total imports against total exports. Panel (c) plots firms' total exports against the share of imports sourced from the United States.

Figure C.3: Total Imports and Imports from the U.S.

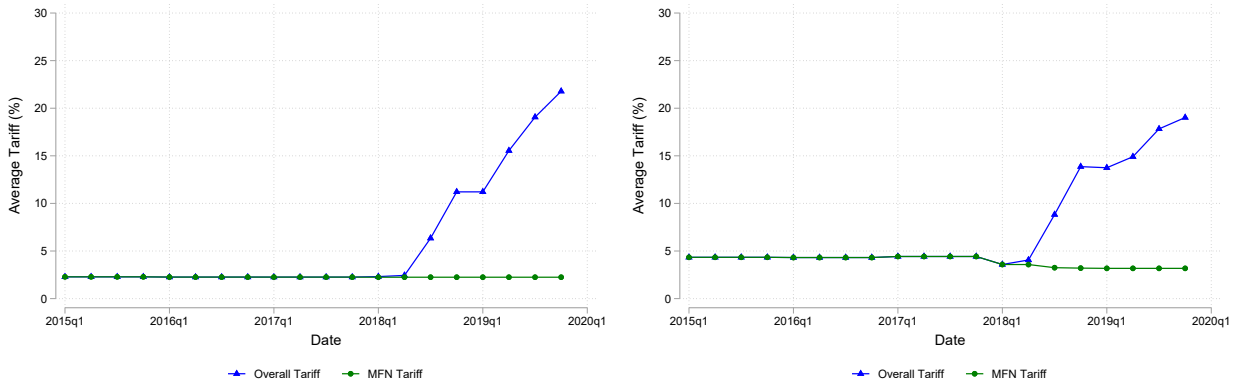


(a) Pooled Sample (2013-2016)

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

Notes: These scatter plots are constructed using customs data for the firms in our sample for all years between 2013 and 2016. Both panels plot total imports against the share of U.S. imports. In panel (a), each firm–year pair is an observation, while in panel (b) outcomes are averaged for each firm over time.

Figure C.4: Weighted Average of U.S. and Chinese Tariffs



(a) U.S. Tariff on Chinese Goods

(b) Chinese Tariff on U.S. 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 MFN tariffs and the blue line denotes overall tariffs (MFN plus trade war tariffs).

Figure C.5: First Page of the Annual Report of Angang Steel Company

(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。

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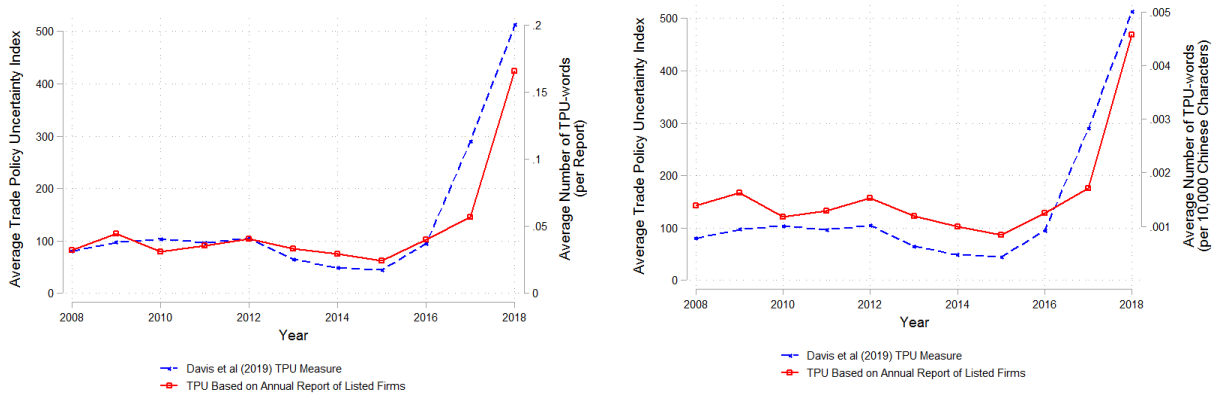
4
释 义
本公司、公司、鞍钢股份 指 鞍钢股份有限公司
本集团 指 鞍钢股份有限公司及其下属子公司
鞍山钢铁 指 鞍山钢铁集团有限公司，本公司的控股股
东。
鞍山钢铁集团 指 鞍山钢铁及其持股 30%以上的公司（不包
含本集团）
鞍钢新钢铁公司 指 鞍钢集团新钢铁有限责任公司，原为鞍山
钢铁的全资子公司。2006 年 1 月，本公司
收购了鞍山钢铁持有的该公司 100%股权，
并注销了该公司的工商登记。
鞍钢 指 鞍钢集团有限公司，本公司的最终控股股
东。
鞍钢集团 指 鞍钢及其持股 30%以上的公司（不包含本
集团）。
鞍钢财务公司 指 鞍钢集团财务有限责任公司
卡拉拉 指 卡拉拉矿业有限公司
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 C.6: Aggregate TPU Based on Annual Reports of Listed Firms and on Davis et al. (2019): Alternative Measure

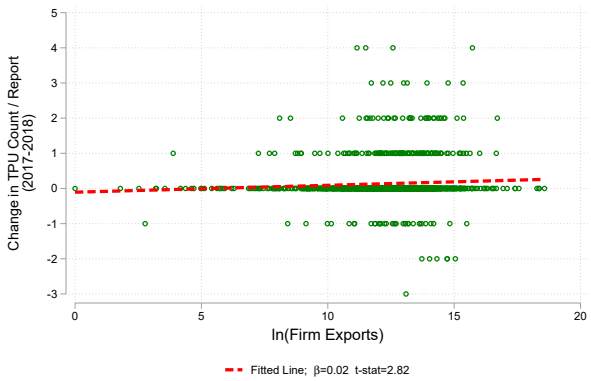


(a) Number of TPU Related Words Per Report

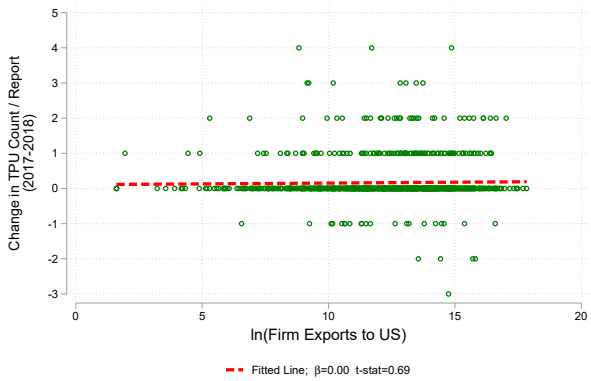
(b) Number of TPU Related Words (per 10,000 Chinese Characters)

Notes: In this figure, the TPU measure counts cases in which trade policy-related words are contained in the same line of 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).

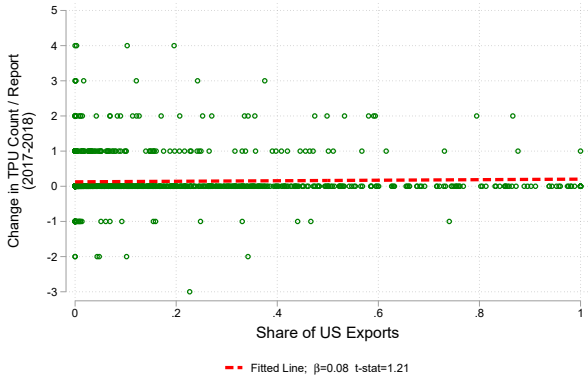
Figure C.7: Change in TPU in 2017-2018 and Initial Export Outcomes



(a) Total Exports



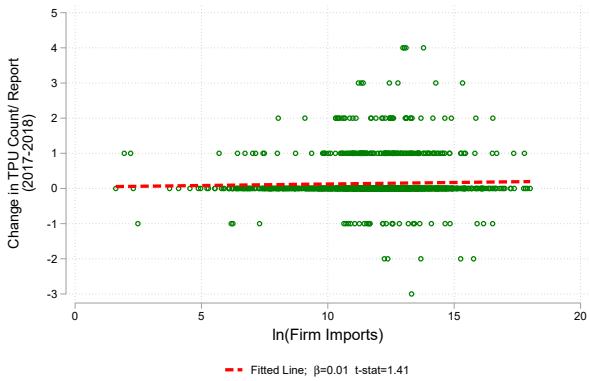
(b) Exports to the United States



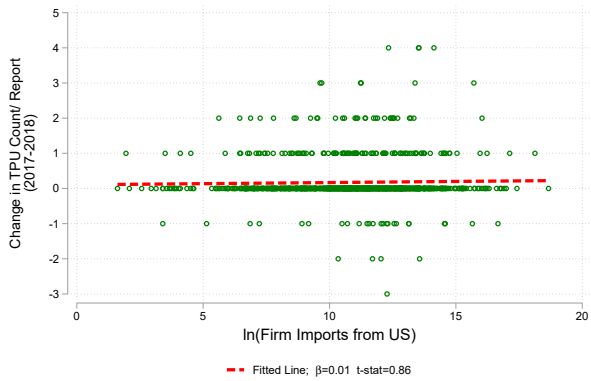
(c) Share of Exports to the United States

Notes: This figure shows the relationship between initial (pre–trade war) firm-level export outcomes (averaged over 2013-2016) and the change in the firm–level TPU measure betwen 2017 and 2018, which is the period used in our regression analysis.

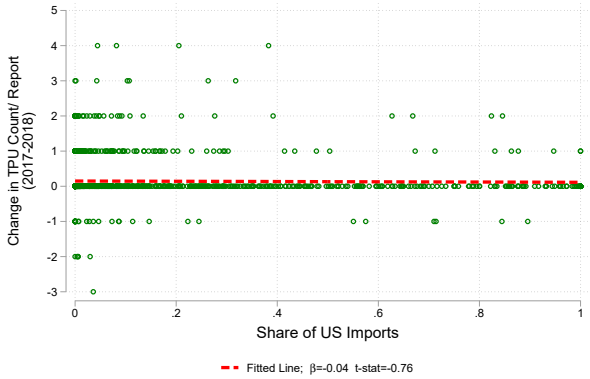
Figure C.8: Change in TPU in 2017-2018 and Initial Import Outcomes



(a) Total Imports



(b) Imports from the United States



(c) Share of Imports from the United States

Notes: This figure shows the relationship between initial (pre–trade war) firm-level import outcomes (averaged over 2013-2016) and the change in the firm–level TPU measure betwen 2017 and 2018, which is the period used in our regression analysis.

Appendix D: Background on Rules on Information Disclosure

Chinese accounting standards have been changed and updated multiple times. Four increasingly refined sets of accounting standards were introduced in 1992, 1998, 2002 and 2006, respectively (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). This suggests a higher financial reporting quality and a more efficient capital market.[54] Compared with IFRS or U.S. Generally Accepted Accounting Principles (GAAP), Chinese accounting standards are more rule-based and rigid, leaving less room for firms to manage earnings via discretionary accruals (Chen et al., 2008).

To promote transparency, stakeholders and the state authority monitor activities of listed firms. China Securities Regulatory Commission (CSRC) has adopted a set of regulations and standards similar to those in the U.S. and Europe (Fan et al., 2011).[55] 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).[56] These regulations require all of China's listed firms to prepare and disclose the "annual report" within 4 months subsequent to the end of financial year. Listed firms are also required to make an "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. The CSRC also requires the annual report of each listed firm to be audited by firms with a qualified CPA.[57]

[54] It is a consensus in the literature that adopting IFRS significantly improves financial reporting quality and efficiency in the capital market. For detailed references, 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.

[55] Detailed background information on China's financial reporting practices and information environment of Chinese listed firms can be found in Fan et al. (2011).

[56] 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.

[57] The "quarterly reports" are exempt from such requirement while the "half-year reports" 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 more detailed information).

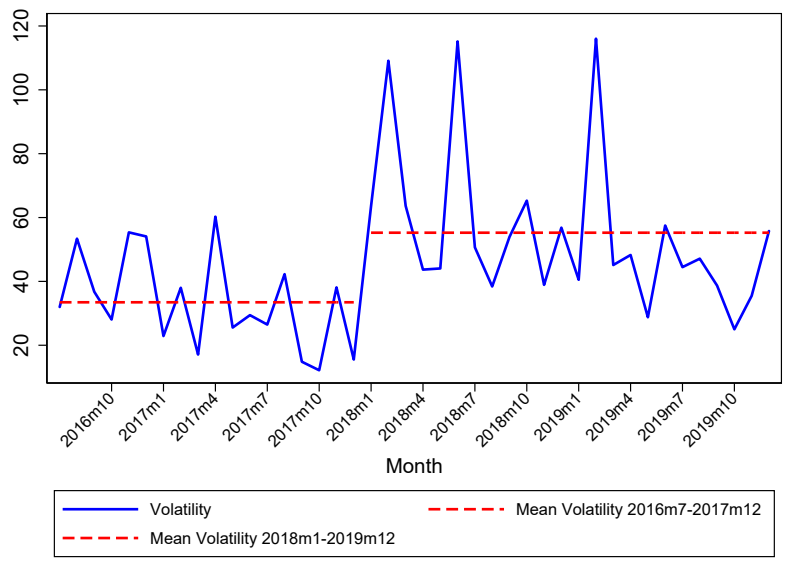
Appendix E: The trade war, economic uncertainty, and stock price volatility

In this section we discuss and provide evidence that the U.S.–China trade war not only raised *trade policy uncertainty*, but also *economic uncertainty* more in general.

Using daily data on the Shanghai Stock Exchange (SSE) composite index, Appendix Figure E.1 plots monthly volatility (standard deviation) of the index comparing the period before the trade war period (2016m7-2017m12) versus the trade war period (2018m1-2019m12). The dashed red lines correspond to the mean volatility in each period and show an increase in volatility after the trade war starts.

This is consistent with findings by Amiti et al. (2021), who measure the impact of trade war tariff announcements on various macroeconomic outcomes. They point out that "These trade announcements also caused a 115% increase in the value of VIX ... consistent with a rise in uncertainty".[58]

Figure E.1: Stock Price Volatility and the U.S.–China Trade War



Notes: This figure shows the volatility of the Shanghai Stock Exchange Composite Index, computed for each month as the standard deviation of daily closing prices.

[58]Note that the VIX (the Chicago Board Options Exchange's CBOE Volatility Index) captures global economic uncertainty.

Appendix F: Measurement of Trade Policy Sentiment

In this section, we describe in detail the construction of the trade policy sentiment (TPS) measure discussed in Section 3.4. To distinguish the first from the second-moment effects, we follow Hassan et al. (2020) and construct, in addition to a measure of trade policy uncertainty (i.e., the measure capturing the second-moment effect), a measure of trade policy sentiment (i.e., the measure capturing the first-moment effect). Our TPS measure counts cases in which trade policy–related words are found in the same line or one line above or below positive– or negative–tone keywords. The definition of TPS is the following:

$$TPS_{it} = \frac{1}{R_{it}} \sum_{w=1}^{R_{it}} \left\{ \mathbb{1}\left[w \in \text{Keywords}^{\text{Trade Policy}} \right] \times \left(\sum_{\forall c \,\middle|\, |w-c| \leq \text{ one line}} S(c) \right) \right\} , \tag{13}$$

where $w = 1, ..., R_{it}$ are the words contained in the annual report of firm i in year t; the length of report R_{it} is measured as the total number of words; and c is the position of the nearest sentiment–related keyword (i.e., positive or negative–tone words); S(.) assigns sentiment so that S(c) equals +1 if c contains positive–tone words such as 'good' or 'strong', while S(c) equals -1 if c includes negative–tone words such as 'bad' or 'weak'. In this procedure, the trade policy keywords are the same as for the TPU measure. Note also that following Hassan et al. (2020), the list of positive– and negative–tone words are obtained from Loughran and McDonald (2011)'s sentiment dictionary, which we adapt to Chinese.[59,60]

[59] Loughran and McDonald (2011)'s dictionary contains 354 positive–tone and and 2,355 negative–tone words.

[60] For robustness, when we used a stricter criteria to construct TPS, requiring that the trade policy–related words are in the same line as the positive– or negative–tone words, the regression results remained qualitatively unchanged.

Appendix G: Robustness Checks

Table G.1: Robustness: Alternative Measures of Trade Intensity

Dependent Variable: ΔTrade Policy Uncertainty	(1)	(2)
Δlog(1+Tariff$^{U.S.}$)	0.167	0.178
	(0.136)	(0.203)
Δlog(1+Tariff^{CHN})	0.672**	0.949*
	(0.321)	(0.491)
Interaction with Trade Intensity Variables		
Δlog(1+Tariff$^{U.S.}$) $\times$ Export-to-Revenue Ratio	-4.237	
	(3.503)	
Δlog(1+Tariff^{CHN})$\times$ Import-to-Cost Ratio	-4.101	
	(6.016)	
Export-to-Revenue Ratio	0.665	
	(0.623)	
Import-to-Cost Ratio	-0.610	
	(0.433)	
Interaction with Trade Engagement Indicators		
Δlog(1+Tariff$^{U.S.}$)$\times$ $\mathbb{1}$(Persistent Exporter)		-0.244
		(0.272)
Δlog(1+Tariff^{CHN})$\times$ $\mathbb{1}$(Persistent Importer)		-0.819
		(0.650)
$\mathbb{1}$[Persistent Exporter]		0.059
		(0.039)
$\mathbb{1}$[Persistent Importer]		0.046
		(0.043)
Observations	2,116	2,116
R-squared	0.082	0.084

Notes: Regressions control for initial firm characteristics, region and 3-digit SIC industry fixed effects. See Table 6 for details.

Table G.2: Robustness: Diversification Patterns

	Dependent Variable: ΔTrade Policy Uncertainty					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\log(1+\text{Tariff}^{U.S.})$	0.445**	0.595***			0.342*	0.413**
	(0.195)	(0.193)			(0.196)	(0.194)
$\Delta\log(1+\text{Tariff}^{U.S.}) \times N_i^{exp,ctry}$	-0.013**	-0.016***			-0.011**	-0.013**
	(0.005)	(0.005)			(0.005)	(0.005)
$N_i^{exp,ctry}$	0.001	0.002*			0.000	0.000
	(0.001)	(0.001)			(0.001)	(0.001)
$\Delta\log(1+\text{Tariff}^{CHN})$			0.516	0.563	0.533	0.552
			(0.487)	(0.461)	(0.498)	(0.472)
$\Delta\log(1+\text{Tariff}^{CHN}) \times N_i^{imp,ctry}$			-0.017	-0.019	-0.019	-0.019
			(0.035)	(0.035)	(0.036)	(0.035)
$N_i^{imp,ctry}$			0.005*	0.006**	0.006*	0.006**
			(0.003)	(0.002)	(0.003)	(0.003)
	Controls for Trade Intensity					
$\mathbb{1}$[Persistent Exporter]	0.043		0.040		0.050	
	(0.044)		(0.036)		(0.044)	
$\mathbb{1}$[Persistent Importer]	0.037		-0.017		-0.018	
	(0.039)		(0.047)		(0.048)	
Export-to-Revenue Ratio		0.261		0.265		0.269
		(0.382)		(0.371)		(0.369)
Import-to-Cost Ratio		-0.802*		-0.924**		-0.960**
		(0.430)		(0.438)		(0.434)
Observations	2,116	2,116	2,116	2,116	2,116	2,116
R-squared	0.085	0.083	0.084	0.084	0.088	0.088

Notes: Regressions control for initial firm characteristics, region and SIC 3-digit industry fixed effects. See Table 6 for details.

Table G.3: Robustness: Financial Position

Dependent Variable: ΔTrade Policy Uncertainty	(1)	(2)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})$	0.069	0.364
	(0.214)	(0.237)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$	0.254	1.112**
	(0.431)	(0.496)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})\times$ Liquidity	0.255	
	(0.547)	
$\Delta\log(1+\text{Tariff}^{\text{CHN}})\times$ Liquidity	1.484	
	(1.227)	
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})\times$ Leverage		-0.381
		(0.339)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})\times$ Leverage		-0.751
		(0.610)
Firm Characteristics	Yes	Yes
Region	Yes	Yes
Industry	Yes	Yes
Observations	2,116	2,116
R-squared	0.082	0.083

Notes: See Table 3 for details. Liquidity is defined as the firm-level difference between current assets and current liabilities, scaled by total assets. Leverage is defined as the firm-level ratio of current liabilities to current assets.

Appendix H: State–Owned Firms

In this appendix, we examine whether our main results differ between state–owned firms and the rest of our sample. We can identify the firm ownership type for the firms in our sample based on China's *Firm Administrative Registration Database*.[61]

The first main result in our paper concerns the impact of tariffs on TPU (Table 3 in the main text). In Appendix Table H.1 we revisit this result allowing for an interaction between a dummy variable for state–owned firms and each tariff measure. We focus on column (5), which includes the full set of control variables. We find that the positive and statistically significant effect of Chinese tariffs on TPU remains unchanged. We also find that the interaction of each tariff measure with the state–owned dummy variables are insignificant.

Our second key result concerns the impact of TPU on investment (Table 8 in the main text). In Appendix Table H.2 we revisit this result adding an interaction term between the TPU measure and the state owned dummy. Once again, we do not find a statistically significant difference between the responses of the state–owned firms and the rest of the firm sample.

[61] China's Firm Registration Database is maintained by China's State Administration for Industry and Commerce (SAIC). The data is confidential and subject to restricted access, and provides administrative information on the entire universe of enterprises in China. These data contain basic information such as firms' name, location, year of establishment, and ownership type. We match these data to COMPUSTAT Global based on firm names.

Table H.1: Trade Policy Uncertainty, Tariffs, and State-Owned Firms: 2017Q4–2018Q4

	Dependent Variable: ΔTrade Policy Uncertainty				
	(1)	(2)	(3)	(4)	(5)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})$	0.292**		0.221*	0.123	0.115
	(0.124)		(0.128)	(0.133)	(0.135)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$		0.734**	0.621*	0.780**	0.726**
		(0.313)	(0.324)	(0.322)	(0.330)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})$	0.196	0.488	0.267	0.269	0.309
$\times$ $\mathbb{1}$[State Owned]	(0.503)	(0.487)	(0.504)	(0.525)	(0.538)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$	-0.103	-0.837	-0.724	-0.846	-0.807
$\times$ $\mathbb{1}$[State Owned]	(0.981)	(1.029)	(1.033)	(0.949)	(0.957)
$\mathbb{1}$[State Owned]	0.030	0.031	0.042	0.057	0.052
	(0.050)	(0.050)	(0.050)	(0.055)	(0.058)
Observations	2,160	2,160	2,160	2,148	2,116
R-squared	0.004	0.005	0.006	0.079	0.081
Firm Characteristics	No	No	No	No	Yes
Region	No	No	No	Yes	Yes
Industry	No	No	No	Yes	Yes

Notes: The dependent variable is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. $\text{Tariff}^{\text{U.S.}}$ denotes the firm-level measure of exposure to U.S. tariffs on imports from China, computed as a weighted average across each firm's set of products exported to the U.S. $\text{Tariff}^{\text{CHN}}$ denotes the firm-level measure of exposure to Chinese tariffs on imports from the U.S., computed as a weighted average across each firm's set of products imported from the U.S. $\Delta\log(1+\text{Tariff}^{\text{U.S.}})$ and $\Delta\log(1+\text{Tariff}^{\text{CHN}})$ are percent changes in $\text{Tariff}^{\text{U.S.}}$ and $\text{Tariff}^{\text{CHN}}$ between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue and capital and 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 H.2: Investment, Trade Policy Uncertainty, and State-Owned Firms

	Dependent Variable: Δlog(Capital)			
	(1)	(2)	(3)	(4)
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
Δ TPU (17Q4-18Q4)	-0.038**	-0.039*	-0.047**	-0.058**
	(0.019)	(0.021)	(0.022)	(0.027)
Δ TPS (17Q4-18Q4)	0.002	0.002	0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Δ TPU (17Q4-18Q4)	0.007	0.012	0.030	0.042
$\times$ $\mathbb{1}$[State Owned]	(0.032)	(0.036)	(0.039)	(0.044)
Δ TPS (17Q4-18Q4)	-0.002	-0.003	-0.005	-0.005*
$\times$ $\mathbb{1}$[State Owned]	(0.002)	(0.002)	(0.003)	(0.003)
$\mathbb{1}$[State Owned]	-0.065**	-0.080**	-0.087**	-0.095**
	(0.029)	(0.033)	(0.036)	(0.038)
Firm Characteristics	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,116	2,115	2,108	2,110
R-squared	0.112	0.116	0.114	0.118

Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. ΔTrade Policy Sentiment (2017Q4-2018Q4) is the change in firm-level trade policy sentiment between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue and capital and 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.

Appendix I: Inventories

Table I.1: Inventories and Trade Policy Uncertainty

	Dependent Variable: Δlog(Inventory Intensity)			
	(1)	(2)	(3)	(4)
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
Δ TPU (17Q4-18Q4)	0.035**	0.005	0.019	-0.012
	(0.016)	(0.020)	(0.020)	(0.021)
Δ TPS (17Q4-18Q4)	-0.005	-0.002	-0.003	-0.001
	(0.003)	(0.003)	(0.004)	(0.004)
Observations	2,071	2,093	2,086	2,090
R-squared	0.152	0.228	0.195	0.191
Firm Characteristics	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes

Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. ΔTrade Policy Sentiment (2017Q4-2018Q4) is the change in firm-level trade policy sentiment between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue, capital and inventory intensity and 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.

Appendix J: The Effect of Tariffs and Dependence on the U.S. Market

In this appendix we explore whether the direct impact of U.S. and Chinese tariffs on investment and profits was larger for firms that more intensively exported to and/or imported from the U.S. For this purpose, we augment equations (11) and (12) to include the interaction between our standard tariff measures and U.S. export and import shares, which we defined in the main text. We estimate:

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

and

$$\begin{aligned}\Pi_{i,t+k} - \Pi_{i,t} = \alpha &+ \beta_1 \Delta \mathrm{TPU}_i \\ &+ \beta_2 \Delta \log(1 + \mathrm{Tariff}_i^{\mathrm{U.S.}}) + \beta_3 \Delta \log(1 + \mathrm{Tariff}_i^{\mathrm{U.S.}}) \times \text{U.S. export share}_i \\ &+ \beta_4 \Delta \log(1 + \mathrm{Tariff}_i^{\mathrm{CHN}}) + \beta_5 \Delta \log(1 + \mathrm{Tariff}_i^{\mathrm{CHN}}) \times \text{U.S. import share}_i \\ &+ \gamma_1 X_i + \gamma_2 \text{U.S. export share}_i + \gamma_3 \text{U.S. import share}_i + \psi_{\mathrm{REG}} + \psi_{\mathrm{IND}} + \varepsilon_i \ .\end{aligned} \tag{J.2}$$

Tables J.1 and J.2 report the estimation results. The coefficients on the interaction terms between U.S. tariffs and the U.S. export share are insignificant; while the coefficients on the interaction terms between Chinese tariffs and the U.S. import share are negative and statistically significant at longer horizons. Thus, while the overall impact of Chinese retaliatory tariffs was insignificant, we find again that Chinese firms that imported more intensively from the U.S. suffer stronger profit declines based on China's retaliatory tariffs.

Table J.1: Investment, Trade Policy Uncertainty, Tariffs, and U.S. Dependence

	Dependent Variable: Δlog(Capital)			
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
	(1)	(2)	(3)	(4)
ΔTrade Policy Uncertainty	-0.040**	-0.040**	-0.047**	-0.056**
	(0.017)	(0.019)	(0.020)	(0.024)
ΔTrade Policy Sentiment	0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Δlog(1+Tariff$^{\text{U.S.}}$)	0.031	-0.007	0.066	0.112
	(0.098)	(0.107)	(0.115)	(0.132)
Δlog(1+Tariff$^{\text{U.S.}}$)	0.194	0.238	0.093	0.103
$\times$ U.S. Export Share	(0.333)	(0.358)	(0.398)	(0.437)
Δlog(1+Tariff^{CHN})	0.289	0.300	0.338	0.402
	(0.198)	(0.215)	(0.233)	(0.258)
Δlog(1+Tariff^{CHN})	-0.909	-1.078	-1.317*	-1.589*
$\times$ U.S. Import Share	(0.636)	(0.688)	(0.731)	(0.831)
Firm Characteristics	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,116	2,115	2,108	2,110
R-squared	0.112	0.115	0.113	0.118

Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. ΔTrade Policy Sentiment (2017Q4-2018Q4) is the change in firm-level trade policy sentiment between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue and capital and are measured in 2017Q4. U.S. export share is defined as the ratio of export to the U.S. to total export during 2013-2016. U.S. import share is defined as the ratio of import to the U.S. 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 J.2: Profit, Trade Policy Uncertainty, Tariffs, and U.S. Dependence

	Dependent Variable: ΔProfit			
	17Q4-18Q4	17Q4-19Q1	17Q4-19Q2	17Q4-19Q3
	(1)	(2)	(3)	(4)
ΔTrade Policy Uncertainty	-24.196	-9.692	-18.516*	-25.572*
	(16.434)	(11.473)	(10.583)	(13.698)
ΔTrade Policy Sentiment	1.316	1.492**	1.206*	1.411**
	(1.003)	(0.647)	(0.638)	(0.643)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})$	83.622	-62.422	-171.723	-40.015
	(141.594)	(93.748)	(111.001)	(92.581)
$\Delta\log(1+\text{Tariff}^{\text{U.S.}})$	-378.157	-58.671	330.025	-53.441
× U.S. Export Share	(432.898)	(312.835)	(313.503)	(295.406)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$	297.802	65.696	66.314	11.953
	(292.421)	(190.766)	(202.013)	(204.929)
$\Delta\log(1+\text{Tariff}^{\text{CHN}})$	-778.782	-1,950.142*	-2,583.684	-1,488.112*
× U.S. Import Share	(829.140)	(1,008.603)	(1,810.348)	(863.076)
Firm Characteristics	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	2,116	2,116	2,112	2,111
R-squared	0.143	0.272	0.196	0.254

Notes: ΔTrade Policy Uncertainty (2017Q4-2018Q4) is the change in firm-level trade policy uncertainty between 2017Q4 and 2018Q4. ΔTrade Policy Sentiment (2017Q4-2018Q4) is the change in firm-level trade policy sentiment between 2017Q4 and 2018Q4. Firm characteristics include profit, revenue and capital and are measured in 2017Q4. U.S. export share is defined as the ratio of export to the U.S. to total export during 2013-2016. U.S. import share is defined as the ratio of import to the U.S. 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.