Trade Policy Uncertainty: Measurement and Impacts on US Firms in Global Value Chains*

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Abstract

This paper studies the effects of trade policy uncertainty (TPU) on the US firms' global value chain links. I adapt a text-based method to construct new measures of trade policy shocks perceived by the US firms. I validate the TPU measure by showing that it correctly identifies text containing discussions on uncertainty about trade policy, that it varies intuitively over time and across sectors, and that it correlates with the firm's responses in investment and inventory in a manner that is highly indicative of trade policy uncertainty. High trade policy uncertainty deters capital investment and induces temporary stockpiling. These results continue to hold after controlling for news about the mean of trade policy shocks, and are robust to other investment and inventory variables. I then explore the impact on the firms' reliance on foreign relationships. Using the firm-level data on global supply chain relationships in 2010-2019, I find that TPU is negatively associated with the US firms' foreign customer ratios. The effects are more pronounced on downstream firms than upstream firms. By contrast, no association between TPU and foreign supplier ratios is found, probably due to the firms' additional offshoring behavior in the trade war.

Keywords: Trade policy uncertainty, Textual analysis, Global value chains, Upstreamness.

JEL Codes: D22, D80, F13, F14, L14.

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1 Introduction

From the United States tariffs on solar panels and washing machines in early 2018 to the ongoing trade talk with China, recent events have renewed concerns about risks emanating from the trade policy and their effects on investment, global sourcing, and other aspects of the firm behaviors. High trade policy risk deters the firm's investment, boosts stockpiling inputs in a short period, and disrupts the existing foreign relationships. The US firms' participation in the global value chains (GVCs) has slowed down since 2018, although the firms' foreign relationships on average increased steadily over time (see Figure 1). This paper constructs a set of firm-level trade policy uncertainty (TPU) measures and examines its impact on firms' behaviors and foreign relationships in the GVCs.

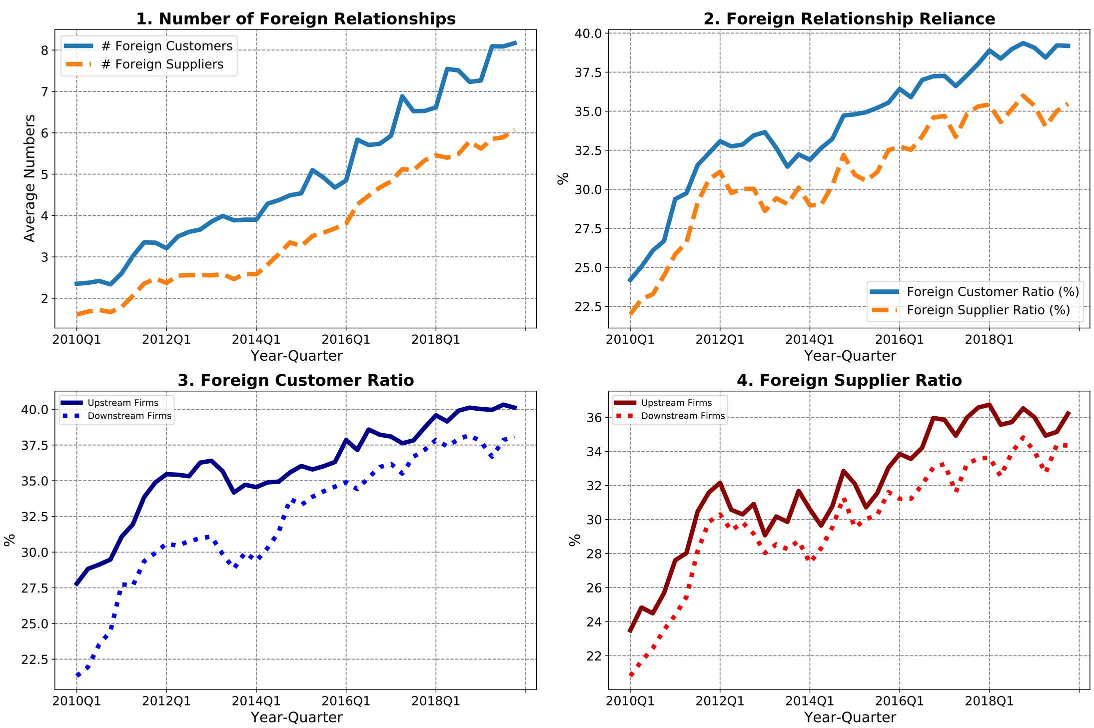


Figure 1. US Firms' Reliance on Foreign Relationships

Notes: This figure shows the US firms' foreign relationships and their ratios over time. Subfigure 1 shows the number of the US firms' foreign suppliers and foreign customers on average over time. Subfigure 2 shows on average firms' foreign customer (supplier) ratio over time. Subfigure 3 and 4 further report firms' foreign reliance by their positions along the US supply chain. Firms in an industry close to the final demand (with *upstreamness* < 2) are labeled as "Downstream", otherwise "Upstream".

Firms in the production networks are exposed to the trade policy more or less. In particular, large corporations in goods sectors usually have a large international sale and reply on global sourcing input. Even for the firms in service sectors, they could be affected by their suppliers or customers indirectly. So, a comprehensive evaluation of the impact of TPU requires measuring firms' direct and indirect exposure to the trade policy. Quantifying the impact of firm-level risk has often proven difficult due to a lack of firm-level data on exposure to a particular risk. Hassan et al. (2019, 2020) propose a text-based method for extracting and isolating first and second moment exposures to shock stemming from specific events.[1] Caldara et al. (2020) adapt the method and build measures of TPU at firm and aggregate level.[2] However, their work focuses more on the macroeconomic effects of TPU and has only a subsection on firm-level analysis on investment. The impact of TPU on other firm activities, such as inventory and foreign relationships, is still unclear.

This paper aims to fill this gap. Inspired by the previous studies, I construct four new measures of trade policy risk faced by individual US firms. The main index - trade policy uncertainty (TPU) is the share of their quarterly earnings conference calls that the participants devote to the trade policy uncertainty. Since the extent of uncertainty (variance) in trade policy is of interest and the contextual index may also capture news about the mean of trade policy shocks, I also construct a trade policy sentiment (TPS) index to control for the first moment shocks. Meanwhile, to control for the general risk and sentiment rather than trade policy, two additional measures are constructed: a non-trade policy uncertainty measure (nonTPU) and a non-trade policy sentiment measure (nonTPS).

The main idea of extracting news from a text on the second-moment (uncertainty) or the first-moment (sentiment) is to count the concurrences of trade policy and moment-specific words. Generally, researchers use uncertainty synonyms as proxies for the second moment and sentiment words (often positive and negative) for the first one. For trade policy-related words, I devise a broad word list gleaned from the list used in Caldara et al. (2020) and trade-related terms, in which I add trending trade terms in the recent trade war, specific trade agreement names, and concurrency

[1] The following example tells the difference between the first moment and the second moment on trade policy. When the US government announces that it will impose a higher tariff on foreign goods next year, a manager of a US exporter would conclude that the high tariffs could hurt its future expected profits (a lower conditional mean), and there is also uncertainty that the tariffs might or might not be implemented (variance of the shock).

[2] Their news-based aggregate TPU can be found on https://www.matteoiacoviello.com/tpu.htm. Based upon the regular expression code in their Appendix, I replicate their firm-level TPU.

of trade and geographic names.[3] The broader list gives me richer measures because more transcripts get a non-zero uncertainty term count. The text used in this paper is publicly listed firms' earnings conference call transcripts. In a typical earnings call, when a firm is exposed to a substantial trade policy shock, either with a relief of trade tension or an escalating trade dispute, the management would highlight its past success, emphasize the prospective earning opportunity, and calm investors' fear of potential bad outcomes.

The TPU index constructed in this paper is also more accurate and precise than the existing ones in the literature. One shortage of the firm-level TPU index in Caldara et al. (2020) is too many zero observations.[4] There are around 2.04% non-zero observations, covering 1021 firms, out of 123,648 transcripts in 2008-2019. Incorporating more trade-related words mitigates the sparsity problem, resulting in 6.09% non-zeros, covering 1810 firms. In addition to the richer indexes, the methodology improvement on capturing the concurrences is subtle. Caldara et al. (2020) counts the frequencies of joint instances of uncertainty synonyms and trade policy terms, conditioning on the distance between these two terms less than ten words. However, with this rubric, I find that the regular expression used in their paper could miscount the concurrences.[5] Miscounting could happen when there are more than two relevant words close to each other. For example, text like "...there is uncertainty in potential tariffs and trade agreement..." has two uncertainty words and two trade policy terms, and would be counted as one if using the code in Caldara et al. (2020) and as four if following the formula in Hassan et al. (2020). To address this, I search separately for each person's speech and count the frequencies of uncertainty synonyms in the neighborhood of the sentences mentioning trade policy (within one sentence). Doing so improves the accuracy and precision of the measures.

Having constructed the measures, I present a body of evidence to support that the TPU index indeed captures a firm's exposure to trade policy uncertainty. At first, I provide an example of how concurrences of trade policy and moment-specific terms are counted in text. Second, I show that the TPU captured varies intuitively across sectors and over time. Third, to address the concern that the index is driven by the invariant characteristics, I regress the TPU on sector-quarter and firm fixed

[3] These word combinations are devised by human auditing the sentences of most frequently mentioning "trade".

[4] This is because of their short searching list for trade policy. They mainly focus on matching "tariff" rather than "trade", to get rid of false positive "trade" terms, such as "all trade" or trade relationships" in Hassan et al. (2019).

[5] Regular expression is a search pattern to capture the joint instances.

effects, extract the residual (with unexplained variation as 66.18%), standardize it, and use it as the independent variable in the empirical analysis. Lastly, for the index validation purposes, I show that the measure correlates to firm's investment and inventory responses in a manner that is consistent with theoretical predictions. Firms perceiving high trade policy uncertainty retrench their investment and stockpile inventory in a short period. The estimation results with the TPU index continue to hold after controlling trade policy sentiment and are robust to other investment proxies and other inventory variables, such as investment rate in other literature, R&D expenditure, and inventory-sales ratio. But the result is not robust if using Caldara et al. (2020) firm-level TPU, implying that the TPU measure in this paper has better predictability.

I then investigate the firms' adjustment of global value chain relationships in response to the trade policy uncertainty shocks. Based on the FactSet Revere dataset, two types of GVC links are considered, i.e., customer and suppliers. Each type is further categorized into domestic and foreign relationships by their partners' headquarters, i.e., US customers, non-US customers, US suppliers, and non-US suppliers. As the 2020 World Development Report (World Bank, 2020) emphasized, the GVC links are usually durable over time. The durability implies some resistance in supplier-customer relation to a trade shock and the firm's reliance on foreign relationships. In the empirical analysis, I focus on the US firms' reliance on foreign relationships, i.e., foreign customer and supplier ratios. The regression analysis shows that the reliance of a firm's foreign customers and foreign suppliers react differently in the responses to trade policy shocks. I find that the firms' foreign customer ratios are negatively associated with trade policy uncertainty, and the effects are more pronounced for downstream suppliers than upstream suppliers. Surprisingly, no association between TPU and the firms' foreign supplier ratios, and few factors could confound the estimations of the firm's foreign supplier ratio. I describe the intuition as follows.

High trade policy uncertainty induces two effects on a firm's GVC links. One is the trade-dampening wait-to-see effect, resulting in less incentive for exporting and expanding foreign market (see Feng et al., 2017; Handley and Limão, 2015, 2017). In the GVCs context, it implies high trade policy uncertainty would deter a firm from reaching new foreign customers and even disrupt the existing foreign relationships. Thus, trade policy uncertainty affects the number of a firm's foreign customers negatively. The other is the trade-boosting precautionary effect in the short run, as firms stockpile inputs temporarily before the uncertainty is resolved

(Alessandria et al., 2019). It implies that existing links have some resistance to the trade shocks, and firms may reshore inputs home or even find new foreign suppliers as backups.

For the US firms' foreign customer links, the negative wait-to-see effect dominates the resistance from the precautionary effect on their foreign customers. This explanation is based on the assumption that it is difficult for a US firm to find new foreign customers when some foreign customer links are disrupted due to the high trade policy uncertainty. This is a reasonable assumption as a firm usually meets its foreign residual demand at its production capacity. The downstream firms facing a higher trade policy uncertainty tend to lose more foreign customer relationships than upstream ones due to the differential demand elasticities. The downstream firms which produce final goods typically face a higher demand elasticity than the upstream firms which produce intermediate inputs (Alfaro et al., 2019). Overall, a proposed high tariff or potential foreign retaliation leads to a decline in exporters' investment in expanding foreign business, especially for the downstream firms selling final goods.

For the US firms' foreign supplier links, the additional offshoring behavior induces an increase in the number of foreign suppliers, and thus misleads the estimation results. Using the country-level TPU indexes from Baker et al. (2016) and the same customer-supplier dataset, Charoenwong et al. (2020) study the American firms' reshoring and offshoring behaviors during the trade war. They find that on average higher US trade policy uncertainty predicts an increase in foreign supplier relationships, with firms shifting suppliers from countries with higher uncertainty to ones with lower uncertainty. The confounding effects from the additional offshoring and the disruptions of existing links lead to the insignificant result.

Literature Review The paper is related to three strands of literature: textual analysis in economics, economics effects of trade policy uncertainty (TPU) in the international trade, and buyer-supplier relationships in the global value chains (GVCs).

Textual Analysis in Economics Study My work relates to the burgeoning literature using textual analysis to construct economic measures. Textual analysis, originated in computational linguistic studies, has been a trending toolkit applied in social science. Thanks to the various computational tools and fast development of natural language processing, using text as data has been trending among economists.

See Gentzkow et al. (2019) for a survey.[6] Among the work, constructing uncertainty or risk factors from text, such as newspapers and firms' financial disclose, has become popular. A seminal work by Baker et al. (2016) (BBD 2016) introduces a news-based index of economic policy uncertainty by quantifying newspaper coverage of policy-related economic uncertainty. Their work invokes a large variety of uncertainty index measuring different economic activities.[7] At the micro-level, another recent influential work by Hassan et al. (2019) construct a new measure of firms' political risk by counting political bigrams (two adjacent words) in the earnings conference call transcripts.[8] Inspired by their method, Caldara et al. (2020) build trade policy uncertainty measures at firm-level and aggregate level from firms' earnings call transcripts and newspapers, respectively. They further study the macroeconomic effects of TPU on investment using a two-country general equilibrium model with nominal rigidities and export participation decisions. Building upon their work, my paper focuses more on TPU index construction and analysis at the firm-level, i.e., index improvement, validation, and firm's actions in responses to the TPU.

Economics Effects of Trade Policy Uncertainty A large body of trade policy uncertainty literature in international trade focus on 2001 China's WTO accession, quantifying the source of trade policy uncertainty as normal trade relationship (NTR) and non-NTR tariff gap (NTR gap). Pierce and Schott (2016) construct the NTR Gap and use it to explain the sharp drop in US manufacturing employment. Crowley et al. (2018) study the effects of reduced TPU on Chinese firms' entry behavior over 2001-2009. Handley, Limão, et al. (2020) examine how the reduced TPU of China's accession to the WTO and the associated commitment to bind its import tariffs affect firms' import decisions. Some recent works examine the TPU effects from the Brexit and the trade war (see Hassan et al., 2020; Graziano et al., 2018; Benguria et al., 2020). In contrast with them focusing on a specific event, I evaluate the trade policy uncertainty using firm-quarter panel data over a decade.

My paper contributes to the findings of TPU effects at the firm level. The economic effects on international business can be viewed from two aspects. On the

[6] Loughran and McDonald (2016, 2019) also provide nice surveys of textual analysis applications in accounting and finance. During the past decade, many researchers used companies' financial disclosures to study their stock return predictability by extracting various indexes, such as readability, sentiment, and document similarity.

[7] BBD shares their economic policy uncertainty index and other researchers' extension works on their Economic Policy Uncertainty website, https://www.policyuncertainty.com/.

[8] They share their index on their firm-level risk website, https://www.firmlevelrisk.com/.

one hand, higher TPU impedes firms' export investment and dampens the desire to build foreign relationships and expand foreign markets (see Handley and Limão, 2015, 2017). This channel is based upon the well-documented wait-to-see effects of the uncertainty on investment.[9] On the other hand, imports surge in a very short period and plunge afterward when there is a trade policy uncertainty shock (see Alessandria et al., 2019). In line with these two theoretical predictions, the estimation results with TPU index shows a long-lasting negative effect on investment rate and a temporary positive effect on inventory growth. Although the results on investment and the above theory are not novel, the evidence of the TPU effects on firm-level stockpiling behavior is new.

Global Value Chain Links My paper also relates to the large and growing literature on the global value chains (GVCs). Antràs and Chor (2021) provide a nice survey on GVCs. Alfaro et al. (2019) and Antràs and Chor (2013) study how firms shape the organizations of their GVCs via a property rights model. They find that the production positions of suppliers and the relative size of elasticities of final demand to the elasticity of substitution matter in the decision of internalizing the GVCs. The production position along the supply chain is measured as "upstreamness" of the industry with respect to final demand from Antràs, Chor, et al. (2012) and Fally (2012). In the regression analysis, I examine the industrial heterogeneous effects of trade policy uncertainty with the upstreamness measure.

More specifically, my paper contributes to a burgeoning literature on firm networks in trade.[10] The 2020 World Development Report (World Bank, 2020) highlights that GVC links are durable and persist over time, especially when the production process requires high levels of input customization or relationship-specific investment. Past work focuses on the formation and duration of supplier network, for example, Eaton et al. (2021), Gereffi et al. (2005), and Monarch and Schmidt-Eisenlohr (2017). Little attention has been paid to how trade policy shock might disrupt supply chains. Moreover, although existing literature shows that firm heterogeneity among both buyer and supplier matters in the production network (see Bernard, Dhyne, et al., 2019; Bernard, Jensen, et al., 2018), little evidence shows how different firms in the upstream and downstream react to trade shocks.

[9]Lots of theoretical and empirical work have documented the impact of uncertainty shocks on investment, see (Bernanke, 1983; Dixit and Pindyck, 1994; Nicholas Bloom, 2009; Baker et al., 2016; Hassan et al., 2019; Caldara et al., 2020).

[10]See Bernard and Moxnes (2018) for a survey, "Trade and Production Network".

The rest of the paper is structured as follows. Section 2 lays out the major data used in this paper. In Section 3, I use public firms' earnings conference calls to construct new trade policy risk measures. Having built the measures, Section 4 provides evidence that the measures indeed capture firms' exposure to trade policy risk. Section 5 discusses and examines the impact of trade policy uncertainty on the US firms' reliance on foreign relationships. Section 6 concludes. I put detailed data preparation and extra tables in the Appendix.

2 Data

The paper mainly uses four datasets, from which I create a firm-quarter panel for the empirical analysis. Specifically, I employ firms' earnings call transcripts as text data, Compustat fundamental as firms' balance sheet data, FactSet Revere as firms' supply chain relationship data, and upstreamness from Antràs, Chor, et al. (2012) as firms' production position measure. The following subsections document the key data feature and important steps in data collecting. I put a more detailed data preparation in the Appendix. In the end, I obtain a panel data with 93,940 observations, covering 3,852 firms listed in the United States between 2010 and 2019.

2.1 Earnings Conference Call Transcript

The text data used to construct the measures is public firms' quarterly earnings conference call transcripts. I collect the transcripts from Standard and Poor's Capital IQ. Public firms typically hold an earnings conference call immediately after they release quarterly or annual financial results. Conference call participants usually include firms' executives, investors, and financial analysts who know the firms' business well. Each call typically consists of two sessions, i.e., a presentation session by management for discussing firms' past performance and important aspects of the released reports, and a question-and-answer (Q&A) session between management and other market participants.

I collect the transcripts from 2008, the earliest year when S&P Capital IQ systematically recorded the calls. At the beginning, there are 123,978 transcripts between 2008 and 2019, covering 4,708 firms. After merging with the cleaned Compustat dataset and truncating time from 2010, there are 93,940 transcripts left. In terms of data structure, each transcript is split into several components, and each component is a speech for a person at a time. A component is set as a search and matching scope. To reduce the impact of irrelevant content in the transcripts, operator speeches and detected safe harbor statements (or forward-looking statements) are removed.[11]

[11] Some common words in the operator speeches and safe harbor statements can over-estimate the contextual index. For example, greetings at the beginning, such as "good morning", and "good day" in the operator speeches, would make the content sentiment more positive. Uncertainty-related words in the disclaimer and safe harbor statements, such as "risk" and "potential", would unexpectedly increase the frequencies of uncertainty mentioned and thus overrate the uncertainty index.

More specifically, the operator components, and the paragraphs mentioning safe harbor keywords in the first presentation component and their preceding paragraphs, are removed. More details are included in the Appendix.

2.2 Firm Fundamental

I obtain firms' basic balance sheet data from S&P Compustat North America on the Wharton Research Data Service (WRDS). I only consider firms with headquarter in the United States (Compustat item *LOC* == "USA"). Entries with missing fiscal quarter are excluded. I also drop firms with duplicated *DATADATE* and firms with single observation in the sample periods (2010Q1-2019Q4). At last, I exclude firms in the utilities Standard Industrial Classification (*SIC*) code within range 4000-4999 and financial sectors (*SIC* 6000-6299).

Note that for dependent variables and firm controls, all percentage change terms, lags or leads of a variable are generated by the firm's fiscal quarters. But the quarter fixed effect included in the regression are calendar quarters associated to the earnings call dates.[12]

2.3 Global Value Chain Links

Supply chain data are from FactSet Revere, currently the most comprehensive database for customer-supplier relationships among US firms.[13] Publicly traded firms are required to disclose of their major customers that contribute to more than 10% of their revenue. Compared with the commonly used Compustat Customer Segment database, which only covers the relationships from financial disclosure, FactSet Revere includes more companies' relationship information from investor presentations, press releases, and news media. Therefore, FactSet Revere extends the coverage more than publicly-traded firms. Although private firms or international firms are not the focus of this paper, the border coverage gives me a more accurate number of foreign customers and suppliers.

I pull the FactSet Revere data via the WRDS from 2010 to 2019. The original data show the direct relationships, with a number of 2,405,196 links covering 34,820 source companies. I focus on customer and supplier relationship types.[14] To build a thorough dataset on US firms' relationships, I first obtain a reversed relationship by flipping the direct relationship and then concatenate it with the direct one. For

[12] Note that I do not use the Compustat item, *DATACQTR*, for the calendar quarters. Because it is associated to the *DATADATE* and use a calendar with year-end in January.

[13] FactSet Revere has been used in recent literature, e.g. Amiti et al. (2021), Charoenwong et al. (2020), and Huang et al. (2019).

[14] Customers include disclosed customers (corresponding to *rel_type* - "CUSTOMER") and out-licensing ("PARTNER-LICENOT"), and suppliers includes disclosed suppliers ("SUPPLIER"), distribution ("PARTNER-DISTRIB"), manufacturing ("PARTNER-MANUFAC"), in-licensing ("PARTNER-LICENIN"), and marketing ("PARTNER-MARKTNG").

example, a direct relationship that Company A's customer is Company B implies a reversed relationship that Company B's supplier is Company A. Doing so doubles the number of relationships and creates substantial variations of foreign customers and foreign suppliers across firms, which is important for the regression analysis. I then merge all overlapping relationship periods and count each firm's (source company's) customers and suppliers in quarters from 2010 to 2019. FactSet Revere specifies each relationship with starting date and ending date. A relationship would contribute to the count of the firm's customers or suppliers in a certain quarter if the link exists at least one day within the quarter. I label its partner's (target company's) location by its headquarter country, or, if not available, its registration country. At last, the relationship-count data are merged with Compustat-Transcript data on firms' 6-digit CUSIP code.

2.4 Measure of Production Position - Upstreamness

To measure a firm's position in the production process, I use an industry-level measure, $Upstreamness_j$, from Antràs, Chor, et al. (2012). The measure is computed as a weighted average of the number of production stages that an industry's output takes to arrive at the final demand, using the 2012 US Input-Output table.[15] Intuitively, the measure can also be interpreted as production stage distance to the final demand, with a minimum value of 1, indicating the industry solely serving the final use.

Using the US domestic I-O Table has two advantages. First, the production linkages are reported at the six-digit I-O industry level. The upstreamness covers 405 industries, ranging from 1 (for example, secondary melting and alloying of aluminum) to 4.805 (petrochemical manufacturing). The highly disaggregate upstreamness measure gives us more variation across industries. Second, it measures directly the production position for the US firms, which are of our interests in this paper.

According to the concordance provided by the BEA, each firm in the sample is assigned with an $Upstreamness_j$ value by its 6-digit NAICS code. Table 1 reports the five least and most upstream manufacturing industries. It is worth noting that the $upstreamness_j$ measure is stable across years (Antràs and Chor, 2018). Replacing the upstreamness with the value calculated from the 2002 US Input-Output table doesn't change the main results.

[15]The 2012 US Input-Out Table is the latest version from the Bureau of Economic Analysis (BEA).

Table 1. Least and Most Upstreamness Industries (Manufacturing)

US IO2012 Industry	Industry Code	Upstreamness
Secondary smelting and alloying of aluminum	331314	1.000
Automobile manufacturing	336111	1.001
Light truck and utility vehicle manufacturing	336112	1.001
Motor home manufacturing	336213	1.003
Ophthalmic goods manufacturing	339115	1.011
Fertilizer manufacturing	325310	3.943
Copper rolling, drawing, extruding and alloying	331420	3.948
Carbon and graphite product manufacturing	335991	4.011
Nonferrous Metal (except Aluminum) Smelting and Refining	331410	4.193
Petrochemical manufacturing	325110	4.805

Exporting Ratio One important sectoral characteristic at the NAICS 3-digit level is the export-usage ratio, $\frac{Export_{s,t}}{Usage_{s,t}}$, where $Usage_{s,t}$ is the sectoral gross output plus imports less exports. Gross output by industry is from the Industry Economic Accounts Data published by the Bureau of Economic Analysis. Exports and imports data are downloaded from the USA Trade Online provided by the US Census Bureau, and it is only available for the sectors of agricultural, mining, and manufacturing. I calculate the sectoral import-usage ratio analogously. In the GVCs regressions, depending on the relationship type of the dependent variable, the sectoral control is added correspondingly, i.e., $\frac{Export_{s,t}}{Usage_{s,t}}$ as a control for the foreign customer and $\frac{Import_{s,t}}{Usage_{s,t}}$ for the foreign supplier.

Table 2 provides the summary statistics for the key variables used in the regression analysis. For ease of interpretation, all trade policy measures are standardized by dividing their standard deviations.

Table 2. Descriptive Statistics

	mean	std	min	25%	50%	75%	max	count
Panel A: Trade Policy Indexes								
$\text{TPE}_{i,t}$	0.028	0.103	0.000	0.000	0.000	0.000	2.652	93,657
$\text{TPU}_{i,t}$ (std.)	0	1	-14.795	-0.152	0.000	0.064	28.855	93,657
$\text{NonTPU}_{i,t}$ (std.)	0	1	-6.890	-0.637	-0.087	0.538	11.125	93,657
$\text{TPS}_{i,t}$ (std.)	0	1	-22.512	-0.118	-0.008	0.072	27.826	93,657
$\text{NonTPS}_{i,t}$ (std.)	0	1	-6.425	-0.612	0.000	0.606	10.353	93,657
$\text{CIMPR}_{i,t}$	0.001	0.009	0.000	0.000	0.000	0.000	0.447	93,657
Panel B: Industrial Controls and Firm Fundamentals								
Export-Usage $\text{ratio}_{s,t}$	0.076	0.039	0.006	0.051	0.063	0.117	0.140	45,167
Import-Usage $\text{ratio}_{s,t}$	0.133	0.110	0.011	0.063	0.095	0.206	0.709	45,167
Upstreamness_j	2.099	0.873	1.000	1.262	1.863	2.750	4.805	90,923
$I_{i,t}/K_{i,t-1} \times 100$	10.104	8.105	0.000	5.306	8.698	12.636	59.693	70,560
%Δ $\text{R\&D}_{i,t}$	4.553	26.673	-78.978	-4.810	2.208	10.022	215.734	36,282
$\text{Inventory}_{i,t}/\text{Sales}_{i,t} \times 100$	40.496	65.654	0.000	0.000	23.306	57.792	663.903	90,220
%Δ $\text{Sales}_{i,t}$	4.688	28.434	-80.995	-4.259	1.977	9.062	210.198	92,407
%Δ $\text{Cost}_{i,t}$	4.200	24.843	-76.813	-4.538	1.908	9.298	181.552	92,483
%Δ $\text{Profit}_{i,t}$	2.386	58.244	-352.248	-7.609	1.983	11.768	349.530	92,589
$\log(Asset_{i,t})$	7.053	1.910	0.874	5.739	7.084	8.330	11.871	93,655
Market-Book $\text{ratio}_{i,t}$	3.256	6.045	-19.177	1.210	2.090	3.766	39.662	93,255
Book Leverage $\text{ratio}_{i,t}$	0.262	0.237	0.000	0.047	0.227	0.407	1.215	93,655
$\text{Profitability}_{i,t}$	0.009	0.055	-0.526	0.001	0.019	0.031	0.120	93,593
Panel C: Firm Global Value Chain Variables								
# nonUS $\text{customers}_{i,t}$	4.963	12.067	0.000	0.000	1.000	5.000	437.000	82,826
# US $\text{customers}_{i,t}$	7.272	12.047	0.000	1.000	3.000	9.000	393.000	82,826
# all $\text{customers}_{i,t}$	12.262	21.959	0.000	1.000	5.000	16.000	697.000	82,826
NonUS/Relationships $\text{c.}_{i,t} \times 100$	34.505	30.693	0.000	0.000	31.579	55.556	100.000	69,146
# nonUS $\text{suppliers}_{i,t}$	3.677	12.532	0.000	0.000	1.000	3.000	396.000	85,718
# US $\text{suppliers}_{i,t}$	6.015	13.541	0.000	0.000	2.000	6.000	256.000	85,718
# all $\text{suppliers}_{i,t}$	9.707	24.319	0.000	1.000	3.000	9.000	563.000	85,718
NonUS/Relationships $\text{s.}_{i,t} \times 100$	31.423	30.639	0.000	0.000	25.000	50.000	100.000	68,407

Notes: This table shows the descriptive statistics of the trade policy indexes, industrial controls, and all firm variables that are used in the subsequent regression analysis. The full sample is from 2010Q1 to 2019Q4. In Panel A, $TPU_{i,t}$ is standardized trade policy uncertainty index. It is the residual extracted from regressing the initial trade policy ratios equation (2) on firm and sector-quarter fixed effects and then standardized by its standard deviation. $NonTPU_{i,t}$, $TPS_{i,t}$, and $NonTPS_{i,t}$ are obtained analogously. $\text{CIMPR}_{i,t}$ is the firm-level trade policy uncertainty in Caldara, Iacoviello, Molligo, Prestipino, and Raffo (2020). In Panel B, export-usage (import-usage) ratio is sectoral exports (imports) divided by the sectoral usage, where the $Usage_{s,t}$ is the gross output plus imports less exports of sector s at quarter t. $Upstreamness_j$ is a measure of industrial position along the US production process at the NAICS 6-digit level. Capital investment, $I_{i,t}/K_{i,t-1}$, is a measure for investment rate and is calculated recursively using a perpetual-inventory method and winterized at the 1st and 99th percentile. %Δ $\text{R\&D}_{i,t}$ is the percentage changes in quarter to quarter R&D expenditure over last quarter's value, winterized at the 1st and 99th percentile. %Δ $\text{Sales}_{i,t}$ is the percentage changes in quarter to quarter sales over last quarter's value, winterized at the 1st and 99th percentile. %Δ $\text{Cost}_{i,t}$ is the percentage changes in quarter to quarter cost over last quarter's value, winterized at the 1st and 99th percentile. %Δ $\text{Profit}_{i,t}$ is the percentage changes in quarter to quarter profit over last quarter's value, winterized at the 1st and 99th percentile. $\text{Inventory}_{i,t}/\text{Sales}_{i,t}$ is the total inventory value divided by the total sales, winterized at the 1st and 99th percentile. Market-Book $\text{ratio}_{i,t}$ is the market equity (ME) divided by book equity (BE), where ME is calculated as end-of-calendar-quarter stock price (PRCCQ) times end-of-quarter common shares outstanding (CSHOQ), and BE is measured at the quarterly frequency using an analogous method in Davis, Fama, and French (2000). Book Leverage $\text{ratio}_{i,t}$ is calculated as long-term debt (DLTTQ) plus debt in current liabilities (DLCQ), and then divided by total assets (ATQ), winterized at the 1st and 99th percentile. $\text{Profitability}_{i,t}$ is measured as operating income before depreciation (OIBDPQ) minus interest (XINT) minus taxes (TXT) and divided by lagged total assets (ATQ), winterized at the 1st and 99th percentile. In Panel C, NonUS/Relationships $\text{c.}_{i,t}$ is the foreign customer ratio of firm i at quarter t, calculated as the total number of non-US customers divided by the number of all customers. NonUS/Relationships $\text{s.}_{i,t}$ is the foreign supplier ratio of firm i at quarter t, calculated as the total number of non-US suppliers divided by the number of all suppliers.

3 Measuring Firm-level Trade Policy Exposure, Uncertainty, and Sentiment

In this section, I describe how I define and extract the trade policy exposure, uncertainty, and sentiment from the text. Following Caldara et al. (2020) and Hassan et al. (2019, 2020), I first search the passages which contain discussions related to trade policy, labeled as trade policy exposure (TPE), and then construct trade policy uncertainty and sentiment to capture firms' perceptions of trade policy news of the variance and the mean, respectively.

3.1 Defining a Measure of Trade Policy Exposure

To construct a measure of trade policy exposure, I search for the terms related to the trade policy. Each transcript is parsed into several components. Each component is a person's speech at a time. I then parse each component into sentences and count the number of trade policy related terms is used. The positions of trade policy terms are marked. At last, I sum over the frequencies of trade policy mentioned and divide by the total number of words in the transcript to take account of the call length. The formula for the trade policy exposure (TPE) is:

$$TPE_{it} = \frac{1}{W_{it}} \sum_{m}^{M_{it}} \sum_{n_m}^{N_{imt}} \sum_{w}^{W_{mn}} \mathbb{1}\Big[w \in \mathbb{T}\Big] \tag{1}$$

where W_{it} is the total number of meaningful words[16], M_{it} is the speaker components in the earnings call transcript for firm i at time t, N_{it} is the tokenized sentences in the component M_{it}, W_{mn} is the words in the component-sentence n_m, $\mathbb{1}[\cdot]$ is an indicator function, and $\mathbb{T}$ are the set of trade policy terms devised from current literature and relevant "trade"-terms.[17] There is a trade-topic sub-index among Hassan et al.

[16] I remove all stop words in the context, such as *the, you, of, etc.*, with the Natural Language Toolkit (NLTK) English stop word list. Moreover, I remove "against" from the list and add "among".

[17] The full set of trade policy terms can be categorized into four lists. The first list includes most of terms used in Caldara et al. (2020), i.e., tariff* (not appearing within either of feed-in, MTA, network, and transportation), import*, export*, (anti-)dumping, free trade, foreign trade*, international trade*, (cross-)border*/custom* within three words of either ban*, tax*, subsid*, control*, quota*, and trade*. Second, I include recent emerging "trade" bigrams, i.e., trade act* /action* /agreement* /deal* /deficit* /surplus /(im)balance* /discussion* /dispute* /liberalization* /polic* /practice* /relationship* /talk* /tension* /treat* /war*. Third, I include specific trade agreements and international trade transaction terms, i.e., GATT, World Trade Organization/WTO, FTA, NAFTA, USMCA, Trans-Pacific Partnership/TPP, Regional Comprehensive Economic Partnership/RCEP, incoterm*, free on board/fob, (cost, insurance, and freight)/cif. Last, after human

(2019) firm-level politic risk indexes. They search bigrams related to trade, such as *"all trade"*, *"up market"*, or *"the trade"* to identify the trade-related transcripts. However, some bigrams are not necessarily related to international trade or trade policy. It raises false-positive concern as their trade index has spikes during 2008-2009. Caldara et al. (2020) address this concern by searching exact trade policy terms instead, focusing more on "tariff" other than "trade". But their discreet list of trade policy seems to be conservative, as their firm-level index is too sparse. I replicate their firm-level TPU index with the regular expression in the appendix, and find that only 2% of the transcripts in 2008-2019 are non-zeros. An audit of earnings call shows that some firms involving global trade business and affected by the trade policy are not being captured. To search thoroughly the passages discussing trade policy while keeping less false-positive captures, a natural way is to extend their searching list with more "trade"-related terms. I extend the trade policy list by including more recent trending trade bigrams, specific trade agreement names, and geographical trade. It gives us more accurate trade policy exposures, with larger variation across sector and time.

3.2 Defining a Measure of Trade Policy Uncertainty

To construct a measure of trade policy uncertainty (TPU), I count the concurrences of trade policy and uncertainty terms. More specifically, to contribute to the TPU, *uncertainty* synonyms are required to be in the neighborhood of one sentence before and after the mentions of trade policy:

$$TPU_{it} = \frac{1}{W_{it}} \sum_{m}^{M_{it}} \sum_{n_m}^{N_{imt}} \left\{ \left(\sum_{w}^{W_{mn}} \mathbb{1}\Big[w \in \mathbb{U}\Big] \right) \times \mathbb{1}\Big[\exists w|_{w \in (n_m-1, n_m, n_m+1)} \in \mathbb{T}\Big] \right\} \tag{2}$$

where $\mathbb{U}$ is the set of uncertainty synonyms from the Oxford English Dictionary. The equation (2) guides the searching algorithm and delivers some subtle improvements in precision. Note that, summing over the uncertainty synonyms around sentences discussing trade policy would avoid double counting. Moreover, instead of searching and finding specific word combination patterns over the entire transcript, I take each component as a search and matching scope. Thus, word combinations satisfying the conditions across different people's speeches would not be taken into account.

auditing the sentences of most frequently mention of word "trade", "trade" and country or region name within the same sentence are taken into account. I use the first 15 US trade partners as country or region names. Note that the word "trading" is not included.

3.3 Defining Additional Measures of Uncertainty and Sentiment

To capture the mean of the firm's trade policy shocks, I construct the measure of trade policy sentiment (TPS) analogously. Instead of counting concurrences of trade policy and uncertainty terms, I count the usages of trade policy terms conditioning on proximity to positive and negative words:

$$TPS_{it} = \frac{1}{W_{it}} \sum_{m}^{M_{it}} \sum_{n_m}^{N_{imt}} \left\{ \sum_{w}^{W_{mn}} Sentiment(w) \times \mathbb{1}\left[\exists w|_{w \in (n_m - 1, n_m, n_m + 1)} \in \mathbb{T} \right] \right\} \tag{3}$$

where $Sentiment(\cdot)$ is a function that assigns a value to each word w:

$$Sentiment(w) = \begin{cases} +1 & \text{if } w \in Positive\_wordlist \\ -1 & \text{if } w \in Negtive\_wordlist \\ 0 & otherwise \end{cases}$$

and the positive and negative word lists are from the Loughran and McDonald (2011) sentiment dictionary. Furthermore, to control for non-trade policy related risk and sentiment, I further define:

$$NonTPU_{it} = \frac{1}{W_{it}} \sum_{m}^{M_{it}} \sum_{n_m}^{N_{imt}} \sum_{w}^{W_{mn}} \mathbb{1}\left[w \in \mathbb{U} \right] - TPU_{it} \tag{4}$$

$$NonTPS_{it} = \frac{1}{W_{it}} \sum_{m}^{M_{it}} \sum_{n_m}^{N_{imt}} \sum_{w}^{W_{mn}} Sentiment(w) - TPS_{it} \tag{5}$$

In addition to the aggregate sentiment index, I create more subtle sentiment indices by the types of speak person and call session, i.e., manager presentation, manager in Q&A, and analyst in Q&A. Replacing the aggregate $TPS_{i,t}$ with $TPS\_mpre_{i,t}$ (or $TPS\_mqna_{i,t}$) and $TPS\_analyst_{i,t}$ in the regression analysis doesn't change the main results, so I use the aggregate sentiment throughout the paper.[18]

[18] Although the sub-sentiment indices are not the focus of this paper, it is worth noting that the trends of managers' and analysts' tone towards trade policy diverse in the trade war (see Figure 4). Managers were quite positive when mentioning trade policy, while the analysts were not. I leave the reasons for the diversion and relevant sentiment study for future research.

4 Validation

I next describe the output of the measure and verify that they indeed capture passages of text that discuss uncertainty associated with international trade topics.

4.1 Example in Context

The following example illustrates how words of trade policy, uncertainty, positive- and negative-tone are contributed to the TPU and TPS by equation (2) and (3), respectively.

Example:
Microchip Technology Incorporated's (ticker: MCHP) is a leading provider of micro-controller, mixed-signal, analog, and Flash-IP solutions. The following is an answer snippet in Q&A session of the Q4 2019 Earnings Call on May 08, 2019.

I think there are 2 possibilities on the trade front. Actually, 3. One – the worst would be that trade talks break, and there's 25% duty not only on the $200 billion of goods but another $325 billion of goods that are threatened. That would be the worst-case scenario. But the other possibilities are there is some very good settlement where whatever the issues are between the 2 countries on IP theft and forced transfers of technology and all those things, there is a system put in place to monitor all these and issues are resolved and the tariffs come down. That would be the best-case scenario. And the other one is that there is some sort of finality where it's not as good as the U.S. wants. . . .

In the example, trade policy terms are captured and highlighted in blue ground. The corresponding sentence is underscored. Then, within a one-sentence distance around the marked trade terms, uncertainty synonyms, positive and negative words are searched. I highlight the uncertainty synonyms in yellow background. Positive words contributed to TPS are colored in green, and negative words are in red.

This example shows some features of similar kinds of textual methods. First, the words captured do present speakers' concern on potential risk on trade policy. In the dialog, the speaker lists two possibilities of future events, one is the worst and the other is the best. No matter which direction of speakers' altitude indicates, this part of the speech represents the extent of trade policy uncertainty perceived. Second, notice that the "possibilities" in the first sentence and "good" in the last sentence are not captured, because we require all concurrences to be within one-sentence distance with trade policy terms. Overall, the sample represents the raw counts of uncertainty words in TPU as 2, positive-tone in TPS as 2, and negative-tone in TPS as 5. Increasing the distance scope within the concurrences would include more words frequencies, while at the cost of decreasing precision. Irrelevant risk or sentiment could be taken into account of trade policy shocks. Third, it is inevitable to include negations, for example, the "not... good" in the last sentence. However, the use of such negation is rare in the analysis as Hassan et al. (2019) document.

Table 3 reports the 50 most frequent words, in the $\mathbb{T}$, $\mathbb{U}$, $Positive\_wordlist$, and $Negative\_wordlist$ used in the construction of TPU and TPS.

4.2 Exposures of Trade Policy Shock

In this subsection, I explore the properties of the key measures, TPE, TPU, and TPS to corroborate that the indexes indeed capture firms' exposure to the trade policy.

Figure 2 shows the trends of aggregate TPE and TPU in each sector at NAICS 2-digit level over time.[19] The aggregate TPE in the blue line is the fraction of transcripts mentioning trade policy ($TPE_{i,t} > 0$) in a sector at the time t. The aggregate TPU is calculated in a similar way and plotted in orange. For the TPE, goods sector, such as *21 Mining*, *31-33 Manufacturing*, *42 Wholesale Trade*, and *44-45 Retail Trade*, typically has a large trade policy exposure (20%) as in it there are many firms having business in the global market or relying on global sourcing. Th For the TPU, there is large degree of variation in TPU across sectors and over time. In particular, sector *31-33 Manufacturing*, *42 Wholesale Trade*, and *44-45 Retail Trade* experience high TPU during 2018-2019, but not in sectors which are not directly affected by the trade war, such as *22 Utility*, *51 Information*, *62 Health Cares*.

Figure 3 plots the average TPU and other existing indices in the literature over time. The average TPU is the simple average of $TPU_{i,t}$ for all firms at time t. The solid dark-blue line is the average TPU calculated from equation (2), and the dashed light-blue line is the firm-level TPU in Caldara et al. (2020). Both of the values refer to the left axis. The dotted orange line referring to the right axis is the trade-topic sub-index in Hassan et al. (2019), shown as the simple average for all firms at time t.

One concern of the firm-level index in Caldara et al. (2020) is that there are too

[19]It is a more complete version of Fig. 1 in Caldara et al. (2020). Sectors with small firm numbers are not reported here. Three sectors have average firm numbers less than 15: *11 Agriculture, Forestry, Fishing and Hunting*, *61 Educational Services*, and *81 Other Services (except Public Admin.)*.

Table 3. 50 Most Frequent Words Captured in the Construction of TPU and TPS

TP_Word	Frequency	Uncertainty_Word	Frequency	Positive_Word	Frequency	Negative_Word	Frequency
export	24130	probably	13084	strong	126480	decline	17079
tariff	18881	risk	12559	good	73086	negative	15147
import	15958	uncertain	9998	positive	39680	loss	11352
trade&china	4500	likely	5472	better	30419	against	9404
trade&global	3091	volatility	5016	improvement	28440	declined	8911
trade war	2132	possible	4821	able	27484	difficult	7791
nafta	1489	concerned	3889	opportunities	27163	challenging	7634
antidumping	943	concerns	2475	improved	26856	challenges	7338
trade tension	846	cautious	2277	progress	20340	restructuring	6376
trade&asia	823	prospects	2102	improve	19614	late	5472
trade dispute	659	concern	1962	benefit	17856	losses	5129
fob	414	volatile	1957	opportunity	17854	closed	4954
international trade	397	variable	1644	great	17666	weak	4897
free trade	377	possibility	1496	despite	17600	closing	4643
trade policies	353	concerning	1248	pleased	16541	volatility	4561
trade&canada	340	pending	1037	best	15273	critical	4302
border&tax	304	doubt	1011	profitability	14419	weaker	3910
trade agreement	304	threat	988	stable	12853	negatively	3369
trade deal	289	exposed	946	improving	12762	recall	3198
trade&brazil	287	chance	792	achieved	12556	declines	3087
trade&india	282	caution	625	efficiency	11966	slow	3040
wto	236	prospect	517	leading	11491	challenge	2822
fta	207	fear	500	strength	11417	impairment	2815
usmca	170	worry	374	favorable	10710	crisis	2809
trade&australia	158	possibilities	356	improvements	10223	weakness	2710
trade&japan	155	likelihood	329	stronger	9534	slowdown	2694
trade&africa	146	unknown	307	success	9277	lost	2683
tpp	139	prospective	301	successful	9073	concerned	2653
trade discussion	134	unclear	273	effective	9008	declining	2486
trade relations	122	variability	262	confident	8871	unfavorable	2428
trade&latin america	122	probability	256	gains	8790	force	2322
trade action	120	instability	236	advantage	8776	slower	2225
trade&german	120	unpredictable	215	greater	8764	cut	2195
trade&korea	119	varying	206	achieve	8725	bad	2062
trade talk	114	speculative	176	innovation	8387	dropped	2025
border&trade	100	probable	149	gain	8059	volatile	1909
trade&middle east	94	bet	144	profitable	6706	problem	1831
foreign trade	83	rumors	143	attractive	6615	delays	1785
trade&south america	66	worries	130	happy	6313	unfortunately	1662
cif	62	sticky	127	leadership	6182	closure	1646
trade&italian	62	chances	124	highest	6175	delayed	1640
trade balance	57	doubtful	118	excellent	5996	problems	1625
trade&ireland	48	tricky	118	excited	5828	bridge	1624
trade practice	47	hesitant	117	efficient	5508	adverse	1597
trade&france	45	fluctuating	100	efficiencies	5366	downturn	1543
border&control	34	unstable	96	successfully	5270	concerns	1488
trade&vietnam	32	hazardous	88	benefited	5237	breakdown	1482
trade&taiwan	27	unresolved	86	optimistic	4580	delay	1456
trade imbalance	17	dangerous	80	enhance	4476	lack	1437
trade surplus	17	reservation	72	strengthen	4273	concern	1411

Notes: This table shows the 50 most frequent words in the trade policy, uncertainty, positive and negative word lists used to construct the TPU and TPS. The *Frequency* column reports the number of occurrences of the corresponding term(s) across all transcripts.

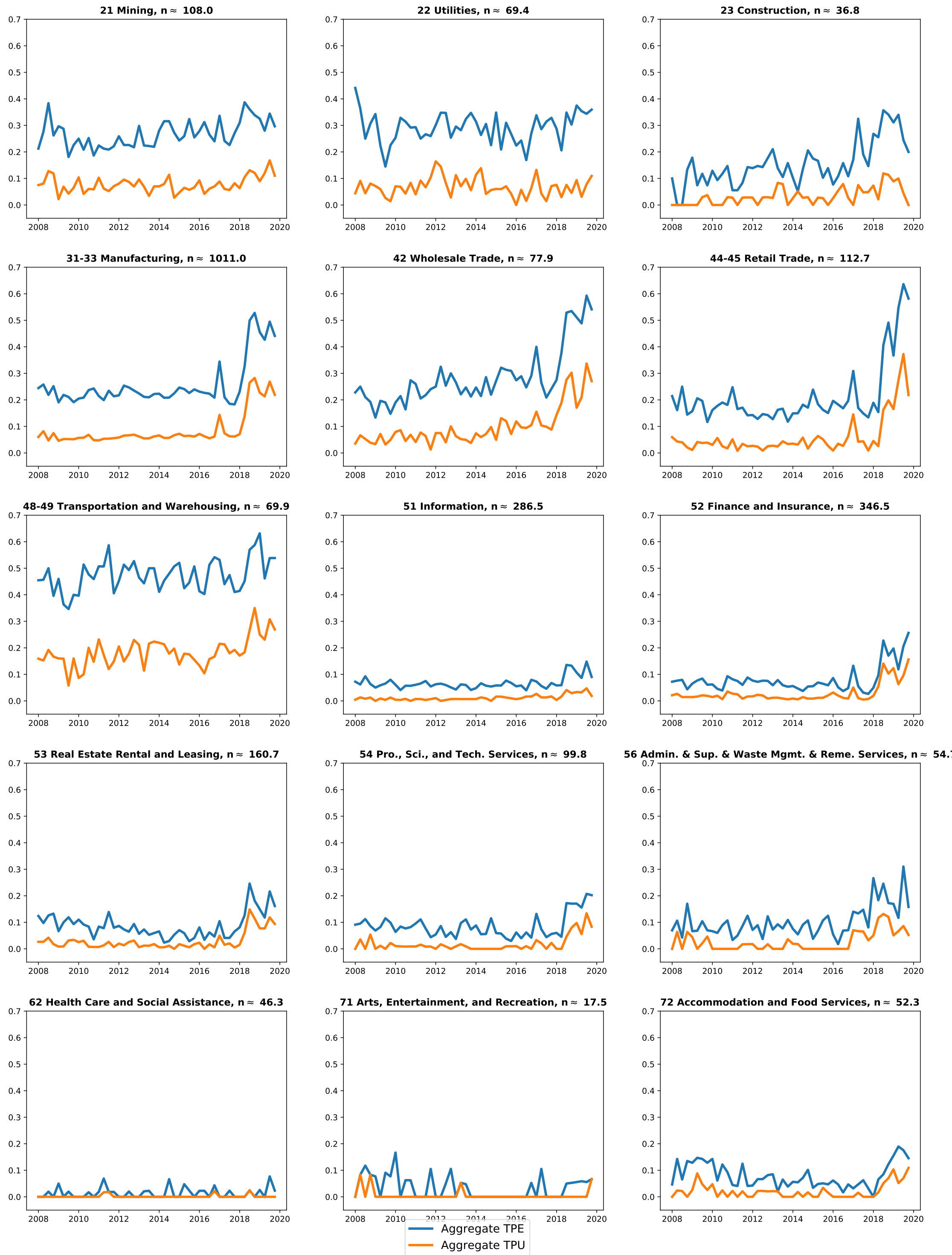


Figure 2. TPE and TPU by Sector over Time

Notes: This graph plots the trends of aggregate trade policy exposure and uncertainty by sector (at 2-digit NAICS). Each subplot shows the average share of firms with positive TPE (in blue) and TPU (in orange) in a given industry over time. The subplot title includes 2-digit NAICS, its corresponding sector name, and average firms number in the industry from 2008 to 2019, n.

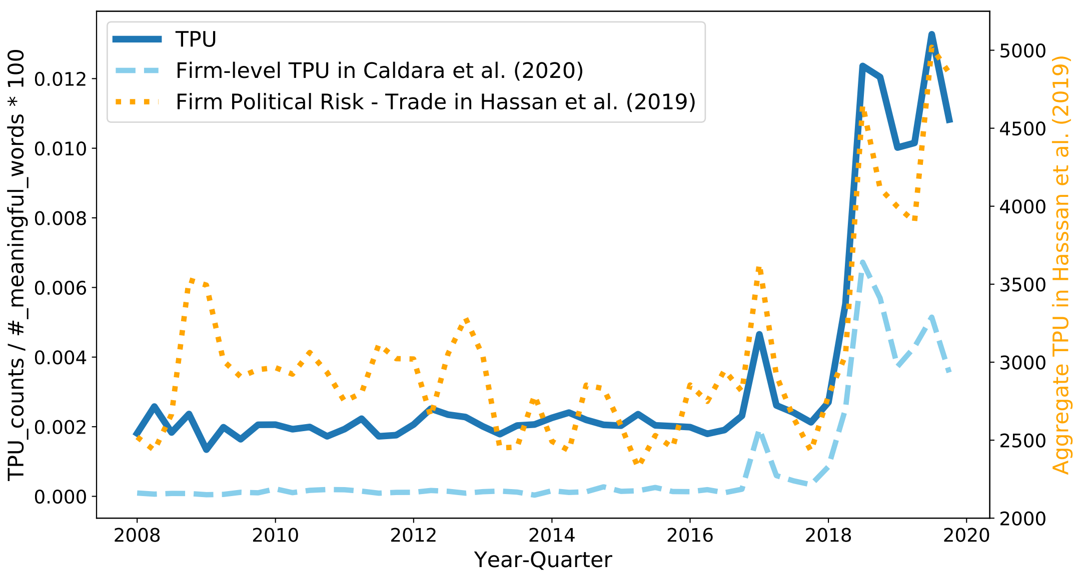


Figure 3. TPU and Comparisons

Notes: The figure shows the trends of the simple average of $TPU_{i,t}$ for all firms, shown as the solid dark-blue line. The firm-level TPU in Caldara et al. (2020) is the dashed light-blue line. Both lines refer to the left axis. The dotted orange line referring to the right axis is the trade-topic sub-index in Hassan et al. (2019).

many zero observations. It contains only 2.04% non-zeros, covering 1021 firms, out of 123,648 transcripts in 2008-2019. My TPU index, in contrast, is richer in the sense of more non-zeros coverage (6.09%) and a larger number of exposed firms (1,810 firms). The richer index gives us more variation across firms and over time.

In figure 3, the TPU has a larger variation across time than the one in Caldara et al. (2020) while preserving the movement in general. Note that the greater average value, shown visually as the solid dark-blue line above the dashed light-blue one, is due to the border word list of trade policy terms and the discreet method of removing meaningless words, such as safe harbor statements and stop words. Including more trade-related words in the trade policy list might also raise false positive concerns. That is, the trade words captured do not reflect the uncertainty stemmed from trade policy but something else. For example, the trade-topic sub-index in Hassan et al. (2019) has spikes around 2009. While the TPU in this paper doesn't have a high average value during the financial crisis, neither nor high sectoral fraction of positive value in figure 2, implying less false positive concerns.

Figure 4 plots the aggregate TPS and other sub-indexes. Not surprisingly, managers typically speak more positively than analysts, who are only measured in the question part in the Q&A session. The aggregate TPS index is driven by the management speeches. Interestingly, there is a divergence of managers and analysts towards trade policy during the trade war, while not in the financial crisis. In particular, for the first two quarters of 2018, unexpected tariff announcements raised analysts' concerns overwhelmingly, and managers tried hard to comfort the public's fear by discussing trade policy issues with a very positive tone. Since the sentiment study is not the focus of this paper, I leave the investigation for future research.

4.3 TPU Variation

One potential concern is that the measures stemming from earnings call systemically reflect aggregate fluctuations and differences in firm-invariant or sector-invariant characteristics along the time. For example, it's normal for a manager working for a multinational company that has many international business to mention its trade performance in the call frequently. If so, the TPU would be high for most of the time. Thus the value of TPU calculated from equation (2) itself would be overrated. To address this, following Handley and Li (2020), I regress TPU on a large set of fixed effects and take the remaining residual as my new TPU index for the regression analysis. Note that in the empirical analysis, I use data from 2010 to 2019 to avoid

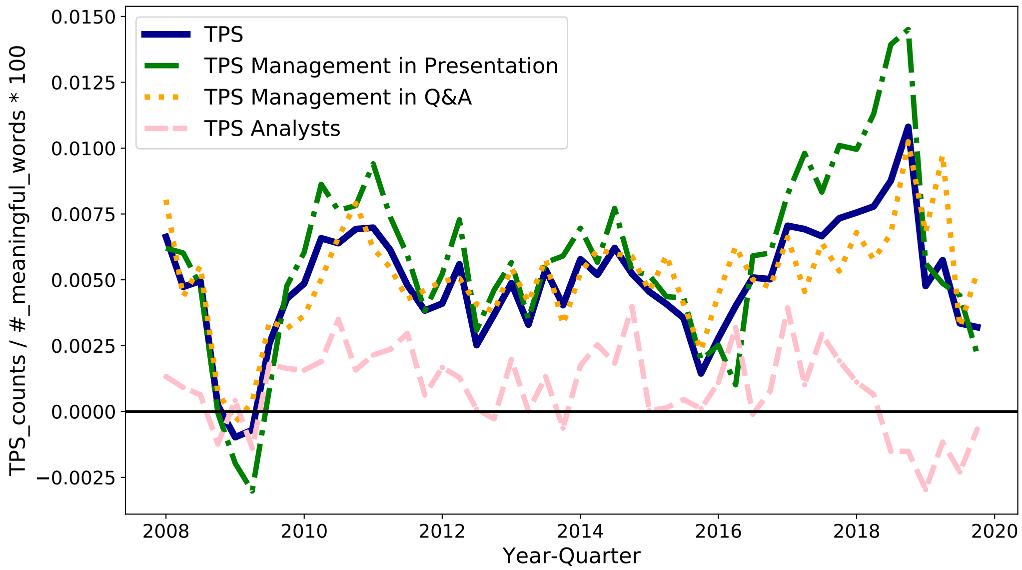


Figure 4. TPS and Its Components

Notes: This figure plots the simple average of $TPS_{i,t}$ of all firms at time t, and its sub-indexes.

the disturbance of the financial crisis. Therefore, when decomposing TPU, I truncate the time from 2010 and exclude the firms in finance (SIC codes 6000-6299) and utility sectors (SIC codes 4900-4999).

Table 4 reports the results. In Column (1), I regress TPU on the quarter, sector, quarter-sector, and firm fixed effects separately, and the R-squared value is reported correspondingly in each row. In Column (2), TPU is regressed incrementally on the quarter, sector, quarter-sector, and firm fixed effects, and the incremental R-squared is shown. In the end, after controlling firm and sector-quarter fixed effects, there are about 68% unexplained residual variation in TPU. I then standardize the remaining variation by dividing the standard deviation, labeled as $TPU_{i,t}(std.)$, and utilize it for the rest of the paper. Analogously, I extract and standardize the remaining residual variations for TPS, nonTPU, and nonTPS.

4.4 Managing Trade Policy Uncertainty

I probe the validity of the measures by examining how TPU relates to the firm's actions. In particular, firms' changes in investment and inventory growth in response

Table 4. Variance Decomposition of TPU

	(1) R-squared	(2) Incremental R-squared
Quarter FE	3.08%	3.08%
Sector FE (3-digit NAICS)	3.48%	3.13%
Sector × Quarter FE	11.72%	5.11%
Firm FE	24.05%	20.36%
Unexplained Residual	-	67.92%
Number of Observations	93,657	93,657
Number of Firms	3,825	3,825
Number of Sectors (3-digit NAICS)	81	81

to trade policy shock are of interest. A valid TPU index should correctly predict firms' responses to the trade policy shocks in a way as theory predicts.

4.4.1 Impact on Investment

Replicating Caldara et al. (2020) Many theoretical and empirical work show that uncertainty can directly reduce the business investment (see Bernanke, 1983; Dixit and Pindyck, 1994; Nick Bloom et al., 2007; Nicholas Bloom, 2009; Baker et al., 2016). Caldara et al. (2020) study how trade policy uncertainty affects investment via a two-country New-Keynesian model with firms' export decisions. One subsection in their paper estimates the dynamic effects of firm-specific trade policy uncertainty on capital accumulation through regression analysis. I replicate their baseline specification with the $TPU_{i,t}$ (std.) in this paper, and show that it generates a similar pattern and magnitude of dynamic effects on capital. Then, I show that the results with my TPU index are also robust when using other investment variables.

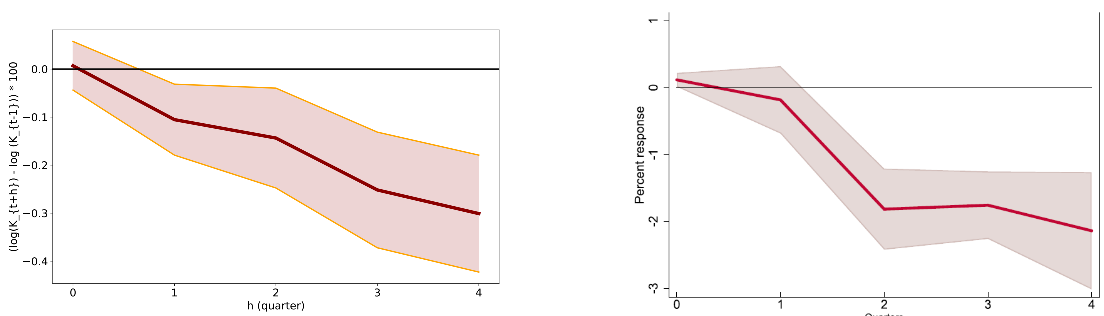
Since the TPU index is built upon the methodology and trade policy word list in Caldara et al. (2020), a valid TPU index should preserve the predictable property. In their paper, one of the main results is that the impact from an increase in trade policy uncertainty on investment builds over time, and the capital stock drops around 2 percent after four quarters.

The specification used in Caldara et al. (2020) for the dynamic effects on investment is

$$\log K_{i,t+h} - \log K_{i,t-1} = \alpha + \beta_h TPU_{i,t} + \zeta' C_{i,t} + \theta_i + \theta_t + \epsilon_{i,t} \tag{6}$$

where dependent variable $\log K_{i,t+h} - \log K_{i,t-1}$ is the log change of capital stocks for firm i from quarter $t-1$ to quarter $t+h$, $K_{i,t}$ is capital stock calculated following Clementi and Palazzo (2019) and Ottonello and Winberry (2020), $C_{i,t}$ are control variables including firm's tobin'q, cash flow, export-usage ratio, one lag of the growth rate of the capital stock, and one lag of the trade policy uncertainty measure, θ_i is firm fixed effects, and θ_t is quarter fixed effects.

Figure 5 shows the response of capital to an increase of TPU. Panel (a) shows the result using $TPU_{i,t}$ and panel (b) shows the original figure in Caldara et al. (2020) for comparison. I follow their method of drawing panel (b) to plot the log difference of capital stock to an increase of $TPU_{i,t}$ (std.) from 0 to 1.3681 (not tabulated), the median value when the original TPU (before taking the residual) is greater than 0. With a broader data coverage, i.e., 2010Q1-2019Q4, the impact of trade policy uncertainty increases over time, indicating a 2.79% (=-0.220*1.3681/10.804*100, summary statistics in Table B.2) drop in investment after four quarters.



(a) Response of Capital to $TPU_{i,t}$ (std.), 2010Q1-2019Q4

(b) Figure 6 in Caldara et al., 2015Q1-2018Q4

Figure 5. Responses of Capital to TPU

Notes: The left panel plots the response of capital stock following an increase in firm-level $TPU_{i,t}$ from 0 to 1.3681, its median value when the original TPU (before taking the residual) is positive than 0. The shaded band shows the one standard error confidence interval. Standard errors are two-way clustered by firm and quarter. The right panel is the Figure 6 in Caldara et al. (2020), where they focus on the 2015Q1-2018Q4 period.

Robustness with Other Investment Variables Since there is no standard way to construct investment, as robustness checks, a valid trade policy uncertainty should correlate significantly with other investment proxies. With a capital investment rate calculated in a way in another literature and Compustat research and development expenses (R&D), I further check the negative association between investment and my TPU index.

The main specification takes the form:

$$y_{i,t} = \beta TPU_{i,t} + \Gamma' X_{i,t} + \delta_{st} + \delta_i + \alpha + \epsilon_{i,t} \tag{7}$$

where the dependent variable is either corporate investment rate or percentage change in R&D expenditure for firm i in the quarter t. The corporate investment rate, $\frac{I_{i,t}}{K_{i,t-1}}$, is calculated recursively using a perpetual-inventory method as described in Hassan et al. (2019) and Stein and Stone (2013). It is, in brief, capital expenditure - capital stock ratio, instead of differences in consecutive capital stock.[20] Percentage change in R&D expenditure ($\%\Delta R\&D_{i,t}$) is the difference between current R&D expenditure ($R\&D_{i,t}$) and its one lag value ($R\&D_{i,t-1}$) divided by the lagged value ($R\&D_{i,t-1}$) and multiplied by 100. The first term on the right-hand side is the TPU of interest. The second term $X_{i,t}$ contains other three trade policy measures, i.e., $TPS_{i,t}$, $nonTPU_{i,t}$, and $nonTPS_{i,t}$, and four firm time-variant characteristics, i.e., one lag of the firm's assets as a control for its size, market-book ratio for its value, book leverage for its indebtedness, and operation income deducted interests and tax for its profitability. $X_{i,t}$ also include a export-usage ratio for sector s at time t to capture sectoral time-varying characteristics in output and trade, and time-invariant upstreamness at industry j level. δ_{st}, δ_i and α represent sector-quarter and firm fixed effects and the constant. Throughout the paper, standard errors are two-way clustered by firm and quarter.

Table 5 reports the estimation results for corporate investment. Column (1) shows the most parsimonious specification where I regress the investment rate on TPU with quarter fixed effects. For investment rate, the coefficient of interest is negative and significant at the 5% level (-0.086, std. err. = 0.035), suggesting that a one standard deviation increase in trade policy uncertainty decreases the investment rate by 0.086 percentage points. Column (2) - (5) build up to the basic specification by adding firm and sector controls, quarter-sector fixed effects, and firm fixed effects. Note that when I include quarter-sector fixed effects in columns (3) and (5), the sector variable,

[20]Note that Compustat reports capital expenditure as a year-to-date variable. The quarterly value is obtained by subtracting its one lag within the same fiscal year, while leaving the first fiscal quarter value as it is.

$\frac{Export_{s,t}}{Usage_{s,t}}$, is absorbed. Because the export-usage ratio is only available for agriculture, mining, and manufacturing sectors, observation numbers in these two columns are less than the others. Adding more fixed effects reduces the size of the coefficient of interest, but it remains statistically significant. The coefficient in column (5) suggests that one standard deviation increase in trade policy uncertainty is associated with a 0.066 percentage point decrease in firms' investment rate (std. err. = 0.030. Economically speaking, it corresponds to a drop of 0.65 percentage (0.066/10.104∗100) in investment relative to the sample mean. Column (6) replicates column (5) with replacing the TPU index in this paper with the one in Caldara et al. (2020), labeled as $\text{CIMPR}_{i,t}$. The coefficient is negative but not statistically significant. Column (7) shows that the negative association is very robust even when we include both TPU indexes, i.e. $TPU_{i,t}$ and $\text{CIMPR}_{i,t}$. It implies the finer TPU index absorb the variation in CIMPR_{it}.

The coefficients on general uncertainty other than trade policy, i.e., $nonTPU_{i,t}$, are negative but not statistically significant in columns (2)-(4). It is significant at the 10% level in columns 5. This is abnormal because general uncertainty should be more negatively associated with the investment. But the next robustness check on R&D expenditures gives me more confidence that $nonTPU_{i,t}$ captures the general risk about the second moment.

Table 6 reports the results for percentage changes in R&D expenditures. In columns (1) to (5), all coefficients of $TPU_{i,t}$ are negative and statistically significant. Not surprisingly, firms' general risk ($nonTPU_{i,t}$) has a more pronounced effects on R&D expenditures. Quantitatively, the coefficients in column (5) represents a one standard deviation increase in TPU deducing R&D expenditure by 4.15% (-0.189/4.553*100), and a one standard deviation increase in NonTPU reducing R&D expenditure by 9.75% (-0.444/4.553*100). Column (6) shows that CIMPR_{it} is negatively associated with R&D expenditure growth. The coefficient is significant at the 10% level (-13.568, std. err. = 6.893). However, when I include both indexes in the regression, column (7) shows again the coefficient of $TPU_{i,t}$ are negative and statistically significant but not for the CIMPR_{it}.

4.4.2 Impact on Inventory

Few recent work studies the anticipation of inventory or input choice to trade policy changes, for example, Alessandria et al. (2019) and Handley, Limão, et al. (2020). Alessandria et al. (2019) find that the US imports increase significantly in months in

Table 5. Effects of TPU on Investment Rate

	$\frac{I_{i,t}}{K_{i,t-1}} \times 100$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{TPU}_{i,t}$ (std.)	-0.086**	-0.081**	-0.069**	-0.080**	-0.066**		-0.077**
	(0.035)	(0.034)	(0.029)	(0.035)	(0.030)		(0.031)
$\text{CIMPR}_{i,t}$						-1.405	3.220
						(3.712)	(3.930)
$\text{TPS}_{i,t}$ (std.)		0.013	0.015	-0.005	0.004	0.011	0.003
		(0.028)	(0.023)	(0.026)	(0.021)	(0.022)	(0.022)
$\text{NonTPU}_{i,t}$ (std.)		-0.001	0.006	-0.019	-0.008	-0.009	-0.008
		(0.046)	(0.035)	(0.042)	(0.032)	(0.032)	(0.032)
$\text{NonTPS}_{i,t}$ (std.)		0.122**	0.072**	0.154***	0.094***	0.096***	0.094***
		(0.049)	(0.034)	(0.046)	(0.032)	(0.033)	(0.032)
N	36,705	36,634	67,873	37,859	70,124	70,124	70,124
R2	0.0269	0.0401	0.0935	0.2135	0.2594	0.2594	0.2595
Controls		X	X	X	X	X	X
Quarter FE	X	X		X			
Quarter × Sector FE			X		X	X	X
Firm FE				X	X	X	X

Notes: This table shows the estimation results for TPU effects on capital investment rate. Estimation is by OLS. The corporate investment rate, $\frac{I_{i,t}}{K_{i,t-1}}$, is calculated recursively using a perpetual-inventory method as described in Hassan et al. (2019) and Stein and Stone (2013). The $\text{TPU}_{i,t}$ (std.) is the trade policy uncertainty index constructed in this paper. $\text{CIMPR}_{i,t}$ is the firm-level TPU in Caldara et al. (2020). Columns (1), (2), and (4) use a sub-sample of agriculture, mining, and manufacturing sectors, and include sectoral export-usage ratios as sectoral control. Other columns include quarter-sector (3-digit NAICS) fixed effects to absorb the time-variant sectoral characteristics. All but column (1) include TPS, NonTPU, NonTPS, lagged log total asset, book-market ratios, book leverage, profitability, and upstreamness as controls.
Standard errors are clustered by firm and quarter. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6. Effects of TPU on R&D Expenditure

	$\%\Delta R\&D_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{TPU}_{i,t}$ (std.)	-0.237***	-0.218***	-0.180**	-0.229***	-0.189**		-0.181*
	(0.072)	(0.075)	(0.074)	(0.073)	(0.078)		(0.097)
$\text{CIMPR}_{i,t}$						-13.568*	-2.333
						(6.893)	(9.397)
$\text{TPS}_{i,t}$ (std.)		0.078	0.069	0.064	0.071	0.111	0.072
		(0.149)	(0.159)	(0.147)	(0.160)	(0.157)	(0.161)
$\text{NonTPU}_{i,t}$ (std.)		-0.507**	-0.416**	-0.557***	-0.444***	-0.444***	-0.444***
		(0.194)	(0.155)	(0.184)	(0.146)	(0.146)	(0.146)
$\text{NonTPS}_{i,t}$ (std.)		-0.061	-0.119	-0.116	-0.178	-0.173	-0.178
		(0.161)	(0.142)	(0.162)	(0.141)	(0.141)	(0.141)
N	25,492	25,314	34,550	25,977	35,451	35,451	35,451
R2	0.0052	0.0080	0.0557	0.0552	0.1028	0.1028	0.1028
Controls		X	X	X	X	X	X
Quarter FE	X	X		X			
Quarter $\times$ Sector FE			X		X	X	X
Firm FE				X	X	X	X

Notes: This table shows the estimation results for TPU effects on R&D expenses. Estimation is by OLS. The dependent variable is percentage changes in R&D expenditure. The $\text{TPU}_{i,t}$ (std.) is the trade policy uncertainty index constructed in this paper. $\text{CIMPR}_{i,t}$ is the firm-level TPU in Caldara et al. (2020). Columns (1), (2), and (4) use a sub-sample of agriculture, mining, and manufacturing sectors, and include sectoral export-usage ratios as sectoral control. Other columns include quarter-sector (3-digit NAICS) fixed effects to absorb the time-variant sectoral characteristics. All but column (1) include TPS, NonTPU, NonTPS, lagged log total asset, book-market ratios, book leverage, profitability, and upstreamness as controls.
Standard errors are clustered by firm and quarter. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

advances of China's MFN status renewal decision but then fall sharply when renewal occurs. They develop an (S, s) inventory model to explain the stockpiling in advances of the uncertainty resolution. Although Compustat only provides aggregate level on inventory, the firm-level data at quarterly frequency allow us to examine the inventory responses to the trade policy shocks broadly.[21]

I run the ordinary least squares regressions of the specification (7) with dependent variables as log difference in inventory, i.e., $\log(Inventory_{i,t+h}) - \log(Inventory_{i,t-1})$.[22]

Table 7 reports the estimation results for inventory responses at horizons $h = 0, 1, 2, 3, 4$. Column (1) shows contemporaneous inventory surges in response to the increase of trade policy uncertainty but dampens due to the general risk other than trade. The coefficient of TPU is 0.176 and statistically significant at 1% level (std. err. = 0.054). The coefficient of NonTPU is -0.155 and statistically significant at 5% level (std. err. = 0.054). Quantitatively, a one standard deviation in $TPU_{i,t}$ boosts inventory growth by 9.89% (0.176/1.780*100), and a one standard deviation in $NonTPU_{i,t}$ reduces inventory growth by 8.71% (-0.155/1.780*100). In column (2), the impact of trade policy uncertainty attenuates with a coefficient of 0.159 (std. err. = 0.081) but is still statistically significant. The coefficient on general uncertainty other than trade policy is negative but statistically insignificant. In columns (3) to (5), the coefficients of TPU and NonTPU are statistically insignificant, implying that the stockpiling behavior is temporary, within one quarter after the increase in TPU. It is also interesting to see that the impact of from TPS and NonTPS builds over time (expect that the coefficients on NonTPS at $h = 0$ and on TPS at $h = 3$ are statistically insignificant).

The analysis on firms' inventory, although coarsely at the aggregate level and not directly related to trade, does provide evidence that trade policy uncertainty has a short-run effect on the inventory growth. The positive correlation between trade policy uncertainty and inventory growth and its differential impact with other firm risks corroborates the theoretical prediction of inventory responses to the trade policy uncertainty.

Readers might worry that the inventory change is driven by the changes in sales, not due to the policy change. To address this, I run a static regression in equation

[21] To my knowledge, there are no international trade data in the balance sheets released by the public firms. So Compustat doesn't include disaggregated data on input imports or foreign goods inventory.

[22] The total inventory value includes merchandise bought for resale and materials and supplies purchased for use in production of revenue.

Table 7. Dynamic Effects of TPU on Inventory

	$(\log Inventory_{i,t+h} - \log Inventory_{i,t-1}) \times 100$				
	(1)	(2)	(3)	(4)	(5)
	h=0	h=1	h=2	h=3	h=4
$\text{TPU}_{i,t}$ (std.)	0.176***	0.159*	0.089	-0.055	-0.102
	(0.054)	(0.081)	(0.093)	(0.117)	(0.141)
$\text{TPS}_{i,t}$ (std.)	0.120*	0.213**	0.226**	0.165	0.352***
	(0.062)	(0.094)	(0.097)	(0.102)	(0.120)
$\text{NonTPU}_{i,t}$ (std.)	-0.155**	-0.155	-0.116	-0.164	-0.178
	(0.062)	(0.110)	(0.138)	(0.172)	(0.204)
$\text{NonTPS}_{i,t}$ (std.)	-0.031	0.427***	0.678***	1.085***	1.307***
	(0.091)	(0.142)	(0.159)	(0.186)	(0.210)
N	61,045	60,656	59,898	59,340	58,217
R2	0.1478	0.1916	0.2347	0.2798	0.3183
Controls	X	X	X	X	X
Quarter × Sector FE	X	X	X	X	X
Firm FE	X	X	X	X	X

Notes: This table shows the dynamic effects of trade policy uncertainty on inventory changes. Estimation is by OLS. The dependent variable is the log difference of the inventory at period $t+h$ and the value at period $t-1$. All columns include TPS, NonTPU, NonTPS, lagged log total asset, book-market ratios, book leverage, profitability, and upstreamness as controls and also include sector-quarter and firm fixed effects.
Standard errors are clustered by firm and quarter. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

(7) with the dependent variable as inventory-sales ratio. The results are included in the appendices, where I also include estimation results for sales, cost, and profit.

5 Effects of TPU on Global Value Chain Relationships

After validating the measures, I explore the effects of TPU on the firms' GVC relationships. The existing trade policy uncertainty literature and previous estimation results infer that there are two effects on a firm's foreign relationships. One is the trade-dampening wait-to-see effect, resulting in less incentive for exporting and expanding foreign market. (See Feng et al., 2017; Handley and Limão, 2015, 2017) In GVCs context, it implies high trade policy uncertainty would deter a firm from reaching new foreign customers and even disrupt the existing foreign relationship. Thus, trade policy uncertainty affects the number of a firm's foreign customers negatively. The other is the trade-boosting precautionary effect, as stockpiling inputs in anticipation of future high tariffs, before the uncertainty is resolved (Alessandria et al., 2019). However, the changes in a firm' GVC links in response to TPU through precautionary effects are ambiguous. As an international buyer in an unstable trade environment, the importer might work more closely with its existing foreign suppliers by purchasing more inputs in the short run, shift suppliers to domestic firms (reshoring), or even reach out new foreign suppliers with low trade policy risk (additional offshoring).[23] If the firm keeps the current foreign suppliers and meanwhile finds few foreign suppliers, TPU might even induce the number of firms' foreign suppliers in the short run. Overall, an international firm's foreign relationships can be negatively associated with TPU because of the seller's wait-to-see effects, and be positively associated with TPU because of the buyer's precautionary effects.

To disentangle the confounding effects, I discuss and examine the TPU impact on the US firms' reliance on foreign customers and foreign suppliers separately. In the later estimations, the dependent variable of interest is a firm's foreign customer (supplier) ratio, calculated as the firm's foreign customer (supplier) number divided by its total customer (supplier) number. The descriptive statistics is in the Table 2 Panel C. The trends of the US firms' foreign relationships and the reliance on average are shown in the Figure 1 subfigure 1 and 2.

Many empirical studies already find that trade policy uncertainty deters the exporting behaviors and negatively correlates with the numbers of exporters. Analogously, I expect that the US firms' foreign customer links are negatively associated with the trade policy uncertainty. This prediction implies that US sellers' negative wait-to-see effect dominates the precautionary resistance effect on its foreign cus-

[23]Few ongoing works focus on global resourcing and firms' additional offshoring behavior during the trade war, see Charoenwong et al., 2020; Handley, Limão, et al., 2020.

tomers.

Moreover, with the highly disaggregate industrial measure available to the US firms, I am wondering what the role of firms' production position is in adjusting relationship composition. To answer this question, we need to refer to the facts and results in the GVCs literature. Alfaro et al. (2019) document that the higher production stages are associated with a low demand elasticity. It means that industries serving the final demand generally have a larger demand elasticity than those producing intermediate goods.

Consider the relationships for US sellers, or exporters in the international context. During the trade war, high tariffs announced or potential retaliation from partner countries makes exporters retrench their investment on expanding foreign market, and hurts the existing relationships, especially for firms selling final goods. Thus trade policy uncertainty is expected to have a larger impact on downstream firms' foreign customer relationships. Therefore, I have the following prediction of the effects on a US firm's reliance on foreign customers.

Hypothesis 1: *An increase in trade policy uncertainty would reduce the US firms' foreign customer relationships. The impact is more pronounced to downstream firms.*

Consider the effects of trade policy uncertainty on relationships for the US buyers, or importers in the international context. News about the proposed tariffs would induce the anxiety of the US firms that rely on global production suppliers, further resulting in stockpiling in a short period.[24] Meanwhile, the firms may find new foreign suppliers in the country with low trade policy uncertainty as backups. The additional offshoring behavior may confound the number of firms' total foreign suppliers. Overall, the prediction of the impact of TPU on a firm's foreign supplier ratio is unclear.

Next, I estimate the TPU effects on GVC links and examine the hypothesis of the heterogeneous effects on firms' production positions for foreign relationships.

I estimate the coefficients in the equation below by ordinary least squares:

$$\begin{aligned} y_{i,t} &= \beta_1 TPU_{i,t} + \beta_2 Upstreamness_j + \beta_3 TPU_{i,t} \times Upstreamness_j \\ &\quad + \Gamma' X_{i,t} + \delta_{st} + \alpha + \epsilon_{i,t} \end{aligned} \tag{8}$$

[24]Unfortunately, transaction values between the trading partners are not observed. I focus on importing extensive margin instead.

where the dependent variable is either foreign customer ratio or foreign supplier ratio for firm i in quarter t. For effects on foreign customer relationship, the coefficients β_1 and β_3 are of our interest. β_1 captures the within-industry effects of an one standard deviation increase in TPU on a firm's foreign reliance. β_3 governs the heterogeneous effects of TPU across different industries. Put together, $(\beta_1 + \beta_3 Upstreamness_j)$ represents the differential effects from a 1 standard deviation increase in TPU on foreign reliance between a firm in industry j that is concerned about the TPU and another one that is not concerned.

The results of the estimation are provided in Table 8. The first three columns show the results for the firms' foreign customer ratios, and the last three columns are for foreign supplier ratios. Column (1) reports the estimates for the equation (8) focusing on the agriculture, mining, and manufacturing sectors, in which I regress firms' foreign customer ratio on trade policy measures, upstreamness, and their interactions. The coefficient on TPU is negative (-1.139, std. err. = 0.482) and statistically significant, implying that hold everything else constant, within the same position along the production process, a one standard deviation increase in TPU would deduce a firm's foreign customer ratio by 3.3% relative to the sample mean (=-1.139/34.505*100). The positive coefficient on $Upstreamness_j$ implies that upstream firms usually have a larger foreign customer fraction than downstream firms, same as the subfigure 3 in Figure (1). The coefficient on the interaction between TPU and $Upstreamness_j$ is positive and statistically significant (0.461, std. err. = 0.196), implying that hold everything else constant, the impact from a 1 standard deviation increase in TPU would be alleviated for a firm locate one more stage away from final demand by 1.34%, relative to the sample mean (=0.461/34.505*100). Therefore, Hypothesis 1 is supported empirically.

In columns (2), I add interactions of trade policy measures and the export-usage ratio. The coefficient on TPU and its interaction with sectoral export-usage ratio indicates that the differential impact from TPU on firms with the same industrial position mainly results from their trade characteristics. This finding is consistent with the intuition that a firm exporting more would be more sensitive to the trade policy shocks. The coefficient of the interaction of TPU and upstreamness is positive and statistically significant (0.384, std. err. = 0.178). Column (3) includes the sector-quarter fixed effects, and thus the sectoral characteristics are absorbed. It shows that even including the wholesale and service sector, the estimation results of coefficients on TPU and its interaction between upstreamness are robust.

The estimation results for the firms' foreign supplier ratios in columns (4)-(6) don't show the same pattern as the TPU impact on the reliance of foreign customers in columns (1)-(3).

Two possible reasons can explain the US firms' strong reliance on foreign suppliers. First, firms' additional offshoring behavior increases the number of foreign suppliers and thus confounds the estimation results. This is supported by Charoenwong et al. (2020), in which they find that on average the US firms actually increase their foreign supplier relationships during the trade war. Second, the strong resistance is due to the large fraction of intermediate goods in the US imports. Trade of intermediate goods generally requires customization and relationship-specific investment. Such relationships typically are more durable than the ones focusing on final goods. To figure out the main reason and disentangle the effects of additional offshoring, further investigation is needed.

Table 8. Effects of TPU on GVC links

	Customers	$\frac{\text{NonUS}_{i,t}}{\text{Relationships}_{i,t}} \times 100$		**Suppliers**	$\frac{\text{NonUS}_{i,t}}{\text{Relationships}_{i,t}} \times 100$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{TPU}_{i,t}$ (std.)	-1.139**	-0.356	-0.880**	0.962*	0.759	0.620
	(0.482)	(0.419)	(0.364)	(0.566)	(0.554)	(0.408)
Upstreamness_j	3.433***	3.431***	4.633***	1.750**	1.747**	4.078***
	(0.803)	(0.803)	(0.861)	(0.847)	(0.847)	(0.899)
$\text{TPU}_{i,t}$ (std.) $\times$ Upstreamness_j	0.461**	0.384**	0.312**	-0.324	-0.295	-0.205
	(0.196)	(0.178)	(0.150)	(0.206)	(0.187)	(0.143)
Export-Usage $\text{ratio}_{s,t}$	161.939***	161.989***				
	(16.944)	(16.945)				
$\text{TPU}_{i,t}$ (std.) $\times$ Export-Usage $\text{ratio}_{s,t}$		-7.282**				
		(2.941)				
Import-Usage $\text{ratio}_{s,t}$				12.692*	12.746*	
				(6.329)	(6.330)	
$\text{TPU}_{i,t}$ (std.) $\times$ Import-Usage $\text{ratio}_{s,t}$					0.872	
					(1.548)	
$\text{NonTPU}_{i,t}$ (std.)	0.127	0.196	0.168	0.219	1.195**	0.002
	(0.507)	(0.647)	(0.310)	(0.442)	(0.481)	(0.322)
$\text{NonTPU}_{i,t}$ (std.) $\times$ Upstreamness_j	-0.106	-0.116	-0.180	-0.119	-0.225	-0.063
	(0.197)	(0.203)	(0.135)	(0.185)	(0.180)	(0.135)
$\text{NonTPU}_{i,t}$ (std.) $\times$ Export-Usage $\text{ratio}_{s,t}$		-0.694				
		(3.950)				
$\text{NonTPU}_{i,t}$ (std.) $\times$ Import-Usage $\text{ratio}_{s,t}$					-5.751***	
					(1.519)	
$\text{TPS}_{i,t}$ (std.)	0.004	-0.180	0.161	-0.769**	-0.432	-0.606*
	(0.421)	(0.528)	(0.340)	(0.360)	(0.440)	(0.344)
$\text{TPS}_{i,t}$ (std.) $\times$ Upstreamness_j	0.023	0.030	-0.047	0.307**	0.268*	0.249**
	(0.137)	(0.136)	(0.107)	(0.143)	(0.150)	(0.122)
$\text{TPS}_{i,t}$ (std.) $\times$ Export-Usage $\text{ratio}_{s,t}$		2.214				
		(3.845)				
$\text{TPS}_{i,t}$ (std.) $\times$ Import-Usage $\text{ratio}_{s,t}$					-2.268	
					(1.712)	
$\text{NonTPS}_{i,t}$ (std.)	-0.202	0.371	-0.128	0.020	0.371	0.145
	(0.482)	(0.564)	(0.366)	(0.564)	(0.634)	(0.396)
$\text{NonTPS}_{i,t}$ (std.) $\times$ Upstreamness_j	0.119	0.077	0.014	-0.077	-0.121	-0.193
	(0.193)	(0.194)	(0.157)	(0.236)	(0.238)	(0.179)
$\text{NonTPS}_{i,t}$ (std.) $\times$ Export-Usage $\text{ratio}_{s,t}$		-6.221*				
		(3.250)				
$\text{NonTPS}_{i,t}$ (std.) $\times$ Import-Usage $\text{ratio}_{s,t}$					-1.927	
					(1.649)	
N	36,230	36,230	66,361	33,470	33,470	65,561
R2	0.0856	0.0858	0.2362	0.0250	0.0254	0.1876
Controls	X	X	X	X	X	X
Quarter FE	X	X		X	X	
Quarter $\times$ Sector FE			X			X

Notes: This table shows the estimation results for TPU effects on firms' foreign customer and supplier ratios. All columns include other three measures, i.e., TPS, NonTPU, NonTPS, and their interactions with upstreamness as controls. Controls also include lagged log total asset, book-market ratios, book leverage, and profitability.
Standard errors are clustered by firm and quarter. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

6 Conclusion Remarks

Trade policy uncertainty has been rising sharply during the last five years. Most of the US firms are more or less affected by the policy shock. In particular, the firms involved in the global value chains respond by retrenching foreign investment, stockpiling input, and adjusting their foreign relationships. This paper constructs the firm-level trade policy uncertainty measures to analyze how firms' supply chain links are affected.

Building on the trade policy terms in Caldara et al. (2020) and methodology in Hassan et al. (2019, 2020), I construct a set of new measures on trade policy uncertainty from the public firms' earnings conference call. Trade policy uncertainty is negatively associated with capital investment rate and positively associated with inventory growth in the short run. These results are consistent with the theory's predictions, supporting the measures indeed capture the trade policy news about the right moments. The impact of trade policy uncertainty on the supply chain is studied from two sides. On the one hand, high trade policy uncertainty makes firms decrease the investment in expanding foreign markets and the incentive in exporting participation. Foreign customer links are thus negatively affected. Moreover, I find that downstream firms lose more foreign customer relationships than upstream firms. On the other hand, the US firms exhibit a strong reliance on foreign suppliers. This might be due to the firms' temporary stockpiling behavior and additional offshoring behavior.

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Appendices

A Data Preparation

A.1 S&P Compustat North America - Firm Fundamentals

Balance sheet data are obtained from Standard and Poor's Compustat Fundamentals North America (quarterly). I pull the data via the Wharton Research Data Service (WRDS). Names in the parenthesis are WRDS variable names.

Data preparation.
I only consider the firms with headquarters located in the United States (LOC == "USA"). The downloaded data are from 2007/10/01 to the most recent. Then, after constructing all variables of interest, I truncate the data time (DATADATE) into 2008/01/01 - 2019/12/31. In the regression analysis, I also exclude financial firms (SIC codes 6000-6299) and utilities (SIC codes 4900-4999).

I drop observations with missing fiscal quarter (DATAFQTR). I also drop multiple observations at the same data reporting date to Xpressfeed (DATADATE) by keeping only one of them, usually with a non-empty calendar quarter (DATACQTR). Moreover, I drop firms who changed fiscal year ends in 2008-2019 and firms with a single observation.

Investment rate.
The investment-capital ratio, $\frac{I_{i,t}}{K_{i,t-1}}$ is constructed using the perpetual-inventory method as described in Stein and Stone (2013) and Hassan et al. (2019) . Specifically, the ratio is defined by the formula:

$$\frac{I_{i,t}}{K_{i,t-1}} = \frac{CAPXQ_{i,t}}{Recursive\_Capital_{i,t-1}}$$

where $CAPXQ_{i,t}$ is the quarterly capital expenditure, and $Recursive\_Capital_{i,t-1}$ is the recursive capital stock calculated as $Recursive\_Capital_{i,t-1} = \Delta PPI \times (1-\delta) \times Recursive\_Capital_{i,t-2} + CAPXQ_{t-1}$, where ΔPPI is the Production Price Index (PPI, obtained from FRED) ratio of time $t-1$ to time $t-2$, δ is depreciation rate and set at 10%, and initial capital stock, $K_{i,0}$, is set as the first available property, plant, and equipment net value (PPENTQ. For most of firms, it starts from fiscal quarter 2007Q4). The variable is winsorized at the first and last percentile.

Note that the quarterly value of capital expenditure (CAPXQ) is converted from the year-to-date variable (CAPXY) in Compustat.

Percentage changes in inventory, sales, cost, and profit.

Inventory, sales, and cost are corresponding to the Compustat items INVTQ, SALEQ, and COGSQ, respectively. Profit is calculated as sales minus cost. I use the basic percentage change formula in the empirical analysis, i.e. $\%\Delta V_{i,t} = \frac{V_{i,t}-V_{i,t-1}}{V_{i,t-1}} \times 100\%$, where V is the variable of interest.

Inventory-Sales ratio.

Inventory (INVTQ) divided by Sales (SALEQ).

R&D-Assets ratio.

Research and Development expense (XRDQ) divided by Assets (ATQ).

Firm size.

Total assets (ATQ).

Market-to-Book ratio.

Market Equity (ME) divided by Book Equity (BE), where

- ME: End-of-calendar-quarter stock price (PRCCQ) times end-of-quarter common shares outstanding (CSHOQ), in $ millions.

- BE: I measure book equity at the quarterly frequency using an analogous method in Davis, Fama, and French (2000), in which they measure on a yearly basis. Specifically, it is shareholders' equity, plus balance-sheet deferred taxes and investment tax credit (TXDITCQ if available), minus the book value of preferred stock. I use the shareholders' equity as reported by Compustat (SEQQ), or the sum of common equity (CEQQ) and the carrying value of the preferred stock (PSTKQ), or total assets (ATQ) minus total liabilities (LTQ) (in that order). Depending on availability, I use the redemption value (PSTKRQ) to estimate the book value of preferred stock. If this data is not available, I use the carrying value for the book value of the preferred stock (PSTKQ).

Book leverage.

Long-term debt (DLTTQ) plus debt in current liabilities (DLCQ), all divided by total assets (ATQ)

Profitability.
Operating income before depreciation (OIBDPQ) minus interest (XINT) minus taxes (TXT), divided by lagged total assets (ATQ).

A.2 Sector and Industry variables

Openness.
I measure the industry openness at the 3-digit level of the North American Industry Classification System (NAICS). I use a standard measure equal to the ratio of an industry's gross output to usage, where usage is gross output plus imports less exports. Gross output by industry are download from the Bureau of Economic Analysis' Industry Economic Accounts Data, and exports/imports by industry are download from the US Census Bureau via USA Trade Online.

Upstreamness.
The upstreamness measure is derived from the 2012 US Input-Output tables under the Bureau of Economic Analysis' Industry Economic Accounts. Antràs, Chor, et al. (2012) construct and provide the measure. It covers 405 industries with BEA I-O industry codes. Based on the concordance between I-O industry code and its related 2002 NAICS codes, a upstreamness value is assigned to a firm by its NAICS code in Compustat.

Note that one I-O industry usually covers more than one 6-digit NAICS industry. So firms with different 6-digit NAICS codes might have the same upstreamness value. Meanwhile, there are two NAICS industries (6-digit NAICS 111336, and 2-digit NAICS 23), each included in more than one I-O industry. For each NAICS industry, I assign the simple average of the upstreamness of the I-O industries involved.

A.3 S&P Capital IQ - Earnings Conference Call Transcript

S&P Capital IQ provides several versions for a single earnings conference call transcript (corresponding to Capital IQ Item key development event *keydeveventtypeid*==48). I keep the latest version after sorting by the transcript creation date.

Since the Capital IQ creates the transcripts for events thoroughly from 2008, I construct firms' trade policy indexes from 2008 to 2019. Prior to 2008, the transcripts were created retroactively.

A component is one or more sentences spoken by a person at a time. For example, a presentation section delivered by an executive is a component. A question asked by an analyst is a component. Likewise, an answer to the question is also a component.

Drop null component and operator components (Item *transcriptcomponenttypeid* == 1 or 7) Remove misleading terms, such as "risk officer", "risk credit officer", "unknown speaker", "unknown participant", "unknown caller", "unknown operator", and "unknown firm analyst". Replace "trade-off", "Trade-off", and "trade off" into "tradeoff".

Detect safe harbor statements and drop it.

Trade policy term lists:

1. Most of trade policy terms in Caldara et al. (2020)
   tariff* not appear within either of feed-in, MTA, network, and transportation. import*, export*, (anti-)dumping, free trade, foreign trade*, international trade*. (cross-)border*/custom* within three words of either ban*, tax*, subsid*, control*, quota*, and trade*.

2. Recent emerging trade bigrams.
   trade act*/action*/agreement*/deal*/deficit*/surplus/(im)balance*/discussion*/dispute*/liberalization*/polic*/practice*/relationship*/talk*/tension*/treat*/war*.

3. Trade agreements and international trade transaction terms
   GATT, World Trade Organization/WTO, FTA, NAFTA, USMCA, Trans-Pacific Partnership/TPP, Regional Comprehensive Economic Partnership/RCEP, incoterm*, free on board/fob, (cost, insurance, and freight)/cif

4. International trade
   trade + country or region name within the same sentence. Word "trading" is not included. I include the first 15 US trade partners as country or region names.

I obtain the uncertainty word list from the Oxford English Dictionary, same as Hassan et al. (2019, 2020). In implementation, I require the uncertainty words be present within one sentence distance of trade policy related words, i.e. occurrence of uncertainty in the same sentence, the previous sentence or the next sentence of trade policy term.

The sentiment measurement is constructed in the same way. I use the word lists of positive and negative from Loughran and McDonald (2016)'s sentiment dictionary. The positive and negative words are required to show up with uncertainty within one sentence distance. Then I sum across these sentiment words by assigning positive word as +1 and negative word as -1.

A.4 FactSet Revere - Firm Supply Chain Relationships

For global supply chain data, I use FactSet Revere supply chain relationships data. The number of firm-level customers and suppliers are constructed by the following steps:

1. Category customer and supplier types.
   From the FactSet supply chain relationship guide, customers include disclosed customers (corresponding to *rel_type* - "CUSTOMER") and out-licensing ("PARTNER-LICENOT"), and suppliers includes disclosed suppliers ("SUPPLIER"), distribution ("PARTNER-DISTRIB"), manufacturing ("PARTNER-MANUFAC"), in-licensing ("PARTNER-LICENIN"), and marketing ("PARTNER-MARKTNG").

2. Duplicate and concatenate the dataset with the flipped relationship.
   Each observation shows a direct relationship (*id*) disclosed by the source company. Meanwhile, it implies a reverse relationship for the company, as a target company to the other. To add all reverse relationships, I flipped all relationships between customers and suppliers and concatenated the flipped dataset with the original one. Thus, the observations are doubled.

   The new dataset now contains all direct and reverse relationships. It provides a more comprehensive network for all companies, especially for public firms.

3. Flatten the time intervals for each relationship.
   Each relationship *rel_type* pair usually have many observations over time. Some of the time intervals overlap. I merge the overlapping time intervals for each specific relationship pair.

   After this step, for the same relationship pair, each observation's time range would be exclusive with others.

4. Count the numbers of customers and suppliers for source company, within each calendar quarter.

Given a time range (calendar quarters from 2008-2019), I count the numbers of customers and suppliers for the source company. Moreover, depending on target companies' location, the total relationship number is decomposed into US, NonUS, and UNKNOWN (if country code is not available). In a relationship, the company pair (source company and target company) does not need to cooperate over the entire quarter to be counted. I count the relationship if there is a relationship revealed in a certain quarter.

For country variable, in lieu of the Compustat (*loc* - headquarter country), I use headquarter country (*home_region*) to identify if a firm is located in the US. If not available, registered country code (*country*) is used.

The cleaned FactSet Revere data is then merged with the cleaned Compustat data using firms' 6-digit CUSIP codes.

B Index Correlation

Table B.1. Correlation

	TPU	TPS	NonTPU	NonTPS	CIMPR	log A	MB	L	P	EX	IM	U
TPU (std.)	1.0000											
TPS (std.)	-0.1063	1.0000										
NonTPU (std.)	0.0127	-0.0109	1.0000									
NonTPS (std.)	-0.0502	0.0581	-0.1334	1.0000								
CIMPR	0.4022	-0.0074	-0.0021	-0.0311	1.0000							
log Asset	0.0002	0.0017	0.0026	-0.0035	0.0333	1.0000						
MB ratio	0.0030	-0.0060	-0.0020	0.0212	-0.0052	-0.0334	1.0000					
Leverage	-0.0021	-0.0001	-0.0103	-0.0002	0.0256	0.2918	-0.0115	1.0000				
Profitability	-0.0026	0.0056	0.0014	0.0383	0.0446	0.4460	-0.0708	-0.0110	1.0000			
Export ratio	-0.0002	-0.0003	0.0002	0.0001	-0.0041	-0.1972	-0.0075	-0.2527	-0.0071	1.0000		
Import ratio	-0.0003	-0.0002	-0.0005	0.0000	0.0276	-0.0454	-0.0293	-0.1660	0.0912	0.4714	1.0000	
Upstreamness	0.0001	0.0000	-0.0002	-0.0003	0.0015	0.1141	-0.0923	0.0837	0.0516	-0.1836	-0.1990	1.0000

Table B.2. Summary Statistics for Variables in Dynamic Effects

	mean	std	min	25%	50%	75%	max	count
$100 \times (\log K_{i,t} - \log K_{i,t-1})$	2.100	8.816	-17.664	-0.876	0.266	2.287	63.988	86,597
$100 \times (\log K_{i,t+1} - \log K_{i,t-1})$	4.401	15.283	-31.674	-1.377	0.842	5.144	102.251	86,264
$100 \times (\log K_{i,t+2} - \log K_{i,t-1})$	6.616	20.422	-43.018	-1.750	1.609	8.394	131.418	85,392
$100 \times (\log K_{i,t+3} - \log K_{i,t-1})$	8.750	24.857	-52.800	-1.995	2.490	11.849	155.608	84,350
$100 \times (\log K_{i,t+4} - \log K_{i,t-1})$	10.804	28.869	-60.708	-2.194	3.488	15.266	179.966	83,259
$100 \times (\log \text{Inventory}_{i,t} - \log \text{Inventory}_{i,t-1})$	1.780	18.371	-102.672	-4.684	1.364	7.679	112.609	61,904
$100 \times (\log \text{Inventory}_{i,t+1} - \log \text{Inventory}_{i,t-1})$	3.409	25.373	-131.317	-6.163	2.684	12.042	151.188	61,519
$100 \times (\log \text{Inventory}_{i,t+2} - \log \text{Inventory}_{i,t-1})$	4.884	29.944	-149.601	-6.549	4.027	15.482	177.035	60,779
$100 \times (\log \text{Inventory}_{i,t+3} - \log \text{Inventory}_{i,t-1})$	6.281	33.288	-162.957	-5.834	5.289	17.607	194.739	60,225
$100 \times (\log \text{Inventory}_{i,t+4} - \log \text{Inventory}_{i,t-1})$	7.557	37.936	-178.910	-7.610	6.634	21.872	215.701	59,096
$100 \times (\log \text{R\&D}_{i,t} - \log \text{R\&D}_{i,t-1})$	1.947	22.927	-136.679	-4.888	2.202	9.563	115.152	36,226
$100 \times (\log \text{R\&D}_{i,t+1} - \log \text{R\&D}_{i,t-1})$	4.105	27.228	-143.150	-5.547	4.045	14.326	137.808	36,002
$100 \times (\log \text{R\&D}_{i,t+2} - \log \text{R\&D}_{i,t-1})$	6.027	31.778	-153.606	-5.771	5.828	18.819	160.416	35,483
$100 \times (\log \text{R\&D}_{i,t+3} - \log \text{R\&D}_{i,t-1})$	7.604	34.765	-156.861	-5.407	7.146	21.837	171.723	37,269
$100 \times (\log \text{R\&D}_{i,t+4} - \log \text{R\&D}_{i,t-1})$	9.279	39.804	-175.562	-6.313	9.378	26.681	188.734	34,339

C Validations: Comparisons with Existing Aggregate TPU

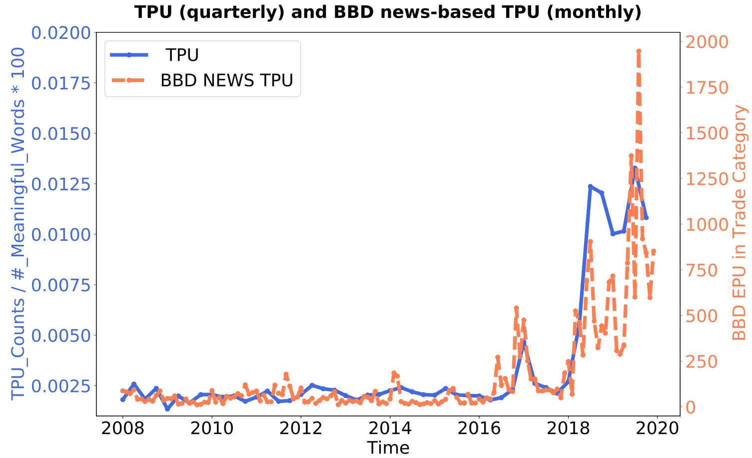

Figure C.1. Average TPU and Aggregate BBD News-Based TPU

Notes: BBD: Baker, Scott R., Bloom, Nick and Davis, Stephen J., (2016) Economic Policy Uncertainty Index: Categorical Index: Trade policy

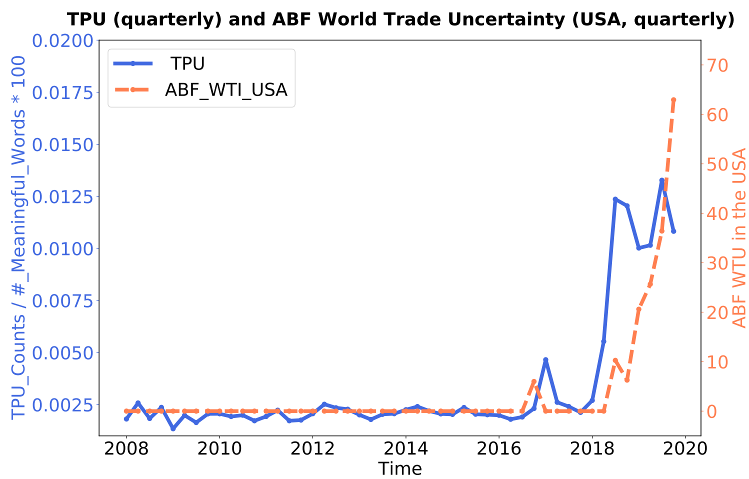

Figure C.2. Average TPU and Aggregate ABF WTU, USA component

Notes: ABF: Ahir, Hites, Nicholas Bloom, and Davide Furceri. The world uncertainty index. Available at SSRN 3275033 (2018).

D Validations: Impact on More Firm Activities

D.1 Robust: Impact on Inventory-Sales Ratio

For more robustness check on the index, I also run the specification in equation (7) dependent vairable as inventory-sales ratio, $Inventory_{i,t}/Sales_{i,t}$, which is calculated as the total inventory value over the sales.

Table D.1 reports estimation results for the firms' inventory-sales ratio. In column (5), the coefficient is 0.214 and statistically significant, suggesting that a one standard increase in TPU is associate with a 0.53 percentage increase in inventory-sales ratio relative to the sample mean $(0.214/40.496 * 100)$.

Table D.1. Effects of TPU on Inventory-Sales Ratio

	$\frac{Inventory_{i,t}}{Sales_{i,t}} \times 100$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{TPU}_{i,t}$ (std.)	0.365**	0.270*	0.187	0.286*	0.214*		0.110
	(0.161)	(0.153)	(0.131)	(0.145)	(0.119)		(0.143)
$\text{CIMPR}_{i,t}$						36.730**	30.203
						(16.705)	(19.202)
$\text{TPS}_{i,t}$ (std.)		-0.083	-0.027	-0.093	-0.044	-0.065	-0.054
		(0.122)	(0.092)	(0.103)	(0.081)	(0.084)	(0.081)
$\text{NonTPU}_{i,t}$ (std.)		-0.089	-0.228	-0.066	-0.209	-0.208	-0.209
		(0.332)	(0.195)	(0.273)	(0.143)	(0.143)	(0.143)
$\text{NonTPS}_{i,t}$ (std.)		-2.023***	-1.229***	-1.948***	-1.241***	-1.240***	-1.237***
		(0.385)	(0.222)	(0.323)	(0.189)	(0.189)	(0.189)
N	42,178	41,859	86,383	43,352	88,953	88,953	88,953
R2	0.0267	0.0446	0.4093	0.6629	0.8178	0.8178	0.8178
Controls		X	X	X	X	X	X
Quarter FE	X	X		X			
Quarter × Sector FE			X		X	X	X
Firm FE				X	X	X	X

Notes: This table shows the estimation results for TPU effects on inventory-sales ratio. Estimation is by OLS. The $\text{TPU}_{i,t}$ (std.) is the trade policy uncertainty index constructed in this paper. $\text{CIMPR}_{i,t}$ is the firm-level TPU in Caldara et al. (2020). Columns (1), (2), and (4) use a sub-sample of agriculture, mining, and manufacturing sectors, and include sectoral export-usage ratios as sectoral control. Other columns include quarter-sector (3-digit NAICS) fixed effects to absorb the time-variant sectoral characteristics. All but column (1) include TPS, NonTPU, NonTPS, lagged log total asset, book-market ratios, book leverage, profitability, and upstreamness as controls.
Standard errors are clustered by firm and quarter. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

D.2 Estimation for Firms' Other Activities

In this section, I include more estimation results for the equation 7 with dependent variable as firms' other activities, i.e., sales growth, cost growth, and profit growth. The cost is the cost of goods sold, including all costs directly allocated by the company to production, such as material, labor and overhead. The profit is the difference between sales and cost of goods sold.

Table D.2 presents the estimation results. Odd columns includes the export-usage ratio, representing the firm sample in agriculture, mining and manufacturing sectors. In even columns, I include quarter-sector fixed effect to absorb the sectoral seasonal characteristics. The coefficients of interest for sales growth, cost growth, and profit growth are significantly insignificant.

Table D.2. Effects of TPU on Firm Other Activities

	$\%\Delta Sales_{i,t}$		$\%\Delta Cost_{i,t}$		$\%\Delta Profit_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{TPU}_{i,t}$ (std.)	0.046	-0.014	0.005	0.014	0.054	0.055
	(0.070)	(0.066)	(0.054)	(0.055)	(0.192)	(0.164)
$\text{TPS}_{i,t}$ (std.)	0.011	0.043	0.001	0.029	0.229	0.276^{**}
	(0.081)	(0.080)	(0.091)	(0.078)	(0.192)	(0.123)
$\text{NonTPU}_{i,t}$ (std.)	-0.130	-0.130	-0.320^{*}	-0.307^{***}	0.046	0.038
	(0.173)	(0.105)	(0.159)	(0.097)	(0.332)	(0.224)
$\text{NonTPS}_{i,t}$ (std.)	1.669^{***}	1.393^{***}	0.604^{***}	0.410^{***}	2.630^{***}	2.909^{***}
	(0.144)	(0.095)	(0.082)	(0.072)	(0.303)	(0.249)
N	43,703	91,151	43,949	91,228	43,967	91,333
R2	0.1325	0.1878	0.0734	0.1395	0.0763	0.1264
Controls	X	X	X	X	X	X
Quarter FE	X		X		X	
Quarter × Sector FE		X		X		X
Firm FE	X	X	X	X	X	X

Notes: This table shows the estimation results for TPU effects on percentage changes in sales, cost, and profit. Estimation is by OLS. Columns (1), (3), and (5) use a sub-sample of agriculture, mining, and manufacturing sectors, and include sectoral export-usage ratios as sectoral control. Columns (2), (4), and (6) include quarter-sector (3-digit NAICS) fixed effects to absorb the time-variant sectoral characteristics. All columns include TPS, NonTPU, NonTPS, lagged log total asset, book-market ratios, book leverage, profitability, and upstreamness as controls and firm fixed effects.
Standard errors are clustered by firm and quarter. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The estimation results support that the measures of TPU and other trade policy indexes indeed capture the shock on the right moment. The coefficients on $TPS_{i,t}$ in columns (5) and (6) in Table D.2 of profit changes are positive and statistically significant, but not for other variables, bolstering that the managers' sentiment index captures the trade policy news about the first moment shock. Lastly, the coefficients on $nonTPS_{i,t}$ are all positive in Table 5 and negative in Table D.1 and statistically significant, supporting that the general sentiment other than trade policy talk captures firms' future conditional earnings in general.