# Trade Networks and Firm Value: Evidence from the US-China Trade War

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***Abstract***

This paper evaluates the financial implications of policy shocks on global production networks. We exploit various announcements of tariff hikes across a wide range of goods by both the US and Chinese governments in 2018-2019 as events, starting with the presidential referendum issued by the Trump administration on 22 March 2018, to study the impact of trade policy shocks on firms' stock market performance. Using various novel datasets, we document significant heterogeneous responses by firms to the announcements, depending on their direct and indirect exposure through global value chains to US-China trade. In particular, US firms that are more dependent on exports to and imports from China have lower stock returns and higher default risks around the announcement dates, while reduced import competition from China plays a limited role. Consistent patterns of stock price reactions are also found among Chinese firms. Two reverse experiments in 2019 further validate how the complex structure of global trade determines firms' stock market reactions to policy shocks.

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## 1. Introduction

A notable feature of globalization in the past few decades is the unprecedented reorganization of economic activities across regions, firms and workers.[1] Such reorganization was driven by the establishment of many complex global value chains, which enhanced connectivity between firms and hence nations. The resulting increase in interdependence of firms and nations has permitted a larger extent of sharing of economic benefits on the one hand (Acemoglu et al, 2016b), but also amplified the propagation of shocks across complex production networks and thus macroeconomic uncertainty on the other (Acemoglu et al., 2015, 2016a; Carvalho et al., 2017).

What are the financial implications of trade linkages across firms from different nations? Recent unexpected and abrupt changes in trade policies around the world have roiled stock markets globally, offering unique real-world "experiments" for a study about the impact of policy shocks on firms in global production networks.[2] In addition, despite comprehensive news coverage, systematic analyses about the impacts of recent trade tensions between countries on individual firms' outcomes are relatively scant, partly due to the lack of up-to-date micro data.

In this paper, we exploit the various announcements of the highly unpredictable US-China trade war in 2018-2019 to evaluate the impact of trade shocks on firms' financial market performance in both the US and China. Our analysis begins with the issuance of the presidential memorandum by the Trump administration on March 22, 2018, which proposed 25% tariffs on over $50 billion worth of Chinese imports.[3] Such unprecedented and abrupt policy

[1] See Goldberg and Pavcnik (2016) about the effects of changing trade policies in the last decades on firms, industries, and economies. Autor, Dorn, and Hanson (2013) and Caliendo, Dvorkin, and Parro (2019) focus specifically on the impact of China's integration in the global economy on the US labor markets.

[2] See, for instance "Dow drops more than 700 points on trade fears, posts worst day since Feb. 8" (source: https://www.cnbc.com/2018/03/22/us-stock-futures-dow-data-fed-and-politics-on-the-agenda.html) and "Things Were Going Great for Wall Street. Then the Trade War Heated Up" (source: https://www.nytimes.com/2019/05/31/business/trump-tariffs-markets.html)

[3] The goal of such tariffs, according to the Trump administration, was to curb the allegedly illicit intellectual property transfer to China and close the wide and persistent US-China trade deficit. The US Trade Representative, based on a seven-month investigation, alleged that the Chinese theft of American intellectual properties costs the US between $225 billion and $600 billion per year. (Source: http://money.cnn.com/2018/03/23/technology/china-us-trump-tariffs-ip-theft/index.html). The Trump administration demanded that China cut its trade deficit with the US by $200 billion in two years. (Source: https://www.cnbc.com/2018/05/22/trumps-demand-that-china-cut-its-us-trade-deficit-is-impossible.html)

announcement offers a unique shock for an event study. The objective of the US government was to raise the prices of imports from Chinese, in order to weaken the competitiveness of Chinese firms and eventually induce the Chinese government to implement policies that are more favorable for US firms.

The US administration's move toward protectionism has ambiguous economic implications. The rationale of raising tariffs and transferring profits from a trade partner to home is based on a conventional mindset that global trade is mostly about exchanges of final goods, rather than intermediate inputs. However, recent work has shown that global trade in the 21st century is more about production sharing by firms located in different countries (Grossman and Rossi-Hansberg, 2006; Baldwin, 2011; Johnson and Noguera, 2012). Firms from different nations are related as buyers and suppliers along global value chains. While tariffs can reduce competition from foreign firms at home, they can also raise the costs of imported inputs and hence production for domestic firms. Domestic consumers and firms that depend heavily on imports, directly or indirectly, suffer the most. The costs of import tariffs on production will also get amplified as tariff-induced increases in production costs and reduced sales are compounded down the supply chains until the final stage, when goods are sold to consumers.

Firms' perceived cuts in profits will be incorporated into their stock prices if the increased input costs cannot be alleviated by either switching to suppliers from other countries or passed through to consumers. Tariffs aiming to protect domestic businesses may also raise the expectations of retaliation from the target country, which will reduce US firms' foreign sales there. If US firms cannot completely replace the lost sales in China with sales from other countries, their future cash flows will decrease, lowering their current stock prices.

There are several advantages to use the 2018-2019 US-China trade war announcements for an event study of firms' trade networks. First, the US and China are the two largest economies in the world, with China's becoming the US's top trade partner by 2017.[4] The escalating trade tension between the two largest economies, in addition to generating significant uncertainty and negative economic impacts on the rest of the world, offer a unique

[4] The two countries together accounted for 39% of global GDP, 25% of global exports and 23% of global imports (Sources: Penn World Table and United Nations Comtrade).

opportunity to clearly identify the impact of trade policy shocks across a large number of firms with heterogeneous participation in trade networks.

Second, the policy announcements, especially the first one on March 22, 2018 when the Trump administration issued the presidential memorandum to propose tariffs on a wide range of Chinese imports, were unprecedented and large. For the most part, investors were largely surprised by the announcement of US tariffs against China, in terms of the timing, magnitude, coverage, and potential costs.[5] According to the efficient market hypothesis, financial markets should quickly incorporate news about the new tariffs into stock prices to reflect any perceived changes in firms' cash flows in the future. As such, the perceived impact of trade shocks on firms can be precisely estimated. In contrast, it is difficult to tease out the impact of tariffs as performance variables based on accounting items, such as return-on-assets, reflect the cumulative effect of many events (e.g., interest rate changes and currency fluctuation) during the accounting period that typically exceeds a quarter. Another advantage of conducting an event study of the impact of trade policy announcements is that the subsequent introduction of detailed product lists and reverse events can be used as validation exercises.

Third, several recently available data sets enable us to construct precise firm-level measures of a US (Chinese) firm's direct and indirect exposure to imports from and exports to China (US) for identification. In particular, we measure a US firm's sales in China as disclosed in the financial reports. To measure a US firm's imports from China at the product level, we use bill of lading records filed with the US customs by all US firms that had waterborne trade of goods. For Chinese firms, we use the most recently available firm-level customs data to measure their exposure to imports from and exports to the US.

To measure a US firm's indirect exposure to US-China trade, we use new buyer-seller matched data to gauge a US firm's exposure to trade with China indirectly through its engagement in the US domestic supply chains. Specifically, we construct four firm-level measures of exposure to trade with China in production networks -- the average revenue from China across downstream firms, the average revenue from China across upstream firms,

[5] The initial targeted list of products covers $50 billion worth of imports from China. Subsequent failure to reach an agreement resulted in the US's proposing to impose 10%-25% tariffs on essentially all imports from China by the end of August 2019, followed by a substantial expansion in the coverage of products tariffed by China. See Bown and Kolb (2019) for details.

average exposure to Chinese inputs across downstream firms, and average exposure to Chinese inputs across upstream firms.

Using the combination of these new data sets, we find significant impact of the announcement of tariff hikes on listed firms in both countries. We find heterogeneous effects across firms within sectors, based on their *direct* exposure to the policy shocks on trade. Around March 22, 2018, US firms having imports from or exports to China experience significantly lower stock returns, compared to those without direct exposure. Specifically, in the 3-day window centered around the event date, our regression results show that controlling for standard firm-level characteristics and industry fixed effects, a 10 percentage-point increase in a firm's share of sales to China is associated with 0.9% lower average cumulative returns, while firms that directly offshore inputs from China have a 1% lower average cumulative return than those that do not. The results are robust to using various standard asset pricing models, alternative model specifications and different lengths of the event window. In addition, firms that were more exposed to tariff hikes experienced higher default risks, as gauged by the growth rate of implied CDS spreads in the short event window. On the Chinese side, we find symmetric patterns of negative stock returns around the March 22 announcement date for the Chinese listed companies that reported imports from or exports to the US.

We also investigate the effect of import competition. Grossman and Levinsohn (1987) find positive stock market responses to favorable shocks to import prices at the industry level. Their study implies that if the US-China trade war raised the prices of Chinese goods, US firms that benefit from the resulting profit shifting should experience an increase in stock prices. We test this hypothesis by constructing industry-level measures of ex ante import competition from China. With a full set of industry-level exposure measures included as regressors, we find a positive and significant impact of tariff-reduced import competition on industry-level stock returns. In particular, industries with a 10-percent higher import share from China ex ante is associated with 0.05% higher stock return responses to the March 22 announcement. It is worth noting that the positive effect due to reduced competition is much smaller in absolute magnitude than the negative effects associated with firms' exposure to either sales in or inputs from China.

We further examine whether firms' indirect exposure to trade with China through domestic supply chain linkages may also affect their responses to various tariff announcements. We find more negative responses by firms that have a larger indirect exposure to exports to and imports from China through (domestic) supply chains, even after controlling for firms' direct output and input exposure considered in the baseline regressions. In particular, we find that US firms that have indirect exposure to Chinese inputs through domestic supply chains, despite having no directly imported inputs from China, tend to experience a more negative stock return. These results imply that the perceived increases in the costs of inputs and production of both the upstream or downstream firms will be passed to the firms connected through domestic trade linkages.

We also find that the stock price decline tends to be larger for firms that have domestic suppliers or buyers deriving a larger share of revenue from China, implying that even if a firm has no direct exposure to US-China trade, its stock return will be more negatively impacted if its downstream buyers or upstream suppliers are perceived to sell less to China due to expected retaliatory tariffs. Interestingly, we find that a US firm's indirect exposure to sales in China on average has a larger impact than direct sales exposure, whereas its indirect input exposure to China has a similar impact as direct input exposure.

We take full advantage of the detailed product lists of tariffs issued by both the US and Chinese government after each announcement date. Although the financial markets have digested the news about the upcoming tariff increases, investors are still uncertain about the details, in particular which specific product will be tariffed and the exact timing of the implementation of the new tariffs. Using the first product lists issued by the US and Chinese governments respectively, we evaluate the impact of tariffs at the firm-product level. Using the event-study approach, we find that US firms with more exported products mentioned in the list issued by the Chinese government experience a larger average decline in stock prices around the date of the official announcement of the product list. Consistently, US firms that have more imported products mentioned in the US list responded more negatively to the announcement as well.

Finally, we use subsequent events that swung market sentiments about the trade war as reverse events to validate our main findings. For instance, the trade talks in Beijing in January

2019 were considered as a trade war truce, closing the gap between the delegations from both countries. Using these events as reverse experiments, we find that firms with a larger share of revenue derived from China or use inputs from China have greater increases in stock prices around the announcement dates. Another reverse event we use is Trump's tweet on Twitter about raising the tariff rate from 10% to 25% on $200 billion worth of Chinese goods in May 2019. We find more negative returns for US firms that have a greater trade exposure to China around the date of Trump's tweet. In sum, subsequent reverse experiments in 2019 confirm our findings based on the first announcement on March 22, 2018 that tariffs were perceived by individual firms as net cost shocks, depending on their heterogeneous exposure to US-China trade.

The paper proceeds as follows. Section 2 offers a literature review. In Section 3, we describe the institutional background of our study by listing the key events before and after the March 22 presidential memorandum. In Section 4, we describe the various unique data sets we use to construct the main variables of interest, in particular, a firm's direct and indirect exposure to US-China trade. Section 5 reports the empirical results. The final section concludes.

## 2. Literature Review

Our research nests and advances over several strands of studies at the intersection between trade and finance. First, it adds to the literature on firm-level responses to trade policy shocks. Prior studies show that firms respond to trade shocks in terms of labor market outcomes (e.g., Autor, Dorn, and Hanson, 2013; Pierce and Schott, 2016), foreign market entry (Crowley *et al.*, 2018), innovation (Autor *et al.*, 2016; Bloom *et al.*, 2016), economic growth (Bloom *et al.*, 2014), tax evasion (Fisman and Wei, 2004; Fisman, Moustakerski and Wei, 2008) and the cost of debt (Valta, 2012). In line with these studies, we evaluate the financial market reactions to the abrupt changes in trade policy.

Second, our paper contributes to the literature on firms' financial outcomes due to engagement in international trade. Prior studies include Bekaert et al. (2016), which document how firms' global engagement affect stock returns; Levine and Schmukler (2006), which examines how firms' participation in trade affects their stock market liquidity; Claessens, Tong, and Wei (2012), which investigates the role of trade developments in transmitting financial crisis to the real economy; and a recent study by Barrot, Loualiche, and Sauvagnat (2019), which shows that firms that are more exposed to import competition carry a larger risk premium, especially if they face a higher risk of displacement. This paper differs from these existing studies by focusing on an unexpected event that exogenously affects many firms along the global value chains between US and China. By linking trade policies to financial markets, our paper is also built on previous studies on the impact of financial frictions and credit conditions on international trade (e.g. Manova, 2008, 2012; Chor and Manova, 2012).

A contemporaneous study by Greenland *et al.* (2019) uses equity market reactions to the US granting of permanent normal trade relations (PNTR) to China in October, 2000 to infer exposure to trade liberalization. Similarly, Bianconi et al. (2019) focus on the effects of the reduction in trade policy uncertainty due to China's accession to the WTO on US firms' stock market returns. Different from these two studies, our paper focuses on the financial implications of protectionist trade policies instead of inferring the exposure from market reactions, as we are able to construct measures on individual firms' exposure using pre-event trade data of both US and Chinese firms.

Our paper also adds to the burgeoning literature on economic networks. Recent studies have documented the impact of firm's internal networks (Giroud and Mueller, 2017; Giroud and Rauh, 2019), banking networks (e.g. Gilge *et al.*, 2016), transportation networks (e.g. Giroud, 2013) and etc. In particular, research has shown how production networks propagate and amplify firm-level shocks to large business-cycle fluctuations (Acemoglu et al., 2012, 2016a; Carvalho and Gabaix, 2013; Di Giovanni, Levchenko, and Mejean, 2018). The trade literature has examined the structure and implications of global value chains (Antràs and de Gortari, 2017; Johnson and Noguera, 2017; Alfaro et al., 2019). Recently available buyer-seller linked data permit detailed analyses of firms' endogenous formation of production networks and the resulting macroeconomic implications (Atalay *et al.*, 2011; Barrot and Sauvagnat, 2017; Bernard, Moxnes, and Saito, 2017; Carvalho *et al.*, 2017; Lim; 2017; Oberfield, 2018; Tintelnot *et al.*, 2019).[6] Contributing to this literature, our paper emphasizes the roles of supply chain

[6] Atalay et al. (2011) study both theoretically and empirically US publicly listed firms' production networks. Barrot and Sauvagnat (2017) study whether firm-level idiosyncratic shocks, due to the occurrence of natural disasters, propagate across production. Bernard, Moxnes, and Saito (2017) use Japanese buyer-seller linked data to analyze how improvement in transportation infrastructure can increase firms' input sourcing and hence their

networks in shaping the impact of costly trade barriers on firms' financial outcomes. As such, our study is also related to the studies on the financial implications of supply chain relationships (e.g. Hertzel et al., 2008; Houston, Lin and Zhu, 2016).

The method in our paper draws heavily from an extensive literature that adopts the event-study approach (see reviews by Schwert, 1981 and MacKinlay, 1997). Several notable event-study analyses that are closely related to ours include Fisman *et al.* (2014), which examines how Japanese and Chinese firms respond to adverse shocks to the Sino-Japanese relations; Wagner *et al.* (2018), which uses Trump's election victory as an event to study the effects of the *potential* policy changes in taxes and trade as proposed during his campaign on US firms' financial outcomes; as well as Crowley *et al.* (2019), which analyzes the effect of the EU's announcement of import restrictions on Chinese firms in the solar panel industry. Our work differs from these studies by directly examining a series of unanticipated trade policy changes between the two largest economies.

Last but not least, our work contributes to the growing literature that examines the macroeconomic impact of the US-China trade war. Two recent studies (Amiti *et al.,* 2019; Fajgelbaum *et al.*, 2019) find that US tariffs significantly increase consumer prices in the US, due to an almost complete pass-through of the tariffs to US prices. Amiti *et al.,* 2019 further compute a sizeable 8 billion USD welfare loss (or 0.04% of US GDP) based on a quantifiable general-equilibrium trade model, as a result of the substantial increases in prices of Chinese imports. Using more disaggregated import price data recorded at the US ports, Cavallo *et al.* (2019) find supporting evidence about complete pass-through of tariffs to US prices.

## 3. Institutional Background and Hypotheses

### *3.1 Trade between US and China: Past and Present*

The Chinese government initiated its open market economic reforms in 1978. In the last four decades or so, the country has grown substantially in terms of aggregate income, investment, consumption, and trade. In 1978, China's overall trade account for less than 1% of

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productivity. Carvalho et al. (2017) quantify the propagation of the Great East Japan Earthquake shocks in 2011 through firms' input-output linkages. Lim (2017), Tintelnot et al. (2017), and Oberfield (2018) respectively develop models of endogenous formation of production networks and the resulting macroeconomic implications.

global trade. In 2013, China surpassed the US to become the largest trading nation in the world,[7] and in 2015, China surpassed Canada as the US's the largest trading partner.[8] While US remained the largest economy in terms of GDP in the world, various studies have predicted that China will surpass the US leading economic status in the foreseeable future.[9]

China was accessed to the World Trade Organization (WTO) in December 2001. As emphasized by Autor, Dorn, and Hanson (2013) and Schott and Pierce (2016), Chinese exports and in particular those to the US skyrocketed since 2001, thanks to the substantial reduction in tariffs by the Chinese government against other WTO member countries and the granting of the permanent normal trade relationship (PNTR) by the US government. Since 1985, China has been running a trade surplus against the US,[10] and increased further, not only in terms of dollar value, but also as a share of US's total trade deficit with the rest of the world and China's GDP (Scott, 2017). The widening bilateral trade deficit with China until recently remained a key reason behind the US government's imposition of tariffs on Chinese imports.

Against this backdrop, Trump was elected the 45th President of the United States in November 2016. During his presidential campaign, he has repeatedly mentioned his plan to revive the US economy by bringing back manufacturing jobs from overseas. Part of the plan was to tax imports, specifically those from China, to protect domestic businesses. As expected, Trump's economic policies have been overall anti-trade, with China being the target in many of them. Trump's complaints about China's economic policies range from its currency manipulation to unfair practices against foreign businesses, with concerns about the continuous rise of China, partly supported by its hallmark "Made in China 2025" initiative and various outward-looking economic and foreign policies. But the most important of all is probably the persistent trade deficit the US has with China and the alleged technology transfers by Chinese individuals and firms through both licit and illicit means. To address these issues, the Trump administration decided to impose tariffs on Chinese products, particularly those in several key

[7] Monaghan, *China Surpasses US as World's Largest Trading Nation, Guardian* (Jan. 10, 2014), https://www.theguardian.com/business/2014/jan/10/china-surpasses-us-world-largest-trading-nation
[8] Source: US Census https://www.census.gov/foreign-trade/statistics/highlights/top/index.html
[9] The World Economy Forum "The world's top economy: the US vs China in five charts" https://www.weforum.org/agenda/2016/12/the-world-s-top-economy-the-us-vs-china-in-five-charts/
[10] US Trade Representative Trade in Goods with China https://www.census.gov/foreign-trade/balance/c5700.html

high-tech and R&D-intensive sectors, to hopefully induce its government to implement policies to improve the business environment for US exports to and investment in China.

In what follows we list five events that we will exploit to evaluate the impact of the US-China trade tensions. The main event of our research is the US government's issuance of the presidential memorandum on March 22, 2018. The other four events will be discussed in detail in the empirical analysis later.

***3.2 Key Events***

- March 22, 2018: The Trump administration issued a presidential memorandum in reference to Section 301 of the *Investigation of China's Laws, Policies, Practices, or Actions* that proposed to impose tariffs on up to $50 billion of Chinese imports as a response to China's alleged theft of US intellectual property. Trump gave US Trade Representative Robert Lighthizer 15 days to come up with a list of products to impose tariffs on. Lighthizer said he would target products that the Chinese government had said in various policy documents it intended to dominate, in particular those mentioned in the "Made in China 2025" plan. The rationales of the Trump administration behind such tariffs against China include:
  1. The large trade deficit between the US and China;
  2. China forced US technology-intensive firms to enter joint ventures with Chinese individuals and share their technology in return for market access;
  3. China's alleged theft of American intellectual property;
  4. Protection against foreign competition for domestic businesses based on national security concerns.
- March 23, 2018: The Chinese government hit back with a list of 128 products that would face 15-25% tariffs should US-China trade negotiations fail.
- April 3, 2018: the US Trade Representative published the provisional list of imports that would be subject to new duties covering about 1,300 Chinese products with approximately $50 billion worth of US imports from China.
- January 7-9, 2019: the trade negotiations between US and China were held in Beijing. The trade talks ended with progress in identifying and narrowing the two sides' differences. Following top-level talks were confirmed.

- May 5, 2019: Using Twitter, President Trump announced to increase the tariff rate on 200 billion dollar worth of Chinese goods from 10% to 25% and threatened to impose 25% tariff on the remaining 325 billion dollar worth of untaxed Chinese goods.

In 2018 and 2019, a series of other critical events were triggered by the announcement of presidential memorandum on March 22, 2018, including the issuance of additional product lists, implementation of the tariff hikes, meetings between senior government officials from both countries, and so on.[11] Our research will first offer a detailed event-study analysis based on the first announcement by the US government on March 22, 2018, as it was the least expected and was considered in retrospect the starting point of an ongoing trade war between the two countries. We will then provide supporting evidence about the effects of the official publication of the specific tariff lists and the reverse events in 2019, which reverted market sentiments unexpectedly.

## 4. Estimating Framework

The primary goal of the research is to assess the financial implications of trade linkages between firms. The first empirical challenge is that trade relationships between firms can arise from any observed or unobserved factors, such as comparative advantage, political uncertainty in the country or region. Many of these factors are time-varying and endogenous. Second, prior studies usually rely on sector-level exposure to measure trade shocks, as data on US firms' input sourcing are quite rare until recently. For example, many studies use import competition measured at the sector level for analysis. Although it is theoretically appropriate, prior studies show that many firms produce multiple products and alter their product lines from time to time (Hoberg and Phillips, 2016). In both cases, a firm's reported main industry cannot precisely capture its exposure to trade.

To circumvent these empirical challenges, we adopt an event study approach along with various new datasets we put together to identify firms' trade exposure. As discussed in the introduction, Trump's announcement of a trade war against China on March 22 was large and

[11] A detailed event list regarding the US-China trade war can be found here: https://en.wikipedia.org/wiki/China%E2%80%93United_States_trade_war

unexpected, offering a unique real-world experiment for an event study. While one may want to wait until detailed micro and macro data become available to assess the economic effect of the trade war, the event-study approach daily stock market data on publicly listed firms permits a real-time analysis. The approach has been frequently used in prior studies for policy evaluation. In addition to the benefit of analyzing the real-time market responses to the announcement of a trade war, another advantage is that it can provide clean evidence on the impact of the policy. The estimation of the long-run economic impact can be biased by other confounding factors or offset by subsequent policies and events.

We construct samples for firms listed in either US or Chinese stock markets, respectively. As reported in Table 1, our US sample comprises 2,309 listed firms for which we can construct measures to gauge their exposure to US-China trade as well as their stock market performances. The sample consists of US firms that are both incorporated and headquartered in the US as identified by Compustat. In other words, we exclude all foreign firms, including Chinese firms, which are listed on the US equity market. We also exclude financial firms. Daily stock return data and the implied CDS spreads are downloaded from Bloomberg. For firms listed on the Chinese stock market, we use the Chinese counterpart of Compustat, the China Stock Market & Accounting Research Database (CSMAR), to conduct a similar set of event-study analyses.

Our main dependent variables are the changes in stock prices around the short window of the trade war announcement. We first define cumulative raw returns (CRR). Let us denote the event date as date 0. We construct the CRR over the 3-day window around the event date of March 22, 2018 as:

$$CRR_i[-1,+1] = \sum_{t=-1}^{+1} R_{it}, \tag{1}$$

where $R_{it}$ is the raw return for stock *i* on date *t*. To take the firm's individual risk level into consideration, we compute the cumulative abnormal return (CAR) of firm *i* as:

$$CAR_i[-1,+1] = \sum_{t=-1}^{+1} AR_{it}, \tag{2}$$

where $AR_{it}$ is the abnormal return for firm *i*'s equities on date *t,* calculated using the standard market model (Capital Asset Pricing Model or CAPM) with the average CRSP return as the market return and the one-month Treasury bill rate as the risk-free rate. The firm's market beta is estimated using historical stock returns over the window from -120 to -20 relative to the event date. Given the abrupt nature of the announcement of tariff hikes by the US government, we use a firm's cumulative stock return over a 3-day window as our main dependent variable of interest. As robustness checks, we will construct variables using longer event windows, and construct the abnormal returns using Fama-French 3-factor model.

There are several potential issues regarding the measure construction in our context. On the one hand, by estimating the "normal" performance, factor models (such as CAPM or Fama-French 3 factor model) conceptually remove the portion of the return that is unrelated to the impact of the policy investigated. For example, it is possible that firms underperform compared to other firms because they are less exposed to general market movements (lower loadings on the market benchmark) according to CAPM. Those firms might also be the ones most sensitive to the expected impact of the trade policy *per se*, thereby making it difficult to separate out the real effect of the policy. On the other hand, market-wide policy changes (such as the announcement of the trade war in our case) may fundamentally affect firms' risks, as indicated by the changes in the factor loadings estimated using sample before and after the event (Schwert, 1981). The abnormal returns based on factor models estimated using historical data thus become less accurate. Due to these two reasons, the raw returns tends to provide a more objective estimation and a more straightforward interpretation. We thus present both sets of results based on CRR and CAR, respectively. As shown in what follows, CRR and CAR generate near-identical results, suggesting that the documented effects are less prone to the problems mentioned above.

We use three different data sources to construct our main independent variables that measure a firm's *direct* exposure to the US-China trade. The first data source is *Factset Revere* that tracks the information on a US publicly listed firm's foreign buyers and sellers. For each US firm in the database, we retrieve the information on its total sales in China, which we then use to construct the share of sales in China.[12] Specifically, the continuous variable, *Revenue_China*, is the share of revenue from China in the firm's total revenue in 2016. This variable measures the relative importance of the Chinese market for each US firm. Intuitively, firms that are more dependent on sales in China are expected to suffer from China's retaliation

[12] The information on a firm's input purchases from China is highly incomplete, preventing us from using it to gauge a firm's exposure to China on the input side.

more. For instance, the portion of revenue derived from China for Apple Inc, Alphabet Inc, and Exxon Mobil is 20.8%, 8.9% and 5.9%, respectively.

The second data source is *the US Bill of Lading database*. The US Customs keeps track of every waterborne import or export transaction. We use information on US waterborne imports to construct a firm's exposure to China on the import side. For 2017, the database contains about 5 million bills of lading for imports from China with the information about the country of the shippers, quantity and product code. This administrative data usually contains errors in the consignee names. To map it to the US listed firms, we first perform a fuzzy-matching process to filter out consignee names with the names of listed firms using character similarity. We then manually check the consignee names with the names of listed firms sourced from Compustat. We construct a dummy variable (*Input_China*) for each firm to indicate whether it has outsourced inputs from China.[13]

The third data source is *China's Customs data*, which contain detailed information on foreign trade transactions at the annual frequency for the universe of Chinese trading firms. Specifically, it provides for each transaction its value, quantity, product type, country a firm imports from or exports to. We merge the customs data with the CSMAR data based on company names and construct two variables: *Revenue_US* is the value of exports to U.S. in 2016 scaled by total revenue in 2016 for Chinese listed firms; and *Input_US* is an indicator set to one if the value of imports to US in 2016 is positive, and zero otherwise.[14]

Table 1 reports the summary statistics of the dependent and independent variables used in the regression analyses, at both the firm and industry levels. The dependent variables of interest at the firm level are various the cumulative raw and abnormal returns around different event dates. In particular, in the sample of 2309 firms, the mean CRR over the 3-day window around March 22 (the first event date), is averaged around -2.6%, with the median equal to -2.9%. The mean and median firm CAR over the 3-day window around the same event, are

[13] The lading information can be transmitted to market participants through various channels. For instance, equity analysts and institutional investors can access this information and inform other investors. Firms could also mention their related businesses with China in their financial reports. We use the lading data in 2016 and 2017 to define the variable *Input_China*. The results are quantitatively similar when the variable defined using either year of data. As the database does not provide transaction value, it is difficult for us to define a continuous variable such as the percentage of input value from China.

[14] The most updated version of China customs database only provides data until 2016, so we use the information in the that year to measure trade exposure.

similar to CRR. We define $RMV\_Change$ as the change in market value around the event window [-1,+1] with zero indicating March 22, 2018. Namely, $RMV\_Change_i[-1,+1] = MV_{i,+1} - MV_{i,-2}$ . Equivalently, $RMV\_Change_i[-1,+1] = MV_{i,-2} \cdot CRR_i[-1,+1]$ . On average the market value of US firms drops by 394.7 million dollars. In total, our sample firms experience 911 billion loss in market value over 3-day event window. We define another variable $AMV\_Change_i[-1,+1]$ to capture the "abnormal" change in market value, which is equal to $MV_{i,-2}$ multiplied by $CAR_i[-1,+1]$ according to the market model. The sample firm on average incurs 422.8 million dollar "abnormal" loss in its market value.

[Table 1 about Here]

The main independent variables of interest are the two measures of a firm's exposure to US-China trade. In particular, the variable *Revenue_China*, which captures a US firm's direct export exposure to China, has the mean equal to 2.5% and median equal to 0. The mean of *Input_China*, which captures a US firm's direct import exposure to China, shows that 24% of the firms directly imported from China in 2016.

Firm-level control variables include firm size (*SIZE*), market-to-book ratio (*MTB*), leverage (*LEV*), and the return-on-assets ratio (*ROA*). The financial data of US firms are from Compustat.[15] Other variables, such as cumulative abnormal returns (CAR) around other event dates and the *indirect* exposure to the trade war, will be discussed when used. The detailed variable definitions can be found in Appendix 2.

## 5. Empirical Results

### *5.1 Validity of the Research Design*

To confirm the validity of the empirical analysis, we first provide evidence that the announcement of the trade war is unexpected by market participants. Figure 1 compares the trajectory of the market benchmark index with the public interests over "trade war" for both the US and Chinese markets. Panel A (right scale) illustrates a sharp fall in the S&P 500 index on March 22, 2018, suggesting that the presidential memorandum was a largely unanticipated

[15] The financial data from Compustat is downloaded on March 21, 2018. The control variables are all based on the fiscal year 2016 as for some firms when the trade war was announced the financial reports for the fiscal year 2017 were not available yet.

event. Specifically, the S&P 500 index dropped by 2.5% on March 22, and by 4.8% from March 21 to March 23. Appendix 1 summarizes the value-weighted average stock returns around three event dates for both US and Chinese firms using their market values as weights. The sample US firms on average experienced 2.3% decline in stock returns on the event date (March 22, 2018) and 4.32% decline from 21 March to 23 March. The dollar loss amounted to 486.6 billion on the event day and 911 billion over the 3-day event window.

Panel A of Figure 1 also plots the public interests over trade war based on the frequency of searches of keyword "trade war" using the Google search engine (left scale). According to prior studies (e.g., Da *et al.*, 2011), the trends in Google searches can be used to measure investors' attention. Public interest in the trade war peaked on March 22, the day when the Trump administration announced 10% tariffs on 50 billion dollar worth of imports from China.[16] Similarly large declines in the S&P 500 index and the corresponding spikes in public interests, despite by a smaller magnitude, are also observed for the other announcement dates (e.g. April 5 when Trump proposed additional tariffs against China).

Panel B of Figure 1 demonstrates a similar pattern from the Chinese market. The public interest over trade war in China is measured by the frequency of searches of the keyword "trade war" on Baidu, the Chinese counterpart of Google (Panel B, left scale). The Chinese market benchmark, the CSI 300 index dropped by 2.9% on the date of announcement and a cumulative 4.5% decline in the three-day event window. As shown in Appendix 1, sample Chinese firms experience 4.1% negative returns on the event date and 3.9% decline over 3-day event window. The whole Chinese sample firms incur losses of 1500 billion RMB (about 237.3 billion USD) on the event day and 1463.6 billion RMB (231.6 billion USD) over the three-day period.

[Figure 1 about Here]

Based on our research of news articles and academic studies, there is no other significant event on March 22, 2018 that can explain the overall market movement, besides the presidential memorandum. The abrupt boost in public interest over "trade war" around this event together with the large market movement suggest that the US announcement of tariff hikes indeed surprised the market and caused significant concerns over the trade tension

[16] The previous spike at a much smaller magnitude happened when the US government announced on March 1, 2018, a 25% tariff on steel and a 10% tariff on aluminum from China and a few other countries.

between the US and China. Building on this policy shock, in what follows, we endeavor to study the heterogeneous effects among firms according to their exposure to the event.

It is worth mentioning that the stock market also responds to the subsequent events. Specifically, on April 2, when China's Ministry of Commerce rolled out the tariffs on the 128 US products as proposed on March 23, 2018, the US stock market index dropped by 2.2% and the Chinese market index dropped by 0.6%. After the US announced tariffs on $50 billion of imports from China, Trump threatened to unleash more tariffs if China retaliates on June 15. In particular, when Trump directed the United States Trade Representative to identify $200 billion worth of Chinese goods for additional tariffs on June 18, the Chinese market fell sharply by 3.5%. Those market reactions amplified the impact of the trade war fear on the financial market. That said, due to several events being clustered around April 2-5, evaluating the impact of each event becomes difficult. In our analysis below, we will focus on the announcement on March 22 as the main event.

***5.2 Firms' Heterogeneous Stock Market Reactions to the Trade War's Announcement***

This section provides the baseline empirical results of the impact of the trade war declaration on the financial markets. In Table 2, we show the preliminary results using a univariate analysis of the relation between a firm's exposure to US-China trade and its market performance. We examine whether the cumulative returns are systematically lower for firms that have more trade exposure to China.

As reported in the first two rows of Panel A in Table 3, US listed firms that are above the median of the sample in terms of the share of sales in China have a 1.1% lower CRR/CAR over the three-day event window compared to firms with the share of sales in China below the median of the sample.[17] In addition, we also find that the "above-median" firms are on average larger in terms of market value, more profitable in terms of ROA, but have lower leverage ratio compared to the "below-median" firms.

[Table 2 about Here]

In Panel B of Table 2, we compare the means of these variables of interest between the two samples that are separated according to whether the firm offshores inputs from China or not, using data from the Bill of Lading database. We find that firms that report some offshoring

[17] The median of the revenue from China is zero.

activities in China have on average 1.3% lower CRR/CAR over the three-day window, compared to firms without any import exposure to China. We also find that firms that offshore inputs from China appear to be bigger and have a higher ROA.

Next, we conduct our event-study analysis by regressing firm's stock returns on the firm's trade exposure to China. As shown in Panel A of Table 3, we find that firms selling proportionally more to China experience relatively lower CRR and CAR around the three-day window. Column (1) shows that a 10 percentage-point increase in a firm's share of sales to China is associated with a 1.2% lower CRR. According to column (2), such correlation drops to 0.9% when the four firm-level characteristics (firm's size, market-to-book ratio, leverage, and ROA) are controlled for. When industry (Fama-French 30 industry portfolios) fixed effects are included as controls in column (3), the relation further drops to 0.45%. This decline indicates that much of the variation in the firms' shares of sales in China and their CRR are captured by the characteristics of the industries they belong to, such as the relative comparative advantage between the US and China. That said, industry-level characteristics cannot sufficiently explain most of the firms' heterogeneous responses to the fear about the US-China trade war within each industry. There is substantial heterogeneity across firms within an industry regarding their exposure to US-China trade, which explains the differential effect of the US-China trade war on firms' market performance. Columns 4-6 show that CAR around the 3-day window declined to a similar amount as measured by CRR for firms with larger revenue from China.

[Table 3 about Here]

We continue to examine whether imports from, rather than exports to, China can also affect a US firm's financial market performance. The regression results are reported in Panel B of Table 3. We find that firms that purchase (offshore inputs) from China have lower average CRR/CAR than firms that do not. The negative correlation is statistically significant regardless of whether we control for firm characteristics or industry fixed effects. Specifically, as column (3) shows, within the same industry, the average CRR is 0.6% lower compared to firms that have zero import from China.

We endeavor to quantify the aggregate effect on the whole market through exports to and imports from China. As shown in Appendix 1, the value-weighted average of CRR[-1,+1] is -4.32%. We first multiply the *Revenue_China* of each individual firm with the regression coefficient (-0.09) in column 2 of Panel A and calculate the value-weighted average using firm's market value on 20 March 2018 as weights. The aggregate effect through the exposure from Chinese imports can be gauged in a similar approach. The calculations suggest the aggregate effect through revenue from China is about -0.52% and the input from China contributes another 0.48% decline to the 3-day stock returns.

To further quantify the dollar loss due to the trade war announcement, we regress the change in market value around the event date on firm's trade exposure to China. As shown in Panel A of Appendix 3, we find results consistent with our baseline estimation in Table 3. After controlling for firm characteristics, a 10% increase in revenue from China is associated with an additional 499 million dollar losses in market value. Similarly, comparing with firms without input from China, firms that outsource input from China incur 312 million dollar worth additional loss in market capitalization. The effect remains significant when industry fixed effects are included. From March 21 to March 23, the sample firm lost 911 billion dollars in total. Based on the coefficients in columns 1 and 3 of Panel A in Appendix 3, we find *Revenue_China* and *Input_China* contribute to the overall dollar loss of -287.7 billion and -173.6 billion, respectively.

Table 4 reports several robustness checks. We use different asset pricing models to adjust the stock returns. Panel A shows the results using Fama-French 3-factor model. We find in general similar results. In Panel B, when we include both independent variables of trade exposure in the same regression, we find quantitatively similar coefficients on both variables in the joint estimation.

[Table 4 about Here]

Firms with heterogeneous exposure to trade with China should display significant variation in firm characteristics, such as firm size and leverage, as shown in Table 2. Although we have controlled for the main four firm characteristics in the regressions to mitigate any omitted variable biases, one may still be worried about potential selection biases arising from firms' non-random decision to trade. To mitigate the selection biases, we employ a propensity score matching approach and construct a sample matched on four firm-level control variables considered in our analysis. The results are presented in Appendix 4. Panel A shows the balance tests for firms with exports to China vis-a-vis firms without. All firm variables are statistically indifferent between the two groups of firms, while the cumulative stock returns are significantly different, a pattern that is consistent with our baseline results reported in Table 3. We also find supporting results from the two samples of firms categorized by their exposure to inputs from China.

One may wonder whether the findings over a short event window are an outcome of firms' overreaction to news. To verify whether the trade-war announcement has any long-lasting impact, we extend our analysis by computing each firm's buy-and-hold abnormal returns (BHAR) for various event windows as its cumulative return over a longer horizon. Following Malmendier *et al.* 2018, it is defined as follows

$$BHAR_i[-X,+Y] = \prod_{-X}^{+Y} R_{it} - \prod_{-X}^{+Y} MR_t,$$

where $R_{it}$ is the daily stock return for stock *i* on date *t*. $MR_t$ is the average return of firms in the market on date *t*. As a falsification test, we replace the dependent variable in column 2 of Table 3 with BHAR[-20,-2], which measures the buy-and-hold abnormal returns from 20 days before the announcement of tariff hikes to 2 days after the announcement. Findings about a negative correlation between BHAR[-20,-2] and the exposure measures would indicate the possibility that our baseline results are driven by some other contemporaneous events during the period.

We then use BHAR[-1,+20], BHAR[-1,+40], BHAR[-1,+60], and BHAR[-1,+80] as dependent variables to estimate the potential medium-term impact of trade policy shocks on firms' performance. The coefficients on the two firm exposure measures estimated using the baseline specification are plotted in Figure 2. In the regression predicting pre-event returns, we fail to reject the null that the two exposure variables (revenue from China and input from China) are indifferent from zero. We find that the effect of the trade war announcement persists in the medium term. For instance, a 10 percentage-point increase in a firm's share of revenue from China is associated with a 2.2% lower buy-and-hold abnormal return in 40 trading days (BHAR[-1,+40]) after the announcement. Firms with inputs from China had 2% lower stock price on average in the medium term (a 40-day period), relative to firms that had no imports from China. Appendix 4 presents these detailed regression results.

The value weighted average of BHAR[-1,+40] is 3.8%. Using a similar approach adopted above for the baseline results, we can infer that the exposure of revenue from China leads to an aggregated medium effect of -1.3% and the exposure of input from China contributes another 1% decline. As the total market capitalization of our sample firm is about 21.1 trillion, the dollar losses in the medium term measured in 40 trading days are approximately 274.3 billion through *Revenue_China* and 211 billion through *Input_China*. With this confirmation of medium-term impact, in the rest of the paper, we still focus on the short windows around the March 22 and subsequent announcements by both countries' governments as events, following the conventional practices in event studies.

[Figure 2 about Here]

***5.3 Default Risk***

The Trump administration's trade policy should have affected not just firms' stock returns but also the wealth of other stakeholders (such as bondholders). We posit that the fear about trade war could also increase the probability of a firm's default. On the one hand, investors could expect the worsened financial performance reflected in the stock prices can increase the chance of bankruptcy or other triggered events (Acemoglu et al., 2016a). On the other hand, due to the uncertainty about the future of US-China trade tension, firms might adopt suboptimal strategies by delaying investment and other long-term plans (Bloom, 2009; Bloom et al., 2007). To test this hypothesis, we use the growth rate of a firm's implied CDS spread in the three-day window around the event to measure a firm's default risk, following prior studies (e.g., Ismailescu and Kazemi, 2010):

$$Default\ Risk_i[-1,+1] = \sum_{t=-1}^{+1} CDSR_{i,t},$$

where $CDSR_{i,t} = \frac{S_{i,t}-S_{i,t-1}}{S_{i,t-1}}$. The $S_{i,t}$ is the implied CDS spread that is constructed with the default probabilities that are based on the Merton (1974) model. The data on firms' (five-year implied) CDS spread are obtained from Bloomberg.

As reported in Table 5, we find that firms' exposure to both imports from and exports to China are associated with higher default risks. Specifically, as reported in column (1), a 10 percentage-point increase in the share of sales to China is associated with a 0.50% higher growth in a firm's default risk. Regarding a firm's offshoring relationship, when we use the

*Input_China* dummy, we find that firms that have some offshoring activities in China have an average 0.45% higher default risk.

[Table 5 about Here]

In sum, not only do firms that are more exposed to US-China trade experienced bigger negative returns in the stock markets around March 22, investors perceive those firms to be riskier, as reflected by larger increases in firms' default risks. These results suggest significant financial implications in the bond market.

### *5.4 Stock Return Reactions of Chinese Firms*

So far, we have examined firms' market reactions to the trade war's announcement using a sample of US publicly listed firms. US tariff hikes (and their announcement) should also affect the export sales of Chinese firms in the US and thus their stock market performance. Therefore, we use the Chinese counterpart of Compustat, the China Stock Market & Accounting Research Database (CSMAR), to conduct a similar set of event-study analyses from the perspective of the Chinese publicly listed firms. To this end, we use a unique China Customs database that contains detailed firm-level information about imports and exports to measure firms' trading activities with the US. The most updated version of the customs database is 2016. We merge the customs database with CSMAR based on firm names. We first use a fuzzy matching algorithm to filter the firm names in China customs database with similar firm names from CSMAR. Then we manually check the accuracy of the matches to generate the final cross-walks between two databases.

[Table 6 about Here]

Panel A of Table 6 first offers the summary of the statistics for a sample of 2,588 Chinese publicly listed firms. The average CRR[-1,+1] around the March 22 event date is -4.1% with a standard deviation of 4.7%. The median firm in the Chinese sample did not import from or export to the US, while the mean share of exports to the US in total sales is a mere 0.9%, with 26% of Chinese firms that have purchased from the US. These statistics show that the Chinese listed firms are not as directly exposed to exports to the US as much as their US counterparts to exports to China. However, on the import side, China is similar to the US. The sample means of size (measured in log value of total market value), market-to-book ratio, leverage ratio, and ROA are 22, 3.0, 0.4 and 0.04, respectively.

Panel B shows the univariate analysis around the announcement on March 22. Comparing with Chinese firms without any exports to US, firms that sold in the US suffered from a 0.7% additional negative return on average. The stock price of Chinese firms that purchased inputs from the US declined 0.5% more relative to firms without inputs from US. The differences in CAR are similar.

Panel C of Table 6 shows the regression results of the event study that confirms the findings in the univariate analysis. Controlling for firm-level characteristics, we find that Chinese publicly listed firms that are more exposed to exports to the US reacted more negatively to the announcement. Specifically, a 10% increase in a firm's share of sale in the US (*Revenue_US*) experienced a 1.3% larger drop in stock prices (column 3 in Panel C.1). The effect remains significant when industry fixed effects are included as regressors.[18] The cumulative raw returns for firms with inputs from US are on average 0.5% lower than firms which did not source inputs from the US. The effect turns insignificant when the sales share in US is also included as a regressor. The primary reason is that the total value of procurement from the US by Chinese firms is only minimal. In sum, the analysis based on Chinese listed firms indicates similar patterns in response to the trade war announcement, especially for firms' export exposure rather than import exposure. Panel C.2 shows the consistent results based on CAR as the dependent variable.

In Panel B of Appendix 3, we find 10-percent increase in revenue from US leads to about 150 million RMB loss in market value. Chinese firms with input from US suffer from additional 173 RMB drop in market value comparing with firms without any purchases from US.

***5.5 Import Competition***

[18] We define an industry using the 2012-version classification of China Securities Regulatory Commission (CSRC). There are 74 industries in total in our sample.

In this subsection, we examine the impact of import competition, which is altered by the trade war event, on the financial market. We define Chinese import penetration at the sector level as follows:

$$\mathrm{IP}_k = \frac{IMP\_CN_k}{SHP_k + IM_k - EXP_k},$$

where $IMP\_CN_k$ is the total imports from China for sector $k$, defined as a NAICS category. $SHP_k$ is the sector shipment value. $EXP_k$ is total exports to the world in a sector. The data was downloaded from Peter Schott's (2008) website (Schott, 2008) and the US Census Bureau. Imports and exports are measured in 2017 while shipment is measured in 2016 because of the data availability. We also construct the sector measure for total exports to China as $\mathrm{Export}_k = \frac{EXP\_CN_k}{SHP_k}$, where $EXP\_CN_k$ is the total exports to China for sector $k$.

The regression results are reported in Table 7. We first regress US firms' cumulative abnormal returns (CAR) on Chinese import competition from and exports to China at the sector level without any controls.[19] The coefficient shows a statistically significant but economically small negative effect. When exports to China at the sector level is included as a regressor, as shown in column 3, the coefficient of import competition actually flips sign, suggesting that results in column 1 are subject to omitted variable bias. Intuitively, the positive coefficient on the measure of ex ante import competition implies that weakened import competition was perceived to benefit firms in sectors facing stronger competition from China more ex ante. These findings are consistent with Grossman and Levinsohn (1987), who document positive responses in stock prices to favorable shocks to import prices in a sample of 6 US industries. That said, it is noteworthy to point out that the economic magnitude of import competition is economically small. According to column 4 when the effect of firm-level exports to and imports from China are jointly estimated in the regression, firms in a sector with a 10-percent higher import penetration is associated with only a 0.05% higher abnormal return. In comparison with the heterogeneity due to different firm-level direct trade exposure, variation in import competition from China across industries plays a much more limited role.

[Table 7 about Here]

[19] For brevity, in the following sections, we only present results based on CAR as dependent variable in the regression models, although we obtain qualitatively and quantitatively similar results for CRR.

### *5.6 Production Networks*

In this subsection, we go beyond a firm's direct engagement in trade with China to examine how a firm's indirect exposure to China through global value chains can also affect its market performance. To this end, we need to construct a firm's domestic production network, which requires the firm-to-firm business relationships among our sample firms.

U.S. listed firms are subject to mandatory supply chain disclosure requirement imposed by Securities and Exchange Commission (SEC). If 10% and above of the revenue of a firm is derived from sales to any single customer, the firm is obliged to disclose such customer and the revenue in the public filings.[20] But firms also voluntarily disclose non-major customers, which compose less than 10 percent of the revenue, in their financial reports. As used by prior studies (e.g. Atalay *et al.*, 2011; Houston *et al.*, 2016), Compustat Segment database contains the supply chain relationships disclosed in the form 10-K (the annual report) filed by firms and capture on average 1,000 supply-chain linkages annually. We in contrast utilize a relatively new data source, Factset Revere, which compiles various public data sources, including annual and quarterly filings (10-K, 8-K, and 10-Q), investor presentations, company websites, and press releases. The coverage of Factset Revere is much broader coverage than that of Compustat Segment as it actively monitors 10,000 global listed firms and captures up to 25,000 buyer-supplier relationships per year.[21]

We focus on relationships identified as customers or suppliers in the database. Specifically, a supplier firm could disclose its customers, whereas a customer firm could also disclose its suppliers. We utilize both types of information in the production network construction. The relationships in the database are characterized by the starting date and the ending date. We restrict the relationships to ones in the past 3 years before the outbreak of the trade war to identify the potential on-going linkages from both upstream and downstream.[22]

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[20] The requirement is ruled under SEC's Statement of Financial Accounting Standards No. 14. See details here: https://www.fasb.org/summary/stsum14.shtml

[21] A detailed comparison of Factset Revere and Compustat Segment can be found here: https://www.longfinance.net/media/documents/DB_TheLogisticsofSupplyChainAlpha_2015.pdf

[22] The current version of the paper is based on Factset Revere data accessed in August 2018. As the supply-chain relationships are derived from the firm's public disclosure, the financial reports in 2017 fiscal year are not completely available to investors. For consistency with our baseline results, we use supply-chain information up to 2016. The period of the past 3-year includes 2014, 2015 and 2016.

We also exclude relationships with either partner that is within not our sample firms (unlisted firms, foreign firms or financial firms), resulting in a directed production network with 5,552 links.

We construct four measure for *indirect* exposures to trade with China, using firm-level production networks and the trade data. The definition follows the practices in Acemoglu *et al.* (2016a), who analyze how shocks are amplified and propagated through industry input-output linkages. Figure 3 and Figure 4 illustrate the rationale of the variable constructions.

[Figure 3 about Here]

The first measure is average exposure of revenue from China across downstream firms (buyers) in the US:

$$Revenue\_China\_Customers_i = \frac{1}{M}\sum_{m=1}^{M} Revenue\_China_{i,m},$$

where $M$ indexes the number of customers firm $i$ has. $Revenue\_China_{i,m}$ measures exposure based on exports to China for customer $m$ of firm $i$. As shown in Panel A of Figure 3, firm A located in the US has three US customers, among which B and C have Chinese firms as their customers. The possible retaliation from China would cut the sales for firms B and C, reducing the demand for inputs from firm A. We plot the customer network of General Electric (GE) in Panel C. As the whole network is large, we only consider the first two customer layers. Namely, only direct customers of GE and the customers of GE's customers are shown as nodes in the graph. The linkages represent business relationships. The size of the node represents the number of supply chain linkages of a given firm. Green nodes indicate a firm that has revenue from China and white node indicates a firm having zero revenue from China.

The second measure is the average exposure of inputs from China across downstream firms (buyers) in the US:

$$Input\_China\_Customers_i = \frac{1}{M}\sum_{n=1}^{M} Input\_China_{i,n}.$$

$Input\_China_{i,n}$ is an indicator equal to one if customer $m$ has outsourced inputs from China, and zero otherwise.[23] As illustrated in Panel B of Figure 3, US firm A has three US customers

[23] As discussed above, the regulation only requires firms to disclose the revenue share of the major customers, a large portion of the supply-chain relationships do not characterize information about the associated revenue derived from this customer. We thus treat all customers equally and construct the simple average measure for research purpose.

among which firms B and C have Chinese firms as their suppliers. The tariff hikes raise the cost of Chinese inputs for B and C, potentially leading to a decline in their total production and the demand for goods produced by firm A. In contrast, if intermediate goods produced by Chinese firms E and F can be sufficiently substituted by goods produced by US firms A. The tariff hikes may also increase the demand for goods produced by firm A and boost its sales. The same product network of GE is plotted in Panel D of Figure 3 where blue nodes indicates a GE's customer that has outsourced input from China.

The third measure is average exposure of revenue from China across upstream firms (sellers) in the US:

$$Revenue\_China\_Suppliers_i = \frac{1}{N}\sum_{n=1}^{N} Revenue\_China_{i,n},$$

where $N$ indexes the number of suppliers firm $i$ has. Panel A of Figure 4 shows that firm A located in the US has three US suppliers, among which B and C have Chinese firms as their customers. The possible retaliation from China would cut the sales to Chinese firms for firms B and C. The potential production downsizing of B and C and the accompanying adverse performance shocks may transmit to firm A. For illustration, we in Panel C draw the two-layer suppliers' network of Boeing with Green nodes indicating firms with non-zero revenue from China and white nodes denoting firms without any revenue from China.

The last measure is the average exposure of inputs from China across upstream firms (sellers) in the US:

$$Input\_China\_Suppliers_i = \frac{1}{N}\sum_{n=1}^{N} Input\_China_{i,n},$$

where $Input\_China_{i,n}$ is an indicator equal to one if supplier $n$ has outsourced inputs from China, and zero otherwise. Panel B of Figure 4 illustrates the construction process. US firm A has three US suppliers among which firms B and C have Chinese firms as their suppliers. The tariff hikes raise the cost of Chinese inputs for B and C, leading to higher prices of their products, thereby raising the production cost of firm A. The firm A thus may suffer from the pass-through effect of the elevated costs amounted by the tariff hikes and experience a negative stock market performance. We plot in Panel D the same two-layer suppliers' network of Boeing as in Panel C of Figure 4. Blue node indicates a firm that purchases from China and white node indicates a firm without inputs from China.

[Figure 4 about Here]

It is worthwhile to note that not all firms necessarily have a public customer or a public supplier. In either of such cases, we fill the indirect measures defined above with zero. As shown in Table 1, the average revenue from China across a firm's customers (suppliers) is 1.6% (2.4%). On average, 20% of a sample firm's customers have outsourced inputs from China. The percentage of a firm's suppliers that have purchased from China is also about 20. Some additional statistics are provided in Appendix 6. Panel A shows the distribution of the number of customers and suppliers on the production network. Consistent with the prior literature (e.g. Atalay *et al.*, 2011), both distributions are highly positively skewed. Firms with largest number of customers in our sample are Microsoft, General electric, IBM, Apple and Oracle. And General electric, Walmart, Boeing, Microsoft and Amazon.com are the sample firms with largest number of customers. Panel B shows descriptive statistics of the indirect measure in two different samples. Panel B.1 is based on the baseline sample of 2,309 firms. On average, a sample firm has 2.4 listed customers and 2.4 listed suppliers. Panel B shows the summary statistics of the variable without filling zero for firms without listed customers or listed suppliers. For instance, the average revenue from China among listed customers is about 3.4%. The percentage of customers that have purchased from China is about 42%.

We estimate the effects of these indirect exposures, together with the direct exposure measures included in the baseline regression. Table 8 shows the impact originated from a firm's customers. The univariate analysis in Panel A indicates comparing with the rest of the sample firms, ones with customers that have non-zero revenue from China experience 1% negative stock returns measured by CRR/CAR. Firms with suppliers that derive revenue from Chinese customers experience 1.1% lower stock returns. The regression results as reported in Panel B suggest when direct exposure from exports to China is included the effects of average revenue from China across a firm's customers and its suppliers are both statistically and economically significant. Specifically, Column 1 presents a 10% higher indirect sales exposure from customers is associated with a 1.1% lower CAR over the 3 days around March 22. Column 2 indicates that a 10% higher indirect sales exposure from suppliers is associated with a 0.89% lower CAR. The effects remain significant when the indirect measures based on customers and suppliers are jointly estimated in the regression model (column 3) and when industry fixed effects are included (column 4). The estimated coefficients in the regression model suggest the indirect exposures to sales in China combined have a larger impact than direct exposure.

We could thus quantify the aggregate impact through direct measure and indirect measures based on the coefficients in Column 3 of Panel B. Over the 3-day event window, the direct exposure from revenue from China generates 0.33% decline, while the indirect sales exposure originated from customers leads to 0.18% of negative returns and the indirect sales exposure originated from suppliers contributes additional 0.34% of losses. The regression results imply that *Revenue_China* is responsible for 69.5 billion losses in the market value, whereas 37.9 losses can be attributed to *Revenue_China_Customer* and 71.7 can be attributed to *Revenue_China_Supplier*.[24]

[Table 8 about Here]

Table 9 presents the estimated impact from indirect exposures of inputs from China. Univariate analysis in Panel A shows significant differences in stock performance between firms with positive indirect exposures vs. ones with zero indirect exposures. Specifically, firms with customers with inputs from China experience 0.9% lower 3-day stock returns than firms without customers purchasing inputs from China. Similar differences can also be observed between firms with suppliers that have purchased from China and ones without. Consistent patterns are confirmed in the regression models as shown in Panel B, except that when industry fixed effect is included the effect of average input from China across customers become weak. It can be inferred that 0.4% decline in stock returns over 3-day window is attributed to the direct exposure, *Input_China*. By comparison, *Input_China_Customer* and *Input_China_Supplier* contribute to 0.2% and 0.23% to the total percentage loss, respectively. In dollar value, *Input_China*, *Input_China_Customer* and *Input_China_Supplier* cause losses of 88.4 billion, 44.2 billion and 50.8 billion, respectively.

[Table 9 about Here]

In sum, our results in Tables 8 and Table 9 show that the structure of a firm's supply chain affects a firm's perception about the effects of tariff hikes regardless of whether the firm has any direct exposure to trade with China or not. And the indirect effect is observed for both

[24] The values are inferred by multiplying the above calculated returns by the total market value of the sample firm (21.08 trillion).

perceived decreases in the demand from downstream firms and increases in the costs of inputs from upstream firms.

### *5.7 Product Lists*

So far, we have established the relationship between stock returns and exposure across firms. We have intuitively assumed that firms with a large portion of revenue derived from China or have purchased inputs from China are more exposed to the trade war. Given the detailed product list of tariffs, we can conduct the event study at the more disaggregated level and examine whether the heterogeneous effects of the trade war (announcement) across firms based on firms' output and input product mixes. Our identification assumption hinges on the fact that when US government issues the Presidential Memorandum investors are still uncertain about the product list for tariff increases from both countries. It is also legitimate to believe that the US government is more likely to impose tariff on product categories where Chinese goods are prevalent in US imports, and *vice versa*.

Next, we exploit the detailed product lists for tariff hikes issued by both countries to evaluate the product-level impact of the adverse shocks. By the end of 2018, US government has issued 3 product lists and Chinese governments correspondingly issued 3 retaliatory product lists. Specifically, US issued product lists on April 3 ($50 billion of Chinese goods), June 15 ($50 billion), and July 10 ($200 billion), respectively. In retaliation to these actions, China hit back by issuing product lists on March 23 (128 products), April 4 ($50 billion of US goods) and August 3 ($60 billion).[25] Each product list cover additional products compared to

[25] Official sources:
China's list on March 23, 2018: http://www.mofcom.gov.cn/article/au/ao/201803/20180302722670.shtml;
US list on April 3, 2018:
https://ustr.gov/sites/default/files/files/Press/Releases/301FRN.pdf;
China's list on April 4, 2018:
http://images.mofcom.gov.cn/www/201804/20180404161059682.pdf;
US list on June 15, 2018:
http://gss.mof.gov.cn/zhengwuxinxi/zhengcefabu/201806/P020180616034361843828.pdf;
US list on July 10, 2018:
https://ustr.gov/sites/default/files/301/2018-0026%20China%20FRN%207-10-2018_0.pdf
China's list on August 3, 2018:
http://www.xinhuanet.com/fortune/2018-08/03/c_1123221094.htm

previous lists. As a confirmatory exercise to support our baseline results above, we will only focus on the responses of US firms to the first US list and the first Chinese list.

***The first product list by the Chinese government*** was issued on March 23 right after the announcement of the Presidential Memorandum on March 22. The list contains 128 products, disaggregated at the Harmonized System (HS) 8-digit level, with the total value of about 3 billion. The tariff list was announced by China's Customs Tariff Commission that raise the tariff rate on pork products and aluminum scrap by 25% and other imported US commodities, such as wine, nuts, fruits and steel piping, by 10%. The implementation of new tariffs, according to Chinese government, is to directly retaliate against tariffs on imported steel and aluminum approved by the Trump's administration. We present the products by their export value to China aggregated at the 4-digit HS level in Panel A of Appendix 8. The product with largest export to China is aluminum scrap. The retaliatory list offers us an opportunity to assess firms' financial market responses based on information at the firm-product level.

The first empirical challenge of this exercise is to identify the products, possibly multiple of them, manufactured by firms. In Compustat and most major firm data sets, firms typically report their main industry only. To this end, we follow the practices in the literature (e.g. Hoberg and Phillips, 2016) to employ a textual analysis on the US firm's product description disclosed in their filings with the regulator (i.e. US Securities and Exchange Commission). Specifically, we create a list of unique keywords that represent products in the international trade based on a list of HS codes from World Bank. The product descriptions for each firm are retrieved from their 10-K files and further cleaned to generate a unique list of products manufactured by individual firms. We then combine these two lists with the products listed in the Chinese tariff list to construct a variable, *Output_China_List*, which measures the percentage of a US firm's products mentioned in the Chinese list. The details about the construction can be found in Appendix 7.

Panel A of Table 10 reports the estimation results about the heterogeneous response based on US firms' output mix. Independent of whether we include the four firm characteristics as controls (column 2) or industry fixed effects (column 3), we find a systematic negative and statistically significant coefficient on *Output_China_List*, suggesting that firms that are more exposed due to proportionally more of their products tariffed by China responded more negatively in the financial market to the March 22 event. Specifically, a 10% higher *Output_China_List* is associated with an additional 1.1% to 1.3% decline in stock prices between March 21 and March 23.

[Table 10 about Here]

***The first product list issued by the US government*** was issued on April 3, 2018. Following up with the March 22 Presidential Memorandum, the United States Trade Representative (USTR) published the provisional list of imports that would be subject to new duties in retaliation to "the forced transfer of American technology and intellectual property." This list, which covered about 1300 Chinese products (at the HS 8-digit level), accounted for approximately $50 billion worth of US imports from China. It covered a wide range of products, including those in the raw material, construction machinery, aerospace and agricultural equipment, electronics, medical devices, and consumer product sectors. The products were chosen based on the target sectors mentioned in the "Made in China 2025" plan. We demonstrate the products with largest input from China in Panel B of Appendix 8. We aggregate the import at the 4-digit HS level and show that automatic data processing machines and machinery accessories are among the products that US import the most from China.

We define a variable, *Input_China_List*, as the percentage of the products purchased from China that are in the corresponding product list according to the Bill of Lading Database matched based on HS codes.[26] The results based on the first US list are reported in Panel B of Table 10. We find systematically that US firms with more inputs covered by the US list experienced a larger stock price decline around March 22. Specifically, one standard deviation higher *Input_China_List* is associated with an additional 0.14% to 0.16% decline in stock prices between March 21 and March 23.

We further exploit the variation in the tariff hikes across products to assess the impact of the list at the intensive margin. Specifically, we compare the planed tariff rates across products after the product list kicks in and the pre-event tariff rate. We first calculate the difference between the new import tariff imposed by the list and the import tariff before the

[26] Bill of Lading Database provides 6-digit HS codes. Since firms may mis-categorize across finely defined codes in their customs records, we match the lading database with the product list using 4-digit HS codes. The results remain similar but noisier when we use 6-digit HS in the matching process.

event at the HS level. We then use bill of lading database to identify firm's specific imports from China at the HS level. *Tariff_Change* is defined as the value-weighted average import tariff hikes using the transaction quantity as the weight due to the reason that we do not have the information on transaction value for each firm. The findings in Panel C of Table 10 suggest 10 percentage point increase in tariff rate leads to a price drop by a range between 1% and 1.5%.

The evidence built on the variation in exposure triggered by the product lists suggest firm's responses to the trade shocks are consistent with the theoretical predictions laid out in previous discussions. Market participants refine and adjust their valuation about firms when the uncertainty about the coverage and magnitudes of the tariff hikes is partially resolved.

### *5.8 Reverse Experiments*

We previously provide evidence that the heterogeneous impact of the trade war is not transitory but last for several months. Several unanticipated subsequent events occurred in 2018 and 2019, offering positive news that trade war may be settled, alleviated, or delayed. In this subsection, we exploit two major events as reverse experiments to further confirm our baseline results.

On January 9, 2019, the US and Chinese officials concluded a three-day trade talk in Beijing. The Commerce Ministry of China issued an extensive statement at the end of this round of trade talk with the US, establishing a foundation for the resolution of each other's concerns. Trump even tweeted that "Talks with China are going very well!" As the trade talks lasted for one day longer than had been previously announced, analysts in the market believed discussions had made progress.

Figure 4 plots the trajectory of search volumes on "trade talks". The public interests over "trade talks" peaked on January 9, 2019 indicated by search engines from both countries. We evaluate firm's stock price responses around this event, which is expected to reverse the adverse effect caused by the trade war.

[Figure 4 about Here]

The results are reported in Table 11. Panel A presents the univariate analysis. As one year has passed since the trade war is announced, we construct the trade exposure measures using the updated data to accommodate the adjustment during this year. In the 3-day window around the event date, firms dependent on more exports to China gained 0.6% larger raw returns relative to firms that do not have revenue from China. Comparing with firms without inputs from China, firms that outsourced inputs from China experienced 0.7% larger raw returns. This pattern is confirmed in the regression as shown in Panel B. But the joint effect of *Input_China* become insignificant when *Revenue_China* is included in the regression. Appendix 6 Panel A shows the reversal effect on Chinese firms. Taken together, the evidence compliments with our baseline results on the impact of the trade linkages between two countries.

[Table 11 about Here]

The trade war continued. On May 5, 2019, Trump posted an unexpected tweet announcing raising the tariff rate on the 200 billion dollar worth of Chinese imports from 10% to 25% and threatened to unleash 25% tariffs on additional Chinese goods. Due to this event, equity markets tumbled and the VIX Index skyrocketed. This abrupt event provides another reverse experiment to validate our main findings. As shown in Panel A of Table 12, US firms that have revenue from China experience significant negative raw returns relative to other firms by 0.5%. US firms that have input from China feature 0.7% lower returns relative to other firms. Panel B shows similar patterns in the regression estimation.

[Table 12 about Here]

We summarize our findings in Figure 5 by plotting the mean and 95% confidence interval for three-day cumulative raw returns around three events. We divide firms into groups according to their exposure to the trade war. Specifically, firms are categorized by terciles with regard to their revenue from China and assigned into high group, middle group, and low group, while firms without revenue from China fall into another group. Similar process applies for firm's exposure of input from China. Panel A and Panel B show the impact of our main event. The results in the first reverse experiment are presented in Panel C and Panel D. The last two panels present the findings in the second reverse experiment. We observe strong pattern that firms suffered from additional losses if they have more trade relationship with China. The trade talks in January 2019 featured an offsetting effect. But the Twitter threat in May further intensified the concerns over the trade war.

## 6. Conclusion

In this paper, we examine the financial market effects of the Trump administration's announcement of a trade war against China on March 22, 2018. The event triggered a sequence of trade-war type events between the two nations. Using an event-study approach, we find heterogeneous market responses to the announcement of tariff hikes across listed firms in both countries, depending on their direct and indirect exposures to US-China trade. We find that US firms that are more dependent on exports to and imports from China have lower stock and higher default risks in the short window around the "trade war" announcement. Similar patterns are also observed for Chinese listed firms by their trade relationship with the US. The results are robust to adjustments to different asset pricing models, alternative model specifications, longer event windows and a matching strategy.

We document that expectations of weakened Chinese import competition due to US tariffs on China play a statistically significant but economically minimal role. However, firms' indirect exposure to US-China trade through domestic supply chains are associated with negative stock return responses that are comparable in magnitude to those of direct exposure. These responses illustrate that the complex structure of global trade plays a crucial role in financial markets. Our findings show that the winners and losers in bilateral trade relationships depend on their position (upstream or downstream) and their extent of participation in the global value chains shared by the two countries.

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## Table 1. Summary Statistics

| Variable | N | Mean | S.D. | P25 | Median | P75 |
|---|---|---|---|---|---|---|
| ***A. Stock market reactions*** | | | | | | |
| CRR[-1,+1] | 2309 | -0.026 | 0.042 | -0.051 | -0.029 | -0.005 |
| CAR[-1,+1] | 2309 | -0.027 | 0.044 | -0.053 | -0.029 | -0.006 |
| RMV_Change[-1,+1] | 2308 | -394.722 | 2450.166 | -123.212 | -18.762 | -0.517 |
| AMV_Change[-1,+1] | 2308 | -422.846 | 2683.917 | -129.817 | -18.626 | -0.508 |
| CRR[-1,+1], Mar 23 | 2309 | -0.021 | 0.040 | -0.041 | -0.019 | 0.000 |
| CAR[-1,+1], Mar 23 | 2309 | -0.023 | 0.043 | -0.042 | -0.020 | -0.001 |
| CRR[-1,+1], Apr 3 | 2305 | 0.000 | 0.041 | -0.017 | 0.000 | 0.018 |
| CAR[-1,+1], Apr 3 | 2305 | -0.001 | 0.044 | -0.019 | -0.001 | 0.017 |
| CRR[-1,+1], Jan 9 | 2127 | 0.026 | 0.046 | 0.003 | 0.025 | 0.049 |
| CAR[-1,+1], Jan 9 | 2127 | 0.026 | 0.053 | 0.002 | 0.024 | 0.048 |
| CRR[-1,+1], May 6 | 2065 | 0.002 | 0.046 | -0.020 | -0.001 | 0.021 |
| CAR[-1,+1], May 6 | 2065 | 0.002 | 0.053 | -0.023 | -0.003 | 0.020 |
| Default Risk[-1,+1] | 2309 | 0.012 | 0.023 | 0.000 | 0.008 | 0.022 |
| ***B. Firm trade exposure*** | | | | | | |
| Revenue_China | 2309 | 0.025 | 0.052 | 0.000 | 0.000 | 0.028 |
| Input_China | 2309 | 0.241 | 0.428 | 0.000 | 0.000 | 0.000 |
| ***C. Production Networks*** | | | | | | |
| Revenue_China_Customer | 2309 | 0.016 | 0.032 | 0.000 | 0.000 | 0.021 |
| Revenue_China_Supplier | 2309 | 0.024 | 0.041 | 0.000 | 0.000 | 0.035 |
| Input_China_Customer | 2309 | 0.201 | 0.331 | 0.000 | 0.000 | 0.364 |
| Input_China_Supplier | 2309 | 0.200 | 0.330 | 0.000 | 0.000 | 0.333 |
| ***D. Industry exposure*** | | | | | | |
| Naics_IP | 2309 | 0.086 | 0.620 | 0.000 | 0.000 | 0.004 |
| Naics_export | 2309 | 0.017 | 0.041 | 0.000 | 0.000 | 0.028 |
| ***E. Product Lists*** | | | | | | |
| Output_China_List | 2309 | 0.029 | 0.020 | 0.018 | 0.029 | 0.039 |
| Input_China_List | 2309 | 0.089 | 0.252 | 0.000 | 0.000 | 0.000 |
| Tariff_Change | 556 | 2.310 | 3.345 | 0.000 | 0.227 | 3.938 |
| ***F. Controls*** | | | | | | |
| SIZE | 2309 | 6.453 | 2.264 | 4.790 | 6.483 | 8.009 |
| MTB | 2309 | 2.320 | 1.796 | 1.249 | 1.687 | 2.732 |
| LEV | 2309 | 0.268 | 0.258 | 0.023 | 0.232 | 0.403 |
| ROA | 2309 | -0.055 | 0.473 | -0.039 | 0.081 | 0.137 |

*Notes*: This table presents the summary statistics for the baseline sample of US firms used in this study. The sample is at the firm level and contains 2,309 listed domestic firms that are both headquartered and incorporated in the US with essential financial data from Compustat and stock price data from Bloomberg. Financial firms are excluded. All variable definitions are in Appendix 2. Continuous variables are winsorized at 1%.

## Table 2. Univariate Analysis

| ***Revenue from China*** | **Revenue_China** | | | | |
|---|---|---|---|---|---|
| | >median (0) | | <median (0) | | |
| | N | Mean | N | Mean | Diff. |
| CRR[-1,+1] | 910 | -0.033 | 1399 | -0.022 | -0.011*** |
| CAR[-1,+1] | 910 | -0.034 | 1399 | -0.023 | -0.011*** |
| RMV_Change [-1,+1] | 909 | -809.448 | 1399 | -125.254 | -684.197*** |
| AMV_Change [-1,+1] | 909 | -868.707 | 1399 | -133.148 | -735.559*** |
| Default Risk [-1,+1] | 910 | 0.019 | 1399 | 0.008 | 0.010*** |
| SIZE | 910 | 6.976 | 1399 | 6.113 | 0.863*** |
| MTB | 910 | 2.278 | 1399 | 2.346 | -0.068 |
| LEV | 910 | 0.243 | 1399 | 0.284 | -0.041*** |
| ROA | 910 | 0.063 | 1399 | -0.132 | 0.195*** |
| ***Input from China*** | **Input_China** | | | | |
| | =1 | | =0 | | |
| | N | Mean | N | Mean | Diff. |
| CRR[-1,+1] | 556 | -0.036 | 1753 | -0.023 | -0.013*** |
| CAR[-1,+1] | 556 | -0.037 | 1753 | -0.024 | -0.013*** |
| RMV_Change [-1,+1] | 556 | -904.124 | 1752 | -233.062 | -671.061*** |
| AMV_Change [-1,+1] | 556 | -968.055 | 1752 | -249.823 | -718.232*** |
| Default Risk [-1,+1] | 556 | 0.02 | 1753 | 0.01 | 0.009*** |
| SIZE | 556 | 7.344 | 1753 | 6.171 | 1.172*** |
| MTB | 556 | 2.098 | 1753 | 2.39 | -0.292*** |
| LEV | 556 | 0.257 | 1753 | 0.271 | -0.014 |
| ROA | 556 | 0.092 | 1753 | -0.101 | 0.193*** |

*Notes*: This table presents the univariate analysis. *CRR [-1,+1]* is the three-day cumulative raw return around March 22, 2018, the date when the Trump administration issued a presidential memorandum in reference to Section 301 of the Investigation of China's Laws, Policies, Practices, or Actions that proposed to impose tariffs on up to $50 billion of Chinese imports as a response to China's alleged theft of US intellectual property. *CAR [-1,+1]* is the three-day cumulative abnormal return around the event date estimated using the standard one-factor market model. *Revenue_China* is the revenue from China that is scaled by total revenue. *Input_China* is an indicator set to one if the firm imports goods from China as indicated by the bill of lading database. Other variables are defined in the appendix 2. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

## Table 3. Revenue and Input from China

***Panel A. Revenue from China***

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | CRR [-1,+1] | | | CAR [-1,+1] | |
| Revenue_China | -0.1155*** | -0.0900*** | -0.0449** | -0.1199*** | -0.0932*** | -0.0469** |
| | (-7.65) | (-6.26) | (-2.57) | (-7.60) | (-6.15) | (-2.48) |
| SIZE | | -0.0035*** | -0.0046*** | | -0.0034*** | -0.0047*** |
| | | (-7.42) | (-9.42) | | (-6.65) | (-8.85) |
| MTB | | -0.0023*** | -0.0016*** | | -0.0023*** | -0.0015** |
| | | (-4.09) | (-2.66) | | (-3.78) | (-2.26) |
| LEV | | 0.0159*** | 0.0112*** | | 0.0168*** | 0.0116** |
| | | (3.71) | (2.59) | | (3.63) | (2.47) |
| ROA | | -0.0002 | 0.0023 | | -0.0014 | 0.0015 |
| | | (-0.06) | (0.59) | | (-0.39) | (0.37) |
| N | 2309 | 2309 | 2291 | 2309 | 2309 | 2291 |
| adj. R-sq | 0.020 | 0.055 | 0.120 | 0.019 | 0.050 | 0.118 |
| Industry FE | No | No | Yes | No | No | Yes |

***Panel B. Input from China***

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | CRR [-1,+1] | | | CAR [-1,+1] | |
| Input_China | -0.0134*** | -0.0098*** | -0.0060*** | -0.0135*** | -0.0098*** | -0.0061*** |
| | (-7.39) | (-5.36) | (-3.10) | (-7.14) | (-5.16) | (-3.03) |
| N | 2309 | 2309 | 2291 | 2309 | 2309 | 2291 |
| adj. R-sq | 0.019 | 0.052 | 0.121 | 0.017 | 0.047 | 0.119 |
| Controls | No | Yes | Yes | No | Yes | Yes |
| Industry FE | No | No | Yes | No | No | Yes |

*Notes*: This table presents the effect of trade war announcement on US firms' values according to their revenue and purchase from China. The dependent variable, *CRR [-1,+1]* is the three-day cumulative raw return around March 22, 2018. *CAR [-1,+1]* is the three-day cumulative abnormal return around the event date estimated using the standard one-factor market model. Panel A shows the effect according firm's revenue from China. *Revenue_China* is the revenue from China that is scaled by total revenue. Panel B shows the effect according to firm's inputs from China. *Input_China* is an indicator set to one if the firm imports goods from China as indicated by the Bill of Lading database. The firm-level controls include size, market-to-book ratio, leverage, and ROA. The definitions of other variables are in Appendix 2. Industry fixed effects are based on Fama-French 30-industry definitions. The *t*-statistics based on robust errors are reported in the parenthesis. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

## Table 4. Robustness Checks

***Panel A. Alternative Variable Definitions: Fama-French 3-Factor Model***

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | CAR [-1,+1], FF 3-factor | | | |
| Revenue_China | -0.0858*** | -0.0394* | | |
| | (-5.27) | (-1.90) | | |
| Input_China | | | -0.0103*** | -0.0057*** |
| | | | (-5.10) | (-2.66) |
| N | 2309 | 2291 | 2309 | 2291 |
| adj. R-sq | 0.030 | 0.108 | 0.030 | 0.109 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | No | Yes | No | Yes |

***Panel B. Joint Estimation***

| | (1) | (2) | (3) |
|---|---|---|---|
| | CAR [-1,+1] | | |
| Revenue_China | -0.1016*** | -0.0821*** | -0.0427** |
| | (-6.36) | (-5.32) | (-2.25) |
| Input_China | -0.0110*** | -0.0081*** | -0.0057*** |
| | (-5.71) | (-4.21) | (-2.81) |
| N | 2309 | 2309 | 2291 |
| adj. R-sq | 0.030 | 0.056 | 0.120 |
| Controls | No | Yes | Yes |
| Industry FE | No | No | Yes |

*Notes*: This table presents the robustness checks to our baseline estimation. Panel A shows the results using cumulative returns adjusted by alternative asset pricing models. *CAR [-1,+1], FF 3-factor* is the 3-day cumulative abnormal return adjusted by the Fama-French 3-factor model. Panel B reports the results for the joint estimation. The definitions of the variables are in Appendix 2. The *t*-statistics based on robust errors are reported in the parenthesis. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

## Table 5. Default Risks

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Default Risk [-1,+1] | | | |
| Revenue_China | 0.0502*** | | 0.0452*** | 0.0226** |
| | (5.32) | | (4.82) | (2.14) |
| Input_China | | 0.0045*** | 0.0036*** | 0.0029** |
| | | (4.19) | (3.36) | (2.46) |
| N | 2309 | 2309 | 2309 | 2291 |
| adj. R-sq | 0.188 | 0.183 | 0.192 | 0.232 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | Yes |

*Notes*: This table presents the effect of trade war announcement on the default risk. The dependent variable *Default Risk [-1,+1]* is the growth rate of the implied five-year Credit Default Swap (CDS) spread around the event window [-1,+1] with zero indicating March 22, 2018. $Default\ Risk_i[-1,+1] = \sum_{t=-1}^{+1} CDSR_{i,t}$, where $CDSR_{i,t} = \frac{S_{i,t}-S_{i,t-1}}{S_{i,t-1}}$. $S_{i,t}$ is the implied CDS spread that is constructed using the default probabilities that are based on the Merton model. The data is from Bloomberg. *Revenue_China* is the revenue from China that is scaled by total revenue. *Input_China* is an indicator set to one if the firm imports goods from China as indicated by the Bill of Lading database. The firm-level controls include size, market-to-book ratio, leverage, and ROA. The definitions of other variables are in Appendix 2. The *t*-statistics based on robust errors are reported in the parenthesis. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

# Table 6. Firm-level Trade Exposure for Chinese Firms

***Panel A. Summary Statistics***

| Variable | N | Mean | S.D. | P25 | Median | P75 |
|---|---|---|---|---|---|---|
| CRR[-1,+1] | 2588 | -0.041 | 0.047 | -0.067 | -0.046 | -0.021 |
| CAR[-1,+1] | 2588 | -0.001 | 0.050 | -0.026 | -0.007 | 0.016 |
| Revenue_US | 2588 | 0.009 | 0.034 | 0.000 | 0.000 | 0.000 |
| Input_US | 2588 | 0.263 | 0.440 | 0.000 | 0.000 | 1.000 |
| SIZE | 2588 | 22.223 | 1.309 | 21.320 | 22.096 | 22.943 |
| MTB | 2588 | 3.039 | 2.644 | 1.230 | 2.297 | 3.984 |
| LEV | 2588 | 0.410 | 0.207 | 0.245 | 0.391 | 0.562 |
| ROA | 2588 | 0.043 | 0.057 | 0.014 | 0.039 | 0.072 |

***Panel B. Univariate Analysis***

| | Revenue_US | | | | |
|---|---|---|---|---|---|
| | >median (0) | | <median (0) | | |
| | N | Mean | N | Mean | Diff. |
| CRR[-1,+1] | 734 | -0.045 | 1854 | -0.039 | -0.007*** |
| CAR[-1,+1] | 734 | -0.005 | 1854 | 0.001 | -0.006*** |
| SIZE | 734 | 22.039 | 1854 | 22.296 | -0.257*** |
| MTB | 734 | 3.180 | 1854 | 2.983 | 0.197* |
| LEV | 734 | 0.371 | 1854 | 0.426 | -0.055*** |
| ROA | 734 | 0.047 | 1854 | 0.041 | 0.007*** |
| | Input_US | | | | |
| | =1 | | =0 | | |
| | N | Mean | N | Mean | Diff. |
| CRR[-1,+1] | 680 | -0.044 | 1908 | -0.039 | -0.005** |
| CAR[-1,+1] | 680 | -0.004 | 1908 | 0.001 | -0.005** |
| SIZE | 680 | 22.271 | 1908 | 22.206 | 0.065 |
| MTB | 680 | 2.845 | 1908 | 3.108 | -0.263** |
| LEV | 680 | 0.390 | 1908 | 0.418 | -0.027*** |
| ROA | 680 | 0.046 | 1908 | 0.041 | 0.005* |

## Table 6. Firm-level Trade Exposure for Chinese Firms

***Panel C. Regression Analysis***

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Panel C.1. CRR[-1,+1] | | | | | |
| Revenue_US | -0.1197*** | | -0.1310*** | | -0.1228*** | -0.1006*** |
| | (-5.51) | | (-5.77) | | (-5.19) | (-4.32) |
| Input_US | | -0.0049** | | -0.0050** | -0.0021 | 0.0004 |
| | | (-2.37) | | (-2.41) | (-0.97) | (0.18) |
| N | 2588 | 2588 | 2588 | 2588 | 2588 | 2588 |
| adj. R-sq | 0.007 | 0.002 | 0.012 | 0.006 | 0.012 | 0.090 |
| Controls | No | No | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | No | No | Yes |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | Panel C.2. CAR[-1,+1] | | | | | |
| Revenue_US | -0.1067*** | | -0.1390*** | | -0.1335*** | -0.1070*** |
| | (-5.04) | | (-6.52) | | (-6.03) | (-4.84) |
| Input_US | | -0.0051** | | -0.0046** | -0.0014 | 0.0003 |
| | | (-2.36) | | (-2.17) | (-0.64) | (0.11) |
| N | 2588 | 2588 | 2588 | 2588 | 2588 | 2588 |
| adj. R-sq | 0.005 | 0.002 | 0.036 | 0.029 | 0.036 | 0.113 |
| Controls | No | No | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | No | No | Yes |

*Notes*: This table presents the declaration effect of the trade war on Chinese firms. The sample consists of 2,588 Chinese firms with essential financial information. Financial firms are excluded. The data is from CSMAR database. *Revenue_US* is the value of exports to the US in 2016 that is scaled by total revenue in 2016. *Input_US* is an indicator set to one if the firm imports goods from US as indicated by China customs database in 2016. *CRR [-1,+1]* is the cumulative raw return around the event date March 22 (March 23 for the Chinese market). *CRR [-1,+1]* is the 3-day cumulative abnormal return adjusted by the standard market model. The firm-level controls include firm size, market-to-book ratio, leverage, and ROA. Variables definitions are in Appendix 2. Industry fixed effects are based on the definitions of China Securities Regulatory Commission (CSRC). The *t*-statistics based on robust errors are reported in the parenthesis. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

## Table 7. Import Competition

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | CAR [-1,+1] | | | |
| IP | -0.0019*** | | 0.0066*** | 0.0050** |
| | (-3.14) | | (3.13) | (2.15) |
| Exports | | -0.0892** | -0.1759*** | -0.1173*** |
| | | (-2.12) | (-4.66) | (-2.87) |
| Revenue_China | | | | -0.0518** |
| | | | | (-2.52) |
| Input_China | | | | -0.0079** |
| | | | | (-2.29) |
| N | 2309 | 2309 | 2309 | 2309 |
| adj. R-sq | 0.000 | 0.006 | 0.050 | 0.059 |
| Firm Controls | No | No | Yes | Yes |

*Notes*: This table presents the effect of the trade war announcement on firm value according to the industry-level exposures. *IP* is the naics-level import penetration defined as total imports from China (2017) divided by total shipment value (in 2016) plus total imports (in 2017) minus total exports (in 2017). *Exports* is a naics industry's total exports to China (in 2017) scaled by its shipment value (in 2016). The *t*-statistics based on standard errors clustered at the naics level and are reported in the parenthesis. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

## Table 8. Transmission through Domestic Production Networks: Revenue from China

***Panel A. Univariate Analysis***

| | Revenue_China_Customer | | | | |
|---|---|---|---|---|---|
| | >median [0] | | <median [0] | | |
| | N | Mean | N | Mean | Diff. |
| CRR[-1,+1] | 807 | -0.033 | 1502 | -0.023 | -0.010*** |
| CAR[-1,+1] | 807 | -0.034 | 1502 | -0.024 | -0.010*** |
| RMV_Change [-1,+1] | 807 | -865.908 | 1501 | -141.393 | -724.515*** |
| AMV_Change [-1,+1] | 807 | -928.32 | 1501 | -151.082 | -777.238*** |
| | **Revenue_China_Supplier** | | | | |
| | >median [0] | | <median [0] | | |
| | N | Mean | N | Mean | Diff. |
| CRR[-1,+1] | 999 | -0.033 | 1310 | -0.021 | -0.011*** |
| CAR[-1,+1] | 999 | -0.034 | 1310 | -0.022 | -0.011*** |
| RMV_Change [-1,+1] | 999 | -818.178 | 1309 | -71.55 | -746.628*** |
| AMV_Change [-1,+1] | 999 | -875.854 | 1309 | -77.12 | -798.735*** |

***Panel B. Revenue from China***

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | CAR [-1,+1] | | | |
| Revenue_China | -0.0698*** | -0.0754*** | -0.0575*** | -0.0319* |
| | (-4.29) | (-4.85) | (-3.46) | (-1.65) |
| Revenue_China_Customer | -0.1055*** | | -0.0905*** | -0.0702*** |
| | (-4.44) | | (-3.77) | (-2.88) |
| Revenue_China_Supplier | | -0.0889*** | -0.0784*** | -0.0455** |
| | | (-4.40) | (-3.83) | (-2.07) |
| N | 2309 | 2309 | 2309 | 2291 |
| adj. R-sq | 0.055 | 0.056 | 0.059 | 0.121 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | Yes |

*Notes*: This table presents the effect of the trade war announcement based on firms' revenue from China and their domestic production networks. *Revenue_China* is the measure of revenue from China for the firm. *Revenue_China_Customer* is the simple average revenue from China across its customers. *Revenue_China_Supplier* is the simple average revenue from China across its suppliers. The firm production network is based on all supply chain relationships in past three years before the trade war announcement from Revere database. Panel A shows the univariate analysis. The regression results are presented in Panel B. The controls include firm size, market-to-book ratio, leverage, and ROA. Variables definitions are in Appendix 2. The *t*-statistics based on robust errors are reported in the parenthesis. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

## Table 9. Transmission through Domestic Production Networks: Input from China

***Panel A. Univariate Analysis***

| | Input_China_Customer | | | | |
|---|---|---|---|---|---|
| | >median [0] | | <median [0] | | |
| | N | Mean | N | Mean | Diff. |
| CRR[-1,+1] | 754 | -0.033 | 1555 | -0.023 | -0.009*** |
| CAR[-1,+1] | 754 | -0.033 | 1555 | -0.024 | -0.009*** |
| RMV_Change [-1,+1] | 754 | -876.156 | 1554 | -161.13 | -715.026*** |
| AMV_Change [-1,+1] | 754 | -940.944 | 1554 | -171.465 | -769.478*** |
| | **Input_China_Supplier** | | | | |
| | >median [0] | | <median [0] | | |
| | N | Mean | N | Mean | Diff. |
| CRR[-1,+1] | 775 | -0.032 | 1534 | -0.023 | -0.009*** |
| CAR[-1,+1] | 775 | -0.034 | 1534 | -0.024 | -0.010*** |
| RMV_Change [-1,+1] | 775 | -946.949 | 1533 | -115.547 | -831.402*** |
| AMV_Change [-1,+1] | 775 | -1000 | 1533 | -123.238 | -892.252*** |

***Panel B. Input from China***

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | CAR [-1,+1] | | | |
| Input_China | -0.0088*** | -0.0088*** | -0.0081*** | -0.0055*** |
| | (-4.59) | (-4.64) | (-4.18) | (-2.73) |
| Input_China_Customer | -0.0075*** | | -0.0067*** | -0.0024 |
| | (-3.23) | | (-2.85) | (-1.00) |
| Input_China_Supplier | | -0.0082*** | -0.0074*** | -0.0063** |
| | | (-3.23) | (-2.91) | (-2.46) |
| N | 2309 | 2309 | 2309 | 2291 |
| adj. R-sq | 0.050 | 0.050 | 0.052 | 0.120 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | Yes |

*Notes*: This table presents the effect of the trade war announcement based on firms' input from China and their domestic production networks. *Input_China* is the measure of input from China for the firm. *Input_China_Customer* is the simple average input from China across its customers. *Input_China_Supplier* is the simple average input from China across its suppliers. The firm production network is based on all supply chain relationships in past three years before the trade war from Revere database. Panel A shows the univariate analysis. The regression results are presented in Panel B. The controls include firm size, market-to-book ratio, leverage, and ROA. Variables definitions are in Appendix 2. The *t*-statistics based on robust errors are reported in the parenthesis. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

## Table 10. Firms' Heterogeneous Responses to Product Lists

***Panel A. Firms' Responses to Chinese List on March 23, 2018***

| | (1) | (2) | (3) |
|---|---|---|---|
| | CAR [-1,+1], Mar 23 | | |
| Output_China_List | -0.1277*** | -0.1144*** | -0.1194*** |
| | (-3.14) | (-2.81) | (-2.96) |
| N | 2309 | 2309 | 2291 |
| adj. R-sq | 0.003 | 0.008 | 0.026 |
| Controls | No | Yes | Yes |
| Industry FE | No | No | Yes |

***Panel B. Firms' Responses to US Product List on April 3, 2018***

| | (1) | (2) | (3) |
|---|---|---|---|
| | CAR [-1,+1], Apr 3 | | |
| Input_China_List | -0.0055* | -0.0063* | -0.0066* |
| | (-1.70) | (-1.95) | (-1.86) |
| N | 2305 | 2305 | 2287 |
| adj. R-sq | 0.001 | 0.006 | 0.025 |
| Controls | No | Yes | Yes |
| Industry FE | No | No | Yes |

***Panel C. Firms' Responses to US Product List on April 3, 2018 According to Tariff Changes***

| | (1) | (2) | (3) |
|---|---|---|---|
| | CAR [-1,+1], Apr 3 | | |
| Tariff_Change | -0.0015*** | -0.0015*** | -0.0010* |
| | (-3.10) | (-3.08) | (-1.89) |
| N | 556 | 556 | 548 |
| adj. R-sq | 0.015 | 0.011 | 0.061 |
| Firm Controls | No | Yes | Yes |
| Industry FE | No | No | Yes |

*Notes*: This table presents US firms' responses to product lists announced by both US and China. We consider two product lists, the first Chinese product list released on March 23, 2018, and the first US product list released on April 3. Panel A presents firms' responses to the Chinese product list. The dependent variables are 3-day cumulative abnormal returns centered on the corresponding event date based on the market model. *Output_China_List* is the percentage of firm's products mentioned in the China's list. Firm's products are identified using textual analysis, which is further explained in Appendix 4. It is a proxy for US firms' exposure to the Chinese product list in terms of revenue losses. Panel B presents firms' responses to the first product list announced by US government on April 3. *Input_China_List* is the percentage of the products purchased from China that are in the corresponding product list according to the Bill of Lading Database matched using HS codes. Panel C reports the firms' responses to the tariff changes imposed by the first US product list released on April 3. *Tariff_Change* is the measure for firm's exposure to the imports tariff hikes. We first calculate the difference between the new import tariff imposed by the list and the import tariff before the event. We then use bill of lading database to identify firm's specific imports from China at HS level. We construct the value-weighted average import tariff hikes using the transaction quantity as the weight due to the reason that we do not have the information on transaction value for each firm. The sample only consists of firms that have imports from China according to the lading database. The controls include firm size, market-to-book ratio, leverage, and ROA. Variables definitions are in Appendix 2. The t-statistics based on robust errors are reported in the parenthesis. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

## Table 11. Trade Talks as a Reverse Experiment

***Panel A. Univariate Analysis***

| ***Revenue from China*** | Revenue_China | | | | |
|---|---|---|---|---|---|
| | >median (0) | | <median (0) | | |
| | N | Mean | N | Mean | Diff. |
| CRR[-1,+1], Jan 9 | 859 | 0.03 | 1268 | 0.024 | 0.006*** |
| CAR[-1,+1], Jan 9 | 859 | 0.028 | 1268 | 0.024 | 0.004* |
| ***Input from China*** | **Input_China** | | | | |
| | =1 | | =0 | | |
| | N | Mean | N | Mean | Diff. |
| CRR[-1,+1], Jan 9 | 330 | 0.032 | 1797 | 0.025 | 0.007** |
| CAR[-1,+1], Jan 9 | 330 | 0.031 | 1797 | 0.025 | 0.006* |

***Panel B. Regression Estimation***

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | CAR [-1,+1], Jan 9 | | | |
| Revenue_China | 0.0591*** | | 0.0534*** | 0.0417* |
| | (3.11) | | (2.71) | (1.70) |
| Input_China | | 0.0054** | 0.0037 | 0.0039 |
| | | (2.01) | (1.32) | (1.30) |
| N | 2127 | 2127 | 2127 | 2112 |
| adj. R-sq | 0.007 | 0.005 | 0.007 | 0.012 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | Yes |

*Notes*: This table shows US firms' responses to the US-China trade talks held in Beijing from 7 to 9 January 2019. We consider the last day of the trade talks as the event day as it conveys the positive signal to the market. *CRR [-1,+1], Jan 9* is the 3-day cumulative raw return centered on January 9, 2019. *CAR [-1,+1], Jan 9* is the 3-day cumulative abnormal return based on the market model. Panel A presents the univariate analysis. Panel B presents the regression results. *Revenue_China* is the revenue from China that is scaled by total revenue. *Input_China* is an indicator set to one if the firm imports goods from China as indicated by the Bill of Lading database updated in 2018. The firm-level controls include size, market-to-book ratio, leverage, and ROA. The definitions of other variables are in Appendix 2. The t-statistics based on robust errors are reported in the parenthesis. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

## Table 12. Twitter Threat as the Reverse of the Reverse Experiment

***Panel A. Univariate Analysis***

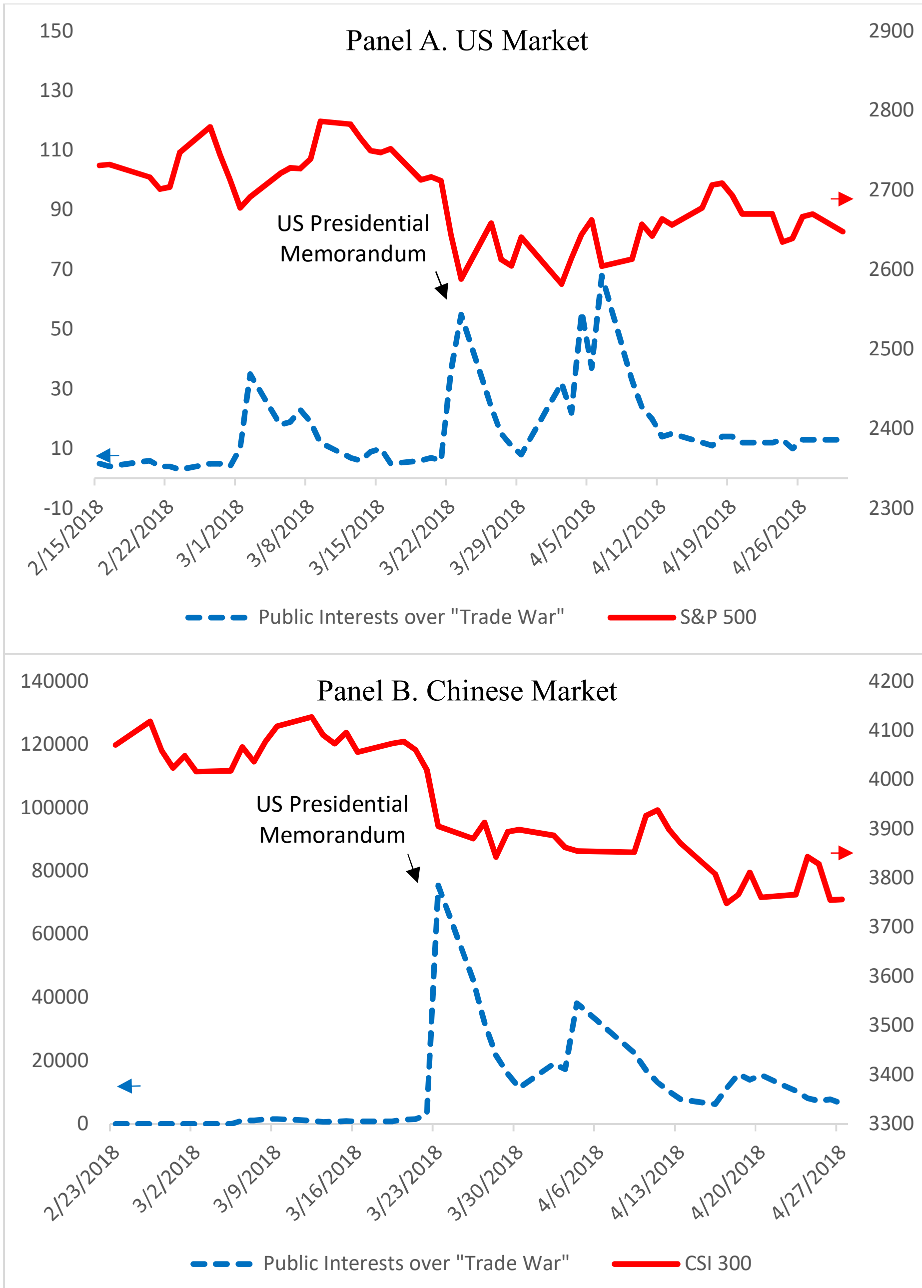
| ***Revenue from China*** | Revenue_China | | | | |
|---|---|---|---|---|---|
| | >median (0) | | <median (0) | | |
| | N | Mean | N | Mean | Diff. |
| CRR[-1,+1], May 6 | 844 | -0.001 | 1221 | 0.005 | -0.005*** |
| CAR[-1,+1], May 6 | 844 | -0.002 | 1221 | 0.004 | -0.006** |
| ***Input from China*** | Input_China | | | | |
| | =1 | | =0 | | |
| | N | Mean | N | Mean | Diff. |
| CRR[-1,+1], May 6 | 329 | -0.003 | 1736 | 0.004 | -0.007** |
| CAR[-1,+1], May 6 | 329 | -0.005 | 1736 | 0.003 | -0.008** |

***Panel B. Regression Estimation***

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | CAR [-1,+1], May 6 | | | |
| Revenue_China | -0.0634*** | | -0.0579*** | -0.0713*** |
| | (-3.01) | | (-2.64) | (-2.71) |
| Input_China | | -0.0054* | -0.0036 | -0.0032 |
| | | (-1.95) | (-1.23) | (-1.00) |
| N | 2065 | 2065 | 2065 | 2050 |
| adj. R-sq | 0.014 | 0.012 | 0.014 | 0.027 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | Yes |

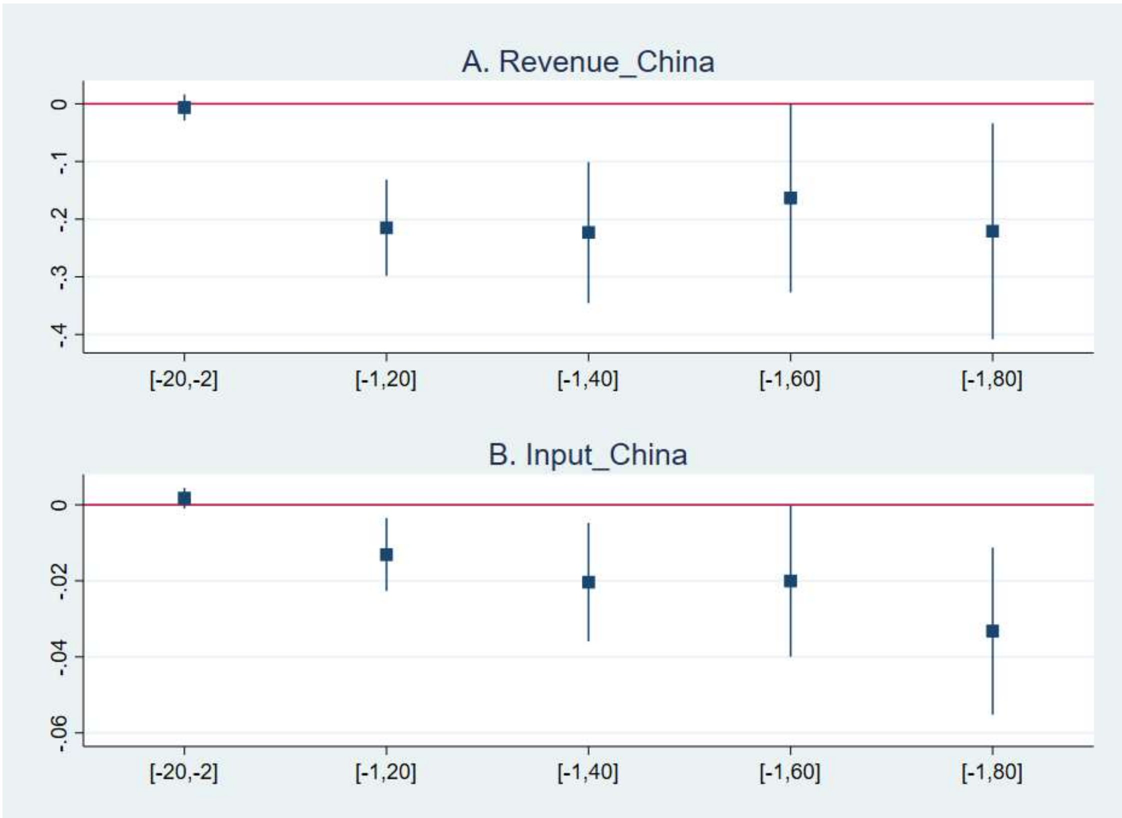
*Notes*: This table shows US firms' responses to the tweets posted by President Trump on May 5, 2019. President Trump threatened to increase the tariff rate on 200 billion of Chinese goods from 10% to 25%. The dependent variable is the 3-day cumulative raw return or abnormal return centering on May 6, 2019, the first trading day after this event. Panel A presents the univariate analysis. Panel B presents the regression results. *Revenue_China* is the revenue from China that is scaled by total revenue. *Input_China* is an indicator set to one if the firm imports goods from China as indicated by the Bill of Lading database updated in 2018. The firm-level controls include size, market-to-book ratio, leverage, and ROA. The definitions of other variables are in Appendix 2. The *t*-statistics based on robust errors are reported in the parenthesis. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

**Figure 1. Public Interests over Trade War and Stock Returns**




*Notes*: This figure presents the time-series of the market index against public interest over the US-China trade war. In panel A, the red solid line indicates the S&P 500 index (right scale). The blue dashed line shows the public interest over trade war as measured by Google Trends (left scale). In panel B, the red solid line indicates the CSI 300 index (right scale). The blue dashed line shows the public interest over trade war as measured by Baidu Index (left scale).

## Figure 2. Medium-term Effects

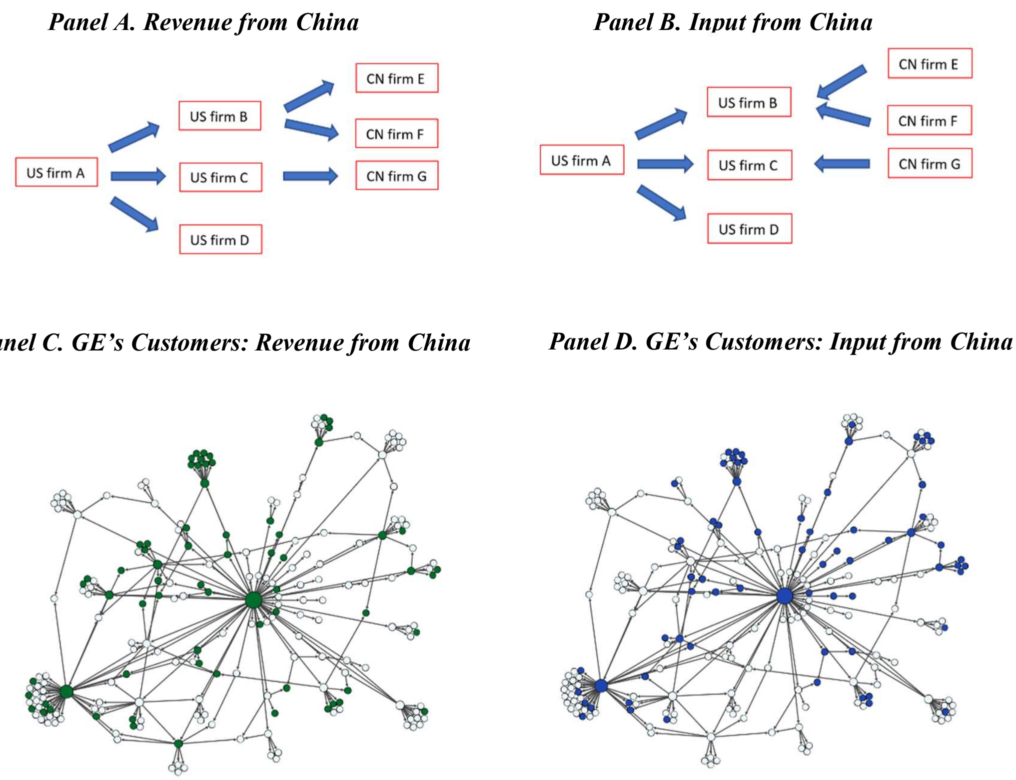



*Notes*: This figure shows the medium-term effect of the trade war declaration on firm value. We first run the following regressions:

$$Y_i = \beta \text{ Exposure}_i + X_i + \varepsilon_i,$$

where $Y_i$ denote buy-and-hold abnormal returns (*BHAR*) over different event windows. Specifically, *BHAR [-1,+X]* is the buy-and-hold abnormal returns around the event window *[-1,+X]* with zero indicating March 22, 2018 adjusted by the market benchmark. $\text{Exposure}_i$ is firm's exposure to the trade war captured by *Revenue_China* or *Input_China*. Panel A plots β of *Revenue_China* using *BHAR* with different windows as dependent variables. Panel B plots β of *Input_China* using BHAR with different windows as dependent variables. The marks indicate the magnitudes of the estimated β. The bars represent the 95% confidence intervals. The detailed regression results are in Appendix 5.

## Figure 3. Firm Production Networks: Customer Side




***Panel A. Revenue from China***

***Panel B. Input from China***

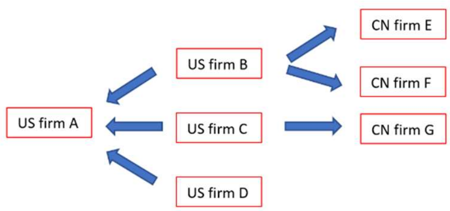
***Panel C. GE's Customers: Revenue from China***

***Panel D. GE's Customers: Input from China***

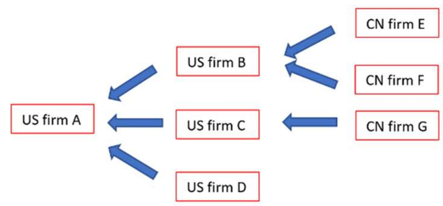
*Notes*: This figure illustrates the firm production networks from the customers' perspectives. In Panel A and Panel B, the direction of the arrows indicates the trade flows. Specifically, in Panel A, the US firm B purchases from firm A and Chinese firm E purchases from US firm B. Similarly, in Panel B, US firm B purchases from US firm A as well as Chinese firms E and F. Panel C presents the network of the customers of General Electric as an example. The graph only contains two layers of customers. Each node represents a firm and the size of the node represents the number of supply chain links of a firm. The node in the center of the graph is General Electric. Green nodes indicate firms that have revenue from China and white nodes indicate ones with zero revenue from China. The direction of the link also shows the trade flow. Panel D shows the same network of the customers of General Electric. But blue nodes indicate firms with input from China and white nodes indicate ones without input from China.

## Figure 4. Firm Production Networks: Supplier Side

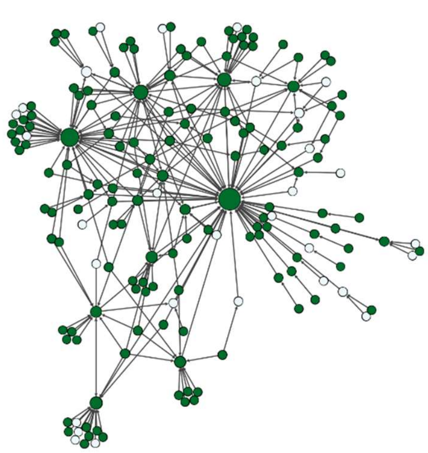
***Panel A. Revenue from China***



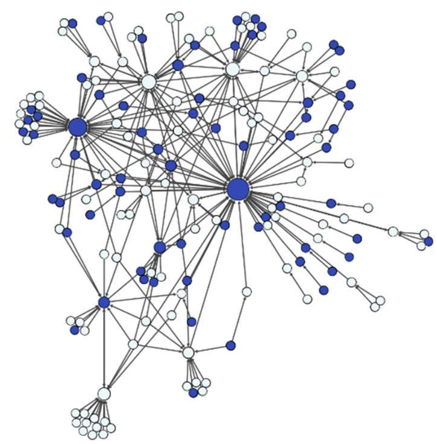

***Panel B. Input from China***




***Panel C. Boeing's Suppliers: Revenue from China***

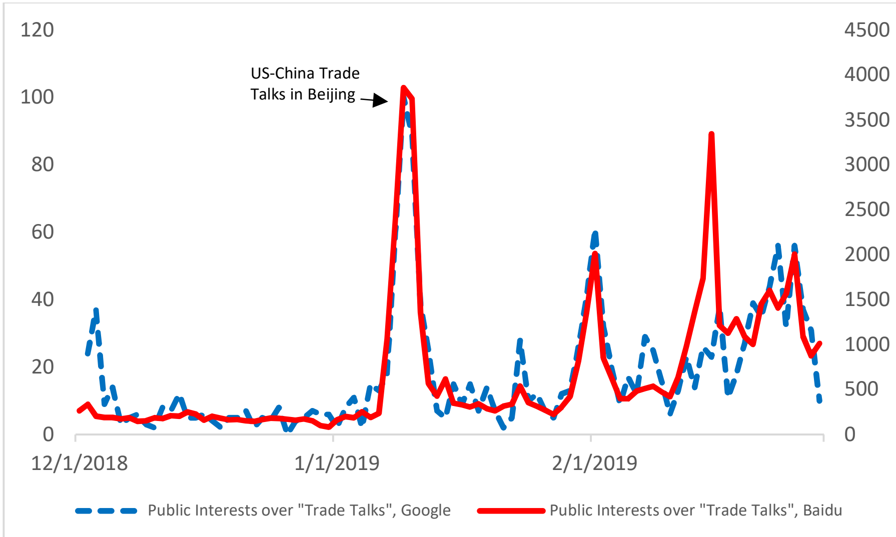


***Panel D. Boeing's Suppliers: Input from China***



*Notes*: This figure illustrates the firm production networks from the suppliers' perspectives. In Panel A and Panel B, the direction of the arrows indicates the trade flows. Specifically, in Panel A, the US firm B sells products to US firm A as well as Chinese firms E and F. Similarly, in Panel B, US firm A purchases from US firm B that purchase from Chinese firms E and F. Panel C presents the network of the suppliers of Boeing as an example. The graph only contains two layers of suppliers. Each node represents a firm and the size of the node represents the number of supply chain links of a firm. The largest node is Boeing. Green nodes indicate firms that have revenue from China and white nodes indicate ones with zero revenue from China. The direction of the link also shows the trade flow. Panel D shows the same network of the suppliers of Boeing. But blue nodes indicate firms with input from China and white nodes indicate ones without input from China.

**Figure 5. Public Interests over US-China Trade Talks**




*Notes*: This figure presents the time-series of public interest over "US-China trade talks". The blue dashed line denotes the public interest over "trade talks" as measured by Google Trends (left scale). The red solid line indicates the public interest over trade war as measured by Baidu Index (right scale).

**Figure 6. Responses to Reverse Events**


*Notes*: This figure presents firms' responses to three events: (1) March 22, 2018, presidential memorandum; (2) January 9, 2019, trade talks in Beijing; and (3) May 6, 2019, Trump's threat on raising tariff rate on 200 billion of Chinese goods from 10% to 25%. We plot the mean and 95% confidence interval for three-day cumulative returns for firms across different groups. Panel A and B present the first event. Panel C and D present the second event. The results for the third event are reported in Panel E and F. In Panel A, C and E, we sort the firms by their revenue from China. We further categorize firms into terciles if they have revenue from China. In Panel B, D, and F, we sort the firms by their input from China.

## Appendix 1. The Market-Wide Impact of Trade War

| | | (1) | (2) | (3) |
|---|---|---|---|---|
| | | Event Date (US Time) | | |
| | Event Windows | 2018-03-22 | 2019-01-09 | 2019-05-06 |
| US Firms | 1-day [0] | -2.31% | 0.61% | -0.47% |
| | 3-day [-1,+1] | -4.32% | 2.25% | -0.93% |
| | 5-day [-2,+2] | -1.54% | 3.29% | -1.38% |
| Chinese Firms | 1-day [0] | -4.09% | 0.67% | -6.65% |
| | 3-day [-1,+1] | -3.86% | 0.41% | -4.55% |
| | 5-day [-2,+2] | -2.56% | 2.72% | -6.95% |

*Notes:* This table summarizes firm's responses in terms of stock returns to the key events considered in this study. We report the average stock returns for our sample US firms and sample Chinese firms. (1) March 22, 2018: The Trump administration issued a presidential memorandum in reference to Section 301 of the Investigation of China's Laws, Policies, Practices, or Actions that proposed to impose tariffs on up to $50 billion of Chinese imports as a response to China's alleged theft of US intellectual property; (2) January 9, 2019: the trade negotiations between US and China ended with progress in identifying and narrowing the two sides' differences; (3) May 6, 2019: the first trading day after President Trump threatened to increase the tariff rate on 200 billion of Chinese goods from 10% to 25%. We present the value-weighted average returns using market value as weights.

## Appendix 2. Variable Definition

| Variable | Definition |
|---|---|
| ***Firm-level Responses*** | |
| CRR[-1,+1] | The cumulative raw returns around the event window [-1,+1] with zero indicating March 22, 2018. $CR_i[-1,+1] = \sum_{t=-1}^{+1} R_{i,t}$, where $R_{i,t}$ is the stock return for firm *i* on date *t*. Source: Bloomberg |
| CAR[-1,+1] | The cumulative abnormal returns around the event window [-1,+1] with zero indicating March 22 adjusted by the market model (CAPM) estimated using the stock return over [-120,-21]. $CAR_i[-1,+1] = \sum_{t=-1}^{+1} AR_{i,t}$, where $AR_{i,t}$ is abnormal return for firm *i* on date *t* adjusted by market model with the average return as the market return. Source: Bloomberg |
| RMV_Change[-1,+1] | The change in market value around the event window [-1,+1] with zero indicating March 22, 2018. $RMV\_Change_i[-1,+1] = MV_{i,+1} - MV_{i,-2}$. Equivalently, $RMV\_Change_i[-1,+1] = MV_{i,-2} \cdot CRR_i[-1,+1]$. Source: Bloomberg |
| AMV_Change[-1,+1] | The change in market value around the event window [-1,+1] with zero indicating March 22, 2018. $AMV\_Change_i[-1,+1] = AMV_{i,+1} - AMV_{i,-2}$. Equivalently, $AMV\_Change_i[-1,+1] = MV_{i,-2} \cdot CAR_i[-1,+1]$. Source: Bloomberg |
| CAR[-1,+1], FF 3-factor | The cumulative abnormal returns around the event window [-1,+1] with zero indicating March 22 adjusted by the Fama-French 3-factor model estimated using the stock return over [-220,-20]. $CAR_i[-1,+1] = \sum_{t=-1}^{+1} AR_{i,t}$, where $AR_{i,t}$ is abnormal return for firm *i* on date *t*. Source: Bloomberg & Ken French Data Library |
| BHAR [-1,+X] | The buy-and-hold abnormal returns around the event window [-1,+X] with zero indicating March 22. $BHAR_i[-1,+30] = \prod_{t=-1}^{+30} R_{i,t} - \prod_{t=-1}^{+30} MR_{i,t}$, where $R_{i,t}$ is the stock return for firm *i* on date *t* and $MR_{i,t}$ is the market return. |
| Default Risk [-1,+1] | The growth rate of implied 5-year Credit Default Swap (CDS) spread around the event window [-1,+1] with zero indicating March 22. $Default\ Risk_i[-1,+1] = \sum_{t=-1}^{+1} CDSR_{i,t}$, where $CDSR_{i,t} = \frac{S_{i,t}-S_{i,t-1}}{S_{i,t-1}}$. $S_{i,t}$ is the implied CDS spread constructed using the default probabilities based on the Merton model as the driving factor. Source: Bloomberg |
| ***Firm-level Measures of Exposure*** | |
| Revenue_China | The revenue from China scaled by total revenue in 2016. Source: Factset Revere |
| Revenue_China_Customer | Revenue_China_Customer is the average revenue from China in 2016 across its listed customers; Source: Factset Revere |
| Revenue_China_Supplier | Revenue_China_ Supplier is the average revenue from China in 2016 across its listed suppliers; Source: Factset Revere |
| Input_China | An indicator set to one if the firm imports goods from China suggested by the bill of lading data in 2016 and 2017; Source: the US Bill of Lading database |

| | |
|---|---|
| Input_China_Customer | The share of firms with Chinese inputs among a firm's listed customers. Source: the US Bill of Lading database and Factset Revere |
| Input_China_Supplier | The share of firms with Chinese inputs among a firm's listed suppliers. Source: the US Bill of Lading database and Factset Revere |
| Revenue_US | The value of exports to the U.S. in 2016 scaled by total revenue in 2016 for Chinese listed firms. Source: China Customs Database & CSMAR |
| Input_US | The value of imports to the U.S. in 2016 scaled by goods and services purchased in 2016 for Chinese listed firms. Source: China Customs Database & CSMAR |
| Output_China_List | The percentage of firm's products mentioned in the China's list identified using textual analysis. The measure proxies for US firms' exposure to the Chinese product list in terms of revenue losses. Details can be found in Appendix 4; Textual Analysis & United States Trade Representative |
| Input_China_List | The percentage of the products purchased from China that are in the corresponding product list according to the Bill of Lading Database matched using 4-digit HS codes. Bill of Lading Database & United States Trade Representative |
| Tariff_Change | Tariff_Change is the measure for firm's exposure to the imports tariff hikes. We first calculate the difference between the new import tariff imposed by the list and the import tariff before the event at HS level; Source: WTO Tariff Database & United States Trade Representative |
| ***Industry-level Measures of Exposure*** | |
| Naics_IP | The naics-level import penetration defined as total imports from China (2017) divided by shipment value (in 2016) plus total imports (in 2017) minus total exports (in 2017). Source: Peter Schott & US Census Bureau |
| Naics_Export | The naics industry's total exports to China (in 2017) scaled by shipment value (in 2016); Source: Peter Schott & US Census Bureau |
| ***Firm-level Controls*** | |
| SIZE | Log of total assets in 2016. Source: Compustat/CSMAR |
| MTB | Market-to-book ratio in 2016. Source: Compustat/CSMAR |
| LEV | Leverage ratio in 2016. Source: Compustat/CSMAR |
| ROA | Return-on-assets in 2016. Source: Compustat/CSMAR |

## Appendix 3. Dollar Value

***Panel A. US Firms***

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | RMV_Change [-1,+1] | | | |
| Revenue_China | -4990.7402*** | -4539.5175*** | | |
| | (-3.10) | (-3.19) | | |
| Input_China | | | -312.1433** | -287.2942* |
| | | | (-2.21) | (-1.92) |
| N | 2308 | 2290 | 2308 | 2290 |
| adj. R-sq | 0.118 | 0.121 | 0.110 | 0.116 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | No | Yes | No | Yes |

***Panel B. Chinese Firms***

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | RMV_Change [-1,+1] | | | |
| Revenue_US | -1503.9277*** | -1057.0175*** | | |
| | (-4.69) | (-3.17) | | |
| Input_US | | | -173.4006*** | -117.7712** |
| | | | (-3.19) | (-2.25) |
| N | 2578 | 2578 | 2578 | 2578 |
| adj. R-sq | 0.302 | 0.354 | 0.304 | 0.355 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | No | Yes | No | Yes |

*Notes*: This table presents impact of trade war on market value in the dollar amount. Panel A is based on a sample of US firm and Panel B is based on Chinese firms. The dependent variable is the change in market value from the day -1 to the day +1 relative to the event date, March 22, 2018. The variable is in millions of US dollar in Panel A and millions of RMB in Panel B.

## Appendix 4. Robustness Checks Using Matched Samples

***Panel A. US Firms: Treated Firms (Revenue_China>0) vs Control Firms (Revenue_China=0)***

| Variable | Treated | Control | Diff | T-value | p-value |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| CRR [-1,+1] | -0.033 | -0.025 | -0.008 | -4.68 | <0.01 |
| CAR [-1,+1] | -0.034 | -0.026 | -0.008 | -4.73 | <0.01 |
| SIZE | 6.973 | 6.958 | 0.015 | 0.15 | 0.88 |
| MTB | 2.265 | 2.304 | -0.039 | -0.51 | 0.61 |
| LEV | 0.243 | 0.242 | 0.002 | 0.16 | 0.87 |
| ROA | 0.062 | 0.060 | 0.002 | 0.20 | 0.84 |

***Panel B. US Firms: Treated Firms (Input_China>0) vs Control Firms (Input_China=0)***

| Variable | Treated | Control | Diff | T-value | p-value |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| CRR [-1,+1] | -0.036 | -0.025 | -0.011 | -5.09 | <0.01 |
| CAR [-1,+1] | -0.037 | -0.026 | -0.011 | -4.85 | <0.01 |
| SIZE | 7.318 | 7.419 | -0.100 | -0.80 | 0.42 |
| MTB | 2.092 | 2.218 | -0.126 | -1.42 | 0.16 |
| LEV | 0.257 | 0.250 | 0.007 | 0.56 | 0.58 |
| ROA | 0.091 | 0.073 | 0.018 | 1.35 | 0.18 |

*Notes*: This table presents the results based on samples matched on firm characteristics. Propensity score matching method is employed to match the firms with larger exposure to the trade frictions to control firms according to the firm-level variables including firm size, market-to-book ratio, leverage, and ROA. Panel A and B show the results for US firms according to their revenue from China and inputs from China, respectively. Columns 1 and 2 show the mean of the variable for treated firms and control firms, respectively. Column 3 shows the difference in the mean between control firms and treated firms. Columns 4 and 5 show the associated t-value and p-value, respectively. The *** denotes significance at the 1% level.

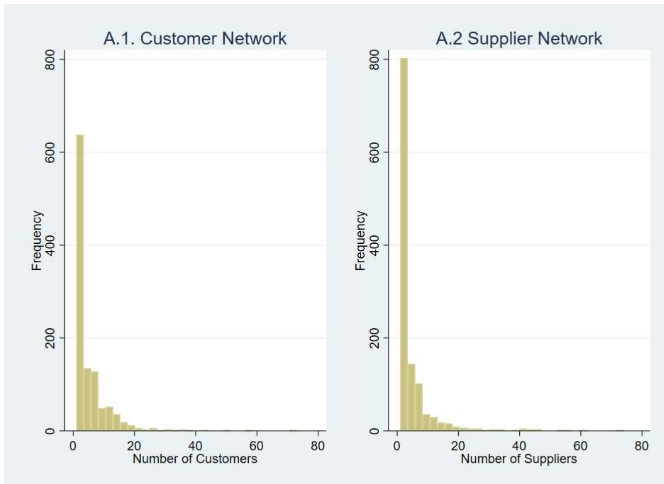
## Appendix 5. Medium-term Effects

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | BHAR [-1,+20] | BHAR [-1,+40] | BHAR [-1,+60] | BHAR [-1,+80] |
| Revenue_China | -0.2156*** | -0.2235*** | -0.1637** | -0.2185** |
| | (-5.08) | (-3.59) | (-1.96) | (-2.28) |
| N | 2281 | 2253 | 2244 | 2214 |
| adj. R-sq | 0.033 | 0.014 | 0.027 | 0.033 |
| | BHAR [-1,+20] | BHAR [-1,+40] | BHAR [-1,+60] | BHAR [-1,+80] |
| Input_China | -0.0131*** | -0.0203** | -0.0201** | -0.0329*** |
| | (-2.69) | (-2.56) | (-1.97) | (-2.93) |
| N | 2281 | 2253 | 2244 | 2214 |
| adj. R-sq | 0.026 | 0.012 | 0.027 | 0.034 |
| Controls | Yes | Yes | Yes | Yes |

*Notes*: This table presents the results for medium-term effects of the trade war announcement. Dependent variable is buy-and-hold abnormal returns (*BHAR*) over different event windows. Specifically, *BHAR [-1,+X]* is the buy-and-hold abnormal returns around the event window *[-1,+X]* with zero indicating March 22 adjusted by the market benchmark. The firm-level controls include size, market-to-book ratio, leverage, and ROA. The definitions of other variables are in Appendix 2. The *t*-statistics based on robust errors are reported in the parenthesis. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

## Appendix 6. The Description of Revere Database

***Panel A. Histogram of Number of Customers and Suppliers***




***Panel B. Summary Statistics of the Firm Production Networks***

| Variable | N | Mean | S.D. | P25 | Median | P75 |
|---|---|---|---|---|---|---|
| ***B.1. Main sample*** | | | | | | |
| ***Customer-side*** | | | | | | |
| Number of customers | 2309 | 2.405 | 5.060 | 0.000 | 0.000 | 3.000 |
| Revenue_China_Customer | 2309 | 0.016 | 0.032 | 0.000 | 0.000 | 0.021 |
| Percentage of customers with revenue from China | 2309 | 0.248 | 0.377 | 0.000 | 0.000 | 0.500 |
| Input_China_Customer | 2309 | 0.201 | 0.331 | 0.000 | 0.000 | 0.364 |
| ***Supplier-side*** | | | | | | |
| Number of suppliers | 2309 | 2.405 | 5.696 | 0.000 | 1.000 | 2.000 |
| Revenue_China_Supplier | 2309 | 0.024 | 0.041 | 0.000 | 0.000 | 0.035 |
| Percentage of suppliers with inputs from China | 2309 | 0.351 | 0.433 | 0.000 | 0.000 | 0.857 |
| Input_China_Supplier | 2309 | 0.200 | 0.330 | 0.000 | 0.000 | 0.333 |
| ***B.2. Sample only including firms with listed firms as customers or suppliers*** | | | | | | |
| ***Customer-side*** | | | | | | |
| Number of customers | 1099 | 5.052 | 6.359 | 1.000 | 3.000 | 6.000 |
| Revenue_China_Customer | 1099 | 0.034 | 0.040 | 0.000 | 0.023 | 0.051 |
| Percentage of customers with revenue from China | 1099 | 0.520 | 0.397 | 0.000 | 0.500 | 1.000 |
| Input_China_Customer | 1099 | 0.422 | 0.370 | 0.000 | 0.400 | 0.714 |
| ***Supplier-side*** | | | | | | |
| Number of suppliers | 1202 | 4.619 | 7.218 | 1.000 | 2.000 | 5.000 |
| Revenue_China_Supplier | 1202 | 0.046 | 0.047 | 0.010 | 0.035 | 0.067 |
| Percentage of suppliers with inputs from China | 1202 | 0.674 | 0.378 | 0.400 | 0.833 | 1.000 |
| Input_China_Supplier | 1202 | 0.385 | 0.371 | 0.000 | 0.333 | 0.667 |

*Notes*: Panel A shows the distribution of the "degree" of nodes in the firm production networks. Specifically, A.1 shows the distribution of the number of listed customers for our sample firms. Firms with largest number of customers in our sample are Microsoft, General electric, IBM, Apple and Oracle. A.2 shows the distribution of the number of listed suppliers for our sample firms. Firms with largest number of customers in our sample are General electric, Walmart, Boeing, Microsoft and Amazon.com. Panel B shows additional descriptive statistics of the firm production networks. B.1 presents the variables based on the main sample including both firms with listed suppliers or customers and firms without. B.2 shows the variables based on a sample only including firms with listed firms as customers or suppliers.

## Appendix 7. The Procedure of Textual Analysis

1. We first retrieve the complete list of HS codes from World Bank website.[27] We only keep the product description of 4-digit HS codes to minimize the potential noise from the more detailed description in 6-digit or 8-digit product codes.

2. We perform a procedure to clean the product list. Specifically, we first keep nouns and drop all stop words, number and symbols. We then singularize all the nouns and create a list of unique words for products. We further manually check the list and correct the remaining errors. The product list we obtain here is referred as ***Master List***.

3. We retrieve all 10-K report filed by US listed firms from SEC EDGAR. Identify item 1 in the 10-K filings that contains the product description. We perform a similar procedure as in (2) and only keep the unique words that appear in ***Master List***. We refer this list as ***Firm List***.

4. We focus on the product list announced by Chinese government on March 23. We perform the similar procedure and find the unique words that appear in ***Master List***. We refer this list as ***Product List***.

5. For each firm, we calculate the percentage of the unique words in ***Firm List*** that also appear in ***Product List***. We use this measure to proxy for firm's exposure to the shocks of Chinese product list.

[27] https://wits.worldbank.org/referencedata.html

## Appendix 8. Additional Summary Statistics of Product Lists

***Panel A. The First Chinese Tariff List: Products with Largest Export to China***

| Rank | HS | Product | Export to China (millions) |
|---|---|---|---|
| 1 | 7602 | Aluminum; waste and scrap | 917.6 |
| 2 | 0203 | Meat of swine; fresh, chilled or frozen | 329.8 |
| 3 | 2207 | Ethyl alcohol, undenatured; of an alcoholic strength by volume of 80% vol. or higher; ethyl alcohol and other spirits, denatured, of any strength | 313.5 |
| 4 | 0206 | Edible offal of bovine animals, swine, sheep, goats, horses, asses, mules or hinnies; fresh, chilled or frozen | 245.2 |
| 5 | 0802 | Nuts (excluding coconuts, Brazils and cashew nuts); fresh or dried, whether or not shelled or peeled | 153.9 |

***Panel B. The First US Tariff List: Products with Largest Import from China***

| Rank | HS | Product | Import from China (millions) |
|---|---|---|---|
| 1 | 8471 | Automatic data processing machines and units thereof, magnetic or optical readers, machines for transcribing data onto data media in coded form and machines for processing such data, not elsewhere specified or included | 47363.5 |
| 2 | 8473 | Machinery; parts and accessories (other than covers, carrying cases and the like) suitable for use solely or principally with machines of headings 84.70 to 84.72 | 10725.9 |
| 3 | 9401 | Seats (not those of heading no. 9402), whether or not convertible into beds and parts thereof | 10414.5 |
| 4 | 8528 | Telephone sets, including telephones for cellular networks or for other wireless networks; other apparatus for the transmission or reception of voice, images or other data (including wired/wireless networks) | 10249.9 |
| 5 | 8443 | Printing machinery; used for printing by means of plates, cylinders and other printing components of heading 84.42; other printers, copying machines and facsimile machines, whether or not combined; parts and accessories thereof | 6903.1 |

*Notes*: This table shows the additional description of the first Chinese product list issued on March 23, 2018 and the first US product list issued on April 3, 2018. Panel A shows the top 5 products (labeled by 4-digit HS code) by total export of US to China. Panel B shows the top 5 products (labeled by 4-digit HS code) by total import of US from China.

## Appendix 9. The Reverse Experiments: Responses of Chinese Firms

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A. CAR [-1,+1], Jan 9 | | | |
| Revenue_US | 0.0788*** | | 0.0737** | 0.0609** |
| | (2.76) | | (2.51) | (2.01) |
| Input_US | | 0.0030* | 0.0013 | -0.0008 |
| | | (1.83) | (0.77) | (-0.42) |
| N | 2582 | 2582 | 2582 | 2582 |
| adj. R-sq | 0.014 | 0.010 | 0.014 | 0.050 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | Yes |
| | (1) | (2) | (3) | (4) |
| | Panel B. CAR [-1,+1], May 6 | | | |
| Revenue_US | -0.0024 | | 0.0109 | 0.0022 |
| | (-0.07) | | (0.29) | (0.06) |
| Input_US | | -0.0031 | -0.0033 | -0.0012 |
| | | (-1.09) | (-1.15) | (-0.37) |
| N | 2569 | 2569 | 2569 | 2569 |
| adj. R-sq | 0.010 | 0.010 | 0.010 | 0.079 |
| Controls | Yes | Yes | Yes | Yes |
| Industry FE | No | No | No | Yes |

*Notes*: This table shows Chinese firms' responses to the subsequent events. We consider two events. The first event is the US-China trade talks held in Beijing from 7 to 9 January 2019. We consider the last day of the trade talks as the event day as it conveys the positive signal to the market. The second event is when President Trump threatened to increase the tariff rate on 200 billion of Chinese goods from 10% to 25%.