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TRADE NETWORKS AND FIRM VALUE: EVIDENCE FROM THE US-CHINA TRADE WAR

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Abstract

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JEL Classification: F10, G12, G14, O24

Keywords: N/A

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Trade Networks and Firm Value: Evidence from the U.S.-China Trade War

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Abstract

This paper evaluates the financial implications of policy shocks for global production networks. We use the announcements of tariff increases on a wide range of goods by the U.S. and Chinese governments in 2018-2019 as events, starting with the presidential memorandum issued by the Trump administration on March 22, 2018, to study the impact of trade policy shocks on firms' stock market performance. Using various novel datasets, we document that firms' stock market responses to the announcements are determined by the degree of their direct exposure to U.S.-China trade and their indirect exposure through the global value chains. In particular, U.S. firms that are more dependent on exports to and imports from China have lower stock returns and higher default risk around the announcement dates, whereas the reduced import competition from China has a limited effect on the firms. We also find consistent patterns of stock market reactions by Chinese firms. Two reverse experiments in 2019 further validate how the complex structure of global trade shapes stock market reactions to policy shocks.

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Keywords: Firm value, event study, trade policy, offshoring, global value chains

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1. Introduction

A notable feature of globalization in the past few decades has been the unprecedented reorganization of economic activities across regions, firms, and workers.[1] This reorganization has been driven by the establishment of numerous complex global value chains, which have enhanced the connectivity between firms and hence nations. Although the resulting increase in the interdependence of firms and nations has allowed for the greater sharing of economic benefits (Acemoglu et al., 2016b), it has also amplified the propagation of shocks across complex production networks and thus increased macroeconomic uncertainty (Acemoglu et al., 2015, 2016a; Barrot and Sauvagnat, 2017; Ozdagli and Weber, 2017; Carvalho et al., 2017).

Thus, the recent phase of globalization has highlighted the need to examine the financial implications of the trade links across firms in different nations. In this respect, the recent unexpected and abrupt changes in trade policies around the world, which have roiled global stock markets globally, offer unique real-world "experiments" for studying the effects of policy shocks on firms in the global production networks.[2] In addition, despite the comprehensive news coverage, there have been few systematic analyses of the effects of the recent trade tensions on the outcomes of individual firms, partly due to the lack of up-to-date micro data.

In this paper, we use various announcements relating to the highly unpredictable U.S.-China trade war in 2018-2019 to evaluate the effects of trade shocks on firms' financial market performance along the supply chains in the U.S. and China. Our analysis begins with the issuance of a presidential memorandum by the Trump administration on March 22, 2018, which proposed that a 25% tariff should be imposed on over $50 billion of Chinese imports.[3] This

[1] See Goldberg and Pavcnik (2016) for information about the effects of the 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 U.S. 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 transfer of intellectual property to China and close the wide and persistent U.S.-China trade deficit. The U.S. trade representative, based on a seven-month investigation, alleged that the Chinese theft of American intellectual property costs the U.S. 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 U.S. 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)

unprecedented and abrupt policy announcement shock offers a unique opportunity for an event study. The objective of the U.S. government was to raise the prices of imports from China to weaken the competitiveness of Chinese firms and eventually induce the Chinese government to implement policies that are more favorable to U.S. businesses.

The economic implications of the U.S. administration's move towards protectionism are ambiguous. The rationale for raising tariffs and transferring profits from a trade partner to home is based on the conventional mindset that global trade mostly involves the exchange of final goods, rather than intermediate inputs. However, studies have shown that global trade in the 21st century has increasingly involved production sharing by firms located in different countries (Grossman and Rossi-Hansberg, 2006; Baldwin, 2011; Johnson and Noguera, 2012; Antràs, 2015). From this perspective, firms from different nations are related as buyers and suppliers along the global value chains. Although tariffs can reduce the competition from foreign firms at home, they can also increase the cost of imported inputs and hence production for domestic firms. As a consequence, domestic consumers and firms that are heavily dependent on imports, directly or indirectly, suffer the most. The cost of import tariffs on production is also amplified because the 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.

If the increased input costs cannot be alleviated by switching to suppliers from other countries or passing the costs onto consumers, the reduced profits will inevitably be incorporated into the firms' stock prices. Moreover, imposing tariffs to protect domestic businesses may also raise the expectations of retaliation from the target country, which in this case would reduce U.S. firms' sales in China. If the U.S. firms cannot completely replace the lost sales in China with sales from other countries, their future cash flows will decrease, thereby lowering their current stock prices. More importantly, these adverse ripple effects may be amplified through the production networks formed by the interlocking supply-chain relationships.

There are several advantages in using the 2018-2019 U.S.-China trade war announcements for an event study of firms' trade networks. First, the U.S. and China are the world's largest economies, with China becoming the top trading partner of the U.S. in 2017.[4] Thus, in addition to generating significant uncertainty and having a negative economic impact on the rest of the world, the escalating trade tension between the two largest economies offers a unique opportunity to clearly identify the effects of trade policy shocks across a large number of firms with heterogeneous participation in trade networks.

Second, the policy announcements, especially the presidential memorandum issued on March 22, 2018 proposing to impose tariffs on a wide range of Chinese imports, were significant and unprecedented.[5] For the most part, investors were surprised by the announcement that the U.S. would impose tariffs on Chinese imports, in terms of the timing, magnitude, coverage, and potential costs.[6] The efficient market hypothesis states that financial markets should quickly incorporate news of new tariffs in their stock price evaluations to reflect any perceived changes in firms' future cash flows, thereby enabling the perceived impact of the trade shock on firms to be precisely estimated. In contrast, it is difficult to determine the impact of tariffs using firm performance variables because accounting variables, such as return-on-assets, reflect the cumulative effects of many events (e.g., interest rate changes and currency fluctuations) during the accounting period, which typically exceeds a quarter. Another advantage of conducting an event study on the impact of trade policy announcements is that the subsequent publication of the detailed product lists and the reverse events can be used as validation exercises.

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

[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).

[5] In what follows, we discuss the potential confounding events around this event date and provide tests to mitigate the associated concerns.

[6] The initial targeted list of products covers $50 billion of imports from China. The subsequent failure to reach an agreement resulted in the U.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.

from and exports to the U.S. To measure U.S. firms' indirect exposure to U.S.-China trade, we use new buyer-seller matched data to gauge firms' indirect exposure to trade with China through their engagement in the U.S. 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; the average exposure to Chinese inputs across downstream firms; and the average exposure to Chinese inputs across upstream firms.

Using these new data sets, we find that the announcement of the tariff increases had significant effects on listed firms in both countries. We find heterogeneous effects across firms within sectors; specifically, the effects vary with the firms' direct exposure to the policy shocks on trade. In the period around March 22, 2018, U.S. firms that import from or export to China experience significantly lower stock returns compared to those without direct exposure. Specifically, in the three-day window centered on the event date, our regression results show that when 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 0.5% lower average cumulative returns, while firms that directly acquire offshore inputs from China have a 0.6% lower average cumulative return than those that do not. These results are robust to various standard asset pricing models, alternative model specifications, and different lengths of the event window. In addition, firms that are more exposed to the tariff increases experience higher default risk, as gauged by the growth rate of the implied credit default swap (CDS) spreads in the short event window. Among the Chinese listed companies, we find symmetric patterns of negative stock returns around the March 22 announcement date for those that report imports from or exports to the U.S.

We also investigate the effect of reduced import competition. Grossman and Levinsohn (1987) find positive stock market responses to favorable shocks to import prices at the industry level. Their results suggest that if the U.S.-China trade war increases the prices of Chinese goods, U.S. firms that benefit from the resulting profit shifting should have higher stock prices. We test this hypothesis by constructing industry-level measures of the 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% higher share of imports from China ex ante are associated with a 0.05% higher stock return response to the March 22 announcement. It is worth noting that the positive effect of the reduced competition is much smaller in absolute magnitude than the negative effects associated with firms' exposure to either sales to or inputs from China.

We further examine whether firms' indirect exposure to trade with China through their domestic supply chains may also affect their responses to various tariff announcements. As predicted by our theoretical model, we find more negative responses by firms that have greater indirect exposure to exports to and imports from China through their (domestic) supply chains, even after controlling for the firms' direct output and input exposure in the baseline regressions. In particular, we find that despite not directly importing inputs from China, U.S. firms that have indirect exposure to Chinese inputs through their domestic supply chains tend to experience more negative stock returns. These results suggest that the perceived increases in the input and production costs of the upstream and downstream firms are passed to the firms they are connected with through their domestic trade links.

We also find that the stock price decline tends to be larger for firms that have domestic suppliers or buyers that derive a large share of their revenue from China. This suggests that even if a firm is not directly exposed to U.S.-China trade, its stock returns will be more negatively affected if its downstream buyers or upstream suppliers are perceived to sell less to China as a result of the expected retaliatory tariffs. Interestingly, we find that, on average, U.S. firms' indirect exposure to sales in China has a larger impact than direct sales exposure, whereas the indirect input exposure to China has a similar impact as direct input exposure.

We take full advantage of the detailed lists of tariffed products issued by the U.S. and Chinese governments after each announcement date. As the financial markets digest the news about the upcoming tariff increases, investors remain uncertain about the details, in particular the specific products that will be tariffed and when the tariffs will be imposed. Using the first product lists issued by the U.S. and Chinese governments, we evaluate the impact of the tariffs at the firm-product level. Using the event-study approach, we find that U.S. firms with more of the exported products included 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. Conversely, the U.S. firms that have more of the imported products mentioned in the U.S. list respond more negatively to the announcement.

Finally, we use subsequent events that invert the market sentiment about the trade war as reverse events to validate our main findings. For instance, the trade talks in Beijing in January 2019 were considered a signal of a trade war truce between the delegations. Using these types of events as reverse experiments, we find that firms with a larger share of revenue derived from China or that use inputs from China have greater increases in stock prices around the announcement dates. Another reverse event is Trump's posting on Twitter in May 2019 about raising the tariffs from 10% to 25% on $200 billion of Chinese goods. We find that U.S. firms with greater trade exposure to China around the date of Trump's tweet experience more negative returns. In sum, the reverse experiments confirm our findings based on the initial 2018 announcement that individual firms perceive the tariffs as net cost shocks, depending on their heterogeneous exposure to U.S.-China trade.

The remainder of this paper proceeds as follows. In Section 2, we review the literature. In Section 3, we describe the institutional background by listing the key events before and after the publication of the presidential memorandum on March 22. 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 U.S.-China trade. Section 5 reports the empirical results. The final section concludes the paper.

2. Literature Review

Our research draws on and advances several strands of research at the intersection of trade and finance. First, we add to the literature on firm-level responses to trade policy shocks. Studies have shown 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 (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 the financial outcomes stemming from firms' engagement in international trade. Bekaert et al. (2016) document how firms' global engagement affects their stock returns. Levine and Schmukler (2006) examine how firms' participation in trade affects their stock market liquidity, whereas Claessens, Tong, and Wei (2012) investigate the role of trade developments in transmitting financial crises to the real economy. In a recent study, Barrot, Loualiche, and Sauvagnat (2019) show 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 studies by focusing on an unexpected event that exogenously affects numerous firms along the global value chains between the U.S. and China. By linking trade policies to the financial markets, our paper also adds to the literature on the effects of financial friction and credit conditions on international trade (e.g., Manova, 2008, 2012; Chor and Manova, 2012).

In another recent study, Greenland et al. (2019) use the equity market reactions to the U.S. granting of permanent normal trade relations (PNTR) to China in October, 2000 to infer the effects of exposure to trade liberalization. Similarly, Bianconi et al. (2019) focus on the effects of the reduced trade policy uncertainty resulting from China's accession to the World Trade Organization (WTO) on U.S. firms' stock market returns. Unlike 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 of individual firm's exposure using pre-event trade data on U.S. 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), and transportation networks (e.g., Giroud, 2013). 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 also examined the structure and implications of global value chains (Antràs and de Gortari, 2017; Johnson and Noguera, 2017; Alfaro et al., 2019). Recently, the availability of buyer-seller linked data has enabled studies to conduct detailed analyses of the endogenous formation of production networks among firms and their 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).[7] Contributing to this body of literature, our paper emphasizes the roles that the supply chain networks play in shaping the impact of costly trade barriers on firms' financial outcomes. As such, our paper 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).

Our paper draws heavily from the extensive body of literature that uses the event-study approach (see reviews by Schwert, 1981 and MacKinlay, 1997). Several notable event studies are closely related to ours. Notably, Fisman et al. (2014) examine how Japanese and Chinese firms respond to adverse shocks to Sino-Japanese relations. Wagner et al. (2018) use Trump's election victory as an event to study the how the potential policy changes on taxes and trade proposed during his campaign might affect the financial outcomes of U.S. firms. Crowley et al. (2019) analyze the effect of the EU's announcement of import restrictions on Chinese firms in the solar panel industry. Our research differs from these studies by directly examining a series of unanticipated trade policy changes between the two largest economies.

Last but not least, our paper contributes to the growing body of literature on the macroeconomic effects of the U.S.-China trade war. In two recent studies (Amiti et al., 2019; Fajgelbaum et al., 2019), the U.S. tariffs are found to significantly increase consumer prices in the U.S. due to the almost complete pass-through of the tariffs to U.S. prices. Moreover, using a quantifiable general-equilibrium trade model, Amiti et al. (2019) find that the substantial increases in the prices of Chinese imports are associated with an $8 billion loss in welfare in the U.S. (or 0.04% of U.S. GDP). Using more disaggregated import price data from U.S. ports, Cavallo et al. (2019) also find evidence supporting the complete pass-through of tariffs to U.S. prices.

[7] Atalay et al. (2011) theoretically and empirically study U.S. 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 networks. Bernard, Moxnes, and Saito (2017) use Japanese buyer-seller linked data to analyze how improvements in transportation infrastructure can increase firms' input sourcing and hence their productivity. Carvalho et al. (2017) quantify the propagation of the Great East Japan Earthquake shocks in 2011 through firms' input-output links. Lim (2017), Tintelnot et al. (2019), and Oberfield (2018) develop models of the endogenous formation of production networks and the resulting macroeconomic implications.

3. Institutional Background and Hypotheses

3.1 Trade between the U.S. and China: Past and Present

The Chinese government initiated its open market economic reforms in 1978. In the four decades since the reforms, the country has grown substantially in terms of aggregate income, investment, consumption, and trade. In 1978, China's overall trade accounted for less than 1% of global trade. In 2013, China surpassed the U.S. to become the largest trading nation in the world,[8] and in 2015, China surpassed Canada as the largest trading partner of the U.S.[9] Although the U.S. remains the largest economy in terms of GDP in the world, various studies have predicted that China will surpass the U.S. as the leading economy in the near future.[10]

China gained entry to the WTO in December 2001. As Autor, Dorn, and Hanson (2013) and Pierce and Schott (2016) point out, Chinese exports, particularly those to the U.S., have skyrocketed since 2001, thanks to China's substantial reductions in tariffs against other WTO member countries and the granting of PNTR by the U.S. Since 1985, China has been running a trade surplus against the U.S.,[11] which has continued to increase in terms of dollar value, and as a share of the U.S.' total trade deficit with the rest of the world and China's GDP (Scott, 2017). The widening bilateral trade deficit with China was a key reason behind the recent imposition of tariffs on Chinese imports by the U.S. government.

Donald Trump was elected the 45th President of the United States in November 2016. During his presidential campaign, he repeatedly mentioned his plan to revive the U.S. 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 of many of them. Trump's complaints about China's economic policies range from complaints about currency manipulation and unfair practices against foreign businesses to concerns about the continuous rise of China, as evidence by the hallmark "Made in China 2025" initiative and China's various outward-looking economic and foreign policies. However, the most important factor is

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[8] Monaghan, "China surpasses US as world's largest trading nation," *The Guardian* (Jan. 10, 2014). https://www.theguardian.com/business/2014/jan/10/china-surpasses-us-world-largest-trading-nation
[9] Source: U.S. Census https://www.census.gov/foreign-trade/statistics/highlights/top/index.html
[10] The World Economic 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/
[11] U.S. Census Bureau, "Trade in goods with China." https://www.census.gov/foreign-trade/balance/c5700.html

probably the persistent trade deficit the U.S. 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 produced in several key high-tech and R&D-intensive sectors, to induce the government to implement policies to improve the business environment for U.S. exporters to and investors in China.

Below, we list the five events that we use to evaluate the impact of the U.S.-China trade tensions. The main event of our research is the issuance of the presidential memorandum on March 22, 2018. The other four events are discussed in detail in the empirical analysis section.

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 imposing tariffs on up to $50 billion of Chinese imports as a response to China's alleged theft of U.S. intellectual property. President Trump gave U.S. trade representative Robert Lighthizer 15 days to come up with a list of products to impose tariffs on. Lighthizer stated he would target products that the Chinese government had indicated in various policy documents that it intended to dominate, in particular those mentioned in the "Made in China 2025" plan. The Trump administration's reasons for imposing tariffs on China include the following.
  1. The large trade deficit between the U.S. and China.
  2. China's policy of forcing U.S. technology-intensive firms to enter into joint ventures with Chinese companies and share their technology in return for market access.
  3. China's alleged theft of U.S. intellectual property.
  4. To protect domestic businesses against foreign competition for national security reasons.
- March 23, 2018: The Chinese government hit back with a list of 128 products that would face 15-25% tariffs should the U.S.-China trade negotiations fail.

- April 3, 2018: The U.S. trade representative published a provisional list of imports that would be subject to the new duties, covering about 1,300 Chinese products corresponding to approximately $50 billion of U.S. imports from China.
- January 7-9, 2019: Trade negotiations between the U.S. and China were held in Beijing. The trade talks ended with progress in identifying and narrowing the differences between two sides. Following top-level talks were confirmed.
- May 5, 2019: On Twitter, President Trump tweeted that he was going to increase the tariffs on $200 billion dollars of Chinese goods from 10% to 25% and threatened to impose a 25% tariff on the remaining $325 billion dollars of untaxed Chinese goods.

In 2018 and 2019, a series of other critical events were triggered by the presidential memorandum issued on March 22, 2018, including the issuance of additional product lists, the implementation of the tariff hikes, and meetings between senior government officials from both countries.[12] We first conduct a detailed event-study analysis based on the initial announcement on March 22, 2018, because it was unexpected and, in retrospect, can be regarded as the starting point of the ongoing trade war between the U.S. and China. We then provide supporting evidence of the effects of the publication of the official tariff lists and the reverse events in 2019, which unexpectedly changed market sentiment.

3.3 Hypotheses

The primary goal of this paper is to empirically examine the financial implications of the trade links between firms, guided by a simple theoretical model as outlined in Appendix 1. Our model, which is built on the general-equilibrium production network model of Tintelnot et al. (2019), features monopolistically competitive firms using labor, domestic inputs and imported inputs to produce goods, which can be sold to domestic consumers, domestic downstream firms, and foreign consumers.

Our model shows that on the one hand, exporting firms' values (profits) will be impacted directly by foreign retaliatory tariffs that reduce foreign demand, but indirectly though the supply chains as domestic downstream firms that export will reduce their demand

[12] A detailed list of the events relating to the U.S.-China trade war can be found here: https://en.wikipedia.org/wiki/China%E2%80%93United_States_trade_war

for domestic inputs. On the other hand, a country's import tariffs will directly raise the cost of production for its firms that use imported inputs, but also indirectly though the supply chains since import tariffs reduce sales of and thus demand from domestic downstream firms. We will empirically assess the differential responses to the tariff announcements due to firms' direct exposure to U.S.-China trade and their indirect exposure through various channels. Specifically, we will empirically examine the following four hypotheses (see Appendix 1 for details):

Hypothesis 1 (direct impact of the foreign partner's import tariffs):

An increase in the foreign partner's import tariffs will lower the value of an exporting firm.

Hypothesis 2 (direct impact of import tariffs):

An increase in import tariffs will lower the value of a firm that uses imported inputs.

Hypothesis 3 (total impact of the foreign partner's import tariffs):

In addition to the direct impact (i.e., reduced export revenue), an increase in the foreign partner's import tariffs will lower a firm's value due to various indirect effects, which arise from (1) higher prices of domestic inputs, (2) higher prices of imported inputs, as well as (3) lower sales to domestic downstream firms.

Hypothesis 4 (total impact of import tariffs):

In addition to the direct impact (i.e., higher prices of imported inputs), an increase in a country's import tariffs will lower a firm's value due to various indirect effects, which arise from (1) higher prices of domestic inputs; (2) reduced sales to foreign consumers; (3) reduced sales to domestic consumers; and (4) reduced sales to domestic downstream firms.

To examine Hypothesis 1, we will gauge the direct exposure to exports of a US (Chinese) firm by its share of exports in total sales. To examine Hypothesis 2, we will measure the direct exposure to imports of a US (Chinese) firm by a dummy of its import participation. To examine the indirect effects according to Hypotheses 3 and 4, we will construct four firm-level measures of US firms' exposure to trade with China in production networks: the average revenue from China across downstream firms; the average revenue from China across upstream firms; the average exposure to Chinese inputs across downstream firms; and the average exposure to Chinese inputs across upstream firms.

4. Estimating Framework

The first empirical challenge is that trade relationships can arise between firms as a result of observable and unobservable factors, such as comparative advantage or political uncertainty in the country or region. Many of these factors are time-varying and endogenous. Second, studies usually rely on the sector-level exposure to measure trade shocks, because until recently, there has been little data available on U.S. firms' input sourcing. For example, many studies base their analyses on the import competition measured at the sector level. Although this is theoretically appropriate, studies have shown that firms tend to produce multiple products and alter their product lines from time to time (Bernard, Redding and Schott, 2011; Hoberg and Phillips, 2016). In these cases, a firm's reported main industry may not precisely capture its exposure to trade.

To circumvent these empirical challenges, we use an event study approach and combine a number of new datasets to identify firms' trade exposure. As discussed in the introduction, Trump's announcement of a trade war against China on March 22, 2018 was significant and unexpected, and thus offers a unique real-world experiment for an event study. Although detailed micro and macro data may be required to assess the economic effects of the trade war, the event-study approach using daily stock market data on publicly listed firms permits real-time analysis. The approach has been frequently used in studies for policy evaluation. In addition to analyzing the real-time market responses to the announcement of the trade war, the event-study approach can provide clear evidence of the impact of the policy. In contrast, estimations of the long-run economic effects can be biased by other confounding factors or offset by subsequent policies and events.

We construct samples of firms listed on the U.S. or Chinese stock markets. As reported in Table 1, our U.S. sample is comprised of 2,309 listed firms, for which we can construct measures to gauge their exposure to U.S.-China trade and their stock market performance. The sample consists of firms that are both incorporated and headquartered in the U.S. as identified by Compustat. In other words, we exclude all foreign firms, including Chinese firms, that are listed on the U.S. equity market. We also exclude financial firms. The daily stock return data and implied CDS spreads are obtained from Bloomberg. For firms listed on the Chinese stock market, we use the Chinese counterpart of Compustat, the China Stock Market and Accounting Research Database (CSMAR), to obtain data for 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 the cumulative raw returns (*CRR*). We denote the event date as date 0, and construct the *CRR* over the three-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 returns (*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 days relative to the event date. Given the abrupt nature of the announcement of the tariff hikes by the U.S. government, we use a firm's cumulative stock return over a three-day window as our main dependent variable of interest. As robustness checks, we construct variables using longer event windows, and construct the abnormal returns using the Fama-French three-factor model.

There are several potential issues in the construction of the measures in our context. First, by estimating the "normal" performance, the factor models (e.g., CAPM or the Fama-French three-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 the general market movements (lower loadings on the market benchmark). Those firms might also be the ones that are most sensitive to the expected impact of the trade policy *per se*, thereby making it difficult to isolate the real effect of the policy. Second, market-wide policy changes (such as the announcement of the trade war in our case) may fundamentally affect the risks that firms face, as indicated by the changes in the factor loadings estimated using the samples before and after the event (Schwert, 1981). The abnormal returns based on factor models estimated using historical data thus become less accurate. For these reasons, raw returns tend to provide more objective estimations and more straightforward interpretations. We thus present the respective results based on *CRR* and *CAR*. In the following, we show that *CRR* and *CAR* generate almost identical results, suggesting that the documented effects are not significantly affected by the abovementioned problems.

We use three different data sources to construct our main independent variables measuring firms' *direct* exposure to the U.S.-China trade. The first data source is Factset Revere, which tracks the information on the foreign buyers and sellers of U.S. publicly listed firms. For each U.S. 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.[13] Specifically, the continuous variable, *Revenue_China*, is the share of the revenue from China in the firm's total revenue in 2016. This variable measures the relative importance of the Chinese market for each U.S. firm. Intuitively, firms that are more dependent on sales in China are expected to suffer more from China's retaliation. For instance, Apple Inc., Alphabet Inc., and Exxon Mobil derive 20.8%, 8.9%, and 5.9% of their revenue from China, respectively.

The second data source is the U.S. bill of lading database. U.S. Customs keeps track of every waterborne import and export transaction. We use the information on the U.S. waterborne imports to determine firms' exposure to China on the import side. For 2017, the database contains about 5 million bills of lading for imports from China, with information on the country of the shipper, quantity, and product code. These administrative data usually contain errors in the consignee names. To map the data to the U.S. listed firms, we first use a fuzzy-matching process to filter out the consignee names with the names of listed firms on the basis of 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.[14]

[13] 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.
[14] The lading information can be transmitted to the market participants through various channels. For instance, equity analysts and institutional investors can access this information and inform other investors. Firms may

The third data source is China's customs data, which contain detailed information on the annual foreign trade transactions of all Chinese trading firms. Specifically, the data provide the value, quantity, product type, source country of imports, and destination country for exports for each transaction. 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 the U.S. in 2016 scaled by the total revenue in 2016 for Chinese listed firms, and *Input_US* is an indicator set to one if the value of imports to the U.S. in 2016 is positive, and zero otherwise.[15]

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 the cumulative raw and abnormal returns around the different event dates. In particular, in the sample of 2,309 firms, the mean CRR over the three-day window around March 22 (the first event date) is around -2.6%, with the median equal to -2.9%. The mean and median firm CAR over the three-day window around the same event are similar to the 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 U.S. firms drops by about $395 million. In total, our sample firms experience $911 billion loss in market value over the three-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 firms on average incur about a $423 million "abnormal" loss in market value.

[Table 1 about Here]

The main independent variables of interest are the two measures of firms' exposure to U.S.-China trade. In particular, the variable *Revenue_China*, which captures U.S. firms' direct export exposure to China, has a mean of 2.5% and the median is equal to 0. The mean of

also mention their related business 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 is defined using either year of data. As the database does not provide the transaction value, it is difficult for us to define a continuous variable such as the percentage of input value from China.

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

Input_China, which captures U.S. firms' direct import exposure to China, shows that 24% of the firms directly imported from China.

The 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 on U.S. firms are from Compustat.[16] Other variables, such as the *CAR* around other event dates and the indirect exposure to the trade war, are discussed in the next section. Detailed definitions of the variables are provided in Appendix 3.

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 can be treated as an unexpected event. Figure 1 compares the trajectory of the market benchmark index with the public interest in the "trade war" for both the U.S. and Chinese markets. Panel A (right scale) shows that there was a sharp fall in the S&P 500 index on March 22, 2018, suggesting that the presidential memorandum was a largely unanticipated event. The S&P 500 index dropped by 2.5% on March 22, and by 4.8% from March 21 to March 23. Appendix 2 summarizes the value-weighted average stock returns around three event dates for both the U.S. and Chinese firms, with the firms' market value as weights. The U.S. firms in our ample experienced on average a 2.3% decline in stock returns on the event date (March 22, 2018), and a 4.3% decline from March 21 to March 23. The losses amounted to $487 billion on the event day and $911 billion over the three-day event window.[17]

Panel A of Figure 1 also plots the public interest in the trade war based on the frequency of keyword searches for "trade war" using the Google search engine (left scale). Research suggests that the trends in Google searches can be used to measure investors' attention (e.g., Da et al., 2011). Public interest in the trade war peaked on March 22, the day the Trump

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

[17] The dollar value is measured in USD when prefixed by $. When prefixed by RMB, the dollar value is measured in RMB.

administration announced the 10% tariffs on $50 billion of imports from China.[18] Similarly large declines in the S&P 500 index and the corresponding spikes in public interest, although smaller in magnitude, are observed for the other announcement dates (e.g., April 5 when Trump proposed additional tariffs against China).

Panel B of Figure 1 shows a similar pattern in the Chinese market. In China, the public interest in the trade war is measured by the frequency of the keyword searches for "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 the announcement and experienced a cumulative 4.5% decline in the three-day event window. As shown in Appendix 2, the Chinese firms in our sample experience 4.1% negative returns on the event date and a 3.9% decline over the three-day event window. Overall, the Chinese sample firms incur losses of RMB1500 billion (about $237.3 billion) on the event day and RMB1463.6 billion ($231.6 billion) over the three-day period.

[Figure 1 about Here]

The abrupt increase in the public interest in the "trade war" around this event together with the large market movement suggest that the U.S. announcement of tariff increases surprised the market and generated significant concern over the trade tension between the U.S. and China. Based on our search of news articles and academic studies, we find no other significant events on March 22, 2018 that can explain the overall market movement in both countries, apart from the presidential memorandum. In the following discussion, we examine the heterogeneous effects of this policy shock among firms based on their exposure to the event.

However, we note that there are two events that could potentially contaminate our estimation. The first is the appointment of the new National Security Advisor, John R. Bolton, announced by Trump on Twitter on March 22, 2018, the date of the presidential memorandum. Yet, it remains unclear why this new appointment would have such an effect on the U.S. and China equity markets. We later show that our results are robust to a sample excluding firms in military related industries, which may be more exposed to this event. The second event is the imposition of the Section 232 tariffs on aluminum and steel imports from all countries

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

announced by the U.S. government on March 1, 2018. The policy came into force on March 23, 2018, which overlaps with our main event window. We mitigate this concern by dropping firms in the steel and aluminum related industries, and our results remain virtually unchanged. To further strengthen our findings for the major event (March 22, 2018), we identify two subsequent events that reverse the market sentiment about the trade war between two countries. We find evidence consistent with our interpretation of our main findings.

In addition to the reverse events discussed below, we note that the stock market responded to other subsequent events. Specifically, on April 2, when China's Ministry of Commerce rolled out tariffs on 128 U.S. products, as proposed on March 23, 2018, the U.S. stock market index dropped by 2.2% and the Chinese market index dropped by 0.6%. After the U.S. announced the tariffs on $50 billion of imports from China, on June 15 Trump threatened to unleash more tariffs if China retaliated. In particular, when Trump directed the U.S. trade representative to identify $200 billion of Chinese goods for additional tariffs on June 18, the Chinese market fell sharply by 3.5%. These market reactions amplified the impact of the fears of a trade war on the financial market. Nonetheless, because several events clustered around April 2-5, the impact of each event is difficult to evaluate. In our analysis below, we focus on the announcement on March 22 as the main event.

5.2 Firms' Heterogeneous Stock Market Reactions to Trade War Announcement

Our following estimation of firms' heterogeneous reactions rests on the premise that information on the structure of the firms' relationships is available to the public so that investors do not underreact to the news of the trade war. We argue that this premise holds. Institutional investors and financial intermediaries have in-house research teams that are capable of estimating the exposure to indirect trade through their access to business databases and the large talent pool in the financial industry. Consistent with the efficient market hypothesis, the unexpected trade shocks prompt traders to compete in acquiring valuable information about firms' trade links. Moreover, investors would have been made more aware of firms' trade partners based on the evidence of the return predictability across economically linked firms documented in early studies (e.g., Cohen and Frazzini, 2008).

This section provides the baseline empirical results on the impact of the declaration of the trade war on the financial markets. In Table 2, we show the preliminary results based on a univariate analysis of the relation between a firm's exposure to U.S.-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 2, U.S. 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 than firms with a share of sales in China below the median.[19] In addition, we find that the "above-median" firms are on average larger in terms of market value and more profitable in terms of ROA, but have a lower leverage ratio than 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 subsamples that are separated according to whether the firms offshore inputs from China. We use data from the bill of lading database to create these subsamples. We find that firms that report some offshoring activities in China have on average 1.3% lower *CRR/CAR* over the three-day window than 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 firms' stock returns on their trade exposure to China. Table 3 reports the point estimates in the OLS regressions based on robust standard errors.[20] As shown in Panel A of Table 3, we find that firms that sell 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 1.2% lower *CRR*. According to column (2), this correlation drops to 0.9% when the four firm-level characteristics (firm 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

[19] The median of the revenue from China is zero.
[20] In untabluated results, available upon request, we show that our results are robust to industry clustering standard errors.

between the U.S. and China. Nonetheless, these industry-level characteristics cannot sufficiently explain most of the firms' heterogeneous responses to the fears about the U.S.-China trade war within each industry. In particular, there is substantial heterogeneity across firms within an industry regarding their exposure to U.S.-China trade, which explains the differential effect of the U.S.-China trade war on firms' market performance. Columns 4-6 show that the *CAR* around the three-day window decline to a similar amount as measured by the *CRR* for firms with larger revenues from China.

[Table 3 about Here]

We continue to examine whether imports from, rather than exports to, China also affect the financial market performance of U.S. firms. 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 than the average of firms that have zero imports from China.

We endeavor to quantify the aggregate effects on the overall market through exports to and imports from China. As shown in Appendix 2, 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 the market value of firms on March 20, 2018 as weights. The aggregate effect through the exposure to Chinese imports can be gauged using 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 in the three-day stock returns.

To further quantify the dollar losses resulting from the announcement of the trade war, we regress the change in market value around the event date on firms' trade exposure to China. As shown in Panel A of Appendix 4, we find results consistent with our baseline estimation in Table 3. After controlling for the firm characteristics, a 10% increase in revenue from China is associated with an additional \$499 million loss in market value. Similarly, compared with firms without inputs from China, firms that outsource inputs from China incur an additional \$312 million loss in market capitalization. The effect remains significant when industry fixed effects are included. From March 21 to March 23, the sample firms lost $911 billion in total. Based on the coefficients in columns 1 and 3 of Panel A in Appendix 4, we find that *Revenue_China* and *Input_China* contribute to overall losses of $287.7 billion and $173.6 billion, respectively.

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

[Table 4 about Here]

Our event study rests on the premise that the event is unanticipated by the public and that there are no obvious confounding events around the event window. After a thorough search of the news media and relevant analyses, we identified two events that may contaminate our analysis. The first is Trump's appointment of a new national security advisor on the same date (March 22, 2018). The second event is that the tariff increases on steel and aluminum announced on March 1 came into effect on March 23, 2018, which overlaps with our event window. For the first event, there is no obvious reason why the appointment would influence the financial markets in the U.S. and China. Our exposure variables are at the firm level and are explicitly defined according to a firm's exposure to the trade tensions. We also include the industry fixed effects to compare the heterogeneous responses among firms in the same sector. As long as the effect of the new appointment clusters at the sector level, our estimation of the trade war effect will not be biased. In the Panel A of Appendix 5, we show that our results remain unchanged for the sample excluding firms in military related industries, which are arguably more exposed to the appointment of the new national security advisor.[21] The second confounding event should be incorporated into the stock prices when the tariffs were first announced. The tariff increase is imposed on few types of goods (steel and aluminum) imported from all countries instead of only China. Thus, the exposure to this event is less likely to be highly correlated with our firm-level measures, which are explicitly defined according to the U.S.-China trade war and consider all types of goods purchased and exported. We also show

[21] A firm is considered to operate in military related industries if its six-digit NAICS is 928110, five-digit NAICS is 33641, two-digit SIC is 97, or four-digit SIC is 3040 or 8422.

in Panel B of Appendix 5 that excluding firms in the steel and aluminum industries does not affect our main results.[22]

Firms with heterogeneous exposure to trade with China should display significant variations in firm characteristics, such as firm size and leverage, as shown in Table 2. Although we control for the four main firm characteristics in the regressions to mitigate any omitted variable biases, concerns remain about the potential selection biases arising from firms' non-random trade decisions. To mitigate the selection biases, we use a propensity score matching approach and construct a sample matched on the four firm-level control variables considered in our analysis. The results are presented in Appendix 6. Panel A shows the balance tests for firms with exports to China vis-a-vis firms without. None of the firm variables are statistically different between the two groups of firms, but 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.

It could be argued that the findings over a short event window are an outcome of firms' overreactions to the news. To verify whether the trade-war announcement has had any long-lasting effects, 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), *BHAR* is defined as

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

where R_{it} is the daily stock return for stock *i* on date *t*. MR_t is the average return of the 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 the tariff hikes to 2 days after the announcement. 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 sample period.

[22] A firm is considered to operate in the steel or aluminum industries if its two-digit SIC is 2 or four-digit SIC is 1000, 1090, 3411, 3412, 3440, 3442, 3444, 3448, 3460, 3490, 3540, or 3541.

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 the trade policy shocks on firm performance. The coefficients on the two firm exposure measures estimated using the baseline specification are plotted in Figure 2. In the regression predicting the pre-event returns, we fail to reject the null hypothesis that the two exposure variables (revenue from China and input from China) are different 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 the 40 trading days (*BHAR[-1,+40]*) after the announcement. Firms with inputs from China have a 2% lower stock price on average in the medium term (a 40-day period), relative to firms that have no imports from China. The detailed regression results are provided in Appendix 7.

The value weighted average of *BHAR[-1,+40]* is 3.8%. Using a similar approach to that used for the baseline results, we can infer that the exposure of revenue from China has to an aggregated medium effect of -1.3% and the exposure of inputs from China contributes another 1% decline. As the total market capitalization of our sample firms 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*. Having confirmed the medium-term impact, in the rest of the paper, we focus on the short windows around March 22 and the subsequent announcements by the governments of both countries as events, following the conventional practices used in event studies.

[Figure 2 about Here]

5.3 Default Risk

In addition to affecting firms' stock returns, the Trump administration's trade policy should have affected the wealth of other stakeholders (such as bondholders). We posit that fears about a trade war may have increased the likelihood of firms defaulting. First, investors could expect the worsened financial performance reflected in the declining stock prices to increase the chances of bankruptcy or other triggered events (Acemoglu et al., 2016a). Second, due to the uncertainty about the future of the U.S.-China trade relations, firms may have adopted suboptimal strategies by delaying investment and other long-term plans (Bloom, 2009; Bloom et al., 2007). To test this hypothesis, following prior studies (e.g., Ismailescu and Kazemi, 2010), 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:

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

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

As reported in Table 5, we find that firms that are exposed to imports from and exports to China are associated with a higher default risk. Specifically, as reported in column 1, a 10 percentage-point increase in the share of sales to China is associated with a 0.50% increase in a firm's default risk. With regard to the firms' offshoring relationships, when we use the *Input_China* dummy, we find that firms that have some offshoring activities in China have an on average 0.45% higher risk of default.

[Table 5 about Here]

In sum, the firms that are more exposed to U.S.-China trade experience bigger negative returns on the stock markets around the time of the March 22 event, and investors perceive these firms to be riskier, as reflected by increases in the firms' default risk. These results suggest the event had significant financial implications in the bond market.

5.4 Stock Return Reactions of Chinese Firms

Thus far, we have examined firms' market reactions to the trade war announcement using a sample of U.S. publicly listed firms. The U.S. tariff hikes (and their announcement) should also have affected the export sales of Chinese firms in the U.S. and thus their stock market performance. Therefore, we use the Chinese counterpart of Compustat, the CSMAR, to conduct a similar set of event-study analyses from the perspective of Chinese publicly listed firms. To this end, we use a unique China customs database that contains detailed firm-level information on imports and exports to measure firms' trading activities with the U.S. The most updated version of the customs database is for 2016. We merge the customs database with the CSMAR data based on the firm names. We first use a fuzzy matching algorithm to filter the firm names in the China customs database with similar firm names from the CSMAR. We then manually check the accuracy of the matches to generate the final matches between the 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 U.S., and the mean share of exports to the U.S. in the total sales is a mere 0.9%, with 26% of Chinese firms having purchased from the U.S. These statistics show that the Chinese listed firms are less directly exposed to exports to the U.S. than their U.S. counterparts are to exports to China. However, on the import side, China firms are similar to U.S firms. The sample means for size (measured as the log value of the 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 time of the announcement on March 22. Compared with Chinese firms that do not export to the U.S., the firms that sold goods in the U.S. suffered an average 0.7% additional negative return. Moreover, the stock prices of Chinese firms that purchased inputs from the U.S. declined 0.5% more than firms without inputs from the U.S. The differences in *CAR* are similar.

Panel C of Table 6 shows the regression results of the event study, which confirm the findings of the univariate analysis. Controlling for the firm-level characteristics, we find that Chinese publicly listed firms that are more exposed to exports to the U.S. react more negatively to the announcement. Specifically, a 10% increase in a firm's share of sales in the U.S. (*Revenue_US*) is associated with a 1.3% larger drop in stock prices (column 3 in Panel C.1). The effect remains significant when the industry fixed effects are included as regressors.[23] The *CRR* for firms with inputs from the U.S. are on average 0.5% lower than for firms that do not source inputs from the U.S. The effect becomes insignificant when the sales share in the U.S. is also included as a regressor, largely because Chinese firms purchase minimal procurements from the U.S. In sum, the analysis based on Chinese listed firms indicates similar patterns of

[23] We define the industries using the 2012 classification of the CSRC. There are 74 industries in our sample.

response to the trade war announcement, especially for firms exposed to exports rather than imports. Panel C.2 shows the consistent results based on CAR as the dependent variable.

In Panel B of Appendix 4, we find that a 10% increase in revenue from the U.S. leads to an approximately RMB150 million loss in market value. Chinese firms with inputs from the U.S. suffer an additional RMB173 million drop in market value compared to firms that do not purchase goods from the U.S.

5.5 Import Competition

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

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

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, and EXP_k is the total global exports in a sector. The data are from Peter Schott's website (Schott, 2008) and the U.S. Census Bureau. The import and export data are from 2017, and the shipment data are from 2016 due to 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 the *CAR* of U.S. firms on the Chinese import competition and exports to China at the sector level without any controls.[24] The coefficient shows a statistically significant but economically small negative effect. When exports to China at the sector level are included as a regressor, as shown in column 3, the sign of the coefficient of import competition is reversed, suggesting that the results in column 1 are subject to omitted variable bias. Intuitively, the positive coefficient on the measure of ex ante import competition implies that the weakened import competition is perceived to provide greater benefits to firms in sectors that face stronger competition from China. These findings are consistent with Grossman and Levinsohn (1987), who document

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

positive stock price responses to favorable shocks to import prices in a sample of six U.S. industries. Nevertheless, it is worth pointing out that the economic magnitude of the import competition is 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 sectors with a 10% higher import penetration are associated with only a 0.05% higher abnormal return. Compared with the heterogeneity due to different degrees of firm-level exposure to direct trade, the variation in the import competition from China across industries plays a much more limited role.

[Table 7 about Here]

5.6 Production Networks

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

We rely on a relatively new database, Factset Revere, which is, to our knowledge, the best available source of supply chain information. The database is based on firms' public disclosures. The Securities and Exchange Commission (SEC) requires U.S. listed firms to make mandatory supply chain disclosures. Specifically, if 10% or more of a firm's revenue is derived from sales to any single customer, the firm is obliged to publicly disclose the customer and the revenue.[25] However, firms also voluntarily disclose non-major customers that account for less than 10% of their revenue in their financial reports. As prior studies (e.g., Atalay et al., 2011; Houston et al., 2016) suggest, we use the Compustat Segment database, which contains the supply chain relationships disclosed in the 10-Ks (annual reports) filed by firms, and captures on average 1,000 supply-chain links annually. In contrast, the Factset Revere database compiles data from a variety of public sources, including annual and quarterly filings (10-K, 8-K, and 10-Q), investor presentations, company websites, and press releases. Thus, Factset Revere provides much broader coverage than the other databases, including Compustat Segment, in terms of the number of firms, countries of origin, and industries. Factset Revere actively

[25] The requirement is ruled under the SEC's Statement of Financial Accounting Standards No. 14. For details, see https://www.fasb.org/summary/stsum14.shtml

monitors 10,000 globally listed firms and captures up to 25,000 buyer-supplier relationships per year.[26]

We acknowledge that the Factset Revere database is probably not complete, as it is built on public disclosures and naturally focused on large public firms. Small customers from which firms derive less than 10% of their revenue may not be included in the firm disclosures and thus may not appear in the database. A potential selection issue may also arise from firms' voluntary disclosures of their suppliers. To make full use of the firm-to-firm relationships in the database, we use a "two-way" matching process to construct the production networks. We first retrieve the relationships identified as customers or suppliers in the database. Specifically, a supplier firm may disclose its customers, whereas a customer firm may also disclose its suppliers. We use both types of information to construct the production networks. Namely, the links in the networks can be either from the supplier side or the customer side. For the links identified on both sides, we only keep one, which enables us to construct production networks with all of the useful information at hand.

The relationships in the database are characterized by the starting date and ending date. We restrict the relationships to those in the three years before the outbreak of the trade war to identify the potential on-going upstream and downstream links.[27] We also exclude relationships with either a partner that is not among our sample firms (unlisted firms, foreign firms, or financial firms), resulting in a directed production network with 5,552 links.

We construct four measures of the *indirect* exposure to trade with China, using firm-level production networks and the trade data. We follow Acemoglu et al. (2016a) in constructing the measures, who analyze how shocks are amplified and propagated through industry input-output links. Figures 3 and 4 illustrate the rationale of the variable constructions.

[Figure 3 about Here]

The first measure is the average exposure to revenue from China across the downstream firms (buyers) in the U.S.:

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

[27] Our analysis is based on Factset Revere data accessed in August 2018. As the supply-chain relationships are derived from firms' public disclosures, the 2017 fiscal year financial reports are not completely available to investors. To maintain consistency with our baseline results, we use the supply-chain information up to 2016. The past three-years are therefore 2014, 2015, and 2016.

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

where M indexes the number of customers of firm i, and $Revenue\_China_{i,m}$ measures the 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 U.S. has three U.S. customers, among which B and C have Chinese firms as their customers. Thus, retaliation from China would reduce the sales to firms B and C, and thus reduce the demand for inputs from firm A. We plot the customer network of General Electric (GE) in Panel C. As the overall network is large, we only consider the first two customer layers, namely, the direct customers of GE and the customers of GE's customers, which are shown as nodes in the graph. The links represent business relationships. The size of a node represents the number of supply chain links of a given firm. The green nodes indicate firms that have revenue from China and the white nodes indicate firms having zero revenue from China.

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

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

where $Input\_China_{i,n}$ is an indicator equal to one if customer *m* has outsourced inputs from China, and zero otherwise.[28] As illustrated in Panel B of Figure 3, U.S. firm A has three U.S. customers, among which firms B and C have Chinese firms as their suppliers. The tariff hikes increase the cost of the 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 the intermediate goods produced by Chinese firms E and F can be sufficiently substituted by goods produced by U.S. firm A, then the tariff hike may also increase the demand for the goods produced by firm A and boost its sales. The same product network of GE is plotted in Panel D of Figure 3, where the blue nodes indicate GE customers that have outsourced input from China.

The third measure is the average exposure to revenue from China across the upstream firms (sellers) in the U.S.:

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

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

where N indexes the number of suppliers firm i has. Panel A of Figure 4 shows that firm A located in the U.S. has three U.S. suppliers, among which B and C have Chinese firms as customers. Retaliation from China would reduce the sales to Chinese firms for firms B and C, and the potential production downsizing of B and C and the accompanying adverse performance shocks could be transmitted to firm A. For illustration, Panel C shows the two-layer supplier network of Boeing, with the 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 to inputs from China across the upstream firms (sellers) in the U.S.:

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

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. U.S. firm A has three U.S. suppliers, among which firms B and C have Chinese firms as their suppliers. The tariff hikes increase the cost of the Chinese inputs for B and C, leading to higher prices for their products, and thereby increasing the production costs of firm A. Thus, firm A could suffer from the pass-through effect of the elevated costs from the tariff hikes and experience a negative stock market performance. In Panel D we plot the two-layer supplier network of Boeing, as in Panel C of Figure 4. The blue nodes indicate firms that make purchases from China and the white nodes indicate firms without inputs from China.

[Figure 4 about Here]

It is worth noting that not all firms necessarily have a public customer or a public supplier. For either case, we assign the value of zero to the indirect measures defined above. 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 outsource inputs from China, and around 20% of a firm's suppliers purchase from China. Some additional statistics are provided in Appendix 8. Panel A shows the distribution of the numbers of customers and suppliers on the production network. Consistent with the literature (e.g., Atalay et al., 2011), both distributions are highly positively skewed. The firms with largest numbers of customers in our sample are Microsoft, General Electric, IBM, Apple, and Oracle, whereas General Electric, Walmart, Boeing, Microsoft, and Amazon.com are the sample firms with the largest numbers of suppliers. Panel B presents the descriptive statistics of the indirect measure in the two 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 ascribing zero for firms without listed customers or listed suppliers. For instance, the average revenue from China among the listed customers is about 3.4%, and about 42% of customers have purchased from China.

We next estimate the effects of the indirect exposure, together with the direct exposure measures included in the baseline regression. Table 8 shows the impact originating from a firm's customers. The univariate analysis in Panel A indicates that compared with the rest of the sample firms, firms with customers that have non-zero revenue from China experience 1% negative stock returns as measured by *CRR/CAR*. Firms with suppliers that derive revenue from Chinese customers experience 1.1% lower stock returns. The regression results reported in Panel B suggest that when direct exposure to exports to China is included in the regression the effects of the average revenue from China across a firm's customers and suppliers are both statistically and economically significant. Specifically, column 1 shows that a 10% increase in the indirect sales exposure to customers is associated with 1.1% lower *CAR* over the three days around March 22. Column 2 shows that a 10% increase in the indirect sales exposure to suppliers is associated with 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 overall indirect exposure to sales in China has a larger impact than that of direct exposure.

We can thus quantify the aggregate impact through the direct and indirect measures based on the coefficients in column 3 of Panel B. Over the three-day event window, the direct exposure to revenue from China generates a 0.33% decline, whereas the indirect sales exposure originating from customers leads to 0.18% negative returns and the indirect sales exposure originated from suppliers contributes an additional 0.34% of losses. The regression results imply that *Revenue_China* is responsible for a loss of US$69.5 billion in market value, with

US$37.9 of the losses being attributable to *Revenue_China_Customer* and US$71.7 to *Revenue_China_Supplier*.[29]

[Table 8 about Here]

Table 9 presents the estimated impact of the indirect exposure to inputs from China. The univariate analysis in Panel A shows significant differences in stock performance between firms with positive indirect exposure vs. firms with zero indirect exposure. Specifically, firms with customers that purchase inputs from China experience 0.9% lower three-day stock returns than firms without customers that purchase inputs from China. Similar differences can be observed between firms with suppliers that purchase goods from China and those that do not. Panel B confirms that the regressions generate consistent patterns, except when the industry fixed effect is included the effect of the average input from China across customers becomes weak. It can be inferred that a 0.4% decline in stock returns over the three-day window is attributable to the direct exposure, *Input_China*. By comparison, *Input_China_Customer* and *Input_China_Supplier* contribute to 0.2% and 0.23% of the total percentage loss, respectively. In dollar value, *Input_China*, *Input_China_Customer*, and *Input_China_Supplier* cause losses of US$88.4 billion, US$44.2 billion, and US$50.8 billion, respectively.

[Table 9 about Here]

In sum, the results given in Tables 8 and 9 show that the structure of a firm's supply chain affects the firm's perception of the effects of tariff hikes regardless of whether the firm has any direct exposure to trade with China. Moreover, the indirect effect is found to lead to perceived decreases in the demand from downstream firms and increases in the costs of the inputs from upstream firms.

5.7 Product Lists

Thus far, we have established the relationship between stock returns and exposure across firms. We have intuitively assumed that firms that derive a large proportion of their revenue from China or purchase inputs from China are more exposed to the trade war. Given the detailed product list of tariffs, we can conduct an event study at a more disaggregated level

[29] The values are inferred by multiplying the above calculated returns by the total market value of the sample firms (US$21.08 trillion).

and examine whether the heterogeneous effects of the trade war (announcement) across firms based on firms' output and input product mixes. Our identification hinges on the assumption that investors were uncertain about the products that would be subject to tariff increases in both countries when the U.S. government issued the presidential memorandum. It is also legitimate to assume that the U.S. government would be more likely to impose tariffs on the product categories of the prevalent Chinese imports in the U.S., and *vice versa*.

Next, we use the detailed product lists for the tariff hikes issued by both countries to evaluate the product-level effects of the adverse shocks. By the end of 2018, the U.S. government had issued three product lists and the Chinese government had issued three retaliatory product lists. Specifically, the U.S. government issued product lists on April 3 ($50 billion of Chinese goods), June 15 ($50 billion), and July 10 ($200 billion). In response, China hit back by issuing product lists on March 23 (128 products), April 4 ($50 billion of U.S. goods), and August 3 ($60 billion).[30] Each product list covers additional products compared to the previous lists. As a confirmatory exercise to support our baseline results, we only focus on the responses of U.S. firms to the first U.S. list and the first Chinese list.

The Chinese government issued its first product list on March 23, the day after the presidential memorandum was released on March 22. The list covers 128 products, disaggregated at the harmonized system (HS) eight-digit level, with a total value of about $3 billion. Announced by China's Customs Tariff Commission, the list includes 25% tariffs pork products and aluminum scrap, and 10% tariffs on other imported U.S. commodities, such as wine, nuts, fruits, and steel piping. According to the Chinese government, the new tariffs were imposed in direct retaliation against the tariffs on imported steel and aluminum approved by

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

the Trump administration. We present the products by their export value to China aggregated at the four-digit HS level in Panel A of Appendix 10. The product with the largest exports to China is aluminum scrap. The retaliatory list provides 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 manufactured by firms. In Compustat and most of the major firm data sets, firms typically report their main industry only. Thus, following the literature (e.g., Hoberg and Phillips, 2016), we conduct a textual analysis of U.S. firms' product descriptions disclosed in their filings with the regulator (i.e., the SEC). Specifically, we create a list of unique keywords for internationally traded products based on the list of HS codes from the World Bank. The product descriptions for each firm are retrieved from their 10-K files and are further cleaned to generate a unique list of products manufactured by individual firms. We then combine these two lists with the products included in the Chinese tariff list to construct a variable, *Output_China_List*, which measures the percentage of a U.S. firm's products mentioned in the Chinese list. The details of the construction are provided in Appendix 9.

Panel A of Table 10 reports the estimation results on the heterogeneous responses based on the output mix of U.S. firms. Independent of whether we include the four firm characteristics as controls (column 2) or industry fixed effects (column 3), we find a systematically negative and statistically significant coefficient on *Output_China_List*, suggesting that firms that have proportionally more of their products tariffed by China, and are thus more exposed to the trade war, respond more negatively in the financial markets 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 22 and March 24.

[Table 10 about Here]

The U.S. government issued its first product list on April 3, 2018. Following the release of the March 22 presidential memorandum, the U.S. trade representative published a provisional list of imports that would be subject to new duties in retaliation to "the forced transfer of American technology and intellectual property." The list covers about 1,300 Chinese products (at the HS eight-digit level), accounting for approximately $50 billion of U.S. imports from China. The products, which include raw materials, construction machinery, aerospace and agricultural equipment, electronics, medical devices, and consumer products, were chosen based on the target sectors mentioned in the “Made in China 2025” plan. We show the products with the largest inputs from China in Panel B of Appendix 10. We aggregate the imports at the four-digit HS level, and show that automatic data processing machines and machinery accessories are among the products that the U.S. imports the most from China.

We define the variable, *Input_China_List*, as the percentage of products purchased from China that are in the corresponding product list according to the bill of lading database matched based on the HS codes.[31] The results based on the first U.S. list are reported in Panel B of Table 10. We find systematically that U.S. firms with more inputs covered by the U.S. list experience larger stock price declines around April 3. Specifically, a one standard deviation higher *Input_China_List* is associated with an additional 0.14% to 0.16% decline in stock prices between April 2 and April 4.

We further use 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 tariffs are imposed and the pre-event tariff rate. We first calculate the difference between the new import tariffs included in the list and the import tariffs before the event at the HS level. We then use the bill of lading database to identify firms’ specific imports from China at the HS level. *Tariff_Change* is defined as the value-weighted average import tariff increases using the transaction quantity as the weight because we do not have the information on the transaction value for each firm. The findings in Panel C of Table 10 suggest that a 10-percentage point increase in the tariff rate leads to a 1% to 1.5% reduction in price.

The evidence based on the variation in the exposure to the tariffs outlined in the product lists suggests that the firms’ responses to the trade shocks are consistent with our theoretical predictions. Specifically, the market participants refine and adjust their valuations of the firms when the uncertainty about the coverage and magnitude of the new tariffs is partially resolved.

5.8 Reverse Experiments

[31] The bill of lading database provides six-digit HS codes. Because firms may mis-categorize across the finely defined codes in their customs records, we match the lading database with the product list using the four-digit HS codes. The results remain similar but noisier when we use the six-digit HS codes in the matching process.

We have provided evidence showing that the heterogeneous effects of the trade war are not transitory but last for several months. Several unanticipated events in 2018 and 2019 offered positive news that the trade war may have been 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, U.S. and Chinese officials concluded a three-day trade talk in Beijing. The Commerce Ministry of China issued an extensive statement at the end of the trade talk with the U.S. to provide a foundation for resolving each other's concerns. Trump even tweeted that the "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 the discussions had made progress.

Figure 5 plots the trajectory of searches on "trade talks." The public interest in "trade talks" can be seen to peak on January 9, 2019 as indicated by the search engines from both countries. We evaluate the firms' stock price responses around this event, which are expected to reverse the adverse effects of the trade war.

[Figure 5 about Here]

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

[Table 11 about Here]

Despite this apparent progress, the trade war continued. On May 5, 2019, Trump posted an unexpected tweet announcing the tariffs would be increased from 10% to 25% on $200 billion of Chinese imports, and threatened to unleash 25% tariffs on additional Chinese goods. As a result, the equity markets tumbled and the VIX Index skyrocketed. This abrupt event provides another reverse experiment with which to validate our main findings. As shown in Panel A of Table 12, U.S. firms that gain revenue from China experience significantly negative raw returns of -0.5% relative to other firms. The U.S. firms that acquire inputs from China have 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 6 by plotting the means and 95% confidence intervals for the three-day cumulative raw returns around the three events. We divide the 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 to the high group, middle group, and low group, while firms without revenue from China fall into another group. A similar process is used to categorize the firms' exposure to inputs from China. Panels A and B show the impact of our main event. The results in the first reverse experiment are presented in Panels C and D. The last two panels present the findings of the second reverse experiment. We observe a strong pattern showing that firms with a stronger trade relationship with China suffer additional losses. Although the trade talks in January 2019 had an offsetting effect, Trump's threat on Twitter in May further intensified the concerns over the trade war.

6. Conclusion

In this paper, we examine the effects on the financial markets 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 the tariff increases across listed firms in both countries. The responses vary according to the degree of the firms' direct and indirect exposure to U.S.-China trade. We find that U.S. firms that are more dependent on exports to and imports from China have lower stock prices and higher default risks in the short window around the time of the "trade war" announcement. Similar patterns are also observed for Chinese listed firms with respect to their trade relationships with the U.S.

The results are robust to adjustments to different asset pricing models, alternative model specifications, longer event windows, and a matching strategy.

We document that the expectation of weakened Chinese import competition due to the U.S. tariffs plays a statistically significant but economically minimal role. However, firms' indirect exposure to U.S.-China trade through domestic supply chains is associated with negative stock return responses that are comparable in magnitude to those associated with direct exposure. These responses indicate that the complex structure of global trade plays a crucial role in the financial markets. Our findings show that the winners and losers in the bilateral U.S.-China trade relationship are determined by their position (upstream or downstream) and the extent of their 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 U.S. 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 U.S. with the essential financial data from Compustat and stock price data from Bloomberg. Financial firms are excluded. All of the variable definitions are in Appendix 3. 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 results of the univariate analysis. *CRR [-1,+1]* is the three-day cumulative raw returns 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 U.S. intellectual property. *CAR [-1,+1]* is the three-day cumulative abnormal returns 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 Appendix 3. 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 the trade war announcement on the value of U.S. firms according to their revenue and purchases from China. The dependent variable, *CRR [-1,+1]*, is the three-day cumulative raw returns around March 22, 2018. *CAR [-1,+1]* is the three-day cumulative abnormal returns around the event date estimated using the standard one-factor market model. Panel A shows the effect according to the firms' revenue from China. *Revenue_China* is the revenue from China scaled by total revenue. Panel B shows the effect according to the firms' inputs from China. *Input_China* is an indicator set to one if a 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 the other variables are in Appendix 3. Industry fixed effects are based on the Fama-French 30-industry definitions. The *t*-statistics based on robust errors are reported in the parentheses. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Robustness Checks

Panel A. Alternative Variable Definitions: Fama-French Three-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 for 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 three-day cumulative abnormal returns adjusted by the Fama-French three-factor model. Panel B reports the results for the joint estimation. The definitions of the variables are in Appendix 3. The *t*-statistics based on robust errors are reported in the parentheses. 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 the 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 default probabilities based on the Merton model. The data are from Bloomberg. *Revenue_China* is the revenue from China scaled by total revenue. *Input_China* is an indicator set to one if a 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 the other variables are in Appendix 3. The *t*-statistics based on robust errors are reported in the parentheses. 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 (Continued)

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 effect of the declaration 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 are from the CSMAR database. *Revenue_US* is the value of exports to the U.S. in 2016 scaled by the total revenue in 2016. *Input_US* is an indicator set to one if a firm imports goods from the U.S. as indicated by the China customs database in 2016. *CRR [-1,+1]* is the cumulative raw returns around the event date March 22 (March 23 for the Chinese market). *CRR [-1,+1]* is the three-day cumulative abnormal returns adjusted by the standard market model. The firm-level controls include firm size, market-to-book ratio, leverage, and ROA. The variables definitions are in Appendix 3. Industry fixed effects are based on the definitions of the CSRC. The *t*-statistics based on robust errors are reported in the parentheses. 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 exposure. *IP* is the NAICS-level import penetration defined as total imports from China (2017) divided by the 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 are reported in the parentheses. 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 the revenue a firm gains from China. *Revenue_China_Customer* is the simple average revenue from China across a firm's customers. *Revenue_China_Supplier* is the simple average revenue from China across a firm's suppliers. The firm production network is based on all of the supply chain relationships in the three years before the trade war announcement from the Revere database. Panel A shows the univariate analysis results. The regression results are presented in Panel B. The controls include firm size, market-to-book ratio, leverage, and ROA. The variable definitions are in Appendix 3. The *t*-statistics based on robust errors are reported in the parentheses. 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 the inputs a firm acquires from China. *Input_China_Customer* is the simple average input from China across a firm's customers. *Input_China_Supplier* is the simple average input from China across a firm's suppliers. The firm production network is based on all of the supply chain relationships in the three years before the trade war from the Revere database. Panel A shows the univariate analysis results. The regression results are presented in Panel B. The controls include firm size, market-to-book ratio, leverage, and ROA. The variable definitions are in Appendix 3. The *t*-statistics based on robust errors are reported in the parentheses. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 10. Firms' Heterogeneous Responses to the Product Lists

Panel A. Firms' Responses to the Chinese List issued 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 the U.S. Product List issued 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 the U.S. Product List issued 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 U.S. firms' responses to the product lists announced by the U.S. and China. We consider two product lists, the first Chinese product list released on March 23, 2018, and the first U.S. product list released on April 3. Panel A presents the firms' responses to the Chinese product list. The dependent variables are the three-day cumulative abnormal returns centered on the corresponding event date based on the market model. *Output_China_List* is the percentage of a firm's products mentioned in the China list. The products are identified using textual analysis, which is further explained in Appendix 9. The variable is a proxy for U.S. firms' exposure to the Chinese product list in terms of revenue losses. Panel B presents firms' responses to the first product list announced by the U.S. 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 U.S. product list released on April 3. *Tariff_Change* is the measure of firm's exposure to the imports tariff hikes. We first calculate the difference between the new import tariffs imposed by the list and the import tariffs before the event. We then use the bill of lading database to identify a firm's specific imports from China at the HS level. We construct the value-weighted average import tariff hikes using the transaction quantity as the weight because we do not have the information on the 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. The variable definitions are in Appendix 3. The t-statistics based on robust errors are reported in the parentheses. 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 U.S. firms' responses to the U.S.-China trade talks held in Beijing from January 7-9, 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 three-day cumulative raw returns centered on January 9, 2019. *CAR [-1,+1], Jan 9* is the three-day cumulative abnormal returns based on the market model. Panel A presents the univariate analysis results. Panel B presents the regression results. *Revenue_China* is the revenue from China 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 the other variables are in Appendix 3. The t-statistics based on robust errors are reported in the parentheses. 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

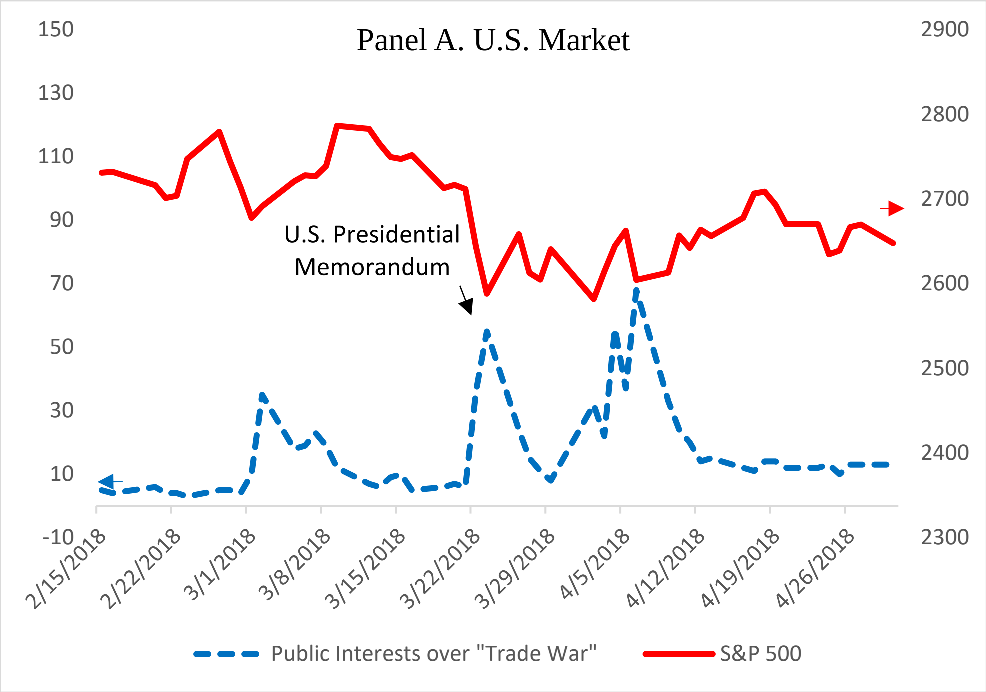
Revenue from China	**Revenue_China**				
	>median (0)		<median (0)		
	N	Mean	N	Mean	Diff.
CRR[-1,+1], May 6	844	-0.001	1221	0.005	-0.005***
CAR[-1,+1], May 6	844	-0.002	1221	0.004	-0.006**
Input from China	**Input_China**				
	=1		=0		
	N	Mean	N	Mean	Diff.
CRR[-1,+1], May 6	329	-0.003	1736	0.004	-0.007**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

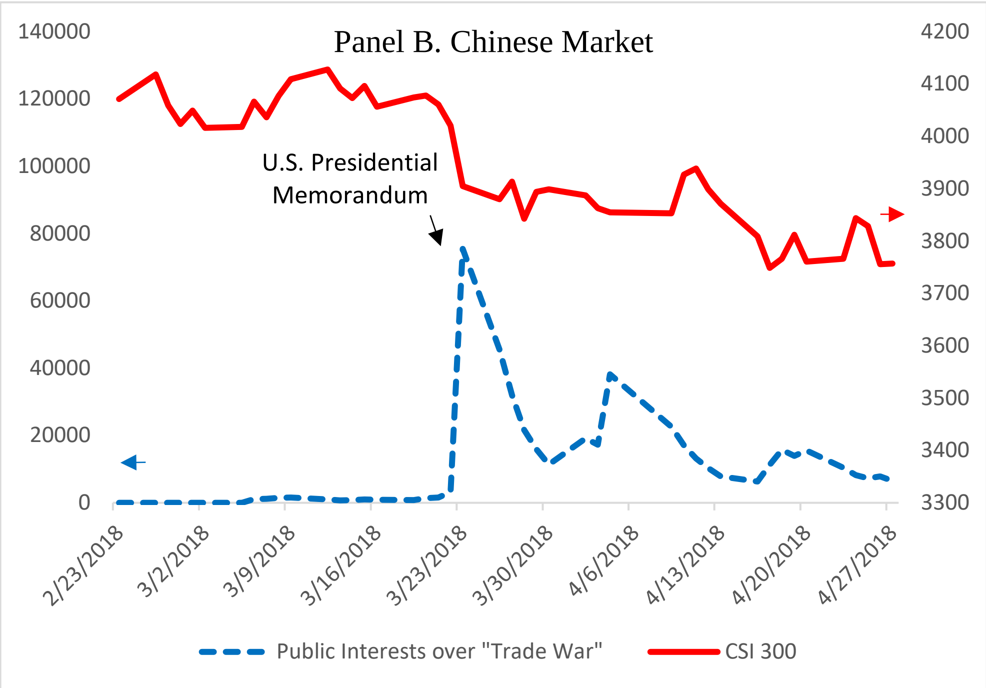
Panel B. Regression Estimation

	(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 U.S. firms' responses to the tweets posted by President Trump on May 5, 2019. President Trump threatened to increase the tariffs on $200 billion of Chinese goods from 10% to 25%. The dependent variable is the three-day cumulative raw returns or abnormal returns centered 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 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 the other variables are in Appendix 3. The *t*-statistics based on robust errors are reported in the parentheses. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

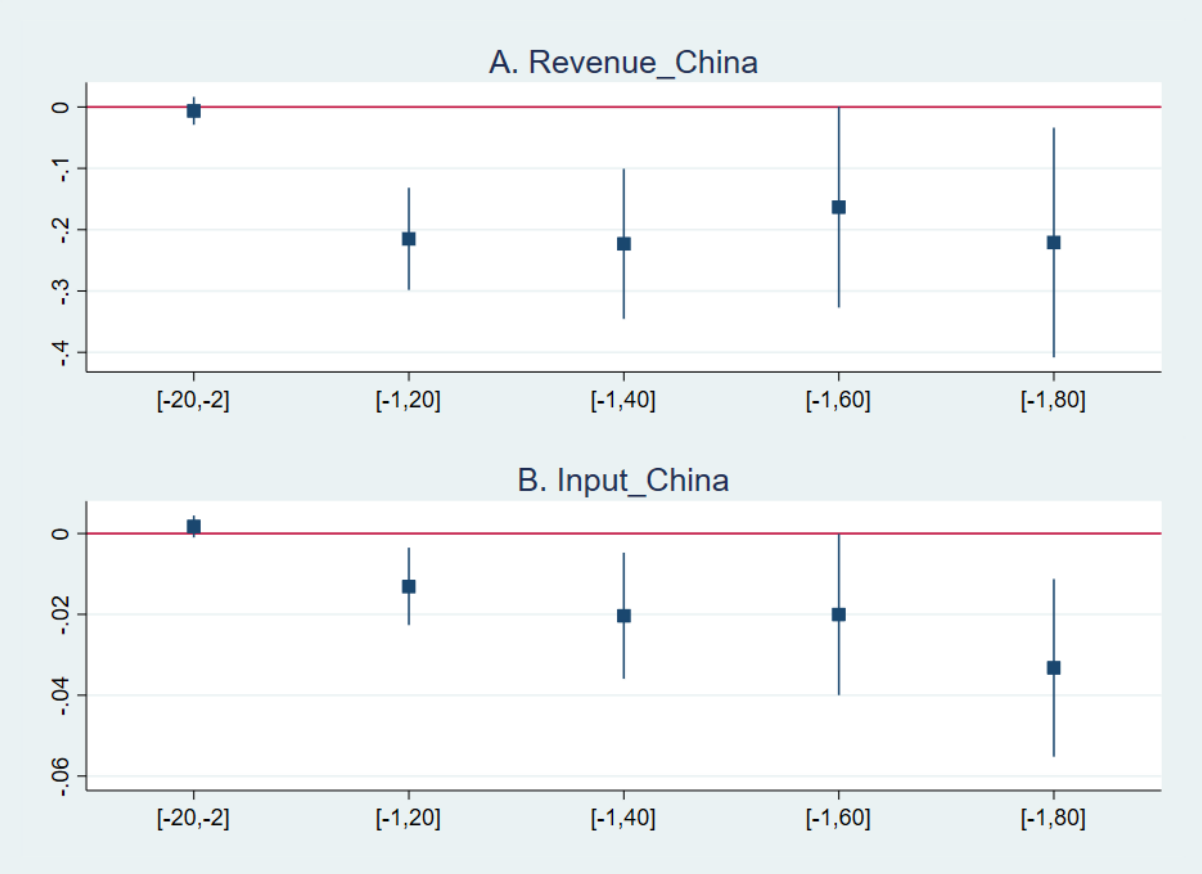
Figure 1. Public Interest in the Trade War and Stock Returns





Notes: This figure presents the time-series of the market index against the public interest in the U.S.-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 in the 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 in the trade war as measured by the Baidu Index (left scale).

Figure 2. Medium-term Effects



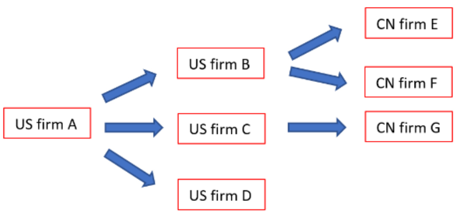
Notes: This figure shows the medium-term effect of the declaration of the trade war on firm value. We first run the following regression:

$$\mathrm{Y}_i = \beta \ \mathrm{Exposure}_i + \mathrm{X}_i + \varepsilon_i,$$

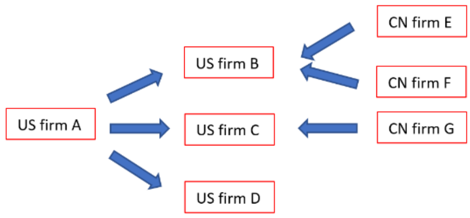
where Y_i denotes the buy-and-hold abnormal returns (*BHAR*) over different event windows. Specifically, *BHAR [-1,+X]* is the buy-and-hold abnormal returns around the event window *[-1,+X]* with zero indicating March 22, 2018 adjusted by the market benchmark. $\mathrm{Exposure}_i$ is a firm's exposure 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 magnitude of the estimated β. The bars represent the 95% confidence intervals. The detailed regression results are provided in Appendix 7.

Figure 3. Firm Production Networks: Customer Side

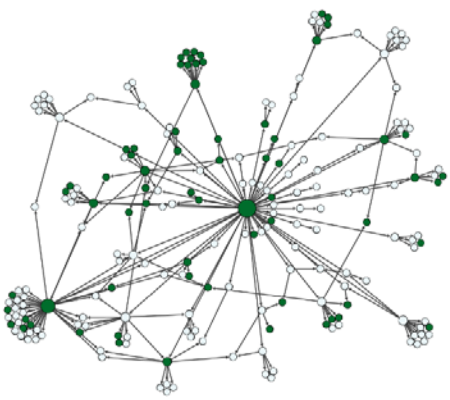
Panel A. Revenue from China



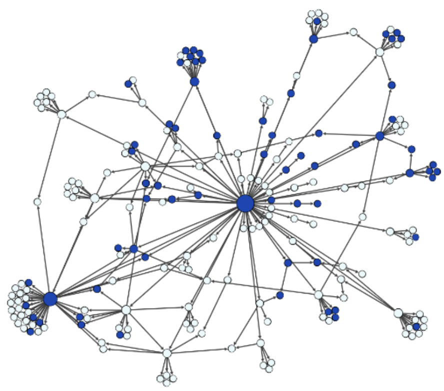
Panel B. Input from China



Panel C. GE's Customers: Revenue from Chi



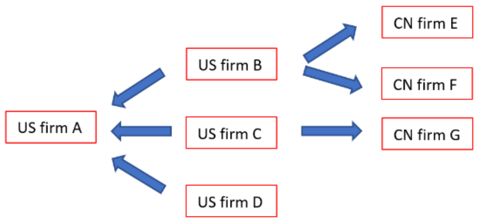
Panel D. GE's Customers: Input from China



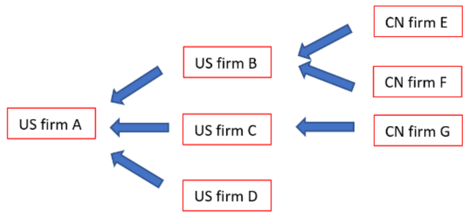
Notes: This figure illustrates the firm production networks from the customers' perspectives. In Panels A and B, the direction of the arrows indicates the trade flow. Specifically, in Panel A, the U.S. firm B purchases from firm A and Chinese firm E purchases from U.S. firm B. Similarly, in Panel B, U.S. firm B purchases from U.S. firm A and 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 firms with zero revenue from China. The direction of the link also shows the trade flow. Panel D shows the same network of customers of General Electric. Here, the blue nodes indicate firms with input from China and white nodes indicate firms without input from China.

Figure 4. Firm Production Networks: Supplier Side

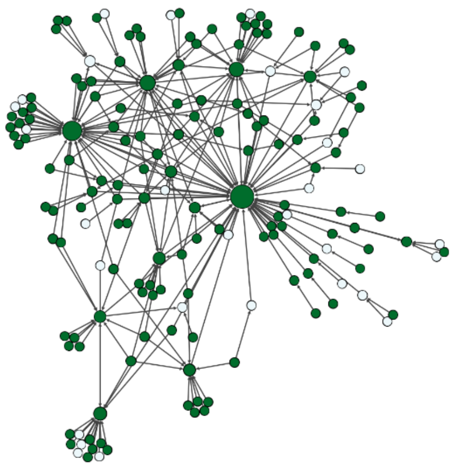
Panel A. Revenue from China



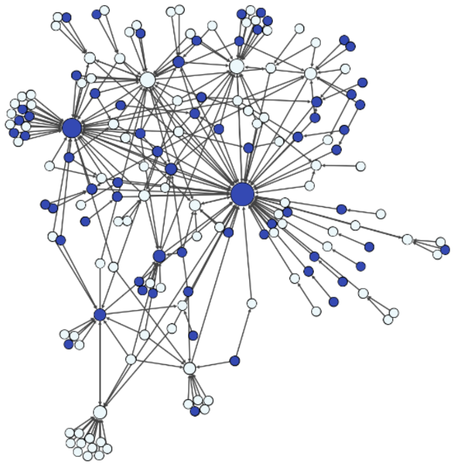
Panel B. Input from China



Panel C. Boeing's Suppliers: Revenue from China

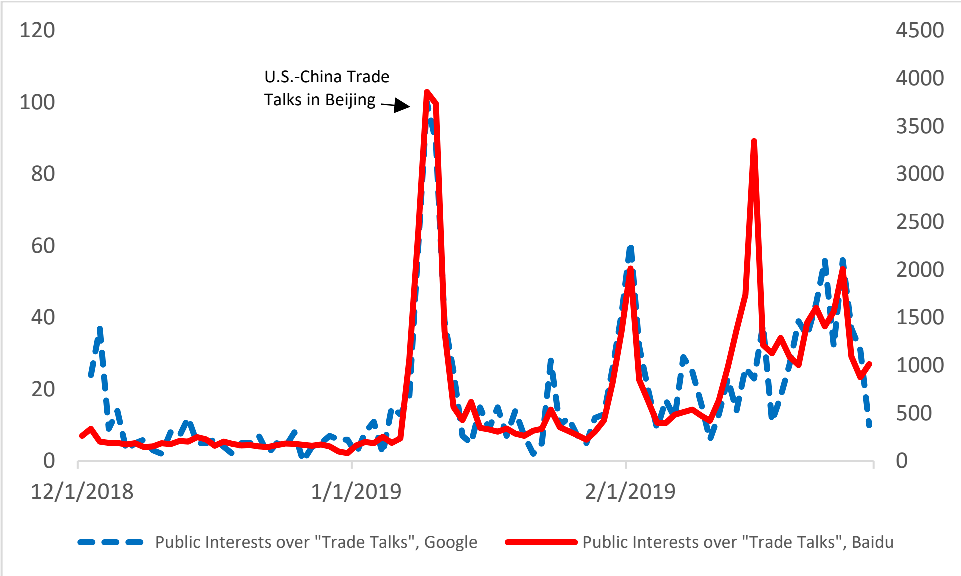


Panel D. Boeing's Suppliers: Input from China



Notes: This figure illustrates the firm production networks from the suppliers' perspectives. In Panels A and B, the direction of the arrows indicates the trade flows. Specifically, in Panel A, the U.S. firm B sells products to U.S. firm A and Chinese firms E and F. Similarly, in Panel B, U.S. firm A purchases from U.S. firm B that purchases 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 firms 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. Here, the blue nodes indicate firms with input from China and white nodes indicate firms without input from China.

Figure 5. Public Interest in the U.S.-China Trade Talks



Notes: This figure presents the time-series of the public interest in "U.S.-China trade talks." The blue dashed line denotes the public interest in "trade talks" as measured by Google Trends (left scale). The red solid line indicates the public interest in the trade war as measured by the 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 the tariffs on $200 billion of Chinese goods from 10% to 25%. We plot the means and 95% confidence intervals for the three-day cumulative returns for firms across different groups. Panels A and B present the first event. Panels C and D present the second event. The results for the third event are reported in Panels E and F. In Panels A, C, and E, we sort the firms by their revenue from China. We further categorize the firms into terciles if they have revenue from China. In Panels B, D, and F, we sort the firms by their input from China.

Appendix 1. Theoretical Appendix - A Simple Model

This section presents a simple model to highlight how firms' direct (through direct imports and exports) and indirect exposure (through *domestic* suppliers and buyers) to trade policy shocks affect their profits and hence cash flows. Our model is built on the general-equilibrium production network model of Tintelnot et al. (2019). However, we will abstract from the recursive feature of the global value chains, focusing on both the partial- and general-equilibrium insights from the model to guide our reduced-form empirical analysis.[32]

1.1 Preferences

There are two countries -- Home (denoted by H) and Foreign (denoted by F). At Home, a representative consumer supplies inelastically one unit of labor. Consumers have identical CES preferences over consumption goods:

$$U_H = \left(\sum_{i\in\Omega_H}(a_{iH}q_{iH})^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}},$$

where Ω_H is the set of varieties available to Home consumers for consumption. a_{iH} is the variety-specific demand shifter; σ is the elasticity of substitution between varieties. We assume that consumption varieties are substitutes (i.e., $\sigma > 1$).

Given the same CES utility function for all consumers at Home, the aggregate demand for variety i, given price p_{iH}, is

$$q_{iH} = \frac{a_{iH}(p_{iH})^{-\sigma}E_H}{P_H^{1-\sigma}},$$

where E_H stands for the aggregate expenditure by Home consumers, and P_H is consumer price index at Home, which equals

$$P_H = \left(\sum_{i\in\Omega_H} a_{iH}^{\sigma-1}p_{iH}^{1-\sigma}\right)^{\frac{1}{1-\sigma}},$$

Similarly, given symmetric CES utility function abroad, Foreign consumer demand for variety i, given its price in Foreign, p_{iF}, can be expressed as

[32] Readers who are interested in the general-equilibrium trade model with input-output linkages are referred to Long and Plosser (1983), Jones (2013), Caliendo and Parro (2015), and Acemoglu et al. (2016). The model here is designed to determine the signs and magnitudes of the direct and indirect impacts.

$$q_{iF} = \frac{a_{iF}(p_{iF})^{-\sigma}E_F}{P_F^{1-\sigma}},$$

where E_F and P_F stand for the aggregate expenditure and consumer price index of Foreign, respectively. a_{iF} is the demand shifter for product i exported from Home.

The price firm *i* charged a Foreign consumer is $p_{iF} = \tau_F p_{iH}$, where $\tau_F \geq 1$ represents the trade cost, including any potential tariff. $\tau_F = 1$ when there is free trade. For simplicity, we assume the same τ_F for all products imported from Home. Relaxing this assumption by making τ_F product-specific is trivial but give us little additional insight.

1.2 Production

Consider firm i producing goods with labor and intermediate inputs, which are supplied by potentially any firms located at Home and Foreign. Production function takes the Cobb-Douglas form as

$$q_i = \Lambda_i z_i \left(m_{iF}^{\lambda_{iF}} \prod_{j\in\Omega_i} m_{ij}^{\lambda_{ij}}\right)^{1-\eta} (l_i)^\eta,$$

where q_i is firm i's output; z_i is its Hicks-neutral productivity; Ω_i is the set of domestic suppliers from which firm i purchases inputs; m_{ij} and m_{iF} are quantities of material purchased from domestic supplier j and the representative foreign supplier, respectively; Λ_i is a constant equal to $\eta^{-\eta}\left(\lambda_{iF}^{\lambda_{iF}} \prod_{j\in\Omega_i} \lambda_{ij}^{\lambda_{ij}}\right)^{-(1-\eta)}$.

The parameter λ_{ij} is the cost share of inputs produced by domestic firm j in firm i's total cost of production, while λ_{iF} is the cost share of foreign inputs in firm i's total cost of production.[33] When firm i is not using inputs from firm j, $\lambda_{ij} = 0$. If it does not use any imported inputs, $\lambda_{iF} = 0$. We assume constant returns to scale, so $\sum_{j=1}^{N_H} \lambda_{ij} + \lambda_{iF} = 1$. Hence, given the Cobb-Douglas production function and cost minimization, $m_{ij} = \frac{\lambda_{ij} c_i q_i}{p_{ij}}$, where p_{ij} is the price firm *i* pays for inputs from firm *j*, while c_i is firm *i*'s marginal cost of production as

[33] Tintelnot et al. (2019) assumes a CES production function instead and allows the cost share of inputs from different supplies to be functions of input prices. We could have done here but since our goal is just to highlight the magnitudes of the cost shocks, we will abstract from a more general set-up here.

$$c_i(z_i) = \frac{\chi_i}{z_i},$$

where $\chi_i \equiv \left(p_{iF}^{\lambda_{iF}} \prod_{j \in \Omega_i} p_{ij}^{\lambda_{ij}}\right)^{1-\eta} w^{\eta}$, in which p_{iF} is the price of imported inputs firm i pays, while w is the equilibrium wage rate, determined by the labor market clearing condition:

$$\sum_{j=1}^{N_H} L_j = L_H,$$

where N_H is the number of active firms at Home.

1.3 Market and Network Structure

Each firm produces a single product, which can be sold as final goods to domestic and foreign consumers, and as inputs to domestic (but not foreign) producers. The assumption that Home's producers do not export goods as inputs to foreign producers is for simplicity and due to the incomplete information about firms' production network in our data. The market clearing condition for firm i's quantities is

$$q_i = q_{iH} + q_{iF} + \sum_{j \in \Phi_i} m_{ji},$$

where Φ_i is the set of all domestic firms purchasing inputs from firm i.

Final-good varieties are differentiated across firms. We assume that each firm is infinitesimally small and compete in monopolistically competitive markets. Thus, each firm is able to generate profits from selling to consumers by charging a constant markup $\frac{\sigma}{\sigma-1}$ over marginal cost, c_i.

When selling to domestic producers, we cannot assume each supplier to be infinitesimally small (from the perspective of the buyers), as in the data, most firms only have a few suppliers. We thus assume Nash bargaining between buyers and sellers in the supply chain. We can assume that the buyers have all bargaining power so that the supplier can only charge prices at marginal costs (Tintelnot et al., 2019). Here, because we will show empirically that reduced sales of domestic producers and suppliers will also affect linked firms' cash flows and thus stock prices, we assume that input suppliers command some bargaining power in Nash bargaining over downstream buyers. In particular, we assume that the matched seller and buyer split the revenue from the input sales, with $\theta < 1$ being the share of the revenue recouped by the seller. That is, firm j will get

$$\theta p_{ij} m_{ij} = \theta \lambda_{ij} c_i q_i = \frac{\theta(\sigma-1)\lambda_{ij} r_i}{\sigma}$$

1.4 Firm Sales and Profits

Firm i's derive revenue from selling to Home consumers, Foreign consumers, and Home producers, as follows

$$r_i = \underbrace{\frac{a_{iH}\chi_i^{1-\sigma} z_i^{\sigma-1} E_H}{P_H^{1-\sigma}}}_{\text{sales to Home consumers}} + \underbrace{I_{iF}\frac{a_{iF}\chi_i^{1-\sigma} z_i^{\sigma-1} \tau_F^{1-\sigma} E_F}{P_F^{1-\sigma}}}_{\text{sales to Foreign consumers}} + \underbrace{\sum\nolimits_{j\in\Phi_i}\frac{(\sigma-1)\lambda_{ji}}{\sigma} r_j}_{\text{sales to Home producers}} ,$$

where I_{iF} is an indicator function equal to 1 if firm i exports to Foreign, and τ_F is the tariff rate imposed by Foreign on imports from Home.

Given monopolistic competition in the final goods markets and the assumed profit sharing rule in Nash bargaining between the matched buyer and seller, firm i's total profit is

$$\pi_i = \underbrace{\frac{a_{iH}\chi_i^{1-\sigma} z_i^{\sigma-1} E_H}{\sigma P_H^{1-\sigma}}}_{\text{profits from Home consumers}} + \underbrace{I_{iF}\frac{a_{iF}\chi_i^{1-\sigma} z_i^{\sigma-1} \tau_F^{1-\sigma} E_F}{\sigma P_F^{1-\sigma}}}_{\text{profits from Foreign consumers}} + \underbrace{\sum\nolimits_{j\in\Phi_i}\frac{\theta(\sigma-1)\lambda_{ji}}{\sigma} r_j}_{\text{profits from Home producers}}$$

Based on this formula, we obtain the following four testable propositions about the direct (partial) and total effects of Home's tariffs and Foreign's retaliatory tariffs on Home firms' values.

Proposition 1 (the direct impact of Foreign's import tariffs):

Assuming no change in the prices of domestic inputs, imported inputs, and sales of domestic downstream firms, an increase in the foreign partner's import tariffs will lower the value of an exporting firm.

Proof:

We can derive the following partial derivative of firm i's value (π_i) due to a small change in Foreign's tariff on imports, τ_F:

$$\frac{\partial \pi_i}{\partial \tau_F} = (1-\sigma)\frac{a_{iF}\chi_i^{1-\sigma} z_i^{\sigma-1} E_F}{\sigma P_F^{1-\sigma}} \tau_F^{-\sigma} < 0 \ \textit{for exporter;}$$

$$\frac{\partial \pi_i}{\partial \tau_F} = 0 \ \textit{for non-exporters.}$$

We will empirically examine the magnitude of these effects by assessing the coefficient on the firm's exporting dummy or export intensity in the regressions.

Proposition 2 (the direct impact of Home's tariffs on imported inputs):

Assuming no change in the prices of domestic suppliers' inputs, foreign suppliers' inputs, and sales of domestic downstream firms, an increase in import tariffs will lower the value of a firm that uses imported inputs

Proof:

We can derive the following partial derivative of firm i's value (π_i) due to a small change in Home's tariff on imported inputs, τ_H as

$$\frac{\partial \pi_i}{\partial \tau_H} = \left(\frac{1-\sigma}{\sigma}\right) \chi_i^{-\sigma} z_i^{\sigma-1} \frac{\partial \chi_i}{\partial p_{iF}} \frac{\partial p_{iF}}{\partial \tau_H} \left[\frac{a_{iH} E_H}{P_H^{1-\sigma}} + \frac{a_{iF} \tau_F^{1-\sigma} E_F}{P_F^{1-\sigma}}\right] < 0 \quad \textit{for exporters}$$

$$\frac{\partial \pi_i}{\partial \tau_H} = \left(\frac{1-\sigma}{\sigma}\right) \frac{\partial \chi_i}{\partial p_{iF}} \frac{\partial p_{iF}}{\partial \tau_H} \frac{a_{iH} \chi_i^{-\sigma} z_i^{\sigma-1} E_H}{\sigma P_H^{1-\sigma}} < 0 \quad \textit{for non-exporters}$$

We will empirically examine the magnitude of this effects by assessing the coefficient on the firm's importing dummy.

Proposition 3 (the total impact of Foreign's import tariffs):

In addition to the direct impact (i.e., reduced export revenue) as discussed in Proposition 1, an increase in the foreign partner's import tariffs will lower a firm's value due to various indirect general-equilibrium effects, which arise from (1) higher prices of domestic inputs, (2) higher prices of imported inputs, as well as (3) lower sales to Home downstream firms.

Proof:

By deriving the complete derivative of π_i, we can obtain the total impact of a higher τ_F on a firm's value as

$$\frac{d\pi_i}{d\tau_F} = \left(\frac{1-\sigma}{\sigma}\right) z_i^{\sigma-1} \left[I_{iF} \frac{a_{iF} \chi_i^{1-\sigma} E_F}{P_F^{1-\sigma}} \tau_F^{-\sigma} + \frac{\partial \chi_i}{\partial p_{iF}} \frac{\partial p_{iF}}{\partial \tau_F} \left(I_{iF} \frac{a_{iF} \tau_F^{1-\sigma} \chi_i^{1-\sigma} E_F}{P_F^{1-\sigma}} + \frac{a_{iD} \chi_i^{-\sigma} E_D}{P_D^{1-\sigma}} \right) \right] + \underbrace{\frac{\partial}{\partial \tau_F}\left(\frac{E_F}{P_F^{1-\sigma}}\right) I_{iF} \frac{a_{iF} \chi_i^{1-\sigma} z_i^{\sigma-1} \tau_F^{1-\sigma}}{\sigma}}_{\textit{reduced aggregate Foreign consumers' expenditure}} + \underbrace{\sum_{j \in \Phi_i} \frac{(\sigma-1)\theta \lambda_{ji}}{\sigma} \frac{\partial r_j}{\partial \chi_i} \frac{\partial \chi_i}{\partial p_{iF}} \frac{\partial p_{iF}}{\partial \tau_F}}_{\textit{reduced sales to Home downstream firms}}$$

We will empirically examine the magnitude of this effects by assessing the coefficient on the firm's importing dummy, together with the weighted average of domestic downstream firms' exposure to sales in Foreign (i.e., China).

Proposition 4 (the total impact of Home's tariffs):

In addition to the direct impact (i.e., higher prices of imported inputs) discussed in Proposition 2, an increase in a country's import tariffs will lower a firm's value due to various indirect general-equilibrium effects, which arise from (1) higher prices of domestic inputs; (2) reduced sales to Foreign households; (3) reduced sales to Home households; and (4) reduced sales to Home downstream firms.

Proof:

By deriving the complete derivative of π_i, we can obtain the total impact the increases of τ_H, the direct impact of a small increase in τ_H on firm i's value (π_i) as

$$\frac{d\pi_i}{d\tau_H} = (1-\sigma) \underbrace{\frac{d\chi_i}{d\tau_H}}_{\text{increased inputs costs}} \left[\frac{a_{iH}\chi_i^{-\sigma} z_i^{\sigma-1} E_H}{\sigma P_H^{1-\sigma}} + I_{iF}\frac{a_{iF}\chi_i^{-\sigma} z_i^{\sigma-1}\tau_F^{1-\sigma} E_F}{\sigma P_F^{1-\sigma}}\right]$$
$$+ \underbrace{\frac{\partial}{\partial\tau_H}\left(\frac{E_H}{P_H^{1-\sigma}}\right)\frac{a_{iH}\chi_i^{1-\sigma} z_i^{\sigma-1}}{\sigma}}_{\text{reduced Home consumers' demand}} + \underbrace{I_{iF}\frac{\partial}{\partial\tau_H}\left(\frac{E_F}{P_F^{1-\sigma}}\right)\frac{a_{iF}\chi_i^{1-\sigma} z_i^{\sigma-1}\tau_F^{1-\sigma}}{\sigma}}_{\text{reduced Foreign consumers' demand}}$$
$$+ \underbrace{\sum_{j\in\Phi_i}\frac{(\sigma-1)\lambda_{ji}\theta}{\sigma}\frac{\partial r_j}{\partial\tau_H}}_{\text{reduced sales of Home downstream firms}}$$

Notice that $\frac{d\chi_i}{d\tau_H}$ is a complete rather than partial differentiation. The increase in domestic tariffs will raise the cost of foreign inputs directly purchased by firm i, but also the cost of domestic inputs as upstream suppliers now need to pay higher prices for imported inputs.

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

Appendix 3. Variable Definitions

Variable	Definition
Firm-level Responses	
CRR[-1,+1]	The cumulative raw returns around the event window [-1,+1] with zero indicating March 22, 2018. $CRR_i[-1,+1] = \sum_{t=-1}^{+1} R_{i,t}$, 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 the abnormal return for firm *i* on date *t* adjusted by the 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 three-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 the 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 the implied five-year 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 a firm's 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 U.S. 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 U.S. 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 a firm's products mentioned in China's list identified using textual analysis. The measure proxies for U.S. firms' exposure to the Chinese product list in terms of revenue losses. Details can be found in Appendix 9; Textual Analysis and 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 four-digit HS codes. Bill of lading database and U.S. trade representative
Tariff_Change	Tariff_Change is the measure of a firm's exposure to the import tariff hikes. We first calculate the difference between the new import tariffs imposed by the list and the import tariffs before the event at the HS level; Source: WTO Tariff Database and U.S. trade representative
Industry-level Measures of Exposure	
Naics_IP	The NAICS-level import penetration defined as total imports from China (2017) divided by the 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 total exports to China (in 2017) scaled by the shipment value (in 2016); Source: Peter Schott and 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 4. Dollar Value

Panel A. U.S. 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 the market value in dollars. Panel A is based on a sample of U.S. firms and Panel B is based on Chinese firms. The dependent variable is the change in the market value from day -1 to day +1 relative to the event date, March 22, 2018. The variable is in millions of U.S. dollars in Panel A and millions of RMB in Panel B.

Appendix 5. Robustness Checks: Confounding Events

	(1)	(2)	(3)	(4)
	Pane A. CAR [-1,+1] Excluding military related industries			
Revenue_China	-0.0932***	-0.0470**		
	(-6.14)	(-2.48)		
Input_China			-0.0096***	-0.0058***
			(-5.04)	(-2.84)
N	2292	2275	2292	2275
adj. R-sq	0.049	0.117	0.046	0.118
	Panel B. CAR [-1,+1] Excluding steel and aluminum related industries			
Revenue_China	-0.0964***	-0.0491***		
	(-6.32)	(-2.58)		
Input_China			-0.0093***	-0.0057***
			(-4.92)	(-2.81)
N	2279	2261	2279	2261
adj. R-sq	0.050	0.116	0.045	0.116
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes

Notes: This table shows the robustness checks considering the confounding events. On March 22, 2018, the date when the Trump administration issued the presidential memorandum, Trump announced on Twitter his appointment of the new National Security Advisor, John R. Bolton. In Panel A, we present the results based on the sample excluding industries related to the military and national security. The second confounding event is that Section 232 tariffs on aluminum and steel announced on March 1, 2018 came into force on March 23, 2018, which overlaps our main event window. We drop firms in the steel and aluminum related industries and present the results in Panel B.

Appendix 6. Robustness Checks Using Matched Samples

Panel A. U.S. 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. U.S. 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. The propensity score matching method is used to match the firms with greater exposure to the trade frictions to control firms according to the firm-level variables including firm size, market-to-book ratio, leverage, and ROA. Panels A and B show the results for U.S. firms according to their revenue from China and inputs from China, respectively. Columns 1 and 2 show the means of the variable for treated firms and control firms, respectively. Column 3 shows the difference in the mean between the control firms and treated firms. Columns 4 and 5 show the associated t-values and p-values, respectively. The *** denotes significance at the 1% level.

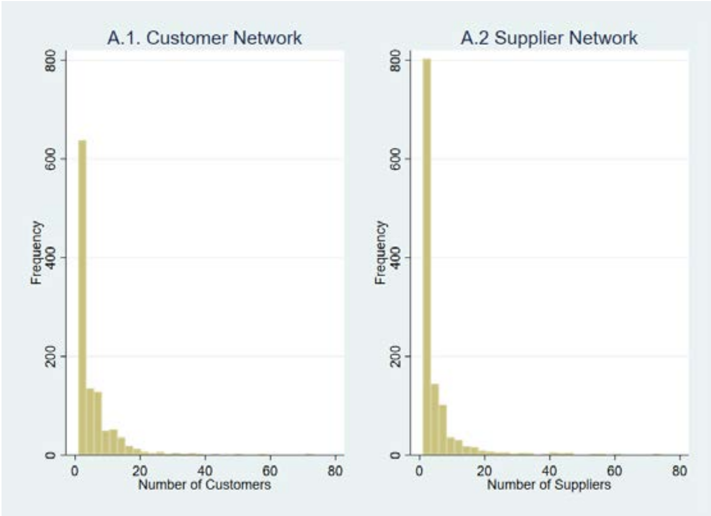
Appendix 7. Medium-term Effects

	(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. The 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 the other variables are in Appendix 3. The *t*-statistics based on robust errors are reported in the parentheses. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Appendix 8. The Description of the Revere Database

Panel A. Histogram of the Numbers 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. The firms with the largest numbers 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. The suppliers with the largest numbers 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 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 9. Procedure for the Textual Analysis

1. We first retrieve the complete list of HS codes from the World Bank website.[34] We only keep the product descriptions of the four-digit HS codes to minimize the potential noise from the more detailed descriptions in six-digit and eight-digit product codes.

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

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

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

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

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

Appendix 10. Additional Summary Statistics of the Product Lists

Panel A. First Chinese Tariff List: Products with the Largest Exports to China

Rank	HS	Product	Export to China (USD 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% 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. First U.S. Tariff List: Products with Largest Import from China

Rank	HS	Product	Import from China (USD 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 descriptions of the first Chinese product list issued on March 23, 2018 and the first U.S. product list issued on April 3, 2018. Panel A shows the top five products (labeled by the four-digit HS code) by total exports from the U.S. to China. Panel B shows the top five products (labeled by the four-digit HS code) by total imports of the U.S. from China.

Appendix 11. 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 is the U.S.-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 tariffs on $200 billion of Chinese goods from 10% to 25%.