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

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Abstract

We study the financial implications of the 2018-2019 U.S.-China trade war for global supply chains. Around the dates when higher tariffs are announced, U.S. firms depending more on exports to and imports from China experience larger declines in stock returns. The negative impact spill over to the affected firms' suppliers and customers through production networks. We also exploit the within-firm variation in exposure according to the detailed lists of tariffed products, and a reverse experiment based on the trade talks in 2019. We explain the findings with a theoretical model that highlights how the complex trade structure shapes shareholder wealth.

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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 permitted the greater sharing of economic benefits (Acemoglu et al., 2016b), it has also amplified the propagation of shocks across complex production networks and hence increased macroeconomic uncertainty (Acemoglu et al., 2016a; Barrot and Sauvagnat, 2016; Carvalho et al., 2017; Lin and Ye, 2018; Ozdagli and Weber, 2017; Pasten, Schoenle, and Weber, 2019).

Against this backdrop, the recent unexpected and abrupt changes in trade costs due to the U.S.-China trade war, which roiled stock markets globally, offer unique real-world "experiments" for studying the effects of policy shocks to firms in global value chains.[2] Moreover, evidence about the effects of the recent trade tensions on firm outcomes is scant, partly due to the lack of real-time micro data, despite the extensive news coverage.

Guided by a theoretical model, in this paper, we use unpredictable tariff announcements during the U.S.-China trade war in 2018-2019 to evaluate the effects of trade shocks on firms' financial market performance. The main event is the issuance of a presidential memorandum by the Trump administration on March 22, 2018, which proposed a 25% tariff on over $50 billion of Chinese imports.[3] We also use the date when the first wave of retaliatory tariffs was announced by the Chinese authorities, the issuance of the detailed lists of products covered by tariffs by both governments, and a reverse experiment based on the trade talks in early 2019 as additional events. These unprecedented and abrupt policy announcements offer a unique opportunity for an event-study analysis.

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[1] The effects of the changing trade policies in the last decades on firms, industries, and economies have been documented in the literature. 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)

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 mindset that global trade mostly involves the exchange of final goods, rather than intermediate inputs. However, studies have shown that global trade in recent years has increasingly involved production sharing with foreign firms (Grossman and Rossi-Hansberg, 2006; Baldwin, 2011; Johnson and Noguera, 2012). Although tariffs can reduce competition from foreign firms at home, they can also increase firms' costs of imported inputs and hence production. As a consequence, domestic consumers and firms that are heavily dependent on imports, directly or indirectly through the global supply chains, suffer the most.[4] The cost of import tariffs on production will also get amplified as the tariff-induced increases in production costs and reduction in sales will be compounded down the supply chains until the final stage when goods are sold to consumers.

If the higher 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 depressing their current stock prices. Furthermore, these adverse effects may be amplified through the interlocking supply-chain networks.

There are several advantages to use the 2018-2019 U.S.-China trade war announcements for an event study. The first advantage is related to the size of the world's largest economies and their relationships.[5] Besides generating significant uncertainty and negative effects on the global economy, the escalating trade tension between the two countries offers a unique opportunity to identify the effects of trade policy shocks across a large number of firms with heterogeneous participation in the shared global value chains.

The second advantage comes from the nature of the policy changes in 2018-2019. The policy announcements, especially the presidential memorandum issued on March 22, 2018 that

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[4] For the differential effects of trade liberalization on consumers, see Fajgelbaum and Khandelwal (2016) who show that poor consumers in the U.S., because of their larger shares of expenditure on tradable goods, benefit more from increased imports; also, see Amiti and Konings (2007), among others, for evidence about how firm productivity would increase due to assess to cheaper and better foreign intermediate inputs, in addition to import competition.

[5] China became the top trading partner of the U.S. in 2017. 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).

proposed a 25% tariff on over $50 billion of Chinese imports, were significant and unprecedented.[6] For the most part, investors were surprised by the announcements, in terms of the timing, magnitude, and coverage of the tariffs.[7] According to the efficient market hypothesis, firms' stock valuation should quickly incorporate the news about the tariff increases to reflect any expected changes in future cash flows. The perceived impact of the trade policy shocks on firms' stock values in principle can be precisely estimated. In contrast, it is difficult to use accounting variables, such as return-on-assets, to assess the impact of tariffs as those variables reflect the cumulative effects of many events (e.g., interest rate changes and currency fluctuations) during the current accounting period, which typically exceeds a quarter. Another advantage of our current research setting is that the subsequent publication of the detailed product lists and the reverse events can be used as validation exercises.

The third advantage relies on the various recently available data sets, which enable us to construct firm-level measures of U.S. firms' *direct* and *indirect* exposure to imports from and exports to China. 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 firms engaged in waterborne trade in the U.S. To measure a U.S. firm's indirect exposure to trade with China through its domestic supply chains, we use new buyer-seller matched data. Specifically, we construct four firm-level measures of exposure to trade with China in production networks: the average revenue from China of a firm's domestic (downstream) buyers; the average revenue from China of a firm's domestic (upstream) suppliers; the average exposure to Chinese inputs of a firm's domestic (downstream) buyers; and the average exposure to Chinese inputs of a firm's domestic (upstream) suppliers.

Based on the new data sets we put together and the theoretical model, we find heterogeneous effects of the tariff announcement across firms with varying degrees of direct and indirect exposure to policy shocks. Specifically, in the three-day window centered on March 22, 2018, our regression results show that U.S. firms that import from or export to China experience significantly lower stock returns compared to those without direct exposure. Controlling for the standard firm-level characteristics and industry fixed effects, we find that a

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

[7] 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.

10 percentage-point increase in a firm's share of sales to China is associated with 0.5% lower average cumulative returns from March 21 to 23, while firms that offshore inputs directly from China have a 0.6% lower average cumulative return than those that do not over the same period. These results are robust to using different standard asset pricing models and different event window length. Moreover, 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 three-day event window. The perceived reduction in import competition in the same sector has a positive impact on stock returns, but the magnitude is much smaller compared to the negative effects.

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 particular, we find that even without direct imports from China, U.S. firms that have indirect exposure to Chinese inputs through their domestic supply chains tend to experience a more negative stock return. 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 the 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, suggesting that even without direct sales in China, a firm's 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. Importantly, due to publicly listed firms' dense production networks, we find that a firm's indirect exposure to sales in China through its domestic customers and suppliers has an economically larger impact on its stock return than its own direct sales exposure. Similarly, a firm's indirect input exposure to China through its domestic supply chains also has a significant effect, which is slightly larger than the direct exposure. These results are consistent with our model predictions.

We then use the detailed lists of tariffed products issued by the U.S. and Chinese governments subsequent to each announcement. As the financial markets digest the news about the upcoming tariff increases, investors remain uncertain about which specific products 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. To identify US firm's exporting products covered by the tariff lists, we employ a textual analysis on firm's disclosure regarding product description. And the product level data in the Lading database enables us to identify firms that have purchased goods from China that are mentioned in the tariff list. Using the event-study approach, we find that U.S. firms with a larger fraction of exported products included in the list issued by the Chinese government tend to have a larger decline in stock prices around the date of the issuance of the product list. Conversely, the U.S. firms that have more of the imported products mentioned in the U.S. tariff list respond more negatively to the announcement.

Finally, we exploit a subsequent reverse event that inverts the market sentiment about the trade war to validate our main findings. The trade talks in Beijing in January 2019 were considered a signal of a trade war truce between the delegations. 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 date.

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 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), innovation (Bloom et al., 2016), trade quality (Fieler, Eslava, and Xu, 2018), markup distortions (Edmond, Midrigan, and Xu, 2015), 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) and Lin and Ye (2018) investigate the role of trade or foreign direct investment in transmitting global financial shocks 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; 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. Unlike this study, 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; 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, 2016; Bernard, Moxnes, and Saito, 2017; Carvalho et al., 2017; Lim; 2017; Oberfield, 2018; Tintelnot et al., 2019; Demir et al., 2020).[8] 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).

[8] Atalay et al. (2011) theoretically and empirically study U.S. publicly listed firms' production networks. Barrot and Sauvagnat (2016) 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.

Our paper draws heavily from the extensive body of literature that uses the event-study approach.[9] 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., 2020), 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.

3. Institutional Background and Hypotheses

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

China has grown substantially in terms of aggregate income, investment, consumption, and trade in the four decades since its open market economic reforms in 1978. It surpassed the U.S. to become the largest trading nation in the world,[10] and in 2015, surpassed Canada as the largest trading partner of the U.S.[11] China's exports, particularly those to the U.S., have skyrocketed since 2001, the year that it was accessed to the WTO. Various studies, most notably Autor, Dorn, and Hanson (2013) and Pierce and Schott (2016), show the negative labor market effects of Chinese imports on the U.S. labor market outcomes.

As expected, Trump's economic policies have been overall anti-trade, with China often being the target. Trump's complaints about China range from currency manipulation and unfair

[9] See reviews by Schwert (1981) and MacKinlay (1997). See Gorodnichenko and Weber (2016) for a recent study on firm's stock responses to monetary policy announcements.
[10] 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
[11] Source: U.S. Census https://www.census.gov/foreign-trade/statistics/highlights/top/index.html

practices against foreign businesses to the persistent trade deficit the U.S. has with China and state-supported industrialization. To address these issues, the Trump administration decided to use import tariffs as a policy tool to induce the Chinese government to implement policy changes that are favorable for U.S. interests.

As listed below, we use four events 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 three events will be 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 the foreign competition for national security reasons.
- March 23, 2018: The Chinese government retaliated 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.

In 2018 and 2019, a series of other critical events were triggered by the presidential memorandum 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 beginning of the ongoing trade war between the two countries. We then provide supporting evidence of the effects of the publication of the official tariff lists and the trade talks in 2019 as a reverse event, which unexpectedly changed market sentiment.

3.3 Hypotheses

The primary goal of this paper is to empirically examine the financial implications of the sharp increases in tariffs for firms connected in global value chains, guided by a simple theoretical model, as outlined in Appendix 1. Our model, 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.[13]

Our model shows that on the one hand, exporting firms' values (profits) will be impacted directly by foreign retaliatory tariffs that reduce foreign sales, but also indirectly through domestic customers (downstream firms) who experience lower foreign sales as well and reduce demand 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 through 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 country's import tariffs):

Increases in the foreign country's import tariffs will lower exporting firms' value.

Hypothesis 2 (direct impact of import tariffs):

[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

[13] Our model abstracts from sales of (US) inputs to foreign (Chinese) firms, in part for simplicity and in part because of our empirical focus on the impact of increased input costs and lost foreign sales for U.S. firms.

Increases in import tariffs will lower the values of firms that use imported inputs.

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

In addition to the direct impact (i.e., due to reduced export revenue), increases in the foreign country's import tariffs will lower firms' values due to various indirect effects, which arise from (1) higher prices of domestic inputs, (2) higher prices of imported inputs, and (3) lower sales to domestic downstream firms.

Hypothesis 4 (total impact of import tariffs):

In addition to the direct impact (i.e., due to higher prices of imported inputs), increases in a country's import tariffs will lower firms' 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 firm by its share of exports in total sales. To examine Hypothesis 2, we will measure the direct exposure to imports of a US 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

We use an event study approach and a combination 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, offering a unique real-world experiment. Our event-study approach tackles endogeneity issues related to time-varying and endogenous factors, such as comparative advantage or political uncertainty, which affect a firm's trade participation. It also advances existing studies that typically rely on sector-level measures of exposure to trade policy shocks (e.g., measures of import competition at the sector level).[14]

[14] Furthermore, 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.

As reported in Table 1, our regression sample is comprised of 2,309 U.S. listed firms, for which we can construct measures of exposure to trade with China and 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.

Our main dependent variables are the changes in stock prices over the short window centered on the announcement date of new tariffs, starting with March 22, 2018. By denoting the event date as date 0, the cumulative raw returns (*CRR*) over the three-day window centered on date 0 is

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

where R_{it} is the raw return for stock *i* on date *t*.

To take a 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 market return set equal to the average CRSP return and the risk-free rate set equal to the one-month Treasury bill 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. For robustness checks, we construct variables using longer event windows, and compute the abnormal returns using the Fama-French three-factor model.

Our main independent variables of interest are a U.S. firm's measure of *direct* exposure to sales in and imports to China. A firm's sales exposure, *Revenue_China*, defined as the share of the revenue derived from China in the firm's total revenue in 2016, captures the relative importance of the Chinese market for a U.S. firm. This variable is retrieved from the Factset Revere database.[15] Intuitively and according to Hypothesis 1, firms that are more dependent on sales in China are expected to suffer more from China's retaliatory tariffs. For instance,

[15] The information on a firm's input purchases from China in Factset Revere is highly incomplete, preventing us from using it to gauge a firm's exposure to China on the input side. Thus, we use the second data source below to measure input from China.

Apple Inc., Alphabet Inc., and Exxon Mobil derive 20.8%, 8.9%, and 5.9% of their revenue from China, respectively; and Apple is expected to have a more negative response to the announcements of tariffs by either government. Factset Revere also provides information on a U.S. publicly listed firm's buyers and sellers. We use this information to construct a U.S. listed firm's domestic production network (See Section 5.3 for more details).

A firm's import exposure measure is constructed using the U.S. bill of lading data. The bill of lading data set contains every waterborne import transaction in the U.S. For 2017, the database contains about 5 million bills of lading for imports from China, with information on the country of origin of the shipper, quantity, and product code.[16] One limitation of this database is the value of each transaction is not provided,[17] preventing us from constructing a continuous measure of the relative importance of inputs from China, like what we did to construct a firm's sales exposure. We thus construct a dummy variable (*Input_China*) for each firm to indicate whether it has outsourced inputs from China.[18] In a robustness check, we show that using the log value of quantities or weights of the imports from China yields consistent results.

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 centered on March 22, 2018 (the first event date) is -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 $MV\_Change = MV_{i,+1} - MV_{i,-2}$ as the change in market value in the event window [-1,+1] centered on March 22, 2018. Notice that equivalently, $MV\_Change_i[-1,+1] = MV_{i,-2} \cdot CRR_i[-1,+1]$. On average, the market value of U.S. firms

[16] These administrative data may 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.

[17] It is because the US customs do not require the shippers to file of the value of the transaction in the bill of lading.

[18] The lading information can be used by market participants through various channels. For instance, equity analysts and institutional investors can access this information and inform other investors. Firms may also mention their related businesses with China in their financial reports. We use the lading data for both 2016 and 2017 to construct the dummy 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. Relatedly, Hoberg and Moon (2017, 2019) employ a textual analysis on firms' filing with regulators to infer to global offshore activities of US listed firms. We differ from these studies by constructing measures based on actual importing records.

drops by about \$395 million. In total, the market loses \$911 billion in value over the three-day event window, according to our sample firms.

[Table 1 about Here]

The independent variable, *Revenue_China*, which captures U.S. firms' direct sales exposure to China, has a mean of 2.5% and the median equal to 0. The mean of *Input_China*, which captures U.S. firms' direct import exposure to China, shows that 24% of firms in our sample directly imports from China.

As in many existing studies, we include firm size (*SIZE*), market-to-book ratio (*MTB*), leverage (*LEV*), and the return-on-assets ratio (*ROA*) as firm-level controls. The data to construct these variables are from Compustat.[19] 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" in the U.S. As is shown, there was a sharp fall in the S&P 500 index (right scale) 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 the U.S. firms, with firms' market values as weights. The U.S. firms in our sample experienced an average 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.[20]

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.,

[19] 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.

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

Da et al., 2011). Public interest in the trade war peaked on March 22, the day the Trump administration announced the 10% tariffs on $50 billion of imports from China.[21] Similarly, large declines in the S&P 500 index and the corresponding spikes in the public interest, although smaller in magnitude, are observed for the other announcement dates (e.g., April 5 when Trump proposed additional tariffs against China).

[Figure 1 about Here]

The abrupt increase in the public interest in the "trade war" around this event together with the large market movement suggests that the U.S. announcement of tariff increases surprised the market and generated significant concerns about 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.

However, two events could potentially contaminate our estimation. The first is the appointment of the new National Security Advisor, John R. Bolton, as announced by Trump on Twitter on March 22, 2018. It is unclear how this announcement would have affected the U.S. equity markets, but we will show later that our results are robust to excluding military-related industries in our sample. The second event is the imposition of Section 232 tariffs on aluminum and steel imports from all countries announced by the U.S. government on March 1, 2018. The policy came into force on March 23, 2018, which overlaps with our event window. We mitigate this concern by dropping firms in the steel and aluminum related industries, and our results remain virtually unchanged.

It is worth emphasizing that our analysis focuses on examining the heterogeneous effects of this policy shock across firms with different degrees of exposure to the US-China trade. Unless firms' trade exposure is somehow related to other non-trade policy changes, it is hard to imagine that our results are driven by the aforementioned policy announcements. To further validate our findings based on the first event on March 22, 2018, we identify a subsequent event that reverses the market sentiment about the trade war between the two countries. We will also use detailed tariffed product lists issued by both the U.S. and Chinese subsequent to the March announcement to verify our main results at the firm-product levels.

Other announcements since March 22, 2018 should also affect the U.S. equity market. For instance, on April 2 when China's Ministry of Commerce rolled out tariffs on 128 U.S.

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[21] 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.

products, the U.S. stock market index dropped by 2.2%. Nonetheless, because several events clustered around April 2-5, the impact of each event is difficult to evaluate. Our analysis below thus focuses on the March 22 announcement, the first of its kind.

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 react to the announcements accordingly. We argue that this premise holds. Institutional investors and financial intermediaries have in-house research teams that are capable of estimating the financial implications of the trade war, through access to their own databases and the large talent pool in the financial industry. The efficient market hypothesis implies that the unexpected trade shocks would prompt traders to compete in acquiring valuable information about firms' trade exposure. Moreover, investors would do their due diligence to study companies' trade partners, given the academic evidence on return predictability across linked firms (e.g., Cohen and Frazzini, 2008).

5.2 Firms' Direct Trade Exposure and Stock Market Reactions

This section presents the empirical results about the impact of the initial announcement of tariff hikes on a US firm's stock returns, based on its direct trade exposure with China. We first show in Table 2 suggestive evidence using a simple univariate analysis on the relation between a firm's exposure to China and its market performance. We find that the cumulative returns are systematically lower for firms that have more trade exposure to China. Specifically, as shown 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.[22] 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. These findings warrant the need to control for these firm characteristics in the regressions.

[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

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

three-day window than firms without any import exposure to China. 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 two measures of direct trade exposure to China. Table 3 reports the point estimates and robust standard errors of the OLS regressions.[23] As shown in Panel A, we find that firms that sell proportionally more to China experience relatively lower *CRR* over the three-day window centered on March 18. Column (1) suggests that a 10 percentage-point increase in a firm's share of sales to China is associated with 0.92% lower *CRR* when the four firm-level characteristics (firm size, market-to-book ratio, leverage, and ROA) are controlled for. We also find firms that purchase (offshore inputs) from China have lower average *CRR* than firms that do not. As column (2) shows, the average *CRR* is 0.96% lower than the average of firms that have zero imports from China. In column (3), when we include both trade exposure measures as independent variables in the regression, we find quantitatively similar coefficients on both variables.

When industry (Fama-French 30 industry portfolios) fixed effects are included in the baseline model, the estimated coefficients of trade variables shrink as shown in column (4). This decline in the magnitudes of the coefficients indicates that much of the variation in the firms' trading activities with China and their *CRR* are captured by industry characteristics (e.g., US's or China's comparative advantage in the sector). Nonetheless, these industry-level characteristics cannot sufficiently explain most of the firms' heterogeneous responses to the expected impacts of the U.S.-China trade war within the industry.

We next compare the announcement effects through the firm's direct trade exposure with that related to the perceived reduction in import competition from and exports to China in same the industry. We define the Chinese import penetration at the industry level as:

$$\text{Industry\_IP}_k = \frac{IMP\_CN_k}{SHP_k + IMP_k - EXP_k},$$

where IMP_CN_k is the total imports from China in sector *k*, defined as a NAICS category, SHP_k is the sector's shipment value, and EXP_k is its exports. The data are from Peter Schott (2008), who in turn obtained the data from the U.S. Census Bureau. The import and export data are from 2017, while the shipment data are from 2016 due to data availability. We also construct the sector measure for total exports to China as $\text{Industry\_Export}_k = \frac{EXP\_CN_k}{SHP_k}$, where EXP_CN_k is the total exports to China for sector *k*.

[23] In unreported results available upon request, we show that our results are robust to using standard errors clustered by industry.

The regression results presented in column (5) show a positive coefficient on the measure of ex-ante import competition and a negative coefficient on export orientation to China. Reduced import competition due to tariffs is perceived to increase profits by more for firms in the sectors that faced stronger competition from China ex-ante. These findings are consistent with Grossman and Levinsohn (1989), who document 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 through the import competition channel is small. 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 direct trade exposure to China, the variation in the import competition from China across industries plays a much more limited role. As expected, the negative coefficient on the measure of export orientation to China implies that U.S. firms operating in an industry that relies more on China as an export market anticipate lower profits.

We quantify the aggregate market effects of the March 22 announcement through the direct sales and import channels. As shown in Appendix 2, the value-weighted average of *CRR[-1,+1]* in our sample is -4.32%. We first multiply each firm's *Revenue_China* with the regression coefficient (-0.092) in column (1) of Panel A, and compute the weighted average of the market decline using firms' market value shares (on March 20, 2018) as weights. The aggregate effect through the exposure to Chinese imports can be gauged similarly. The calculations suggest that the aggregate effect of the announcement due to firms' sales exposure is about -0.54%, while that due to the input exposure adds another -0.47% to the three-day stock market return.[24] In other words, about 23% of the 4.32% stock market decline is attributed to firms' direct trade exposure. The remaining 77% can come from increased in market uncertainty related to the announcement, as well as firms' indirect exposure through global supply chains, which will be discussed in Section 5.3.

In Panel B of Table 3, we present the results based on the CAPM-adjusted abnormal returns. We find that over the three-day window, the estimates of a firm's *CAR* decline due to its exposure to China are very similar in magnitude to those based on its *CRR*.[25]

[Table 3 about Here]

[24] In a table available upon request, we find consistent and robust results based on estimations using the dollar value changes in market capitalization (*MV_Change*) as dependent variables.

[25] 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*.

Besides affecting firms' stock returns, the U.S. government's sudden move in trade policy towards China should also impact the wealth of the firms' other stakeholders (such as bondholders). In particular, the fear about a trade war may have increased the likelihood of firms' defaults. Firms' deteriorating financial performance increases the probability of bankruptcy (Acemoglu et al., 2016b). The increased uncertainty about the future U.S.-China economic relations may induce postpone investment and other long-term plans, or adopt suboptimal strategies (Bloom, 2009; Bloom et al., 2007). To examine whether the tariff announcement raises default risks, we follow prior studies (e.g., Ismailescu and Kazemi, 2010) to 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 firms' (five-year implied) CDS spreads are obtained from Bloomberg.

As reported in Panel C of Table 3, we find that firms that are more exposed to imports from and exports to China are associated with a higher default risk. Specifically, as is shown in column (1), a 10 percentage-point increase in a firm's share of sales to China is associated with a 0.50% increase in its default risk. On the import side, firms that have reported imports from China have an on average 0.45% higher risk of default. In sum, not only that firms' exposure to trade with China affects their stock price reactions to the March 22 announcement, it also raises investors' perception of risks among the more exposed firms. In other words, the event impacts not only the equity markets but also the bond markets.

5.2.1 Robustness Checks

We conduct four robustness checks. First, our event study rests on the premise that the event is unanticipated by the public and there is no obvious confounding event around the event date. After a thorough search of news and relevant reports, we identified two events that may bias our results. The first is Trump's appointment of a new national security advisor on the same date (March 22, 2018). The second event is about the increase in tariffs on steel and aluminum based on Section 232, which was announced on March 1 and went into effect on March 23.

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 measures are constructed at the firm level. We also include the industry fixed effects to compare the heterogeneous responses across 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. Nevertheless, we exclude in the regression sample firms in the military-related industries, which can potentially be affected by the news about the appointment of the new national security advisor.[26] As shown in columns (1)-(2) of Panel A in Appendix 4, our results remain unchanged after those firms are excluded from the sample.

Regarding the second confounding event, it is worth noting that the increased tariffs are imposed on steel and aluminum imports from all countries, not only from China. Hence, firms' exposure to this confounding event is less likely to be correlated with our firm-level measures of exposure to China. We show in columns (3)-(4) of Panel A that excluding firms in the steel and aluminum industries does not affect our main results.[27]

Second, we check the robustness of our results by using different asset pricing models to adjust the stock returns. As is shown in Panel B of Appendix 4, using the Fama-French three-factor model to estimate firms' CARs yield quantitatively similar results based on our baseline CAR measures. Third, we partially address the shortcoming of relying only on a firm's import dummy to gauge its import exposure by using the average ratio of its quantity imported from China to the total quantity imported at the HS 6-digit product level.[28] As is shown in Panel C, we find that firms that have a larger fraction of their imports from China also tend to experience a larger decline in stock prices around March 22.

Next, 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 5. 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

[26] 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.

[27] 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.

[28] Specifically, for each firm-product, we compute the ratio of import quantity from China to import quantity from the world at the HS 6-digit level. We then compute *Qimp_China/Qimp*, by taking the average of the ratios across HS 6-digit categories within each firm.

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.

5.2.2 Medium-term Impact

One can argue that the findings over a short event window simply reflect outcomes of firms' overreaction to the news. To verify whether the trade-war announcement has any long-lasting effects, we extend our analysis by using a firm's buy-and-hold abnormal returns (*BHAR*) over longer event windows. Following Malmendier et al. (2018), we define a firm's *BHAR* as

$$BHAR_i[-X,+Y] = \prod_{-X}^{+Y}(1+R_{it}) - \prod_{-X}^{+Y}(1+MR_t),$$

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 columns (1) and (2) of Panel A, 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. 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 used in the baseline specification are plotted in Figure 2 (see the detailed regression results in Appendix 6).

In the pre-event regression, we fail to reject the null hypothesis that the two exposure variables are different from zero. However, we find that the effect of the trade war announcement persists in the medium term. Specifically, a 10 percentage-point increase in a firm's share of the revenue from China is associated with a 2.3% lower buy-and-hold abnormal return in the 40 trading days (*BHAR[-1,+40]*) after the announcement. Firms that imported inputs from China have a 2% lower stock price on average in the medium term (a 40-day period), relative to firms that did not. Having confirmed the medium-term impact, in the rest of the paper, we focus on the short windows centered on March 22 and the subsequent announcements by both countries' governments as events, following the conventional practices used in event studies.

[Figure 2 about Here]

5.3 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.

We rely on a relatively new database, Factset Revere, which is, to our knowledge, the best available source of supply chain information. The Securities and Exchange Commission (SEC) requires U.S. listed firms to make mandatory supply chain disclosure. In particular, a publicly listed firm is obliged to publicly disclose any customer that commands 10% or more of its revenue.[29] 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) have shown, the Compustat Segment database, which is built on the information on firms' supply chain relationships as disclosed in their 10-Ks (annual reports), 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 a much broader coverage than the other databases, including Compustat Segment, in terms of the number of firms, countries of origin, and industries. Specifically, Factset Revere actively monitors 10,000 globally listed firms and captures up to 25,000 buyer-supplier relationships per year.[30]

Although the Factset Revere database represents the best available commercial database of its kind, we acknowledge that the coverage of the database is probably incomplete, as it is built on public disclosure and hence has a large-firm focus. For instance, small customers of a firm that account for less than 10% of the firm's revenue may not be included in its disclosure and thus may be omitted in the database. A potential selection issue may also arise from firms' voluntary disclosure 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 all reported information of a firm's customers and suppliers in the database. A supplier firm may disclose a customer, while the same customer may not report the supplier as a connection. Using information reported from either side of a relationship permits the construction of a more complete production network among U.S. firms.

[29] 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
[30] A detailed comparison of Factset Revere and Compustat Segment can be found here: https://www.longfinance.net/media/documents/DB_TheLogisticsofSupplyChainAlpha_2015.pdf

The relationships in the database are characterized by the start date and end 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.[31] We also exclude relationships from the sample if either side is excluded in our regression sample, namely unlisted, foreign, or financial firms. The final sample of our publicly listed firm network covers 5,552 buyer-seller links.

We construct four measures of the *indirect* exposure to trade with China, using the firm production network and trade data. We follow Acemoglu et al. (2016a) in constructing these exposure measures to analyze how shocks are amplified and propagated through 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 sales in China across a firm's (downstream) buyers in the U.S.:

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

where M indicates the number of firm i's customers, while $Revenue\_China_{i,m}$ measures firm i's indirect exposure to sales to China through customer m. 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, which will then lower the demand for inputs from firm A. We plot the actual customer network of General Electric (GE) in Panel C. As the overall network is large, we only consider the first two layers of customers, namely, the direct customers of GE and the customers of GE's customers. Each node represents a U.S. company, while the links represent buyer-seller relationships. The size of a node represents the number of buyer-seller links a firm has. If the node is green, it means that the firm has revenue from China, with the white nodes indicating zero revenue from China.

The second measure is the average exposure to inputs from China across a firm's buyers (downstream) in the US:

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

[31] 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.

where $Input\_China_{i,n}$ is an indicator equal to one if customer *m* has outsourced inputs from China, and zero otherwise.[32] 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 lowering their production and thus the demand for goods from firm A. In contrast, if the intermediate goods produced by Chinese firms E and F can be sufficiently substituted by goods produced by firm A, then the tariff hike may also increase the demand for the goods produced by firm A and boost its sales. The same production network of GE is plotted in Panel D of Figure 3, with now the blue nodes indicating GE's U.S. customers that have outsourced input from China.

The third measure is the average exposure to revenue from China across a firm's (upstream) suppliers in the U.S.:

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

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 some 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 a firm's (upstream) suppliers 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. 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 purchase inputs from China and the white nodes indicate firms without inputs from China.

[32] 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.

[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 inputs from China.

Appendix 7 offers additional statistics. Panel A of Appendix 7 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 the 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.2 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 4 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 derive revenue from China experience a 1% decline in stock returns, as measured by either *CRR* or *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 through customers (*Revenue_China_Customer*) is associated with a 1.1% lower *CAR* over the three days centered on March 22. Column (2) shows that a 10% increase in the indirect sales exposure through suppliers (*Revenue_China_Supplier*) is associated with a 0.89% lower *CAR*. The effects remain significant when the indirect measures based on customers and suppliers are jointly estimated in the regression model (column (3)) and when industry fixed effects are included (column (4)). Interestingly, as shown in column (3) the combined magnitude of the coefficients for indirect measures (0.0915+0.0782) is significantly larger than the coefficient for the direct measure (0.0594).

[Table 4 about Here]

We can thus quantify the aggregate impact through the direct and indirect measures. Similar to the practice in assessing the aggregate impact of direct exposure, we first multiply the given measure of each individual firm with the coefficients in column (3) of Panel B and calculate the value-weighted average using the firms' market values on March 20, 2018 as weights. Over the three-day event window, the direct exposure to revenue from China generates a 0.35% decline in aggregate stock market returns, whereas the indirect sales exposure through domestic customers is associated with a 0.18% drop in aggregate stock returns, with the indirect sales exposure through domestic suppliers contributing another 0.34% losses.[33] The regression results imply that according to our firm sample, the market loses about US$73.8 billion due to direct sales exposure, while indirect sales exposure through customers accounts for an additional US$37.9 billion loss, while indirect sales exposure through suppliers adds another US$71.7 billion loss.[34] In other words, despite the aggregate impact of each indirect exposure channel is smaller than that of the direct exposure, the sum of the two indirect exposure effects is quantitatively larger.

Table 5 presents the estimated impact of the indirect exposure to Chinese inputs, through either domestic customers or suppliers. The univariate analysis in Panel A shows significant differences in stock performance between firms with positive indirect exposure versus firms with zero indirect exposure. Specifically, firms with customers that purchase inputs from China experience an average 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 presents consistent regression results, except in column (4) when the industry fixed effects absorb the effect of the indirect input exposure through customers. Specifically, column (3) suggests firms that directly purchase inputs from China (*Input_China*) experience a 0.8% lower stock return compared to those that do not on average. Firm's indirect input exposure through customers (*Input_China_Customer*) and the input exposure through suppliers (*Input_China_Supplier*) both demonstrate a significant effect on stock returns, indicating a combined magnitude of the coefficients slightly larger than the direct measure. Using a similar approach discussed above,

[33] For example, to infer the aggregate impact of indirect exposure from the revenue from China across customers, we calculate the value-weighted average of *Revenue_China_Customer* using market values on March 20, 2018 as weights and multiply the average with the coefficient (-0.0915) in column (3) of Panel B Table 4.

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

we combine the estimated coefficients in column (3) and the given exposure measures to infer the aggregate impact on the market. The direct input exposure leads to a 0.38% decline for the whole market, while indirect measures *Input_China_Customer* and *Input_China_Supplier* contribute to additional 0.20% and 0.23% drops, respectively.

[Table 5 about Here]

In sum, the results reported in Tables 4 and 5 collectively show that the structure of a firm's supply networks affects the perceived effects of tariff hikes on the firm, even when it has no direct trade relationship with China. The indirect effect is found to reduce a firm's cash flows due to lower demand from affected customers (in the downstream of the supply chain) and an increased input and thus production costs through domestic suppliers (in the upstream of the supply chain).

5.4 Product Lists

Thus far, we have established the relationship between firms' stock returns and their trade exposure. 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 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.

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 (USD 50 billion of Chinese goods), June 15 (USD 50 billion), and July 10 (USD 200 billion). In response, China hit back by issuing product lists on March 23 (128 products), April 4 (USD 50 billion of U.S. goods), and August 3 (USD 60 billion).[35] Each product list covers additional products compared to the

[35] 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;

previous lists. As a confirmatory exercise to support our baseline results, which focus on the first tariff announcement date, 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 as a retaliation to the U.S. tariffs on imported steel and aluminum. The product with the largest exports to China in the list 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 fraction of a U.S. firm's products mentioned in the Chinese list. The details of the construction are provided in Appendix 8.

Panel A of Table 6 reports the estimation results on the heterogeneous responses based on the output mix of U.S. firms. Independent of whether the four firm characteristics (column (2)) or industry fixed effects (column (3)) are controlled for, we find a 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

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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

Output_China_List is associated with an additional 1.1% to 1.3% decline in stock prices between March 22 and March 24.

[Table 6 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 8-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. Using the product level trade data, we find 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 a firm’s fraction of products purchased from China that are covered by the April 3 tariff list.[36] As Panel B of Table 6 shows, U.S. firms with more inputs covered by the U.S. tariff list experience a larger decline in stock prices in the 3-day window centered on April 3. Specifically, a one standard deviation increase in *Input_China_List* is associated with an additional 0.14% (column (2) when firm characteristics are controlled for) to 0.17% (column (3) when industry fixed effects are also controlled for) 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 tariff increase and the pre-event tariff rates. We first calculate the difference between the new import tariff rate according to the tariff list and the original tariff rate at the HS 8-digit level. We then use the bill of lading database to identify firms’ specific imports from China at the same level. *Tariff_Change* is defined as the value-weighted average import tariff increases, using transaction quantities as weights.[37] The findings in Panel C of Table 6 suggest that a 10-percentage point increase in the firm’s average tariff rate results in a 0.9% (column (2) when firm characteristics are controlled for) to 1.4% (column (3) when industry fixed effects are also controlled for) reduction in stock returns.

[36] 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.
[37] Recall that we do not have the information on the transaction value for each firm.

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. Furthermore, it also reveals that market participants refine and adjust their valuations of the firms when the uncertainty about the coverage and magnitude of the new tariffs is gradually resolved.

5.5 The Reverse Experiment

We have already offered evidence showing that the heterogeneous effects of the tariff announcements are not only transitory, but medium-term. 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 a major event as the reverse experiment 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 7. 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 sales to China (above the median of the share of revenue from China) gain 0.6% larger raw returns relative to firms that are less dependent. Compared with the firms without inputs from China, the firms that outsource inputs from China experience a 0.7% larger gain in stock returns. This pattern is confirmed in the regression shown in Panel B. However, the effect of *Input_China* become insignificant when *Revenue_China* is included in the same regression (column (4)).

[Table 7 about Here]

5.6 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 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 Chinese counterpart of Compustat, the CSMAR database, 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. We 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.

Appendix 9 presents the results for Chinese markets. Panel A of Appendix 9 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 0.9%,[38] with 26% of Chinese firms having purchased from the U.S. Panel B of Appendix 9 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 Appendix 9 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 1.4% larger drop in stock prices (column (1) in Panel C). The *CAR* 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

[38] This ratio might be biased downward because we use the total sales in the consolidated financial statement as the scale, which include sales from all subsidiaries of the listed company.

U.S. is also included as a regressor, largely because Chinese firms purchase minimal procurements from the U.S. The effect of revenue from US remains significant when the industry fixed effects are included as regressors.[39] We conduct the same revere experiment exploiting the event of the US-China trade talks in January 2019. Panel D of Appendix 9 suggests an offsetting positive effect of the trade talks. Taken together, the evidence here based on Chinese listed firms indicates similar patterns of response to the trade war announcement, especially for firms exposed to exports rather than imports.

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, U.S. firms' indirect exposure to trade with China through domestic supply chains have an economically larger negative impact on their stock returns than their 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.

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

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Table 1. Summary Statistics

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%.

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
MV_Change[-1,+1]	2308	-394.722	2450.166	-123.212	-18.762	-0.517
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	0.236	0.424	0.000	0.000	0.000
Industry_IP	2309	0.086	0.620	0.000	0.000	0.004
Industry_Export	2309	0.017	0.041	0.000	0.000	0.028
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	0.199	0.329	0.000	0.000	0.357
Input_China_Supplier	2309	0.200	0.329	0.000	0.000	0.333
D. 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	544	2.361	3.364	0.000	0.256	4.267
E. 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	-0.041	0.366	-0.039	0.081	0.137

Table 2. Univariate Analysis for Direct Trade Exposure

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, and zero otherwise. Other variables are defined in Appendix 3. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

A. 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***
MV_Change[-1,+1]	909	-809.448	1399	-125.254	-684.197***
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	0.062	1399	-0.108	0.171***
B. Input from China	**Input_China**				
	=1		=0		
	N	Mean	N	Mean	Diff.
CRR[-1,+1]	544	-0.036	1765	-0.023	-0.013***
CAR[-1,+1]	544	-0.037	1765	-0.024	-0.013***
MV_Change[-1,+1]	544	-920.268	1764	-232.649	-687.619***
Default Risk [-1,+1]	544	0.02	1765	0.01	0.010***
SIZE	544	7.363	1765	6.173	1.190***
MTB	544	2.087	1765	2.391	-0.304***
LEV	544	0.256	1765	0.271	-0.015
ROA	544	0.096	1765	-0.083	0.179***

Table 3. Revenue and Input from China

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. In Panel A, the dependent variable, *CRR [-1,+1]*, is the three-day cumulative raw returns around March 22, 2018. *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, and zero otherwise. 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. Panel B presents the responses of the firms measured by cumulative abnormal returns. *CAR [-1,+1]* is the three-day cumulative abnormal returns around the event date estimated using the standard one-factor market model. Panel C 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. The *t*-statistics based on robust standard errors are reported in the parentheses. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Cumulative Raw Returns

	(1)	(2)	(3)	(4)	(5)
			CRR [-1,+1]		
Revenue_China	-0.0921***		-0.0814***	-0.0429**	-0.0490***
	(-6.42)		(-5.56)	(-2.44)	(-2.77)
Input_China		-0.0096***	-0.0079***	-0.0052***	-0.0076***
		(-5.22)	(-4.23)	(-2.68)	(-4.06)
Industry_IP					0.0050**
					(2.13)
Industry_Export					-0.1222***
					(-3.59)
N	2309	2309	2309	2291	2309
adj. R-sq	0.055	0.052	0.061	0.124	0.065
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No

Panel B. Cumulative Abnormal Returns

	(1)	(2)	(3)	(4)
		CAR [-1,+1]		
Revenue_China	-0.0952***		-0.0845***	-0.0447**
	(-6.30)		(-5.47)	(-2.36)
Input_China		-0.0096***	-0.0079***	-0.0054***
		(-5.06)	(-4.07)	(-2.68)
N	2309	2309	2309	2291
adj. R-sq	0.050	0.046	0.055	0.121
Controls	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes

Panel C. Default Risks

	(1)	(2)	(3)	(4)
		Default Risk [-1,+1]		
Revenue_China	0.0499***		0.0450***	0.0228**
	(5.28)		(4.79)	(2.15)
Input_China		0.0045***	0.0036***	0.0028**
		(4.10)	(3.28)	(2.39)
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

Table 4. Transmission through Domestic Production Networks: Revenue from China

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 standard errors are reported in the parentheses. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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***

	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***

Panel B. Revenue from China

	(1)	(2)	(3)	(4)
	CAR [-1,+1]			
Revenue_China	-0.0718***	-0.0774***	-0.0594***	-0.0339*
	(-4.42)	(-5.00)	(-3.59)	(-1.76)
Revenue_China_Customer	-0.1065***		-0.0915***	-0.0707***
	(-4.49)		(-3.82)	(-2.91)
Revenue_China_Supplier		-0.0889***	-0.0782***	-0.0445**
		(-4.43)	(-3.86)	(-2.04)
N	2309	2309	2309	2291
adj. R-sq	0.055	0.056	0.059	0.123
Controls	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes

Table 5. Transmission through Domestic Production Networks: Input from China

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 standard errors are reported in the parentheses. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Univariate Analysis

	Input_China_Customer				
	>median [0]		<median [0]		
	N	Mean	N	Mean	Diff.
CRR[-1,+1]	752	-0.033	1557	-0.023	-0.009***
CAR[-1,+1]	752	-0.033	1557	-0.024	-0.009***

	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***

Panel B. Input from China

	(1)	(2)	(3)	(4)
	CAR [-1,+1]			
Input_China	-0.0087***	-0.0088***	-0.0080***	-0.0054***
	(-4.50)	(-4.57)	(-4.12)	(-2.65)
Input_China_Customer	-0.0077***		-0.0069***	-0.0024
	(-3.30)		(-2.92)	(-1.01)
Input_China_Supplier		-0.0084***	-0.0076***	-0.0063**
		(-3.30)	(-2.99)	(-2.47)
N	2309	2309	2309	2291
adj. R-sq	0.049	0.050	0.052	0.122
Controls	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes

Table 6. Firms' Heterogeneous Responses to the Product Lists

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 U.S. 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 estimated percentage of a firm's products mentioned in the China list. The products are identified using textual analysis, which is further explained in Appendix 8. 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 standard errors are reported in the parentheses. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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***	-0.1070***	-0.1173***
	(-3.14)	(-2.64)	(-2.89)
N	2309	2309	2291
adj. R-sq	0.003	0.011	0.029
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*	-0.0064**	-0.0066*
	(-1.70)	(-1.98)	(-1.87)
N	2305	2305	2287
adj. R-sq	0.001	0.005	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	-0.0014***	-0.0014***	-0.0009*
	(-2.92)	(-2.83)	(-1.70)
N	544	544	536
adj. R-sq	0.014	0.011	0.060
Firm Controls	No	Yes	Yes
Industry FE	No	No	Yes

Table 7. Trade Talks as a Reverse Experiment

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 standard errors are reported in the parentheses. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

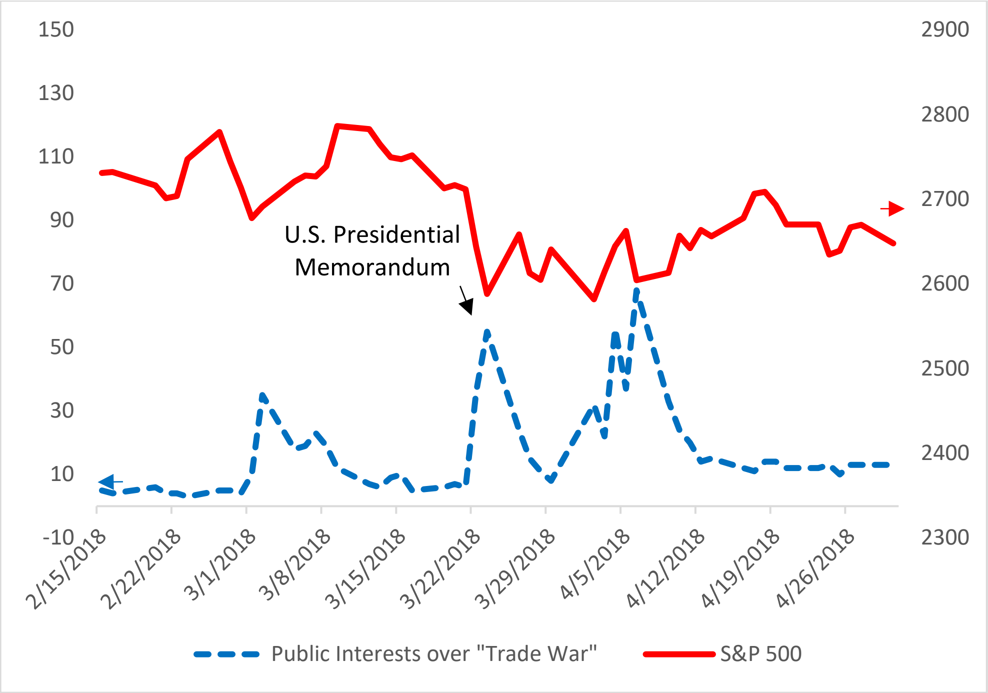
Panel A. Univariate Analysis

	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_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

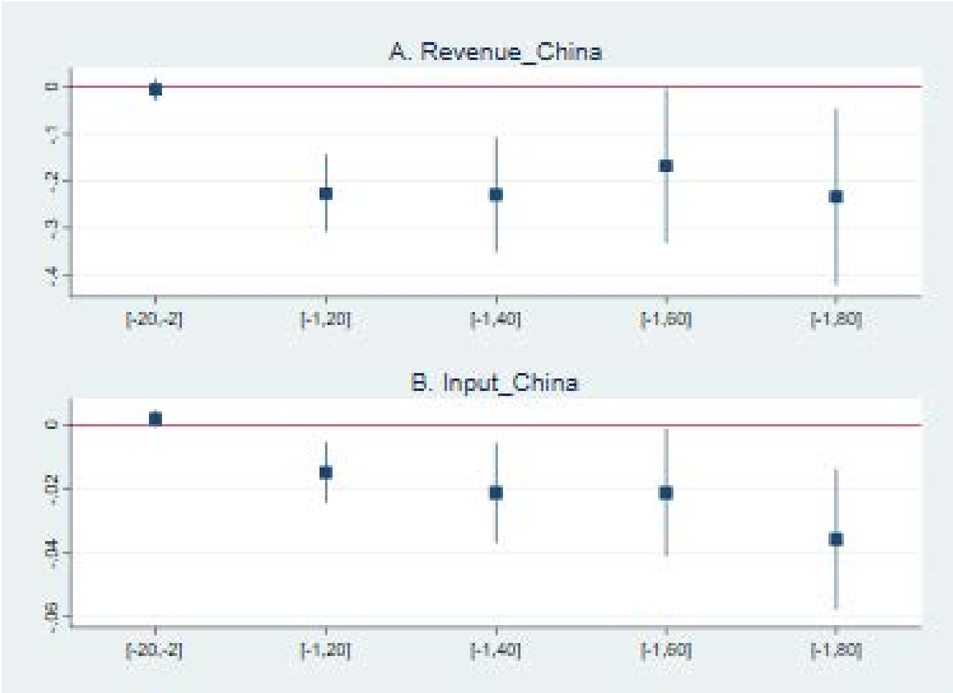
	(1)	(2)	(3)	(4)
	CAR [-1,+1], Jan 9			
Revenue_China	0.0605***		0.0547***	0.0426*
	(3.17)		(2.76)	(1.73)
Input_China		0.0056**	0.0038	0.0040
		(2.06)	(1.37)	(1.33)
N	2127	2127	2127	2112
adj. R-sq	0.007	0.005	0.007	0.012
Controls	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes

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



This figure presents the time-series of the market index against the public interest in the U.S.-China trade war. 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).

Figure 2. Medium-term Effects



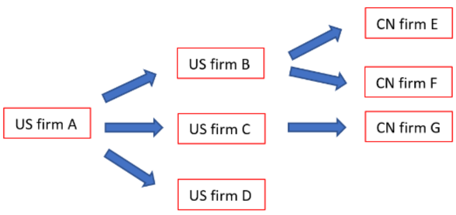
This figure shows the medium-term effect of the declaration of the trade war on firm value. We first run the following regression:

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

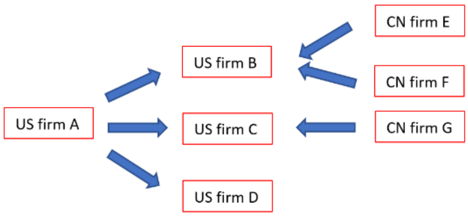
where Y_i denotes the buy-and-hold abnormal returns (*BHAR*) over different event windows. Specifically, *BHAR [-1,+X]* is the buy-and-hold abnormal returns around the event window *[-1,+X]* with zero indicating March 22, 2018 adjusted by the market benchmark. We also consider an event window *[-20,-2] for falsification tests.* 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 markers indicate the magnitude of the estimated β. The bars represent the 95% confidence intervals. The detailed regression results are provided in Appendix 6.

Figure 3. Firm Production Networks: Customer Side

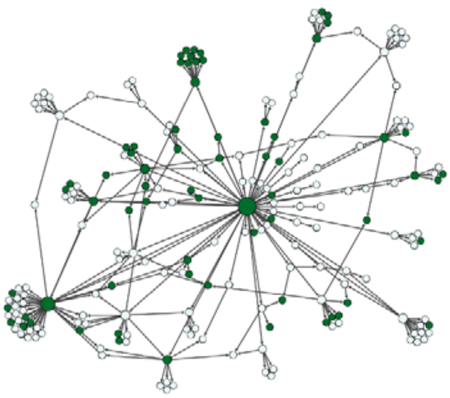
Panel A. Revenue from China



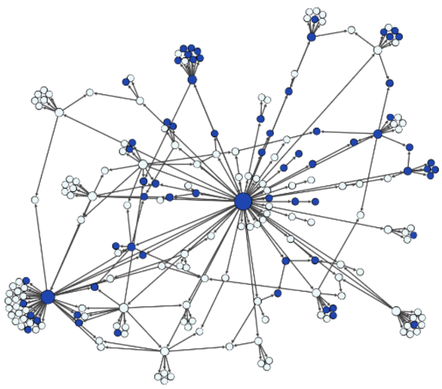
Panel B. Input from China



Panel C. GE's Customers: Revenue from China

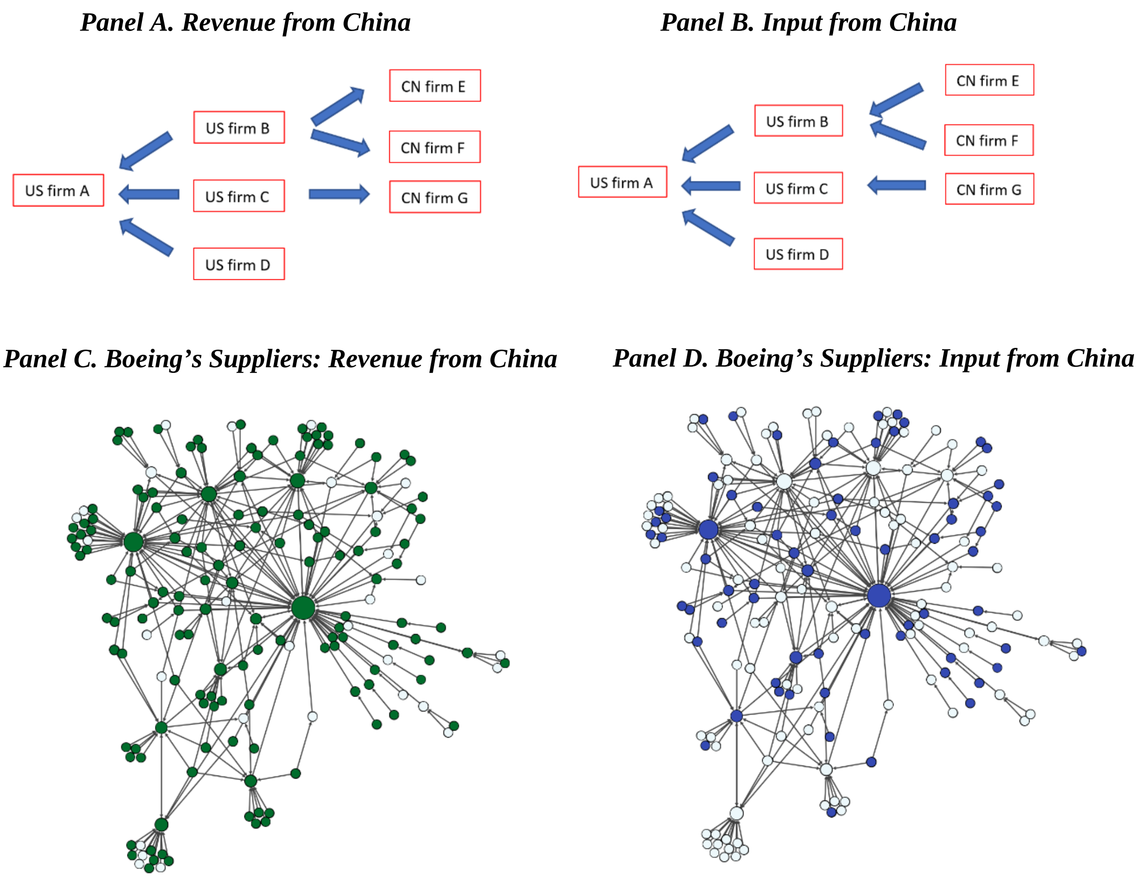


Panel D. GE's Customers: Input from China



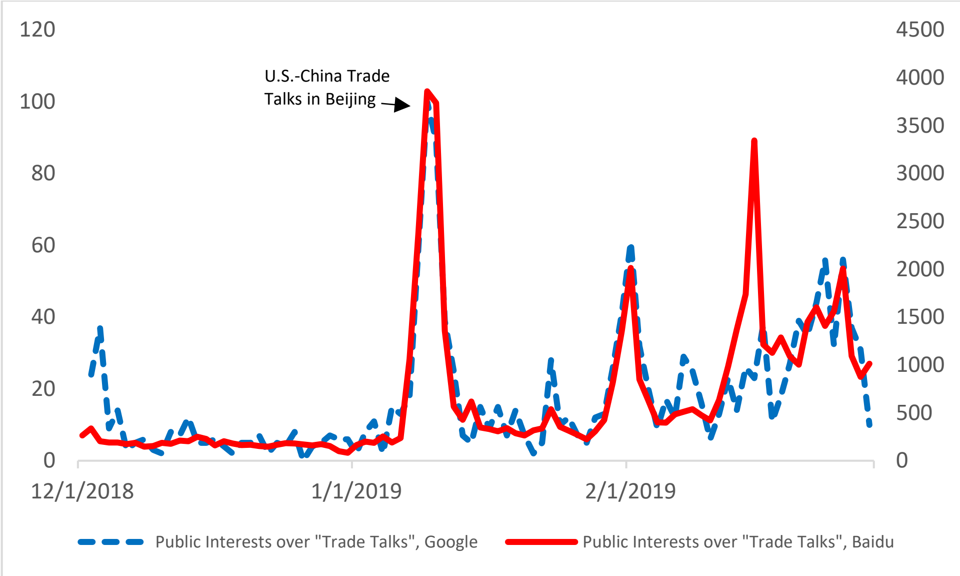
This figure illustrates the firm production networks from the customers' perspectives. In Panels A and B, the direction of the arrows indicates the trade flow. Specifically, in Panel A, the U.S. firm B purchases from firm A and Chinese firm E purchases from U.S. firm B. Similarly, in Panel B, U.S. firm 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



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



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), the Chinese counterpart of Google.

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.[40]

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

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

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

[40] 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.

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.[41] 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

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

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

[41] 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.

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

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

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

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

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

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

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

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

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 and (2) January 9, 2019: the trade negotiations between the U.S. and China end with progress in identifying and narrowing the two sides' differences. present the value-weighted average returns using the market value as weights.

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

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
MV_Change[-1,+1]	The change in market value around the event window [-1,+1] with zero indicating March 22, 2018. $MV\_Change_i[-1,+1] = MV_{i,+1} - MV_{i,-2}$. Equivalently, $MV\_Change_i[-1,+1] = MV_{i,-2} \cdot CRR_i[-1,+1]$. 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. $CAR_i[-1,+1] = \sum_{t=-1}^{+1} AR_{i,t}$, where $AR_{i,t}$ is the abnormal return for firm *i* on date *t*. Source: Bloomberg & Ken French Data Library
BHAR [-X,+Y]	The buy-and-hold abnormal returns around the event window [-X,+Y] with zero indicating March 22. For example, $BHAR_i[-1,+30] = \prod_{t=-1}^{+30}(1+R_{i,t}) - \prod_{t=-1}^{+30}(1+MR_{i,t})$, where $R_{i,t}$ is the stock return for firm *i* on date *t* and $MR_{i,t}$ is the market return. Source: Bloomberg
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
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, and zero otherwise; 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	An indicator set to one if a firm imports goods from the U.S. as indicated by the China customs database in 2016. Source: China Customs Database & CSMAR

Output_China_List	The estimated 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 8. Source: 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. Source: 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_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
Industry_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 (at) in 2016. Source: Compustat
MTB	Market-to-book ratio in 2016 defined as market value of assets (csho*prcc_f+lt) over book value of assets (at). Source: Compustat
LEV	Financial leverage ratio in 2016 defined as long term debt (dltt) plus debt in current liabilities (dlc), divided by assets (at). Source: Compustat
ROA	Return-on-assets in 2016 defined as operating income before depreciation (oibdp) divided by assets (at). Source: Compustat

Appendix 4. Robustness Checks

This table shows the robustness checks. Panel A shows the results based on a sample excluding firms in military related industries and a sample excluding firms in steel and aluminum related industries. Panel B 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 C shows the results using alternative measures for input from China. For each firm-product, we compute the ratio of import quantity from China to import quantity from the world at the HS 6-digit level. We then compute *Qimp_China/Qimp*, by taking the average of the ratios across HS 6-digit categories within each firm. 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 standard errors are reported in the parentheses. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Excluding Some Industries

	(1)	(2)	(3)	(4)
	CAR [-1,+1]			
	Excluding military related industries		Excluding steel and aluminum related industries	
Revenue_China	-0.0848***	-0.0450**	-0.0884***	-0.0474**
	(-5.48)	(-2.37)	(-5.70)	(-2.48)
Input_China	-0.0077***	-0.0051**	-0.0075***	-0.0051**
	(-3.95)	(-2.48)	(-3.87)	(-2.48)
N	2292	2275	2279	2261
adj. R-sq	0.054	0.120	0.054	0.119
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes

Panel B. Alternative Variable Definitions: Fama-French Three-Factor Model

	(1)	(2)	(3)	(4)
	CAR [-1,+1], FF 3-factor			
Revenue_China	-0.0881***		-0.0764***	-0.0375*
	(-5.43)		(-4.61)	(-1.80)
Input_China		-0.0102***	-0.0086***	-0.0052**
		(-5.02)	(-4.16)	(-2.37)
N	2309	2309	2309	2291
adj. R-sq	0.030	0.029	0.035	0.111
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes

Panel C. Alternative Measures for Input from China

	(1)	(2)
	CAR [-1,+1]	
Qimp_China/Qimp	-0.0132***	-0.0082**
	(-3.99)	(-2.46)
N	2309	2291
adj. R-sq	0.043	0.119
Controls	Yes	Yes
Industry FE	No	Yes

Appendix 5. Robustness Checks Using Matched Samples

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.

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***	-4.57	<0.01
CAR [-1,+1]	-0.034	-0.025	-0.009***	-4.66	<0.01
SIZE	6.972	6.896	0.076	0.76	0.45
MTB	2.275	2.221	0.054	0.71	0.48
LEV	0.243	0.227	0.016	1.59	0.11
ROA	0.062	0.058	0.004	0.43	0.67

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	-0.027	-0.010***	-4.57	<0.01
CAR [-1,+1]	-0.037	-0.028	-0.009***	-4.39	<0.01
SIZE	7.363	7.524	-0.161	-1.28	0.20
MTB	2.087	2.091	-0.003	-0.04	0.97
LEV	0.256	0.265	-0.008	-0.63	0.53
ROA	0.096	0.084	0.011	0.96	0.34

Appendix 6. Medium-Term Impacts

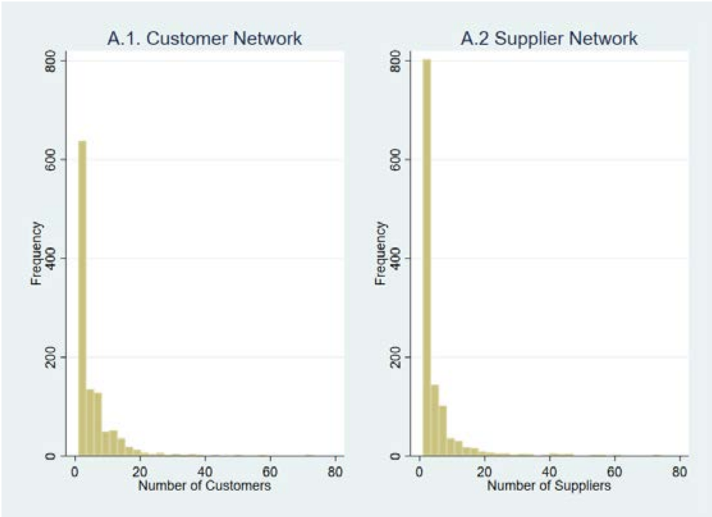
This table presents the results for medium-term effects of the trade war announcement. The dependent variable is buy-and-hold abnormal returns (*BHAR*) over different event windows. Specifically, *BHAR [-1,+X]* is the buy-and-hold abnormal returns around the event window *[-1,+X]* with zero indicating 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 standard errors are reported in the parentheses. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
	BHAR [-1,+20]	BHAR [-1,+40]	BHAR [-1,+60]	BHAR [-1,+80]
Revenue_China	-0.2265***	-0.2292***	-0.1682**	-0.2338**
	(-5.39)	(-3.68)	(-2.01)	(-2.44)
N	2281	2253	2244	2214
adj. R-sq	0.041	0.015	0.024	0.035
	BHAR [-1,+20]	BHAR [-1,+40]	BHAR [-1,+60]	BHAR [-1,+80]
Input_China	-0.0150***	-0.0213***	-0.0214**	-0.0358***
	(-3.06)	(-2.66)	(-2.09)	(-3.17)
N	2281	2253	2244	2214
adj. R-sq	0.033	0.013	0.024	0.036
Controls	Yes	Yes	Yes	Yes

Appendix 7. The Description of the Revere Database

This table shows the description of the Revere Database. 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.

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	0.199	0.329	0.000	0.000	0.357
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	0.329	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	0.417	0.369	0.000	0.400	0.682
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	0.384	0.370	0.000	0.333	0.667

Appendix 8. Procedure for the Textual Analysis

1. We first retrieve the complete list of HS codes from the World Bank website.[42] 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.

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

Appendix 9. Responses of Chinese Firms

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). *CAR [-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. Panel A presents the summary statistics for the Chinese sample. The univariate analysis is reported in Panel B. Panel C presents the regression tables. Panel D shows Chinese firms' responses to the subsequent reverse event, the U.S.-China trade talks 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 *t*-statistics based on robust standard errors are reported in the parentheses. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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***

	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**

Panel C. Regression Analysis

	(1)	(2)	(3)	(4)
	CAR[-1,+1]			
Revenue_US	-0.1390***		-0.1335***	-0.1070***
	(-6.52)		(-6.03)	(-4.84)
Input_US		-0.0046**	-0.0014	0.0003
		(-2.17)	(-0.64)	(0.11)
N	2588	2588	2588	2588
adj. R-sq	0.036	0.029	0.036	0.113
Controls	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes

Panel D. Reverse Experiment of the Trade Talks

	(1)	(2)	(3)	(4)
	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