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

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Abstract

We study the financial impact of the 2018-2019 U.S.-China trade war on firms engaged in global supply chains. Around the dates when higher tariffs were announced, U.S. firms depending more on exports to and imports from China experienced larger declines in market values. Guided by a model that identifies various direct and indirect trade channels through which tariffs affect firms' profits, we examine the transmission of tariff shocks through firms' suppliers and customers. We confirm our results by exploiting the within-firm variation in product exposure based on two tariff lists and a positive trade negotiation as a reverse experiment.

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1. Introduction

A notable feature of economic globalization in recent decades has been the development of many complex global supply chains connecting firms globally. Such enhanced global connectedness permits the greater sharing of economic benefits across firms and countries on the one hand, but amplifies the propagation of shocks across production networks and thus raises macroeconomic uncertainty on the other.[1]

Against this backdrop, the recent unexpected and abrupt changes in trade barriers arising from the U.S.-China trade war, which roiled stock markets globally, offer unique real-world "experiments" for a study of the effects of policy shocks on firms connected through global supply chains.[2] This paper exploits the various tariff announcements by both the U.S. and Chinese governments in 2018-2019 to conduct several event-study analyses about the effects of the perceived increases in trade barriers on firms' financial market performance. Our analysis focuses on the Trump administration's issuance of a presidential memorandum on March 22, 2018, which proposed a 25% tariff on over $50 billion of Chinese imports.[3] We also use as additional events the dates when the first wave of retaliatory tariffs was announced by the Chinese government, when the detailed lists of products subject to tariffs were published by either government, and when the trade talks in Beijing in early 2019 suddenly raised optimism towards a potential trade deal. All these surprising events, as verified by Google search hikes for instance, can be treated as exogenous events for an analysis of the impact of the supply chain disruption on companies' financial outcomes.[4] According to the efficient

[1] See the literature on the propagation of shocks across product networks, which include, among others, Acemoglu et al. (2016a), Barrot and Sauvagnat (2016), Carvalho et al. (2017), Ozdagli and Weber (2017), Pasten, Schoenle, and Weber (2019).

[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)

[4] 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.

market hypothesis, firms' stock valuation should quickly incorporate the news about the upcoming tariff hikes to reflect any expected changes in future cash flows.[5]

The economic implications of the U.S. government's move towards protectionism are ambiguous. Supporters of the U.S. tariffs on foreign goods would argue that tariffs can shift profits from a trade partner back home. However, as various studies have already shown, global trade in recent years has increasingly involved production sharing with foreign firms (Grossman and Rossi-Hansberg, 2006; Baldwin, 2011; Johnson and Noguera, 2012). Despite alleviating foreign competition, tariffs will raise the costs of inputs and production for firms that directly use imported inputs. They may pass the increased costs to other firms connected through supply chains, including those that do not use foreign inputs. Moreover, tariffs may raise the chance of retaliation by the target country, reducing profits of domestic firms that rely on export revenue from that country. Again, firms' indirect sales exposure matters. Domestic firms that have no direct sales in the target country can still be impacted indirectly, if their customers on the supply chains lose exports to the target country after the imposition of retaliatory tariffs and decide to reduce input demand. In sum, domestic consumers and firms that are dependent on imports and exports, directly or indirectly through the global supply chains, will be impacted by higher tariffs.[6]

Guided by a simple model that identifies the various possible direct and indirect trade channels through which higher tariffs reduce a firm's profits, we conduct several event-study analyses using a number of new granular data sets we put together. We find heterogeneous effects of the tariff announcement across firms with varying degrees of exposure to the policy shocks. Specifically, we find that U.S. firms that import from or export to China experience significantly lower stock returns over the three-day window centered on March 22, 2018, compared to those without any direct exposure. Controlling for the standard firm-level characteristics and industry fixed effects, a 10 percentage-point increase in a firm's share of sales to China is associated with a 0.5 percentage-point lower average cumulative return from March 21 to 23, while firms that offshore inputs directly from China have a 0.6 percentage-point lower average cumulative return than those that do not over the same period. These results

[5] 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.

[6] 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.

are robust to using different standard asset pricing models and various event-window length. We also find higher default risks, as gauged by the growth rate of the implied credit default swap (CDS) spreads, among the more exposed firms over the three-day period centered on the announcement date. The perceived tariff-reduced import competition in the same sector has a positive but economically insignificant effect on firms' stock returns.

Using the firm data to reconstruct the stock market index, we find that about 23% of the market value loss from March 21 to 23 as a result of the U.S. first announcement of tariffs on Chinese products can be attributed to firms' direct import and export exposure to China, with the remaining 77% coming from changes in the other macroeconomic conditions at the sector or national level, such as increased market uncertainty, or firms' indirect exposure through global supply chains.

We thus examine whether firms' indirect exposure to trade with China through domestic supply chains may also affect their responses to the various tariff announcements. To this end, we use newly available buyer-seller linked data to construct four firm-level indirect exposure measures: (1) the average share of revenue from China across a firm's domestic (downstream) buyers; (2) the average share of revenue from China across a firm's domestic (upstream) suppliers; (3) the average exposure to Chinese inputs across a firm's domestic (downstream) buyers; and (4) the average exposure to Chinese inputs across a firm's domestic (upstream) suppliers.

As predicted by our theoretical model, we find that firms with a greater indirect exposure to exports to and imports from China through their (domestic) supply chains have a larger average decline in stock returns around the tariff announcement date, even after controlling for the firms' direct sales and input exposure. Regarding indirect input exposure, we find that U.S. firms connected to more domestic suppliers or buyers that import inputs from China tend to experience a more pronounced decline in stock returns. Regarding indirect sales exposure, we find that U.S. firms connected to more domestic suppliers or buyers that export to China also tend to have a larger decline in stock returns. Importantly, due to publicly listed firms' dense production networks, a firm's indirect exposure to sales in China through its domestic supply chains has an economically larger impact on its stock return, compared to its own direct sales exposure; while a firm's indirect input exposure to China through its domestic supply chains is slightly larger than that of direct exposure.

We then exploit the detailed lists of tariffed products issued by the U.S. and Chinese governments respectively subsequent to the initial tariff announcement to evaluate the impact of the tariffs at the firm-product level.[7] Even though the financial markets digest the news about the upcoming tariff increases, investors remain uncertain about which specific products will be tariffed and when the new tariffs will be imposed. Our event-study analysis shows that U.S. firms with a larger fraction of exported products covered by the list issued by the Chinese government tend to have a larger negative market response around the date of the issuance of the list, while U.S. firms that have proportionally more imported products mentioned in the U.S. tariff list respond more negatively to the announcement.

Finally, as a validation exercise, we exploit the timing of the trade talks in Beijing in January 2019, which offered a positive signal about a potential trade war truce, as a reverse event. We find that firms with a larger share of revenue derived from China or use Chinese inputs tend to have a greater rise in stock prices around the announcement date. We also find consistent patterns of market reactions among Chinese listed firms to the various tariff announcements during the U.S.-China trade war.

The remainder of this paper proceeds as follows. Section 2 reviews the literature. Section 3 describes the model that is relegated to the appendix, and lists the testable hypotheses and the key events used in our empirical analysis. Section 4 describes the various unique data sets we put together for our analysis. Section 5 reports the empirical results. The final section concludes.

2. Literature Review

Our research draws on and advances several strands of literature at the intersection of trade and finance. First, we add to the studies about the economic effects of trade shocks. Studies show that increased import competition, particularly from China, depresses labor market participation and wages (e.g., Autor, Dorn, and Hanson, 2013; Pierce and Schott, 2016), incentivizes firms' innovation (Bloom et al., 2016), enhances product quality (Fieler, Eslava, and Xu, 2018), reduces markup distortions (Edmond, Midrigan, and Xu, 2015), permits tax evasion (Fisman and Wei, 2004; Fisman, Moustakerski, and Wei, 2008), and raises the cost of debt (Valta, 2012). Our paper contributes to these studies by evaluating the impact of abrupt trade policy changes on firms' financial market performance.

Second, our paper contributes to the literature on the financial implications of firms' participation in global trade (Bekaert et al. 2016; Claessens, Tong, and Wei, 2012; Lin and Ye,

[7] To identify the US firms' exported products that were covered by the tariff lists, we conduct a textual analysis on the firms' disclosed product description. To identify US firms' imported goods from China that were mentioned in the tariff list, we exploit the product-level information in the lading database.

2018; Barrot, Loualiche, and Sauvagnat, 2019),[8] by focusing on the impact of unexpected trade policy shocks on firms with heterogeneous exposure to trade linkages. By relating trade policies to firms' performance in the financial markets, our paper naturally contributes to the literature on the relation between financial frictions and trade (e.g., Manova, 2008; Chor and Manova, 2012).

Third, our paper adds to the burgeoning literature on economic networks. 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 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 detailed analyses of the endogenous formation of firms' production networks and their resulting macroeconomic outcomes (Atalay et al., 2011; Barrot and Sauvagnat, 2016; Bernard, Moxnes, and Saito, 2017; Carvalho et al., 2017; Lim, 2017; Oberfield, 2018; Demir et al., 2020; Tintelnot et al., 2020).[9] Other studies have documented the propagation of shocks through firm's internal networks (Giroud, 2013; Giroud and Mueller, 2019). Our paper contributes to the network literature by showing the effects of tariff-triggered supply chain disruptions on firms' financial outcomes. As such, it also relates to the studies on the financial implications of supply chain relationships (e.g., Hertzel et al., 2008; Houston, Lin, and Zhu, 2016).

Fourth, our paper belongs to an expanding literature that exploits the sudden changes in the U.S.-China economic relations to study firms' real-time responses to policy changes using financial data. Among others, Greenland et al. (2019) use firms' equity market reactions to the U.S. granting of permanent normal trade relations (PNTR) to China in 2000 to infer their exposure to future trade shocks.[10] Consistent with our main findings, Amiti, Kong, and

[8] 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.

[9] 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. Tintelnot et al. (2020), and Oberfield (2018) develop models of the endogenous formation of production networks and the resulting macroeconomic implications.

[10] Similarly, Bianconi et al. (2019) examine the effects of the reduced trade policy uncertainty resulting from China's accession to the World Trade Organization (WTO) on U.S. firms' stock market returns.

Weinstein (2020) also find significant declines in stock returns around the tariff announcement dates for the U.S. firms that were more exposed to trade with China. By embedding the event-study estimated reduction in firms' stock returns in a *q* theory of investment, the authors find significant negative effects of the various rounds of tariffs in 2018-2019 on listed firms' investment growth. As one of the first papers exploring the financial market impact of the U.S.-China tariffs, our paper is still distinct from subsequent studies by focusing on the various direct and indirect effects of tariff hikes through the global supply chains on the stock markets.

Fifth, our paper draws heavily from the extensive body of event studies in economics and finance.[11] Most notable of all is Fisman et al. (2014), which examines the adverse impacts of deteriorating Sino-Japanese relations on the two countries' firms' market reactions. Another recent study is Crowley et al. (2019), who study the effects of the EU's announcement of import restrictions on the stock returns of Chinese solar panel firms.

Last but not least, our paper contributes to the growing body of literature on the macroeconomic effects of the U.S.-China trade war (e.g., Amiti et al., 2019; Cavallo et al., 2019; Fajgelbaum et al., 2020). Amiti et al. (2019) and Fajgelbaum et al. (2020) find that the U.S. tariffs significantly increase U.S. consumer prices due to the almost complete pass-through of the tariffs.[12] Fajgelbaum et al. (2020) furthermore find, based on a general-equilibrium model, the tariff-induced increases in prices resulted a $7.2 billion aggregate real income loss in the U.S. by the end of 2018.

3. Background and Hypotheses

3.1 Background

Since its economic reforms in 1978, China has grown substantially in terms of aggregate income, investment, consumption, and trade in four decades. It surpassed the U.S. to become the largest trading nation in the world,[13] and in 2015, surpassed Canada as the U.S.'s largest trading partner.[14]

Trump's economic policies since the beginning of his presidency have been overall anti-trade, with China often being the target. His complaints about China ranged from currency manipulation and unfair practices against foreign businesses, to the persistent U.S. trade deficit

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[11] 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.
[12] 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.
[13] 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
[14] Source: U.S. Census https://www.census.gov/foreign-trade/statistics/highlights/top/index.html

with China.[15] There are also critical concerns about China's policy of forcing U.S. technology-intensive firms to enter into joint ventures with Chinese companies, sharing technology in return for market access, as well as its alleged theft of the U.S. intellectual property. To address these issues and hope to induce policy changes in China that would be more favorable to U.S. businesses, the Trump administration issued a presidential memorandum in reference to Section 301 to propose tariffs on Chinese products in March 2018.

As discussed in the introduction, we use the March 18 announcement as the key event, together with three other events to evaluate the financial market impact of the U.S.-China trade tension.[16] Details about the four events are as follows:

1. March 22, 2018: The Trump administration unexpectedly issued a presidential memorandum in reference to Section 301 of the *Investigation of China's Laws, Policies, Practices, or Actions*. The memorandum proposed a 25% tariff on up to $50 billion of Chinese imports as a response to China's alleged theft of U.S. intellectual property. Trump gave the U.S. trade representative, Robert Lighthizer, 15 days to come up with a list of products to impose tariffs on.
2. March 23, 2018: The Chinese government retaliated by imposing tariffs of 15-25% on a list of 128 products, should the U.S.-China trade negotiations fail.
3. April 3, 2018: The U.S. trade representative published a provisional list of imports that would be subject to the new duties of 25%, covering about 1,300 Chinese products and approximately $50 billion of imports from China.
4. January 7-9, 2019: Trade negotiations between the U.S. and China were held in Beijing. The trade talks ended with some progress in identifying and narrowing the differences between two sides. Subsequent top-level talks were confirmed.

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 from the event studies using the other three announcements as events.

3.2 Model and Hypotheses

The primary goal of this paper is to empirically examine the financial implications of the sharp increases in tariffs for firms connected through global supply chains, guided by a

[15] China's exports, particularly those to the U.S., have skyrocketed since 2001 when it was accessed to the WTO. Various studies, most notably Autor, Dorn, and Hanson (2013) and Pierce and Schott (2016), show significant negative effects of increased Chinese imports on the U.S. labor market outcomes.
[16] A detailed list of all 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

simple theoretical model as outlined in Appendix 1. Our model, built on the general-equilibrium production network model of Tintelnot et al. (2020), features two countries (Home = U.S. and Foreign = China), monopolistically competitive firms using labor, domestic inputs and imported inputs to produce goods. Firms' output can be sold to domestic downstream firms as inputs, as well as final goods to domestic and foreign consumers.[17]

The model shows various direct and indirect (general-equilibrium) effects of Home's import tariffs and Foreign's retaliatory tariffs (see Appendix 1 for details). Foreign's retaliatory tariffs will directly reduce Home firms' exports to Foreign and thus profits. There will be two indirect general-equilibrium effects on Home firms' profits. The first indirect effect arises from reduced input demand from Home's buyers (downstream firms), which lose export sales in Foreign. Yet another indirect effect originates from higher prices of Foreign inputs, due to the tariff-induced increases in Foreign firms' production costs.

Regarding the impact of Home's own tariffs, firms that directly import inputs will obviously suffer from higher costs of inputs and hence production. Firms that do not directly import inputs will also be affected due to their engagement in domestic supply chains. There will also be two indirect general-equilibrium effects. The first indirect effect arises from higher prices of domestic inputs provided by certain Home's (upstream) suppliers, which import inputs directly and pass down part of the tariff-triggered increased costs to their buyers. Another indirect effect arises from the reduced sales of and thus demand for inputs from Home's buyers (downstream firms), as some of them cut down production due to the tariff-induced increase in production costs.

The following testable hypotheses summarize these theoretical arguments.

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

An increase in a foreign country's import tariffs will lower the values of firms exporting there.

Hypothesis 2 (direct impact of import tariffs):

An increase 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), an increase in the foreign country's import tariffs will lower domestic firms' values due to two indirect effects, which arise from (1) higher prices of imported inputs from foreign suppliers and (2) lower sales to domestic downstream firms that lose exports.

[17] 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.

Hypothesis 4 (total impact of import tariffs):

In addition to the direct impact (i.e., due to higher imported inputs prices), an increase in a country's import tariffs will lower domestic firms' values due to two indirect effects, which arise from (1) higher prices of domestic inputs from suppliers that pass down the cost shocks and (2) lower sales to domestic downstream firms that cut down production.

The following section discusses how we empirically examine these hypotheses.

4. Regression Specification and Data

We adopt an event study approach, exploiting several exogenous policy announcements by the U.S. and Chinese governments in 2018-2019 and a number of recently available datasets, to study the heterogeneous effects of the U.S. and Chinese tariffs on U.S. firms' financial market performance. By focusing on the unexpected U.S. surprising tariff announcement on March 22, 2018 and three subsequent events as discussed above, the event-study approach is largely immune from endogeneity issues related to firms' endogenous trade participation.

We estimate the following regression specification using the cross-section of firms.

$$Y_i = \alpha + \beta Exposure_i + \boldsymbol{X}_i + \varepsilon_i, \qquad (1)$$

where Y_i measures firm *i*'s stock return or other financial market performance. The key regressor of interest, $Exposure_i$, is a measure of firm *i*'s trade relationship with China. $\boldsymbol{X}_i$ is a vector of firm controls, including firm size, market-to-book ratio, leverage, and return on assets. ε_i is the error term. A detailed description of the construction of all variables will be discussed in the following section.

We measure firm *i*'s stock return as the change in its stock price over the short window centered on the date of the announcement of new tariffs. By denoting the event date as date 0, the cumulative raw returns (*CRR*) over the three-day window centered on date 0 is

$$CRR_i[-1, +1] = \sum_{t=-1}^{+1} R_{it}, \qquad (2)$$

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

To take firm *i*'s risk level into consideration, we compute the cumulative abnormal returns (*CAR*) of firm *i* as

$$CAR_i[-1, +1] = \sum_{t=-1}^{+1} AR_{it}, \qquad (3)$$

where AR_{it} is the abnormal return for firm *i*'s equities on date *t*, calculated using the standard capital asset pricing model (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 tariff announcement by the U.S. government, we will mainly use a firm's *CRR* over a three-day window as the dependent variable, and use *CAR* to provide complementary evidence. For robustness checks, we will repeat the main analysis over a longer time horizon, and compute firms' abnormal returns using the Fama-French three-factor model.

To empirically examine the four hypotheses listed in the previous section, we use several data sources to measure a firm's direct and indirect exposure to trade with China. A firm's direct input exposure measure is constructed using the U.S. bill of lading (BOL) data. The BOL data cover all transactions of waterborne imports into the U.S. For 2017, the data contain about 5 million BOL records from China, with information on the country of origin of the shipper, quantity, and product code.[18] One limitation of this database is that BOL does not provide the value of each transaction, which prevents the construction of a continuous measure of the relative importance of Chinese inputs. We thus construct a dummy variable (*Input_China*) for each firm to indicate whether it has outsourced inputs from China.[19] In a robustness check, we show that using the log value of quantities or weights of the imports from China yields consistent results.

A firm's direct sales exposure, *Revenue_China*, is measured as the share of revenue derived from China in the firm's total revenue in 2016. The information to construct this variable is from the Factset Revere database.[20] Intuitively and according to Hypothesis 1, firms that are more dependent on sales in China are expected to respond more negatively to China's retaliatory tariffs. For instance, Apple Inc., Alphabet Inc., and Exxon Mobil derive 20.8%, 8.9%, and 5.9% of their revenue from China, respectively; and Apple's stock return is expected to drop more in response to the Chinese government's announcements of tariffs.

[18] 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.

[19] 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.

[20] 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.

Besides assessing the direct effects of tariffs, we will also examine the various channels of the indirect effects, as outlined in Hypotheses 3 and 4. To this end, we will use the newly available buyer-seller linked data from Factset Revere to construct four firm-level measures of exposure to trade with China in production networks: (1) the average revenue from China of a firm's domestic (downstream) buyers; (2) the average revenue from China of a firm's domestic (upstream) suppliers; (3) the average exposure to Chinese inputs of a firm's domestic (downstream) buyers; and (4) the average exposure to Chinese inputs of a firm's domestic (upstream) suppliers.

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.

Table 1 reports the summary statistics of the dependent and independent variables used in the regression analyses, at both the firm and industry levels. 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.[21] The market lost a total of $911 billion over the three days, according to our sample firms, implying an average market value loss of around $395 million for each U.S. firm.

[Table 1 about Here]

The mean of U.S. firms' direct input exposure to China, *Input_China*, is 0.24, implying that 24% of U.S. listed companies directly imports from China. U.S. firms' sales exposure, *Revenue_China*, has a mean of 2.5% and the median equal to 0. 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 controls. The data to construct these variables are from Compustat.[22] Appendix 3 provides detailed definitions of the variables.

[21] Notice that equivalently, $MV\_Change_i[-1,+1] = MV_{i,-2} \cdot CRR_i[-1,+1]$.

[22] 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.

5. Empirical Results

5.1 Validity of the Research Design

To confirm the validity of the event study, we first provide evidence that the first tariff announcement by the U.S. government 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, the S&P 500 index (right scale) dropped by 2.5% on March 22, 2018, and by 4.8% from March 21 to March 23. The weighted average stock returns, with weights equal to the U.S. firms' market value shares in our sample, dropped by 2.3 percentage-points on March 22, 2018, and by 4.3 percentage-points from March 21 to March 23, corresponding to a $487 billion market value loss on the event day and $911 billion loss over the three-day event window. Appendix 2 lists the weighted sample average returns over different event window lengths around the same event.

Figure 1 also plots the public interest in the trade war based on the frequency of keyword searches for "trade war" using the Google search engine (left scale). Research suggests that the trends in Google searches can be used to measure investors' attention (e.g., Da et al., 2011). Public interest in the trade war peaked on March 22, the day when the Trump administration announced the 25% tariffs on $50 billion of imports from China.[23] Similarly, abrupt declines in the S&P 500 index and "trade war" search spikes are observed for the other announcement dates (e.g., April 5 when Trump proposed additional tariffs against China), despite by smaller magnitudes. These results suggest that the market was surprised by the U.S. tariff announcement, especially by the first one on March 22.

[Figure 1 about Here]

Based on our search of news articles and academic studies, we find no other significant events on March 22 that can explain the overall market movement in the U.S., 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 Bolton, as announced by Trump on Twitter on March 22, 2018. The second event is the imposition of Section 232 tariffs on aluminum and steel imports from all countries, which was announced by the U.S. government on March 1, 2018 and came into force on March 23, 2018. It is unclear how these events would contaminate our results, given our focus on the heterogeneous effects of policy announcements across firms with different degrees of exposure to the U.S.-China trade. Unless

[23] 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.

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. Nevertheless, we will conduct robustness checked by dropping firms in industries that are likely to be affected.

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. 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, and a subsequent event that reverses the market sentiment about the trade war in January 2019. We will also use detailed tariffed product lists issued by either the U.S. and Chinese government subsequent to the March announcement to verify our main results at the firm-product level.

Finally, our hypotheses that firms' stock returns with change depending on their heterogeneous exposure to U.S-China trade rests on the premise that information on firms' participation in trade and supply-chain relationships are available to investors. This premise will likely hold for various reasons. First, 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. Second, the unexpected trade shocks would also prompt traders to compete in acquiring valuable information about firms' trade exposure. Third, 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 evidence about the impact of the March 22 tariff announcement by the U.S. government on U.S. firms' stock returns, based on their direct trade exposure with China. Table 2 provides suggestive evidence using a simple univariate analysis. We find that the cumulative returns are systematically lower for firms that have trade exposure to China. Specifically, as shown in the first two rows of Panel A, U.S. listed firms that export to China have a 1.1 percentage-point lower *CRR/CAR* over the three-day event window than firms that do not.[24] In addition, we find that these exporting firms are on average larger in terms of market value and more profitable in terms of ROA, but have a lower leverage ratio. These findings warrant the need to control for these firm characteristics in the regressions.

[Table 2 about Here]

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

In Panel B of Table 2, we compare the means of these variables of interest between the two subsamples of firms separated according to whether they offshore inputs from China or not. We find that firms that import inputs from China have on average a 1.3 percentage-point lower *CRR/CAR* over the three-day window than firms without any input exposure to China. Firms that offshore inputs from China also appear to be bigger and have a higher ROA.

Next, we regress firms' stock returns on the two measures of direct trade exposure to China. Table 3 reports the OLS regression results.[25] Panel A shows that firms that sell proportionally more to China have a relatively lower average *CRR* over the three-day window centered on March 22, 2018, while those that import inputs from China tend to have lower *CRR* than firms that do not. Column (1) suggests that a 10 percentage-point increase in a firm's share of sales to China is associated with a 0.92 percentage-point lower *CRR* when the four firm characteristics (firm size, market-to-book ratio, leverage, and ROA) are controlled for. As column (2) shows, the average *CRR* is 0.96 percentage-point lower than the average of firms that have zero imports from China. Column (3) shows that the coefficients on both exposure measures remain quantitatively similar when they are jointly estimated in the regression.

When industry (Fama-French 30 industry portfolios) fixed effects are included in column (4), the estimated effects of the direct input exposure shrinks to 0.5 percentage-points, while that on sales exposure shrinks to 0.43 percentage-points (for a 10 percentage-point increase in the Chinese export share). This reduced magnitude 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 explain a significant within-industry firms' heterogeneous responses to the tariff announcement, which rely on individual firms' supply-chain participation.

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

$$\text{Industry\_IP}_k = \frac{IMP\_CN_k}{SHP_k + IMP_k - EXP_k}, \tag{4}$$

where IMP_CN_k stands for 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.[26] We also construct the sector

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

[26] The data are from 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.

measure for total exports to China as $\text{Industry\_Export}_k = \frac{EXP\_CN_k}{SHP_k}$, where EXP_CN_k represent total exports to China in sector *k*.

The regression results presented in column (5) show a positive coefficient on the measure of ex-ante import competition from 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 noting that the magnitude of the effect of reduced import competition is small. Firms in sectors with a 10 percentage-point higher import penetration are associated with only a 0.05 percentage-point higher return. Compared with the effects due to different degrees of firms' 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 input 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 stock returns 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.[27] In other words, about 23% (= (0.54 + 0.47)/ 4.32) of the negative market response is attributed to firms' direct trade exposure. The remaining 77% can come from changes in the other macroeconomic conditions at the sector or national level, such as increased market uncertainty, 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 estimated declines in a firm's cumulative

[27] 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.

abnormal return (*CAR*) due to its exposure to China are close in magnitude to those based on its *CRR*.[28]

[Table 3 about Here]

Besides affecting firms' stock returns, the U.S. government's sudden change 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, as deteriorating firms' financial performance should increase their probability of bankruptcy (Acemoglu et al., 2016b). The increased uncertainty about the future U.S.-China economic relations may induce firms to postpone investment and other long-term plans, or adopt suboptimal strategies (Bloom, 2009). 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:

$$Default\ Risk_i[-1, +1] = \sum_{t=-1}^{+1} CDSR_{i,t}, \quad (5)$$

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 from Bloomberg.

As reported in Panel C of Table 3, 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 percentage-point increase in its default risk. On the import side, firms that import inputs from China have an average 0.45 percentage-point higher default risk. In sum, not only that firms' exposure to trade with China affects their stock price responses to the March 22 announcement, it also raises investors' perception of risks among the more exposed firms. In other words, the U.S. policy announcement 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 March 22, 2018. There is no obvious reason why the appointment would influence the financial

[28] 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*.

markets in the U.S. and China. Moreover, as long as the effect of the new appointment clusters at the sector level, our estimation of the trade war effect will not be biases as industry fixed effects are always included. 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.[29] As shown in columns (1)-(2) of Panel A in Appendix 4, our results remain unchanged after those firms are excluded from the sample.

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. It is worth noting that the increased tariffs were imposed on steel and aluminum imports from all countries, not only from China. Hence, firms' exposure to this confounding event is unlikely to be correlated with firms' exposure to China. We show in columns (3)-(4) in Panel A that excluding firms in the steel and aluminum industries does not affect our main results.[30]

Second, we check the robustness of our results by using different asset pricing models to adjust firms' stock returns. As is shown in Panel B of Appendix 4, using the Fama-French three-factor model to estimate firms' CARs yield results that are quantitatively similar to our baseline results. 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.[31] As is shown in Panel C, we find that firms that have a larger fraction of imports from China also tend to experience a larger decline in stock returns 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 standard firm characteristics in the regressions to mitigate any omitted variable biases, concerns still remain about the potential firms' selection into trade. 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. As shown in Appendix 5, while there is no statistically difference in the four firm variables between the group of firms that export to China vis-a-vis those that do not, their respective cumulative stock returns are significantly different, a pattern that is consistent with our baseline results reported

[29] 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.
[30] 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.
[31] 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.

in Table 3. We also find supporting results from the two samples of firms categorized based on their input exposure to 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

$$BHAR_i[-X, +Y] = \prod_{-X}^{+Y}(1 + R_{it}) - \prod_{-X}^{+Y}(1 + MR_t), \qquad (6)$$

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 of Table 3 with *BHAR[-20,-2]*, which measures the buy-and-hold abnormal returns from 20 days before the announcement of the tariff hikes to 2 days after the announcement. A negative correlation between *BHAR[-20,-2]* and the exposure measures would indicate the possibility that our baseline results are driven by some other contemporaneous events during the sample period. In the pre-event regression, we fail to reject the null hypothesis that the two exposure variables are different from zero.

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 tariff announcement on firms' 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). 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 percentage-point 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 percentage-point lower stock return 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 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 supply 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 Compustat Segment database, commonly used by prior supply-chain analyses (e.g., Atalay et al., 2011; Houston et al., 2016), is built with the information on supply-chain relationships firms disclosed in their 10-Ks (annual reports).[32] It captures about 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 cover more firms and industries than Compustat Segment and other supply-chain data sets. Specifically, Factset Revere actively monitors 10,000 globally listed firms and captures up to 25,000 buyer-supplier relationships per year.[33]

Although the Factset Revere database represents the best available commercial database of its kind, we acknowledge that the coverage of the database is still incomplete, as it is built on public disclosure and hence has a large-firm focus. For instance, small customers that account for less than 10% of a firm's revenue is more likely to be excluded in the firm's disclosure and thus omitted in the database. Another potential selection issue may arise from firms' voluntary disclosure of their suppliers. We use a two-way matching process that exploits information reported from either side of a relationship in the database to construct a more complete production network. We first retrieve all reported information of a firm's customers and suppliers in the database, respectively. As a supplier firm may disclose a customer, while the same customer may not report the supplier as a link, the two-way matching process will increase the number of valid links substantially.

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 onset of the trade war to identify the potentially on-going upstream and downstream links.[34] We also exclude relationships from

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[32] The Securities and Exchange Commission (SEC) requires U.S. listed firms to make mandatory supply chain disclosure. Each listed company is obliged to publicly disclose any customer that commands 10% or more of its revenue. 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. Firms also voluntarily disclose non-major customers that account for less than 10% of their revenue in financial reports.

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

[34] 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.

the sample if either side is excluded in our regression sample, namely unlisted, foreign, or financial firms. The final network sample covers 5,552 buyer-seller links.

As discussed above, 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) to construct these exposure measures to analyze the propagation of shocks through input-output linkages. Figures 3 and 4 illustrate the rationale behind the variable construction.

[Figure 3 about Here]

The first indirect exposure measure is a firm's average sales exposure to China across its domestic (downstream) customers:

$$Revenue\_China\_Customers_i = \frac{1}{M}\sum_{m=1}^{M} Revenue\_China_{i,m}, \quad (7)$$

where M indicates the number of firm i's domestic customers, while $Revenue\_China_{i,m}$ measures firm i's direct sales exposure to China. 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 foreign sales of firms B and C, which will then lower their 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. As is shown, GE itself sells to China, but over one-third of its first and second-tier customs, especially the more connected ones, also sell to China.

The second indirect exposure measure is a firm's average input exposure to China across its domestic (downstream) customers:

$$Input\_China\_Customers_i = \frac{1}{M}\sum_{n=1}^{M} Input\_China_{i,n}, \quad (8)$$

where $Input\_China_{i,n}$ is an indicator equal to one if customer m has outsourced inputs from China, and zero otherwise.[35] 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 Chinese inputs for B and C, potentially lowering their output and thus demand for goods from firm A. The production network of GE is plotted in Panel D of Figure

[35] 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.

3, with now the blue nodes indicating GE's U.S. customers that have sourced inputs from China. As is shown, GE itself uses imported inputs from China, but over one-third its first and second-tier customs, especially the more connected ones, also source inputs from China.

The third indirect exposure measure is a firm's average sales exposure to China across its domestic (upstream) suppliers:

$$Revenue\_China\_Suppliers_i = \frac{1}{N}\sum_{n=1}^{N} Revenue\_China_{i,n}, \qquad (9)$$

where *N* is 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 firms B and C's sales to Chinese customers. The potential production downsizing of B and C and the accompanying adverse performance shocks could reduce their supply of and increase prices of inputs to firm A. As an 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. As it turns out, a majority of Boeing's first and second-tier U.S. suppliers also sell to China.

The last measure is a firm's average input exposure to China across its domestic (upstream) suppliers:

$$Input\_China\_Suppliers_i = \frac{1}{N}\sum_{n=1}^{N} Input\_China_{i,n}, \qquad (10)$$

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 firm A's production costs. Thus, firm A could suffer from the pass-through effect of the elevated costs from the tariff hikes. Panel D plots the two-layer supplier network of Boeing, as in Panel C of Figure 4. The blue nodes indicate firms that purchase inputs from China while the white nodes indicate firms without inputs from China. As it also turns out, a majority of Boeing's U.S. suppliers source inputs from China.

[Figure 4 about Here]

It is worth noting that not all firms necessarily have a public customer or a public supplier. In either case, we assign the value of zero to the missing indirect exposure 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 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 GE, Walmart, Boeing, Microsoft, and Amazon.com are the sample firms with the largest numbers of suppliers. Panel B presents the descriptive statistics of the firms' indirect exposure measures. 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. 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 tariff announcements through firms' indirect exposure. Table 4 shows the impact of indirect sales exposure through a firm's suppliers and customers. The univariate analysis in Panel A indicates that compared with the rest of the sample firms, firms with some customers that have sales in China experience a 1 percentage-point lower stock returns, as measured by either *CRR* or *CAR*. Firms with suppliers that derive revenue from China experience a 1.1 percentage-point lower stock returns. The regression results reported in Panel B show significant effects of the tariff announcement on firms' *CAR* through the two indirect sales exposure channels (through a firm's customers' and suppliers' sales exposure to China), even after firm's direct sales exposure to China is also controlled for. These results provide supporting evidence for Hypothesis 3. Specifically, column (1) shows that a 10 percentage-point increase in indirect sales exposure through domestic customers (*Revenue_China_Customer*) is associated with a 1.1 percentage-point lower *CAR* over the three days centered on March 22. Column (2) shows that a 10 percentage-point increase in indirect sales exposure through domestic suppliers (*Revenue_China_Supplier*) is associated with a 0.89 percentage-point lower *CAR*. The effects remain significant when both indirect exposure measures are jointly estimated in the regression (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 exposure measures (0.0915 + 0.0782) is significantly larger than the coefficient for the direct measure (0.0594).

[Table 4 about Here]

To quantify the aggregate impact through the direct and indirect exposure, respectively, we first multiply the given measure of each individual firm with the corresponding coefficients in column (3) of Panel B to compute the value-weighted average effect of each channel, with weight equal to the firms' market values on March 20, 2018. Over the three-day event window, firms' direct sales exposure to China corresponds to a 0.35 percentage-point decline in aggregate stock market returns. The indirect sales exposure through domestic customers is associated with an additional 0.18 percentage-point drop in aggregate stock returns, whereas the indirect sales exposure through domestic suppliers contributes another 0.34 percentage-point decline in aggregate stock returns.[36] These computation based on our firm sample implies a roughly US$73.8 billion market value loss due to direct sales exposure, US$37.9 billion loss due to the indirect sales exposure through customers, and another US$71.7 billion loss due to indirect sales exposure through suppliers.[37] In other words, despite a smaller aggregate impact of each of indirect exposure channels, the sum of the two indirect exposure effects is quantitatively larger than that of direct exposure. Column (4) show that even when industry fixed effects are included, the effects of both sale exposure through customers and suppliers remain statistically significant and economically similar.

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 input exposure versus firms without. Specifically, firms with customers that purchase inputs from China experience an average 0.9 percentage-point additional decline in three-day stock returns than firms without. Similar differences can be observed between firms with suppliers that import inputs from China and those that do not. Panel B presents consistent regression results that support Hypothesis 4. Specifically, column (3) suggests that firms that directly purchase inputs from China (*Input_China*) on average experience a 0.8 percentage-point lower stock return compared to those that do not. Firm's indirect input exposure through customers (*Input_China_Customer*) and through suppliers (*Input_China_Supplier*) both demonstrate significant effects on stock returns, indicating a combined magnitude of the coefficients slightly larger than the direct measure. Using a similar approach discussed above, 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 percentage-point aggregate market value decline, while indirect exposure measures *Input_China_Customer* and

[36] 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.

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

Input_China_Supplier contribute additional 0.20 and 0.23 percentage-point drops in aggregate stock returns, respectively. It is worth noting that when industry fixed effects are included as regressors in column (4), the effect of input exposure through customers become insignificant, while that through suppliers remain statistically significant and similar in magnitude.

[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 effects of perceived tariff hikes on the firm's value, even when it has no direct trade relationship with China. Indirect trade exposure is found to reduce a firm's cash flows due to lower demand from affected domestic customers and suppliers, and an increased input and thus production costs through domestic suppliers.

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 list of tariffed products, we can conduct an event study at a more granular level and examine whether the heterogeneous effects of the tariff announcements 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 Trump issued the presidential memorandum in March 2018.

By the end of 2018, the U.S. government had issued three tariff lists and the Chinese government had issued three retaliatory tariff lists. Specifically, the U.S. government issued its the tariff 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 tariff lists on March 23 (128 products), April 4 (USD 50 billion of U.S. goods), and August 3 (USD 60 billion).[38] Each product list covers additional products compared to the previous lists. As a confirmatory

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

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.

On March 23, 2018, the Chinese Customs Tariff Commission issued its first product list, 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, amounting to a total import value of about $3 billion. The list proposes 25% tariffs on pork products and aluminum scrap, and 10% tariffs on other imported U.S. commodities, such as wine, nuts, fruits, and steel piping.[39]

The first challenge of this exercise is to identify the products produced by each listed firm. In Compustat and most of the major firm data sets, firms typically report only their main industry. Following the literature (e.g., Hoberg and Phillips, 2016), we conduct a textual analysis of U.S. firms' product descriptions as 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 produced by individual firms. We then combine these two lists with the products covered 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 firms' output mix. Regardless of whether the four firm characteristics (column (2)) or industry fixed effects (column (3)) are controlled for, there is a negative and statistically significant correlation between firms' *Output_China_List* and their 3-day CAR centered on March 23, 2018. These results suggest that not only firms with a larger sales exposure experience a larger drop in market value as documented above, those that have proportionally more products tariffed by China's Customs respond more negatively in the financial markets to the March 23 announcement. Specifically, a 10 percentage-point increase in the fraction of products covered by the first Chinese tariff list is associated with an additional 1.1 to 1.3 percentage-point decline in stock prices between March 22 and 24.

[Table 6 about Here]

[39] 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 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.

We define the variable, *Input_China_List*, as a firm's fraction of imported products from China that are covered by the April 3 tariff list.[40] As Panel B of Table 6 shows, U.S. firms with more inputs covered by the U.S. tariff list experience more negative returns in the 3-day window centered on April 3. Specifically, a 10 percentage-point increase in the fraction of Chinese inputs covered by the U.S. tariff list is associated with an additional 0.06% (column (2) when firm characteristics are controlled for) to 0.07% (column (3) when industry fixed effects are also included) decline in stock prices between April 2 and April 4.

We further use the variation in the tariff rate changes across products to assess the impact of the announcement of the tariff list at the intensive margin. Specifically, we first compute the difference between the new tariff rate according to the tariff list and the original tariff rate at the HS 8-digit product level. We then use the BOL data to identify firms' specific imports from China at the same product level. *Tariff_Change* is defined as the weighted average tariff increases, using transaction quantities as weights.[41] 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 percentage-point (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.

The evidence based on the within-firm variation in the exposure to the tariffs across products suggests that firms' responses to the trade policy shocks are consistent with our theoretical predictions. Furthermore, it also reveals that market participants refine and update their valuations of the firms when the uncertainty about the details of the new tariffs is gradually resolved.

5.5 The Reverse Experiment

[40] 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.
[41] Recall that we do not have the information on the transaction value for each firm.

We have already offered evidence confirming that the heterogeneous effects of the tariff announcements are not only transitory, but medium-term. Several unanticipated events in 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 mostly believed that the discussions had made progress. As shown in Figure 5, the public interest in "trade talks", as indicated by the frequency of searches using the main search engines from both countries, peaked on January 9, 2019. We hence evaluate the firms' stock price responses around this date, which are expected to offset the cumulative 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 trade data to accommodate the adjustments during this year. In the three-day window centered on the event date, firms that have sales in China gain an additional 0.6 percentage-point raw returns relative to firms that do not sell to China. Compared with the firms without inputs from China, the firms that outsource inputs from China experience a 0.7 percentage-point larger gain in stock returns. This pattern is confirmed by the regression results reported in Panel B. However, the effect of *Input_China* becomes 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 tariff 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.[42] Therefore, we conduct a similar set of event-study analyses from the perspective of Chinese publicly listed firms. To this end, we use a Chinese customs dataset that

[42] Carpenter and Whitelaw (2017) and Carpenter et al. (2020) suggest that in recent years, stock price informativeness of the Chinese market is comparable to that of the US market.

contains firm-product level information on each Chinese firm's transactions of imports from and exports to 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 match firm names from China's customs data with those from the CSMAR data. We then manually check the accuracy of the matches to generate the final matches between the two datasets. We construct two variables: *Revenue_US*, which is the value of exports to the U.S. as a share of a Chinese listed firm's total revenue in 2016; and *Input_US*, which is an indicator equal to one if a Chinese's firm imports into the U.S. in 2016 is positive, and zero otherwise.

Appendix 9 presents the results for Chinese listed companies. Based on a sample of 2,588 firms, Panel A shows that 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. The mean share of exports to the U.S. in the total sales is 0.9%,[43] with 26% of Chinese firms importing inputs from the U.S. Panel B reports the univariate analysis centered on March 22. Compared with Chinese firms that do not export to the U.S., those that do suffer an additional 0.7 percentage-point drop in market value on average. Moreover, Chinese firms that purchase inputs from the U.S. experienced an additional 0.5 percentage-point decline in market value, compared to those that do not. Similar results are found when firms' *CAR*s are used as dependent variables.

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 percentage-point increase in a firm's share of sales in the U.S. (*Revenue_US*) is associated with a 1.4 percentage-point larger drop in stock prices (column (1) in Panel C). The *CAR* of firms that source inputs from the U.S. are on average 0.5 percentage-point lower than for firms that do no. The effect becomes insignificant when the sales share in the U.S. is also included as a regressor, largely because relatively fewer Chinese firms purchasing inputs from than selling to the U.S. The effect through direct sales exposure to the U.S. remains significant when the industry fixed effects are controlled for.[44] We find supporting evidence based on the same reverse experiment explored above, based on the U.S.-China trade talks in January 2019 (see Panel D of Appendix 9). Taken together, the

[43] 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.
[44] We define the industries using the 2012 classification of the CSRC. There are 74 industries in our sample.

evidence based on Chinese listed firms indicates consistent patterns of market reactions to the various tariff announcements during the U.S.-China trade war, especially for firms exposed to exports rather than imports.

6. Conclusion

In this paper, we study the financial impact of the 2018-2019 U.S.-China trade war on firms engaged in global supply chains. Around the dates when higher tariffs or detailed tariff lists were announced, we find that U.S. firms that are more dependent on exports to and imports from China have lower stock returns and higher default risks. Similar patterns are also observed for Chinese listed firms, depending on their trade relationships with the U.S. The results are robust to computing returns using different asset pricing models, alternative regression specifications, longer event windows, and a matching strategy.

We find that the expectation of weakened Chinese import competition due to the U.S. tariffs plays an economically minimal role. U.S. firms' indirect exposure to trade with China through domestic supply chains have an economically stronger negative impact on their stock returns than their direct trade exposure, confirming our theoretical predictions. These responses indicate that the complex structure of global trade plays a crucial role in determining firms' financial market performance. 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 supply chains shared by the two countries.

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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**				
	>0		= 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				
	> 0		= 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				
	> 0		= 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				
	> 0		= 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				
	> 0		= 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.

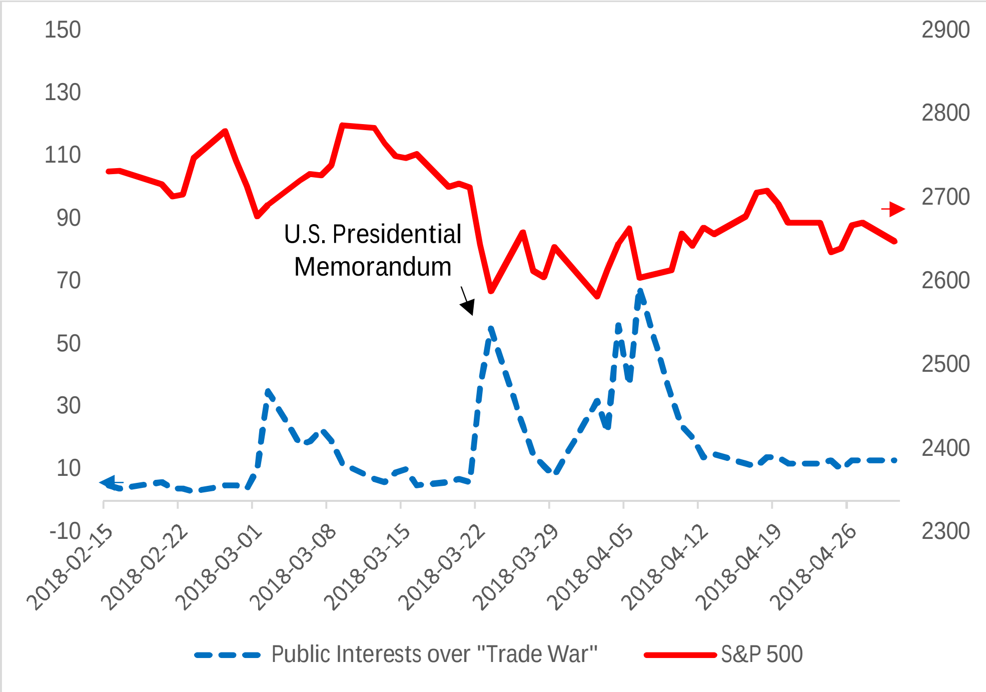
Panel A. Univariate Analysis

	Revenue_China				
	> 0		= 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

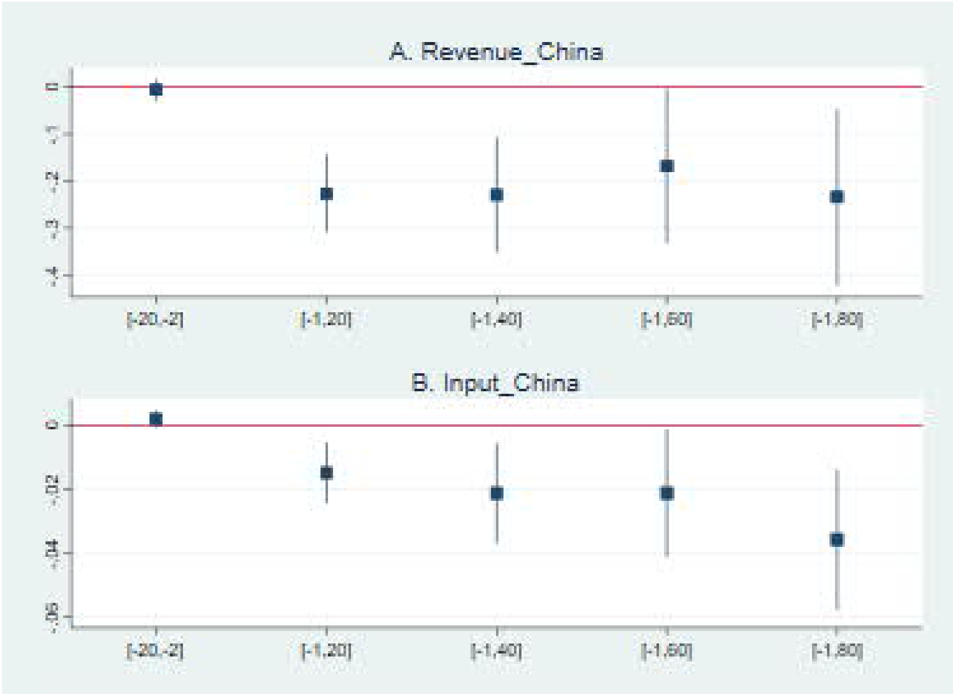
	(1)	(2)	(3)	(4)
	CAR [-1,+1], Jan 9			
Revenue_China	0.0605***		0.0547***	0.0426*
	(3.17)		(2.76)	(1.73)
Input_China		0.0056**	0.0038	0.0040
		(2.06)	(1.37)	(1.33)
N	2127	2127	2127	2112
adj. R-sq	0.007	0.005	0.007	0.012
Controls	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes

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



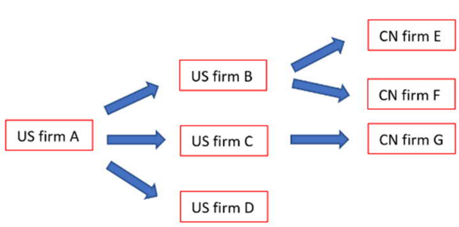
This figure shows the medium-term effect of the declaration of the trade war on firm value. We first run the following regression:

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

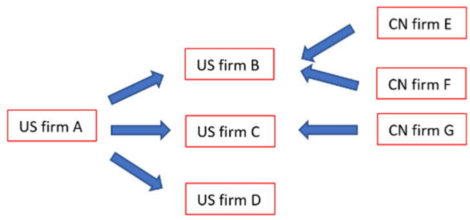
where Y_i denotes the buy-and-hold abnormal returns (*BHAR*) over different event windows. Specifically, *BHAR [-1,+X]* is the buy-and-hold abnormal returns around the event window *[-1,+X]* with zero indicating March 22, 2018 adjusted by the market benchmark. We also consider an event window *[-20,-2] 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

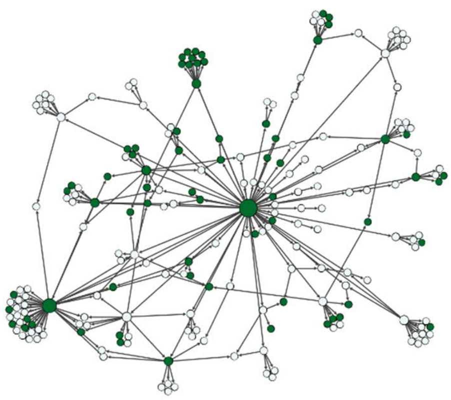
Panel A. Revenue from China



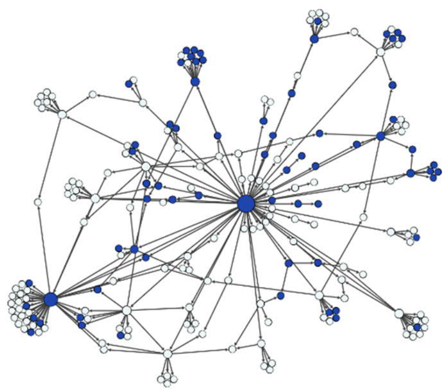
Panel B. Input from China



Panel C. GE's Customers: Revenue from China



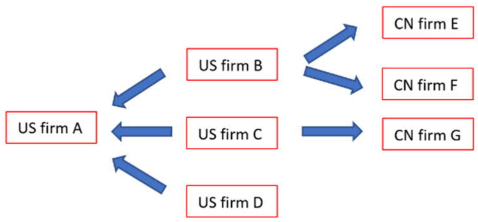
Panel D. GE's Customers: Input from China



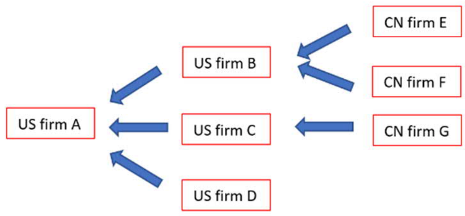
This figure illustrates the firm production networks from the customers' perspectives. In Panels A and B, the direction of the arrows indicates the trade flow. Specifically, in Panel A, the U.S. firm B purchases from firm A and Chinese firm E purchases from U.S. firm B. Similarly, in Panel B, U.S. firm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

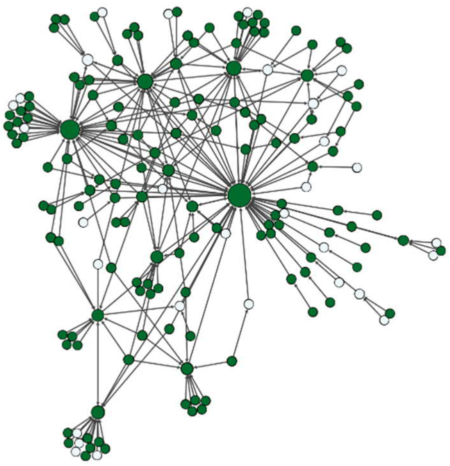
Panel A. Revenue from China



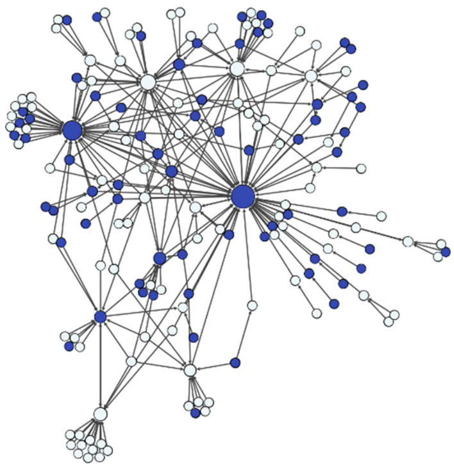
Panel B. Input from China



Panel C. Boeing's Suppliers: Revenue from China

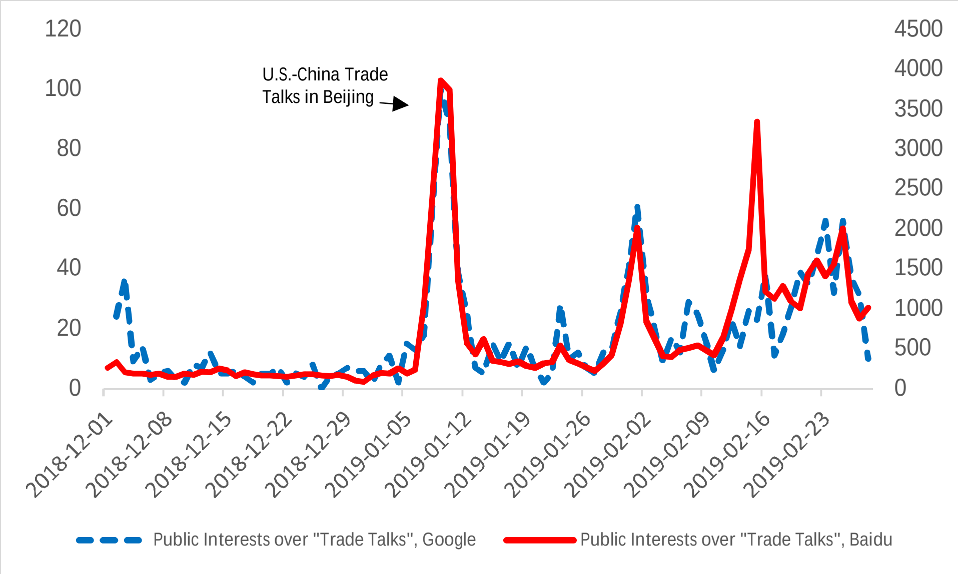


Panel D. Boeing's Suppliers: Input from China



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. (2020). However, we will abstract from the recursive feature of the global value chains, and focus on both the partial- and general-equilibrium insights from the model to guide our reduced-form empirical analysis.[45]

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

[45] 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 offers 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.[46] 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

[46] Tintelnot et al. (2020) assume 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., 2020). 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 domestic input prices, imported input prices, 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:

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

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

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

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

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

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

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

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

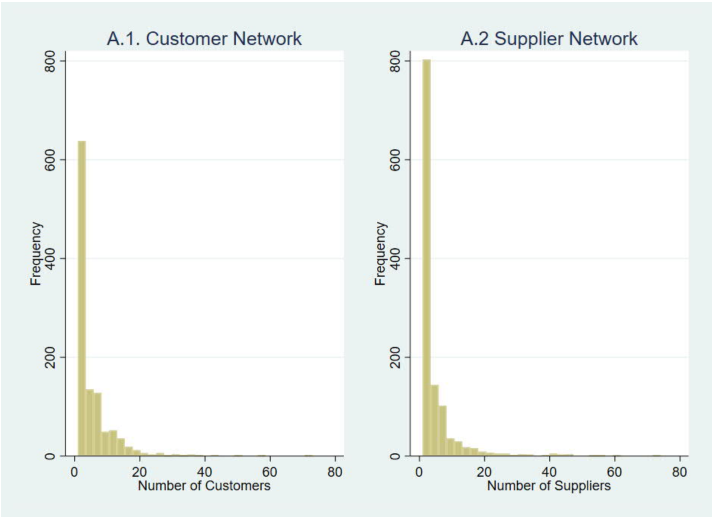
This table presents the results for medium-term effects of the trade war announcement. The dependent variable is buy-and-hold abnormal returns (*BHAR*) over different event windows. Specifically, *BHAR [-1,+X]* is the buy-and-hold abnormal returns around the event window *[-1,+X]* with zero indicating 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.[47] 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.

[47] 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				
	> 0		= 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