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Trade networks and firm value: Evidence from the U.S.-China trade war☆

Yi Huang [a], Chen Lin [b], Sibo Liu [c], Heiwai Tang [d,*]

[a] *Fanhai International School of Finance, Fudan University and CEPR, Shanghai, China*
[b] *Faculty of Business and Economics at the University of Hong Kong*
[c] *Department of Accountancy, Economics and Finance at Hong Kong Baptist University*
[d] *HKU Business School at the University of Hong Kong*

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ABSTRACT

We study the financial implications of the 2018–2019 U.S.-China trade war for global supply chains. Around the dates when higher tariffs are announced, U.S. firms that depend more on exports to and imports from China experience larger declines in market value, with the negative effect spilling over to the affected firms' suppliers and customers through production networks. The trade war effect is mainly concentrated among U.S. firms that sell to Chinese customers with low R&D intensity or outsource to Chinese differentiated input suppliers. We also exploit the within-firm variation in tariff exposure according to the detailed product lists and conduct a reverse experiment based on the 2019 trade talks. To explain the findings, we propose a theoretical model that highlights how complex trade structures shape shareholder wealth.

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* Corresponding author.
E-mail addresses: huang_y@fudan.edu.cn (Y. Huang), chenlin1@hku.hk (C. Lin), siboliu@hkbu.edu.hk (S. Liu), tangecon@hku.hk (H. Tang).

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1. Introduction

In recent decades, globalization has driven an unprecedented reorganization of economic activities across regions, firms, and workers.[1] This reorganization has been accompanied by the establishment of complex global supply chains, which have made firms, and hence nations, more interdependent. While such interdependence has permitted greater sharing of economic benefits between firms and nations (Acemoglu et al., 2016b), it has also amplified the propagation of shocks across complex production networks and thus increased macroeconomic uncertainty (Acemoglu et al., 2016a; Barrot and Sauvagnat, 2016; Ozdagli and Weber, 2017; Lin and Ye, 2018a, 2018b; Pasten et al., 2020; Carvalho et al., 2021).

Against this backdrop, the abrupt changes in trade barriers caused by the U.S.-China trade war since March 2018 can serve as a unique real-world experiment for studying the effects of policy shocks on firms linked to global supply chains.[2] We exploit tariff announcements by the U.S. and Chinese governments in 2018–2019 to evaluate the effects of trade shocks on firms' financial market performance in both countries, due to their *direct* and *indirect* exposure to U.S.-China trade. Our analysis focuses on the Trump administration's presidential memorandum of March 22, 2018, which proposed new and significant tariffs on over 50 billion USD of Chinese imports.[3] As additional events, we exploit the dates when the Chinese authorities announced the first wave of retaliatory tariffs, when both countries' governments issued the detailed lists of products that are tariffed, and when a constructive trade talk took place in early 2019 that reverted market sentiment.

The economic implications of the U.S. move toward protectionism are ambiguous. On the one hand, raising tariffs on imported goods can reduce competition from foreign firms and hence shift profits from a trade partner to the home country. On the other hand, given that global trade increasingly involves production sharing with foreign firms (Grossman and Rossi-Hansberg, 2006; Baldwin, 2011; Johnson and Noguera, 2012), tariffs can backfire by increasing the cost of imported inputs and hence production. As a result, consumers and firms that depend heavily on imports, either directly or indirectly through global supply chains, suffer.[4] Furthermore, the adverse effects of import tariffs on costs and sales can be amplified as they propagate down supply chains until the final stage when goods are sold to consumers.

Firms that cannot alleviate the increase in input costs by switching to suppliers from other countries suffer reduced profits, which inevitably are incorporated into their stock prices. Moreover, given that the imposition of tariffs to protect domestic businesses may raise expectations of retaliation, stock prices of U.S. companies with exposure to the Chinese market should come under pressure as a result of an expected reduction in their exports to China. These adverse effects may also be amplified through interlocking supply chains.

There are at least two advantages of using the 2018–2019 tariff announcements by the U.S. and China for an event study of the impact of supply chain disruptions on companies' financial market performance. First, these announcements, especially the presidential memorandum issued on March 22, 2018 that proposed new tariffs on over $50 billion in Chinese imports, were significant and unprecedented.[5,6] For the most part, investors were surprised by the timing, magnitude, and coverage of the announced tariffs.[7] According to the efficient market hypothesis, stock valuations should quickly incorporate news about tariff increases to reflect expected changes in future cash flows. In contrast, it is difficult to use accounting variables, such as the return on assets (ROA), to assess the effect of tariffs, as those variables reflect the cumulative effects of many events (e.g., interest rate changes and currency fluctuations) during the same accounting period. Meanwhile, we are able to use the subsequent publication of detailed product lists and a reverse experiment in 2019 to validate our main findings.

Second, various data sets enable us to measure U.S. firms' *direct* and *indirect* exposure to imports from and exports to China. In particular, U.S. firms' financial reports provide data on their sales in China, while bills of lading filed with U.S. Customs and Border Protection can be used to measure U.S. firms' import exposure to China at the product level. To measure a U.S. firm's indirect exposure to trade with China through its domestic supply chains, we use new buyer–seller linked data. Specifically, we construct four firm-level measures of exposure to trade with China via production networks: the average revenue from China of a firm's domestic (downstream) buyers; the average revenue from China of a firm's domestic (upstream) suppliers; the average exposure to Chinese inputs of a firm's domestic (downstream) buyers; and the average exposure to Chinese inputs of a firm's domestic (upstream) suppliers.

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1 The literature documents the effects of changing trade policies on firms, industries, and economies. Autor et al. (2013) and Caliendo et al. (2019) focus on the impact of China's integration in the global economy on the U.S. labor market.

2 See, for instance, "Dow drops >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 For the differential effects of trade liberalization on consumers, see Fajgelbaum and Khandelwal (2016), who show that poor consumers in the U.S. benefit more from increased imports because they spend a larger share of their income on tradable goods; also, see Amiti and Konings (2007), among others, for evidence about how firm productivity increases due to access to cheaper and better foreign intermediate inputs, in addition to import competition.

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

6 The value is measured in USD when prefixed by $. When prefixed by RMB, the value is measured in RMB.

7 The initial list of targeted products covers $50 billion in 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.

Based on these newly constructed data sets and a theoretical model, we find that tariff announcements have heterogeneous effects across firms with varying degrees of direct and indirect exposure to trade policy shocks. Specifically, in the three-day window centered on March 22, 2018, our regression results show that U.S. firms that import from or export to China experience significantly lower stock returns than those without direct exposure. Controlling for the standard firm-level characteristics, we find that a one standard deviation increase in a firm's share of sales to China is associated with a 0.48% lower average cumulative return from March 21 to 23. Over the same period, a one standard deviation increase in firms' share of inputs directly from China leads to a 0.29% lower average cumulative return. These results are robust to using different standard asset pricing models. Moreover, firms more exposed to tariff hikes experience a higher default risk than other firms, as gauged by the growth rate of implied credit default swap (CDS) spreads in the three-day event window. Meanwhile, the perceived reduction in import competition within a given sector has a positive effect on stock returns, but it is of a much smaller magnitude than the negative effects. These results suggest that equity analysts use information on individual companies' trade exposure to China to evaluate the differential effects of tariff hikes on firms' future earnings, which we empirically verify using data on analysts' forecasts.

We next investigate how supply chain characteristics affect the expected tariff effects. From the perspective of exports to China, we find that U.S. firms that invest more in research and development (R&D) suffer a smaller decline in stock returns on average. This finding suggests that exporters with higher innovative capacity are less affected by trade frictions, as their Chinese buyers need to incur higher switching costs to find substitutes for the more differentiated products. On the contrary, from the perspective of imports, we find stronger tariff effects for firms importing differentiated inputs from China, as switching to alternative suppliers is probably costlier.

We further examine whether firms' indirect exposure to trade with China through domestic supply chains affect their market responses to the tariff announcements. As predicted by our theoretical model, we find more negative market responses among firms that have greater indirect exposure to exports to and imports from China through their domestic supply chains. On the import side, we find that after controlling for direct import exposure, U.S. firms having indirect exposure to Chinese inputs through their domestic supply chains tend to suffer a more negative stock return in response to the tariff announcement. These results suggest that the perceived increases in upstream and downstream firms' input and production costs are passed to firms with which they are linked through domestic trade. On the export side, we find that firms with domestic suppliers or buyers that derive a large share of their revenue from China tend to suffer larger declines in stock prices. This result suggests that even for firms that have no direct sales in China, market expectation about China's retaliatory tariffs that reduce sales in the upstream or downstream of their supply chains will still lower their stock returns.

Importantly, due to publicly listed firms' dense production networks, we find that a firm's indirect exposure to inputs from and sales in China through its domestic customers and suppliers has an economically larger impact on its stock returns than its own direct sales exposure. These results are consistent with our model predictions.

We conduct additional analysis using the detailed lists of tariffed products issued by the U.S. and Chinese governments subsequent to each announcement. Initially, tariff hike announcements generally leave investors uncertain about the timing and the product scope of the tariff effects. Thus, we use the first product lists issued by the U.S. and Chinese governments, respectively, to evaluate the impact of tariffs at the firm-product level.[8] We find that the stock prices of U.S. firms that export a larger fraction of products covered by the list issued by the Chinese government tend to drop more around the date of issuance of the product list. Likewise, there is a larger negative market response among U.S. firms that import more of the products mentioned in the U.S. tariff list.

To validate our main findings, we conduct a reverse experiment using a subsequent event—the trade talks in Beijing in January 2019—that reverted market sentiment about the trade war. The trade talks were widely believed to signal a truce between the U.S. and China. We find that firms with a larger share of revenue from China or use inputs from China experience greater stock price increases around the announcement date.

Finally, we study a sample of Chinese listed firms and document a pattern consistent with the trade war effect found for U.S. companies, especially among firms that derive a larger share of revenue from the U.S. We also collect Chinese listed firms' supply chain information from their annual reports to construct domestic production networks and find that the adverse effects of tariff announcements spread through a firm's production networks as well.

The remainder of this paper proceeds as follows. In Section 2, we review the literature. In Section 3, we describe the institutional background by listing key events before and after the publication of the presidential memorandum on March 22, 2018. In Section 4, we describe the data sets used to construct the main variables of interest, including direct and indirect exposure to U.S.–China trade. Section 5 reports the empirical results. The final section concludes the paper.

2. Literature review

Our research draws on and advances several strands of research at the intersection of trade and finance. First, we add to the literature on firm-level responses to trade shocks, which includes studies about firms' responses to trade shocks reflected in labor market outcomes (e.g., Autor et al., 2013, 2016; Pierce and Schott, 2016), innovation (Bloom et al., 2016), trade quality (Fieler et al., 2018), markup distortions (Edmond et al., 2015), tax evasion (Fisman et al., 2014), and costs of debt (Valta, 2012). In line with these studies, we evaluate firms' financial market reactions to changes in trade policy.

[8] To identify U.S. firms' exported products that are included in tariff lists, we conduct a textual analysis of firms' product description disclosures. To identify U.S. firms' imported goods from China that are included in tariff lists, we use product-level information in the lading database.

Second, our paper contributes to the literature on the financial outcomes of firms' engagement in international trade (Bekaert et al., 2016; Levine and Schmukler, 2006; Claessens et al., 2012; and Lin and Ye, 2018a, 2018b).[9] Closely related to ours is Barrot et al. (2019), which show a higher risk premium among firms with a larger exposure to import competition, due to a higher risk of displacement. Our paper differs from these studies by using an unexpected event that exogenously affects firms along the global supply chains shared by the U.S. and China.[10] A related study by Greenland et al. (2021) uses equity market reactions to the U.S. decision to grant China permanent normal trade relations (PNTR) status in October 2000 to infer firms' exposure to policy changes. Our study instead focuses on the financial implications of protectionist trade policies, based on firms' exposure to trade policy shocks measured with pre-event trade data.

Our paper also adds to the burgeoning literature on networks, regarding firms' internal networks (Giroud and Mueller, 2019), transportation networks (e.g., Giroud, 2013), and production networks (Acemoglu et al., 2012, 2016a; Di Giovanni et al., 2018). The literature in particular studies the role of production networks in driving large business cycle fluctuations via the propagation and amplification of granular shocks. The trade literature examines the structure and implications of global value chains (Antràs and De Gortari, 2017; Johnson and Noguera, 2012; Alfaro et al., 2019). The recently available buyer–seller linked data enables detailed analyses of the endogenous formation of production networks among firms and the resulting macroeconomic implications (Atalay et al., 2011; Barrot and Sauvagnat, 2016; Huneeus, 2018; Oberfield, 2018; Bernard et al., 2019; Dhyne et al., 2021; Arkolakis et al., 2021; Carvalho et al., 2021; Demir et al., 2020).[11] Contributing to this body of literature, our paper emphasizes how supply chain networks determine the effect of trade barriers on firms' financial outcomes. As such, our paper contributes to the studies on the financial implications of supply chain linkages (e.g., Hertzel et al., 2008; Houston et al., 2016).

This paper also draws heavily on the extensive "event study" literature.[12] Several notable event studies that are closely related to ours include Fisman et al. (2014), who examine how Japanese and Chinese firms respond to adverse shocks to Sino-Japanese relations, and Crowley et al. (2019), who analyze the effect of the E.U.'s announcement of import restrictions on Chinese firms in the solar panel industry. Our research differs from these studies by examining the direct and indirect effects of the trade cost shocks on individual stock market returns, based on a series of unanticipated trade policy changes by the two largest economies.

Last but not least, our paper contributes to the growing literature on the macroeconomic, trade and labor-market effects of the U.S.-China trade war.[13] Studies by Amiti et al. (2019) and Fajgelbaum et al. (2020) both find almost complete pass-throughs of the U.S. tariffs to U.S. prices.[14] Based on a quantifiable general-equilibrium trade model, Fajgelbaum et al. (2020) furthermore find a small static welfare loss in the U.S. (or 0.04% of U.S. GDP) arising from the tariffs imposed by both countries. That said, Fajgelbaum et al. (2020) find significant reallocation of global trade across countries and sectors in response to the tariffs imposed by both the U.S. and Chinese governments, and a surprisingly increase in global trade volume. Using firm-trade linked data, Handley et al. (2020) report significant negative impacts of the 2018–2019 U.S. import tariffs on the U.S.'s export growth through supply chain linkages. Aaron and Pierce (2019) find larger employment declines among the U.S. manufacturing industries that are more exposed to tariff hikes, suggesting that the negative effects from rising input costs outweigh the positive effects from import protection.

Perhaps closest to our paper are the two studies by Amiti et al. (2020, 2021), as they also use the U.S. listed firms' stock market reactions to infer the impacts of the expected tariff hikes. Amiti et al. (2020) find significant negative impacts of tariff announcements on U.S. stock prices, returns to capital, and hence aggregate investment. Based on a specific-factor model and changes in firms' stock market prices around the tariff announcement dates, Amiti et al. (2021) estimate a significantly larger dynamic welfare loss associated with the U.S.-China trade war than static loss identified in the literature, due to expected TFP losses, lower real wages and inflation, in addition to lower returns to affected firms that are dependent on trade with China. We focus instead on the direct and indirect supply-chain effects of tariffs on U.S. and Chinese companies.

[9] 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. Meanwhile, Claessens et al. (2012) and Lin and Ye (2018a, 2018b) investigate the role of trade or foreign direct investment in transmitting global financial shocks to the real economy.

[10] By linking trade policies to the financial markets, our paper also adds to the literature on the effects of financial friction and credit conditions on international trade (e.g., Manova, 2008; Chor and Manova, 2012).

[11] 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 et al. (2019) 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. (2021) quantify the propagation of the Great East Japan Earthquake shocks in 2011 through firms' input–output links. Dhyne et al., 2021 and Oberfield (2018) develop models of the endogenous formation of production networks and the resulting macroeconomic implications.

[12] See reviews by Schwert (1981) and MacKinlay (1997). See Gorodnichenko and Weber (2016) for a recent study on firms' stock responses to monetary policy announcements.

[13] There are many other papers in this burgeoning literature that are omitted in our review due to space constraint. Readers are referred to Fajgelbaum and Khandelwal (2021) for a systematic and comprehensive review of the literature.

[14] Using more disaggregated import price data from U.S. ports, Cavallo et al. (2021) also find evidence supporting the complete pass-through of tariffs to U.S. prices.

3. Institutional background and hypotheses

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

Since introducing open market reforms in 1978, China has grown substantially in terms of aggregate income, investment, consumption, and trade. It became the world's largest trading nation (surpassing the U.S.) in 2013[15] and the largest trading partner of the U.S. (overtaking Canada) in 2015.[16] China's exports, particularly those to the U.S., have skyrocketed since 2001, the year it joined the World Trade Organization (WTO). Various studies, most notably Autor et al. (2013) and Pierce and Schott (2016), show significant negative effects of imports from Chinese on U.S. labor market outcomes.

As expected, the economic policies of the Trump administration have been anti-trade overall, with China often being the target. The administration's complaints about China range from currency manipulation and unfair practices against foreign businesses to the persistent trade deficit the U.S. has with China and the country's “Made in China 2025” industrial policy. To address these issues, the Trump administration decided to use import tariffs as a policy tool to induce the Chinese government to implement policy changes favorable to U.S. interests.

As discussed in the introduction, we use four events to evaluate the impact of U.S.-China trade tensions.[17] The main event is the issuance of the March 22, 2018 presidential memorandum. Details about this and the other three events are listed below.

3.2. Key events

- March 22, 2018: The Trump administration issued a presidential memorandum in response to the findings of a United States Trade Representative (USTR) investigation of China's laws, policies, practices, and actions related to intellectual property, innovation, and technology (the “Section 301 investigation”). The memorandum proposed imposing tariffs on up to $50 billion of Chinese imports as a response to China's alleged theft of U.S. intellectual property.[18] President Trump gave USTR Robert Lighthizer 15 days to come up with a list of products on which to impose tariffs. Lighthizer stated that he would target products that the Chinese government had indicated in various policy documents that it intended to dominate, particularly those mentioned in China's “Made in China 2025” plan.
- March 23, 2018: The Chinese government retaliated with a list of 128 products that would face 15–25% tariffs should the U.S.–China trade negotiations fail.
- April 3, 2018: The USTR published a provisional list of imported items that would be subject to potential tariffs up to 25%, encompassing 1334 Chinese products and corresponding to approximately $50 billion of U.S. imports from China.
- January 7–9, 2019: Trade negotiations between the U.S. and China were held in Beijing. The trade talks ended with progress in identifying and narrowing the differences between the two sides. A continuation of high-level discussions was confirmed.

We first conduct a detailed event study based on the initial announcement on March 22, 2018, as this unexpected event can, in retrospect, be regarded as the beginning of the U.S.-China trade war. We then provide supporting evidence on the effects of publication of the official tariff lists and conduct a reverse experiment based on the trade talks in early 2019.

3.3. Hypotheses

The primary goal of this paper is to empirically examine the financial implications of sharp tariff increases for firms connected in global supply chains. As outlined in Appendix 1, our paper is guided by a simple theoretical model built on the general-equilibrium production network model of Dhyne et al., 2021. Our model features two countries (“home country” = the U.S. and “foreign country” = China), as well as monopolistically competitive firms using labor, domestic inputs, and imported inputs to produce goods, which can be sold to domestic consumers, domestic downstream firms, and foreign consumers.[19]

The model shows various direct and indirect effects of the home country's import tariffs and the foreign country's retaliatory tariffs (see Appendix 1 for details). The foreign country's retaliatory tariffs, for instance, directly reduce the sales (and thus profits) of the home country's exporting firms. Moreover, there are two indirect general-equilibrium effects. One effect arises from the reduced demand for inputs from the home country's customers (downstream firms), which also suffer lower export sales in the foreign country. The other indirect effect on the home country's firms is the higher prices of inputs from the foreign country due to the tariff-induced increase in foreign firms' production costs.

Meanwhile, the home country's tariffs have a direct impact on firms that use imported inputs due to the higher imported input prices. Firms that do not directly import inputs will still suffer an indirect effect owing to their position in domestic supply

[15] 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.

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

[17] A detailed list of all events relating to the U.S.–China trade war can be found in the summary provided by Peterson Institute of International Economics: https://www.piie.com/blogs/trade-and-investment-policy-watch/trumps-trade-war-timeline-date-guide.

[18] Besides, the Trump administration cited the following reasons for imposing tariffs on China: 1) A large trade deficit between the U.S. and China; 2) China's policy of forcing U.S. technology-intensive firms to enter into joint ventures with Chinese companies and share their technology in return for market access; 3) A need to protect domestic businesses.

[19] Our model abstracts from sales of (U.S.) 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 on U.S. firms.

chains. The indirect effect arises from higher domestic input prices, as some of the home country's suppliers (upstream firms) experience a cost shock due to the higher imported input prices after the home country's imposition of tariffs. Another indirect effect arises from the reduced sales of, and thus demand for inputs from, the home country's customers (downstream firms), which will also suffer from higher imported input costs and thus lower profits.

The following hypotheses summarize these theoretical derivations.

Hypothesis 1 (direct impact of the foreign country's import tariffs): Increases in the foreign country's import tariffs lower the value of the home country's exporting firms.

Hypothesis 2 (direct impact of the home country's import tariffs): Increases in the home country's import tariffs lower the value of the home country's firms that use imported inputs.

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

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

We will empirically examine all four hypotheses using various firm-level trade, supply-chain, and financial data sets. The empirical analysis is conducted mainly for the U.S. mostly due to data availability. We will also try to conduct as many parallel analyses as possible for China as long as the corresponding data are available.

4. Estimating framework

We use an event-study approach and a combination of new data sets to measure firms' trade exposure. By focusing on the U.S. government's unexpected tariff announcement on March 22, 2018, our event study addresses endogeneity issues related to time-varying and endogenous factors that might affect a firm's trade participation, such as comparative advantages or political uncertainty. It also advances related studies that typically rely on sector-level measures of exposure to trade policy shocks (e.g., import competition at the sector level).[20] Note that our event study rests on the assumption that the U.S. government's tariff announcement provides the market with news about firms' intrinsic value, which in turn leads to price movements.

As reported in Table 1, our regression sample comprises 2309 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. stock market. We also exclude financial firms. The daily stock return data and implied CDS spreads are obtained from Bloomberg.

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

$$Y_i = \alpha + \beta Exposure_i + \boldsymbol{X}_i + \varepsilon_i \tag{1}$$

where Y_i denotes one of the dependent variables of interest of firm *i*, measuring its stock market responses to the tariff announcements. $Exposure_i$ is a measure that gauges firm *i*'s trade relationship with China, with β being our coefficient of interest. $\boldsymbol{X}_i$ is a vector of firm characteristics, including firm size, market-to-book ratio, leverage, and ROA. ε_i is the error term.

Next, we describe in detail the construction of the variables used in the regression. Our main dependent variables are the changes in stock prices over short windows centered on the different event dates, beginning with the tariff hike announcement of March 22, 2018. By denoting the event date as date 0, the cumulative raw returns (*CRR*) over the three-day window centered on date 0 are calculated as

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

where R_{it} is the raw return for stock *i* on date *t*. Given the abrupt nature of the U.S. government's tariff hike announcement, we use a firm's cumulative stock return over a three-day window as our main dependent variable of interest. In robustness checks, we construct alternative measures of firm performance, such as the cumulative abnormal returns (*CAR*), using different asset pricing models.

Our main independent variables of interest are measures of a U.S. firm's *direct* exposure to sales in and imports from China. A firm's sales exposure, *Revenue_China*, defined as the share of revenue from China in the firm's total revenue in 2016, captures the relative importance of the Chinese market for the firm. This variable is retrieved from the Factset Revere database.[21] According to

[20] Furthermore, previous studies show that firms tend to produce multiple products and alter their product lines from time to time (Bernard et al., 2011; Hoberg and Phillips, 2016). In these cases, a firm's reported main industry may not precisely capture its exposure to trade.

[21] The data for this variable was retrieved from Factset Revere database in March 27, 2018. As the audited annual reports in 2017 for most firms were not announced, we rely on the revenue information in 2016 as a benchmark to quantify the implied changes in investor's perceptions about firm's fundamentals due to the trade war. 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 inputs from China.

Table 1
Summary statistics.

Variable	N	Mean	S.D.	P25	Median	P75
A. Stock Market Reactions						
CRR[−1,+1]	2309	−0.026	0.042	−0.051	−0.029	−0.005
MV_Change[−1,+1]	2308	−291.053	981.775	−123.212	−18.762	−0.517
Default Risk[−1,+1]	2309	0.012	0.023	0.000	0.008	0.022
EPS Forecasts	51,546	2.980	4.574	0.620	2.300	4.527
B. Trade Exposure						
Revenue_China	2309	0.025	0.052	0.000	0.000	0.028
Input_China	2309	0.122	0.298	0.000	0.000	0.000
Industry_IP	2309	0.078	0.560	0.000	0.000	0.009
Industry_Export	2309	0.016	0.038	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	0.096	0.205	0.000	0.000	0.084
Input_China_Supplier	2309	0.105	0.220	0.000	0.000	0.099
D. Product Lists						
Output_China_List	2309	0.028	0.016	0.018	0.029	0.039
Input_US_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. Other Firm Characteristics						
SIZE	2309	6.449	2.244	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
R&D	2309	0.095	0.188	0.000	0.002	0.098

Notes: This table presents the summary statistics for main variables of U.S. firms used in this study. The baseline sample is at the firm level and contains 2309 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. The variable of earnings per share forecasts (*EPS Forecasts*) is at the forecast level and sourced from IBES.

Hypothesis 1, firms that are more dependent on sales in China are expected to suffer more from China's retaliatory tariffs. For instance, tariff announcements by either government should hit Apple Inc., which derives 20.8% of its revenue from China, harder than Alphabet Inc. (8.9% exposure to China) and Exxon Mobil (5.9% exposure to China).

The measure of a firm's import exposure is constructed using U.S. bill of lading data set, which covers every waterborne import transaction in the U.S. For 2017, the database contains about 5 million bills of lading for imports from China, with information on the quantity, the weight, and the product code.[22] One limitation of this data set is the lack of information on the value of each transaction.[23] To quantify a US firm's input purchase from other country, we rely on the information of the total weight in kilogram for each transaction that appears in the bill of lading database.[24] We source the data from USA Trade Online and construct the average prices per kilogram (kg) of US imports at the product level. The Harmonized System (H.S.) product codes[25] provided in the U.S. bill of lading database allows us to match the estimated price data from USA Trade Online with the weight data from the bill of lading data set.[26] The ratio of a firm's inputs from China (*Input_China*) to its total imported inputs is defined as follows.

$$\mathrm{Input\_China}_i = \frac{\sum_{t=2016}^{2017}\sum_{k}^{K}\mathrm{weight}_{i,k,China,t} \times \mathrm{prc}_{k,t}}{\sum_{t=2016}^{2017}\sum_{l}^{L}\sum_{k}^{K}\mathrm{weight}_{i,k,l,t} \times \mathrm{prc}_{k,t}} \tag{3}$$

where $\mathrm{weight}_{i,k,l,t}$ is the total weight in kg of transactions in product category k imported by a US firm i from country l in year t. K is the total number of product categories in the firm i's imports in this period. $\mathrm{prc}_{k,t}$ is the average unit price per kg for a product category k

[22] These administrative data may contain errors in the consignee names. To map the data to U.S. listed firms, we first use a fuzzy matching process to filter out consignee names with the names of listed firms on the basis of character similarity. We then manually check the consignee names against the names of listed firms sourced from Compustat.
[23] This information is not provided because shippers are not required to state the value of the transaction in the bill of lading.
[24] It is difficult to rely on the information of the quantity of inputs as units of measurement differ across product categories. For example, it is difficult to compare the value of one barrel of oil with that of one piece of equipment.
[25] 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 use 4-digit HS code to link with estimated prices from the USA trade online.
[26] Source: https://www.census.gov/foreign-trade/reference/products/catalog/usatradeonline.html.

imported by US firms in year t computed using data from USA Trade Online.[27] Importantly, we only focus on input offshoring of capital goods and intermediate goods and exclude any imported final goods using the UN Broad Economic Categories (BEC) list.[28] The denominator is thus the total value of input purchased by a US firm between 2016 and 2017.[29] The numerator captures the estimated value of inputs from China.[30] This measure is set to zero if a firm has no input purchase from China.

This measure of the inputs imported from China is subject to two potential issues. The first issue is related to measurement errors. As we do not have the transaction values in the bill of lading database, we turn to use the average price for imports purchased by US firms, leading to measurement errors. Even in the same product category, the value of the product can vary significantly across exporters. Our measure thus serves as a compromised solution.[31] In what follows, we apply a split instrumental variable approach to further alleviate the measurement error issues (Farber et al., 2021). The second issue is about whether investors and analysts in the financial markets may be sophisticated enough to understand all elements in this nuanced measure and assess the relevant data. In tables available upon request, we show that our findings are robust to a simple dummy variable for each firm to indicate whether it has outsourced inputs from China.

Factset Revere also provides information on U.S. listed firms' buyers and sellers, as the Securities and Exchange Commission (SEC) requires U.S. listed firms to publicly disclose any customer that commands 10% or more of revenue.[32] We use this information to construct a firm's domestic production network. In particular, we construct four firm-level measures of U.S. firms' exposure to trade with China in production networks: the average revenue from China across downstream firms, the average revenue from China across upstream firms, the average exposure to Chinese inputs across downstream firms, and the average exposure to Chinese inputs across upstream firms.

Table 1 reports the summary statistics of the dependent and independent variables used in the regression analyses at both the firm and industry levels. The dependent variables of interest at the firm level are the cumulative raw returns around the different event dates. In the sample of 2309 firms, the *CRR* over the three-day window centered on March 22, 2018 (the first event date) have a mean value of −2.6%, with the median equal to −2.9%. We define $MV\_Change = MV_{i,+1} - MV_{i,-2}$ as the change in market value over the event window [−1,+1] centered on March 22, 2018. Notice that, equivalently, $MV\_Change_i[-1,+1] = MV_{i,-2} \cdot CRR_i[-1,+1]$. Over the three-day window centered on the first event date, the market value of U.S. firms drops by about \$291 million on average, while the market loses \$672 billion in value in total, based on our sample firms. Continuous firm variables are winsorized at 1% to mitigate the effect of outliers.[33]

The independent variable *Revenue_China*, which captures U.S. firms' direct sales exposure to China, has a mean of 2.5% and a median of 0. *Input_China*, which captures U.S. firms' direct import exposure to China, shows a mean of that 12.2% and a median of 0.[34]

As in many other studies, we include firm size (*SIZE*), market-to-book ratio (*MTB*), leverage (*LEV*), and the ROA ratio (*ROA*) as firm-level controls. The data used to construct these variables are from Compustat.[35] Other variables, such as indirect exposure to the trade war, are discussed in the next section. Appendix 3 provides detailed definitions of the variables.

5. Empirical results

5.1. Validity of the research design

To confirm the validity of the empirical analysis, we first provide evidence that the announcement of the trade war can be treated as an unexpected event. Fig. 1 plots the trajectory of the benchmark S&P 500 Index (right scale) alongside a measure of public interest in the trade war in the U.S. (left scale). As can be seen, there is a sharp fall in the S&P 500 Index on March

[27] USA Trade Online provides information on value and weight of US imports at the product level on a monthly basis. We compute the average monthly price at the 4-digit HS code level and then calculate the yearly measure.

[28] The latest version of the classification method can be found here: https://unstats.un.org/unsd/trade/classifications/bec.asp#documents.

[29] We use the period between 2016 and 2017 to define our measure for input from China. The results are quantitatively similar when the variable is defined using either year of data.

[30] 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 businesses related to China in their financial reports.

[31] According to multiple studies on the effects of tariff hikes during the U.S.-China trade war (Amiti et al., 2019; Fajgelbaum et al., 2020), the rate of tariff pass-through is very close to 100%. To the extent that data on imports (from China) are computed based on duty-exclusive prices, the findings of nearly complete pass-through imply that the USD prices of imports from China into the U.S. do not change on average during the period under study (i.e., sticky prices). Thus, our results should not be biased significantly in either direction.

[32] 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.

[33] Indirect exposure measures based on the direct firm trade exposures already winsorized are not winsorized again. Industry level measures constructed using aggregated data are not winsorized.

[34] Among our sample firms (obs = 2309), 56.6% have non-US sales, 49.4% of them have sales in China; 26.6% use imported inputs, while 23.6% of them import them from China. One may be concerned that our listed firm sample does not represent the distribution of manufacturing and service companies in the U.S. economy. It is true that in a sample, as expected, proportionally fewer service firms engage in foreign sales (50.9%) and imports (20.1%) than non-service (tradable) firms, of which 63.9% have foreign sales and 35.1% use imported inputs. Since our sample of listed companies are on average much larger than the non-listed ones, the fractions of firms engaged in importing and exporting are naturally much larger than those of the universe of U.S. companies, consistent with the findings in the literature on heterogeneous firms in trade (Bernard et al., 2018). That said, as our focus is on the differential impact of the trade shocks on firms with different exposure to trade with China, rather than the aggregate impacts in the financial market or the real economy, the over-representation of large firms in our sample should not be an issue.

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

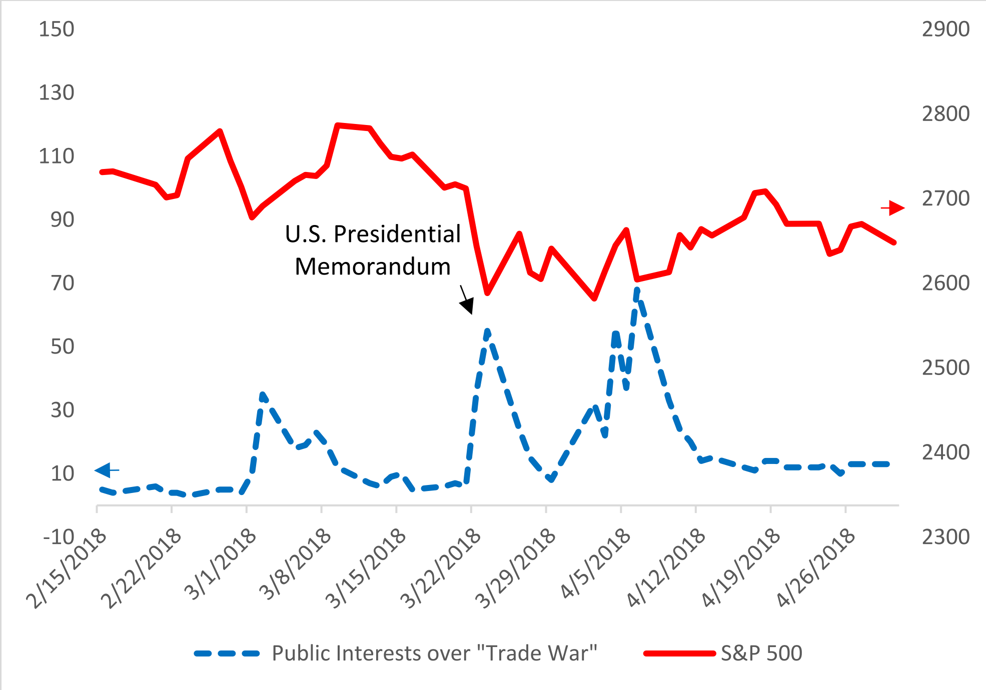

Fig. 1. Public interest in the trade war and stock returns.
Notes: This figure presents the time-series of the market index against the public interest in the U.S.-China trade war. The red solid line indicates the S&P 500 index (right scale). The blue dashed line shows the public interest in the trade war as measured by Google Trends (left scale).

22, 2018, suggesting that the presidential memorandum was a largely unanticipated event. The S&P 500 Index drops by 2.5% on March 22 and by 4.8% from March 21 to March 23. Appendix 2 summarizes the value-weighted average stock returns around the three event dates for U.S. firms, with firms' market values as weights. The U.S. firms in our sample experience an average 2.2% drop in stock returns on the main event date (March 22, 2018), with their average return from March 21 to March 23 falling 4%. The losses amount to $377 billion on the event date and $672 billion over the three-day event window.

The measure of public interest in the trade war is based on the frequency of keyword searches for “trade war” using the Google search engine. Research suggests that Google search trends can be used to measure investors' attention (e.g., Da et al., 2011). Public interest in the trade war peaks on March 22, 2018, the day the Trump administration announced new tariffs on over $50 billion in imports from China.[36] For the other announcement dates, including April 5, 2018 (when the Trump administration proposed additional tariffs against China), large declines in the S&P 500 Index and corresponding spikes in public interest in the trade war can again be observed, although they are smaller in magnitude.

The abrupt increase in public interest in the trade war together with the large market movement around the first event date suggests that the U.S. government's tariff hike announcement surprised the market and generated significant concerns about trade tensions between the U.S. and China. Based on our search of news articles and academic studies, we find no other significant events on March 22, 2018 that can explain the overall market movement in both countries, apart from the presidential memorandum.

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

It is worth emphasizing that our analysis focuses on the heterogeneous effects of U.S.-China trade policy shocks across firms with different degrees of exposure to U.S.-China trade. Unless firms' trade exposure is somehow related to other non-trade policy changes, it is hard to imagine that our results are driven by the aforementioned policy announcements. To further validate our findings based on the first event on March 22, 2018, we identify a subsequent event in 2019 that reverses the market sentiment

[36] A previous (and much smaller in magnitude) spike in public interest 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 some other countries.

about the U.S.-China trade war. We also use the detailed lists of tariffed products issued by both the U.S. and Chinese governments subsequent to the March announcement to verify our main results at the firm–product level.

Other announcements subsequent to March 22, 2018 should also affect the U.S. equity market. For instance, on April 2, 2018, when China's Ministry of Commerce rolled out tariffs on 128 U.S. products, we observe a 2.2% drop in the S&P 500 index.[37] Nonetheless, because several events are clustered around April 2–5, the impact of each one is difficult to evaluate. Our analysis below thus focuses on the March 22 announcement, the first of its kind.[38]

Our estimation of heterogeneous market reactions to tariff hike announcements across firms rests on the premise that information on the structure of firms' relationships is available to the public and that investors react accordingly. We argue that this premise holds. Institutional investors and financial intermediaries have in-house research teams with access to their own databases and deep talent pools, which are capable of estimating the financial implications of trade wars. The efficient market hypothesis suggests that unexpected trade shocks will prompt traders to compete to acquire valuable information about firms' trade exposure. Moreover, investors are likely to 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 empirical results regarding the impact of the initial tariff hike announcement on U.S. firms' stock returns according to their direct trade exposure to China. First, in Table 2, we show suggestive evidence using a simple univariate analysis on the relation between a firm's exposure to China and its market performance. We find that the cumulative returns are systematically lower for firms that have more trade exposure to China. Specifically, as shown in the first two rows of Panel A, U.S. listed firms that are above the median of the sample in terms of the share of sales in China have a 1.1% lower *CRR* over the three-day event window than firms with a share of sales in China below the median.[39] In addition, we find that the above-median firms, on average, are larger in terms of firm size and more profitable in terms of ROA but have a lower leverage ratio than the below-median firms. These findings raise the need to control for these firm characteristics in the regressions.

In Panel B, we compare the means of the variables of interest between two subsamples of firms separated according to whether they directly offshore inputs from China. Based on a firm's import dummy create using bill of lading data, we find that firms that report some offshoring activities in China, on average, have 1.2% lower *CRR* over the three-day window than firms without any import exposure to China. It is worth noting that firms that offshore inputs from China tend to be bigger and have a higher ROA.

Next, we conduct our event study analysis by regressing firms' stock returns on their two measures of direct trade exposure to China. Table 3 reports the point estimates and robust standard errors of the ordinary least squares (OLS) regressions. As shown in Panel A, we find that firms selling proportionally more to China experience lower *CRR* over the three-day window centered on March 22, 2018. Specifically, column (1) suggests that a 10 percentage-point increase in a firm's share of sales to China is associated with 0.92% lower *CRR*, after the four firm-level characteristics (i.e., firm size, market-to-book ratio, leverage, and ROA) are controlled for. Put differently, one standard deviation (0.052 as in Table 1) increase in revenue from China leads to a 0.48% lower return. We also find that firms purchasing inputs from China experience negative stock performance. As shown in column (2), one standard deviation (0.298 as in Table 1) increase in input from China is associated with a 0.29% lower return. In column (3), when we include both trade exposure measures as independent variables in the regression, we find quantitatively similar coefficients on both variables.

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

We next compare how much of the market response is attributable to firms' direct trade exposure and how much is attributable to the perceived reductions in import competition from China and exports to China among firms in the same industry. We define 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 is the total imports from China in sector k, defined according to the North American Industry Classification System (NAICS), SHP_k is the sector's shipment value, and EXP_k is its exports. The data are from Schott (2008), who in turn obtains 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 in the time when trade war announced. We also construct a sector measure for total exports to China as $\text{Industry\_Export}_k = \frac{EXP\_CN_k}{SHP_k}$, where EXP_CN_k is the total exports to China for sector k. While we now have industry measures at the NAICS level, U.S. listed firms are

[37] This product list was published on March 23, 2018 and came into force on April 2, 2018.

[38] Following the empirical specification in Amiti et al. (2020), we compute the average return combining the two main events under study – the Trump administration's memorandum on Mar 22, 2018 and the announcement of tariffs on $200 billion Chinese products on Sep. 17, 2018. The main results remain robust when the two events are jointly considered.

[39] The median of revenue share from China is zero.

Table 2
Univariate analysis.

Revenue from China	Revenue_China				
	>median (0)		≤median (0)		
	N	Mean	N	Mean	Diff.
CRR[−1,+1]	910	−0.033	1399	−0.022	−0.011***
MV_Change[−1,+1]	909	−541.449	1399	−128.359	−413.091***
Default Risk [−1,+1]	910	0.018	1399	0.008	0.010***
SIZE	910	6.963	1399	6.116	0.847***
MTB	910	2.279	1399	2.347	−0.068
LEV	910	0.243	1399	0.284	−0.041***
ROA	910	0.062	1399	−0.108	0.171***
Input from China	Input_China				
	>median (0)		≤median (0)		
	N	Mean	N	Mean	Diff.
CRR[−1,+1]	496	−0.036	1813	−0.024	−0.012***
MV_Change[−1,+1]	496	−551.731	1812	−219.698	−332.033***
Default Risk [−1,+1]	496	0.019	1813	0.01	0.009***
SIZE	496	7.314	1813	6.213	1.102***
MTB	496	2.06	1813	2.392	−0.332***
LEV	496	0.256	1813	0.271	−0.015
ROA	496	0.092	1813	−0.078	0.170***

Notes: This table presents the results of the univariate analysis. *CRR[−1,+1]* is the three-day cumulative raw returns around March 22, 2018, the date when the Trump administration issued a presidential memorandum in reference to Section 301 of the Investigation of China's Laws, Policies, Practices, or Actions that proposed to impose tariffs on up to $50 billion of Chinese imports as a response to China's alleged theft of U.S. intellectual property. *Revenue_China* is the revenue share from China in 2016. *Input_China* is the ratio defined as the estimated value of imported goods from China over total estimated value of imported goods from the world. It is calculated using product weight from the bill of lading database in 2016 and 2017 and the estimated average unit price per kilogram (kg) from USA Trade Online. Other variables are defined in Appendix 3. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

likely to operate in multiple sectors; as such, we retrieve information on the primary NAICS categories of firms' segments from the Compustat Segment database. When a U.S. firm operates in multiple NAICS categories, we calculate the average value of the trade measure for the firm.

The regression results presented in column (5) show a positive coefficient on the measure of *ex-ante* import competition and a negative coefficient on export orientation to China. Reduced import competition due to tariffs is perceived to increase profits more for firms in sectors that face 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, the economic magnitude through the import competition channel is small; firms in sectors with a 10% higher import penetration are associated with only a 0.05% higher return than other firms. Compared with the heterogeneity arising from differences in firm-level direct trade exposure to China, the variation in 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 industries that rely more on China as an export market anticipate lower profits.[40] It is worth noting that despite major differences in empirical specifications, our findings for the three-day window around the March 22, 2018 tariff action are comparable to those in Amiti et al. (2020).

The U.S. government's sudden change in trade policy toward China should have an impact on not only firms' stock returns but also the wealth of their other stakeholders (such as bondholders). In particular, trade war fears may increase the likelihood of default, as deteriorating financial performance increases the probability of bankruptcy (Acemoglu et al., 2016b). An increase in uncertainty about future U.S.-China economic relations may induce firms to postpone investments and other long-term plans, or adopt suboptimal strategies (Bloom, 2009). To examine whether the March 22, 2018 announcement raises default risks, we follow prior studies (e.g., Ismailescu and Kazemi, 2010) and 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:

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

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 obtained from Bloomberg.

As reported in Panel B of Table 3, we find that firms that are more exposed to imports from and exports to China are associated with a higher default risk. Specifically, as shown in column (1), one standard deviation increase in a firm's share of sales to China is associated with a 0.25% increase in its default risk. On the import side, firms that have imported from China have a 0.15%

[40] It is rather challenging to quantify the aggregation effect of the tariffs based on our regression results that include industry fixed effects and at this stage, omit the general equilibrium and network effects.

Table 3
Revenue and inputs from China.

Panel A. Cumulative Raw Returns

	(1)	(2)	(3) CRR [−1,+1]	(4)	(5)
Revenue_China	−0.0923***		−0.0878***	−0.0454***	−0.0503***
	(−6.44)		(−6.12)	(−2.60)	(−2.90)
Input_China		−0.0098***	−0.0084***	−0.0057**	−0.0081***
		(−4.08)	(−3.51)	(−2.38)	(−3.37)
Industry_IP					0.0058**
					(2.34)
Industry_Export					−0.1503***
					(−4.03)
N	2309	2309	2309	2291	2309
adj. R-sq	0.056	0.048	0.059	0.123	0.064
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No

Panel B. Default Risks

	(1)	(2) Default Risk [−1,+1]	(3)	(4)
Revenue_China	0.0499***		0.0476***	0.0242**
	(5.31)		(5.13)	(2.30)
Input_China		0.0049***	0.0042***	0.0030**
		(3.30)	(2.84)	(2.01)
N	2309	2309	2309	2291
adj. R-sq	0.187	0.179	0.190	0.230
Controls	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes

Panel C. Analyst Forecasts

	(1)	(2) EPS Forecasts	(3)
Revenue_China × Post	−1.7854***		−1.6295***
	(−6.31)		(−6.18)
Input_China × Post		−0.2432***	−0.2074***
		(−5.33)	(−4.92)
N	51,546	51,546	51,546
adj. R-sq	0.919	0.919	0.919
Firm-Analyst FE	Yes	Yes	Yes
Date FE	Yes	Yes	Yes

Notes: This table presents the effect of the trade war announcement on the value of U.S. firms according to their revenue and purchases from China. 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 share from China. *Input_China* is the ratio defined as the estimated value of imported goods from China over total estimated value of imported goods from the world. It is calculated using product weight from the bill of lading database in 2016 and 2017 and the estimated average unit price per kilogram (kg) from USA Trade Online. 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 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 by Bloomberg using default probabilities based on the Merton model. The *t*-statistics in Panels A and B are based on robust standard errors and are reported in parentheses. Panel C shows the effect of the trade war announcement on analyst's forecasts on firm's earnings per share. The estimation sample is at the forecast level from IBES, covering the three months before and after the event month, March 2018. *Post* is set to one for days after the event date and zero otherwise. *EPS Forecasts* is the forecasts on a firm's earnings per share (EPS) made by analysts. Firm-analyst fixed effects and date fixed effects are included. Standard errors are clustered at the analyst level. The *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

higher risk of default on average. This shows that the March 22, 2018 tariff announcement affects not only the equity markets but also the bond markets by raising investors' perception of risk among firms more exposed to China.

Importantly, our event-study approach is premised on analysts and sophisticated investors paying attention to listed companies' supply-chain exposure. Therefore, as an external validity test, we examine whether equity analysts perceive the expected changes in firms' future earnings or cash flows due to rising trade tension. We collect analysts' forecasts from the Institutional Broker's Estimate System (IBES) database and construct a sample at the forecast level. Specifically, the sample consists of forecasts made by analysts about a firm's earnings per share for a given fiscal year. We retrieve the forecasts issued by analysts during the period between December 1, 2018, and June 31, 2018, or three months before and after the event month. We estimate the following difference-in-differences model.

$$\text{EPS Forecast}_{i,w,t} = \alpha + \beta \text{Input\_China}_i \times \text{Post}_t + \gamma \text{Revenue\_China}_i \times \text{Post}_t + \rho_{i,w} + \tau_t + \varepsilon_{i,w,t} \quad (6)$$

where EPS $\text{Forecast}_{i,w,t}$ is the earning per share (EPS) forecast for firm i made by analyst w issued on date t. Input_China_i and Revenue_China_i are trade exposure measures used in our baseline estimation. Post_t is an indicator set to one for forecasts issued after March 22, 2018. $\rho_{i,w}$ denotes analyst–firm pair fixed effects. τ_t is date fixed effects. The analyst-firm pair fixed effects capture all firm invariant characteristics and thus absorb the standalone trade exposure measures. The individual features in forecasting behavior are also captured by analyst-firm pair fixed effects.

As reported in Panel C of Table 3, we show that a listed company's earnings per share predicted by analysts tends to be more negative if the firm is more exposed to trade with China through either export or import linkages. These results suggest that analysts have roughly in mind what our model describes in terms of trade networks.

5.2.1. Robustness checks

We conduct a battery of robustness checks. First, we demonstrate that our results remain unchanged under alternative asset pricing models. To take a firm's individual risk level into consideration, we compute the cumulative abnormal returns (*CAR*) of firm i as

$$CAR_i[-1,+1] = \sum_{t=-1}^{+1} AR_{it} \tag{7}$$

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 Center for Research in Security Prices (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. The results remain robust, as shown in columns (1) and (2) of Panel A in Appendix 4. We also construct a cumulative abnormal measure using the Fama–French three-factor model and obtain quantitatively similar results, as shown in columns (3) and (4) of Panel A in Appendix 4.

Second, our event study is premised on the event being unanticipated by the public and there being no obvious confounding event around the event date. Through a thorough search of news and relevant reports, we identify three events that may bias our results. The first event is an announcement of a federal funds rate increase by the Federal Open Market Committee (FOMC) on March 21. While this increase had been largely expected, it is still likely to have affected markets (see Cieslak et al., 2019; Lucca and Moench, 2015). To mitigate this concern, we control for firms' responses to past FOMC announcements. We have collected data for each of the FOMC announcements since 2000 and obtain 144 events. In the next step, we calculate a firm's stock return over the 3-day window centered on each of the event dates, and the corresponding market return over the 3-day window. After regressing the firm's 3-day returns on the market return for each stock respectively across all 144 events between 2000 and 2017, we retrieve the estimated coefficient (beta) for each individual stock. We define this cross-sectional measure as *FOMC beta* to capture firm's general responses to the monetary policy. As shown in results reported in columns (1) and (2) in Panel B of Appendix 4, our results are robust to the model including this variable.[41] In addition, a recent study finds that the drifts after 2015 seem to disappear (Kurov et al., 2021).

The second event is President Trump's appointment of a new national security advisor, John R. Bolton, on the same date as the main event in our study (March 22, 2018). There is no obvious reason why this appointment would influence financial markets in the U.S. and China. Our exposure measures are constructed at the firm level, and we also include industry fixed effects to compare heterogeneous responses across firms in the same sector. As long as the effect of the appointment clusters at the sector level, our estimation of the trade war effect will not be biased. Nevertheless, we exclude firms in military-related industries from the regression sample, as news about the appointment of a new national security advisor could potentially affect such firms.[42] As shown in columns (3) and (4) of Panel B in Appendix 4, our results remain unchanged after excluding these firms from the sample.

The third event concerns the increase in tariffs on steel and aluminum, imposed under Section 232 of the Trade Expansion Act of 1962; the increase was announced on March 1, 2018 and went into effect on March 23, 2018. It is worth noting that the increase applied to steel and aluminum imports from all countries, not only those from China. Hence, firms' exposure to this confounding event is less likely to be correlated with our firm-level measures of exposure to China. We show in columns (5) and (6) of Panel B that excluding firms in steel- and aluminum-related industries does not affect our main results.[43]

Third, the trade war event might also create expectations about potential new trade policies between the U.S. and other countries as well as the potential effect due to geopolitical links among countries. We first retrieve the data on the shares of revenue from different countries and regions for our sample firms from Factset Revere database. To gauge the effect of geopolitical links, we collect the data on votes in the United Nations (UN) General Assembly to measure the bilateral distance between countries as used in Mityakov et al. (2013). Two countries are considered ideologically close if they voted similarly on different subjects discussed in the United Nations (UN) General Assembly. Countries that are ideologically more distant from China are in turn less

[41] We also adopt an alternative approach. We define a firm's 3-day cumulative returns (CRR) and cumulative abnormal returns (CAR) for 144 events and calculate the average. In the tables available upon request, we show that our results remain robust after including any of these two variables.

[42] A firm is considered to operate in military-related industries if its six-digit NAICS is 928,110, five-digit NAICS is 33,641, two-digit SIC is 97, or four-digit SIC is 3040 or 8422.

[43] A firm is considered to operate in the steel or aluminum industries if its two-digit SIC is 33 or four-digit SIC is 1000, 1090, 3411, 3412, 3440, 3442, 3444, 3448, 3460, 3490, 3540, or 3541.

likely to be affected by the announcement of the trade war. We follow the refined measure proposed in Bailey et al. (2017) using a dynamic ordinal spatial model to estimate state ideal points. We construct the following measure.

$$\text{Geopolitically Weighted Revenue Share}_\text{i} = \frac{\sum_{\text{j}=1}^{\text{N}} \text{Revenue\_share}_{\text{i,j}} \times \text{Ideological Distance}_\text{j}}{\sum_{\text{j}=1}^{\text{N}} \text{Ideological Distance}_\text{j}} \tag{8}$$

where $\text{Revenue\_share}_{\text{i,j}}$ is the revenue share of firm *i* from country *j*. $\text{Ideological Distance}_\text{j}$ is the absolute ideological distance between country *j* from China using the estimated state ideal points from Bailey et al. (2017). We use the measure based on the UN vote data in 2017, the year before the announcement of the trade war. We plot this absolute distance measure in Online Appendix Fig. 1. The above constructed measure thus captures the average revenue share from all countries weighted by a country's ideological distance from China. We report the results in Panel C of Appendix 4. As shown in columns (1), the coefficient on Geopolitically Weighted Revenue Share is positive and significant, indicating that firms relying on revenue from countries that are on average ideologically distant from China suffer less from the trade war. Geopolitical tension indeed plays an important role in shaping the effect of the trade tensions. But the coefficients on our key variables of interest, namely, revenue from China and imported inputs from China, remain robust. Next, we continue to create separate measures to quantify a U.S. firm's share of revenue from the Middle East, the European Union, and Africa. As shown in columns (3) and (4), the coefficient on a firm's revenue from the Middle East suggests that there are big effects in terms of economic magnitudes, but they are not statistically significant due to the limited amount of identifying variation, making it impossible to draw firm conclusions. The effect of the tariff hikes for firms selling to Africa is negative but insignificant, potentially due to China's increasingly strong geopolitical ties with Africa. The insignificant coefficient, again, suggests that perhaps there are too few firms trading with the continent for us to obtain precise estimated impacts. We conclude that geopolitical links and confounding events may generate meaningful impact on firms with exposure to non-China regions. That said, our baseline results on trade exposure to China remain robust, suggesting that the remaining confounders cannot fully absorb the effect of US-China trade conflicts.

Fourth, tariff hike announcements may generate fears about other non-tariff measures against a U.S. firm's Chinese subsidiaries. As our trade exposure measure is based on the share of sales in China, it may reflect not only exports but also revenue directly generated by U.S. firms' Chinese subsidiaries. We thus investigate whether foreign subsidiaries' sales instead of exports are driving our results. Specifically, we collect information on U.S. firms' subsidiaries from the Wharton Research Data Services (WRDS) Company Subsidiary database. We postulate that firms with more Chinese subsidiaries are more likely to be concerned about non-tariff measures. In Panel D of Appendix 4, we show that the results remain robust when controlling for the number of Chinese subsidiaries. We also include in the regression model an interaction between a firm's share of revenue from China and its number of Chinese subsidiaries, based on the following conjecture. If the non-tariff effect captured by Chinese subsidiaries absorbs the effect captured by revenue share, we would expect firms with both a larger revenue share from China and more Chinese subsidiaries to experience a stronger negative effect. However, as shown in columns (2) and (4) in Panel D of Appendix 4, the coefficients of the interaction are either significantly positive or not distinguishable from zero. In conclusion, it seems that Chinese subsidiaries' sales cannot absorb the entire tariff effect.

Fifth, we check the robustness of the results when using firm size weightings in the regression model, and the results remain similar, as reported in Panel E of Appendix 4.

Sixth, we conduct additional test to account for the potential measurement error problems for our variable *Input_China*. Specifically, we estimate the split instrumental variable regression proposed by Farber et al. (2021) in our own context. In particular, we divide the original US import sample for each sample firm into two groups evenly and randomly.[44] We next construct our measure of the exposure for purchasing from China, *Input_China*, using each of the two groups separately. As a demonstration, we denote one measure as *Input_China1*, the other as *Input_China2*. We then estimate an OLS model regressing *Input_China1* on *Input_China2*, and retrieved the predicted *Input_China1* to be used to replace the original independent variable *Input_China* in our baseline estimation. We consider two estimation models, one with industry fixed effects and one without. We repeat this exercise 200 times and report the results in Appendix 5. Panel A presents the summary statistics of the estimated coefficients generated in these 200 trials. Panel B shows the distribution of the coefficients of the two models considered. Both models show consistently that most of the coefficients are significant and slightly larger than our baseline estimation as reported in columns (3) and (4) of Table 3 Panel A. We thus conclude that the findings are robust to this alternative approach and the measurement error issue is only moderate.

Lastly, 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 four main firm characteristics in the regressions to mitigate any omitted variable biases, concerns remain about potential selection bias arising from firms' non-random trade decisions. To mitigate selection bias, we use a propensity score matching approach and construct a sample matched on the four firm-level control variables considered in our analysis. The results are presented in Appendix 6. Panel A shows the balance tests for firms with and without exports to China. None of the four firm variables are statistically different between the two groups, but the cumulative stock returns are significantly different, a pattern that is consistent with our baseline results reported in Table 3. We also find consistent results when grouping firms according to their exposure to inputs from China.

[44] As it is technically impossible to construct the variable for firms with only one transaction with China in the period of interest, we exclude 50 firms from our sample.

5.2.2. Medium-term impact

One can argue that the findings over a short event window simply reflect a market overreaction. To verify whether the major event of March 22, 2018 considered in our study 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

$$BHAR_i[-X,+Y] = \prod_{-X}^{+Y}(1+R_{it}) - \prod_{-X}^{+Y}(1+MR_t) \tag{9}$$

where R_{it} is the daily stock return for stock i on date t. MR_t is the average return of firms in the market on date t. As a falsification test, we replace the dependent variable in columns (1) and (2) of Panel A of Table 3 with *BHAR[−3,−1]*, which measures the *BHAR* from three days to one day before the tariff hike announcement. A negative correlation between *BHAR[−3,-1]* and the exposure measures would indicate the possibility that our baseline results are driven by some other contemporaneous events during the sample period. We then use *BHAR[−1,+20]*, *BHAR[−1,+40]*, *BHAR[−1,+60]*, and *BHAR[−1,+80]* as dependent variables to estimate the potential medium-term impact of the trade policy shock on firm performance. The coefficients on the two firm exposure measures used in the baseline specification are plotted in Fig. 2 (see the detailed regression results in Appendix 7).

In the pre-event regression, we fail to reject the null hypothesis that the two exposure variables are different from zero. However, we find that the effect of the tariff hike announcement persists in the medium term. For example, a 10 percentage-point increase in a firm's share of revenue from China is associated with a 2.3% lower *BHAR* in the 40 trading days (*BHAR[−1,+40]*) after the announcement. Having confirmed the medium-term impact, in the rest of the paper, we focus on the short windows centered on the different event dates (i.e., March 22, 2018 and the dates of subsequent announcements by the U.S. and China), following conventional practices used in event studies.

5.3. Characteristics of global supply chains

In this subsection, we explore the role of specific supply chain characteristics in influencing the effect of the trade war on U.S. firms. We investigate two characteristics, one on the export side and the other on the import side. First, from the perspective of exports (i.e., exposure due to sales to China), we use a firm's R&D spending to quantify its innovative capacity. Firms with higher innovative capacity are more able to produce the more differentiated products, raising their immunity to trade frictions and thus their Chinese customers switching costs. We include in the regression the variable *R&D*, defined as the ratio of a firm's R&D expenses to its total assets, and its interaction with the firm's revenue share from China. Columns (1) and (2) of Table 4 indicate that the interaction is significantly positive, after industry fixed effects are controlled for. The results confirm our conjecture that the identified effects of tariffs on firms' exports are mainly driven by those with low innovative capacity, similar to the findings in Hombert and Matray (2018).

Next, from the perspective of imports from China, we examine input complexity (i.e., differentiated versus homogeneous inputs). Firms that purchase differentiated products from China would incur higher switching costs than firms that purchase mainly homogeneous products. Using the detailed product categories in the lading database and the definition of product differentiation introduced by Rauch (1999), we construct two measures: *Input_China (Differentiated Products)*, which capture the share of a U.S. firm's differentiated goods imported from China, and *Input_China (Homogeneous Products)* measures a U.S. firm's imports of homogeneous goods from China over total imports. By doing so, we split the original variable *Input_China* into two variables.[45] As shown in columns (3) and (4) of Table 4, the negative tariff effect is concentrated among firms purchasing more differentiated products from China.

In sum, innovative firms and ones that outsource more homogeneous goods are less vulnerable to trade frictions. In the following sections, we continue to investigate how trade shocks propagate through domestic supply chains.

5.4. Domestic production networks

In this subsection, we extend our analysis beyond a firm's direct engagement in trade with China and examine how indirect exposure to China through domestic 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 Securities and Exchange Commission (SEC) requires U.S. listed firms to make supply chain disclosure. In particular, they are obliged to publicly disclose any customer that commands 10% or more of revenue.[46] Firms also voluntarily disclose non-major customers that account for <10% of revenue in their financial reports. As studies (e.g., Atalay et al., 2011; Houston et al., 2016) have shown, the Compustat Segment database, which is built on information on supply chain relationships as disclosed in 10-K filings (annual reports), captures on average 1000 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

[45] We cannot simply include an interaction, as the standalone term *Input_China* is essentially aggregated from detailed transaction data. It is thus more appropriate to separate the variable by the type of import according to the definitions in Rauch (1999).

[46] 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.

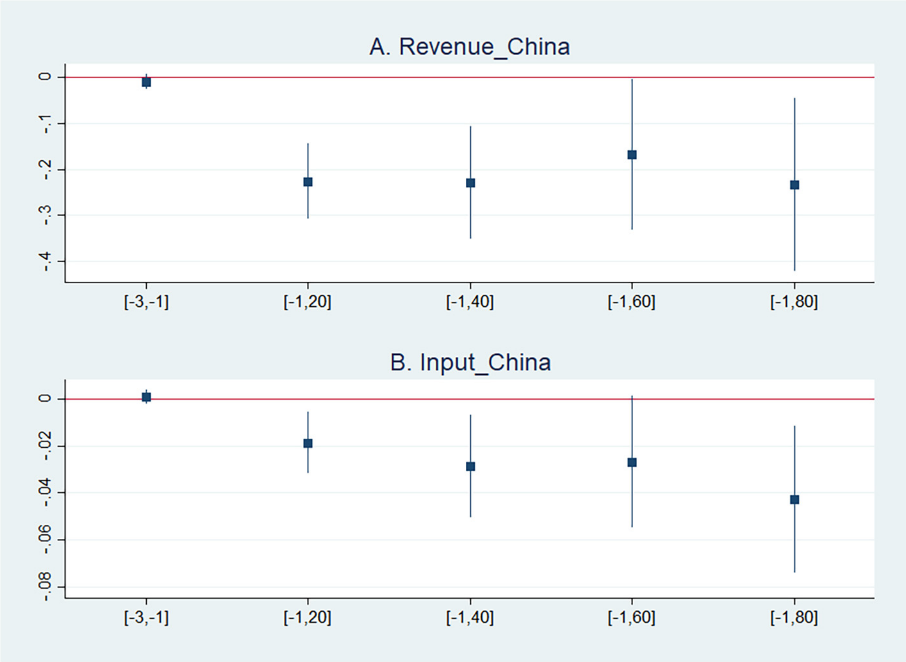

Fig. 2. Medium-term effects.
Notes: This figure shows the medium-term effect of the declaration of the trade war on firm value. We first run the following regression:

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

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 $[-3,-1]$ *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 7.

presentations, company websites, and press releases. Thus, Factset Revere provides much broader coverage than other databases, including Compustat Segment, in terms of the number of firms, countries of origin, and industries. Specifically, Factset Revere actively monitors 10,000 globally listed firms and captures up to 25,000 buyer–supplier relationships per year.[47]

Although Factset Revere is the best available commercial database of its kind, we acknowledge that its coverage is probably incomplete, as it is built on public disclosures and hence has a large-firm focus. For instance, small customers that account for <10% of a firm's revenue may not be included in disclosures and thus may be omitted in the database. A potential selection issue may also arise from firms' voluntary disclosure of suppliers. To fully exploit information on firm-to-firm relationships in the database, we use a “two-way” matching process to construct production networks. We first retrieve all reported information on a firm's customers and suppliers. A supplier firm may disclose a customer, while the same customer may not report the supplier as a connection. Using information reported from either side of a relationship permits the construction of a more complete production network among U.S. firms.

The Factset Revere data set specifies the start and end dates of relationships. We restrict the relationships to those in the three years before the outbreak of the trade war to identify the potentially ongoing upstream and downstream links.[48] Furthermore, we exclude relationships when either side is excluded from our regression sample unlisted, foreign, or financial firms. The final sample of our publicly listed firm network covers 5552 buyer–seller links.

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

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

[48] Our analysis is based on Factset Revere data accessed in March 2018. As the supply-chain relationships are derived from firms' public disclosures, fiscal year 2017 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.

Table 4
Characteristics of a firm's supply chains.

	(1)	(2)	(3)	(4)
	CRR [−1,+1]			
Revenue_China	−0.1207***	−0.0805***	−0.0907***	−0.0466***
	(−6.44)	(−3.87)	(−6.31)	(−2.67)
Revenue_China × R&D	0.4337***	0.3736***		
	(3.96)	(3.34)		
R&D	−0.0454***	−0.0299***		
	(−4.26)	(−2.59)		
Input_China	−0.0084***	−0.0055**		
	(−3.52)	(−2.30)		
Input_China (Differentiated Products)			−0.0097***	−0.0069**
			(−3.11)	(−2.26)
Input_China (Homogeneous Products)			0.0115	0.0107
			(0.34)	(0.33)
N	2309	2291	2309	2291
adj. R-sq	0.074	0.129	0.058	0.123
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes

Notes: This table presents the effect of the trade war announcement on the value of U.S. firms by their revenue from China and the firm's R&D expenditures. *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 the ratio defined as the estimated value of imported goods from China over total estimated value of imported goods from the world. It is calculated using product weight from the bill of lading database in 2016 and 2017 and the estimated average unit price per kilogram (kg) from USA Trade Online. *R&D* is the R&D expenditures scaled by total assets. *Input_China (Differentiated Products)* is the ratio of the estimated value of purchased differentiated products from China over the total estimated value of imported goods. *Input_China (Homogeneous Products)* is the ratio of the estimated value of purchased homogenous products from China over the total estimated value of imported goods. 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.

The first measure is the average exposure to sales in China across a firm's (downstream) buyers in the U.S.:

$$Revenue\_China\_Customers_i = \frac{1}{M}\sum_{m=1}^{M} Revenue\_China_{i,m} \tag{10}$$

where M indicates the number of firm i's customers, and $Revenue\_China_{i,m}$ measures firm i's indirect exposure to sales to China through customer m. As illustrated in Panel A of Fig. 3, U.S. firm A has three U.S. customers, among which firms B and C have Chinese firms as customers. Thus, retaliation from China would reduce sales to firms B and C, which will then have lower 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. A green node means that the firm has revenue from China, while a white node indicates zero revenue from China.

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

$$Input\_China\_Customers_i = \frac{1}{M}\sum_{m=1}^{M} Input\_China_{i,m} \tag{11}$$

where $Input\_China_{i,m}$ is the share of estimated import value from China for customer m.[49] As illustrated in Panel B of Fig. 3, U.S. firm A has three U.S. customers, among which firms B and C have Chinese firms as suppliers. Tariff hikes increase the cost of Chinese inputs for firms B and C, potentially lowering their production and thus their demand for goods from firm A. In contrast, if the intermediate goods produced by Chinese firms E and F can be sufficiently substituted by goods produced by firm A, then tariff hikes may also increase the demand for goods produced by firm A and boost its sales. The production network of GE is plotted in Panel D of Fig. 3, now with blue nodes indicating GE's U.S. customers that have outsourced inputs from China.

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

$$Revenue\_China\_Suppliers_i = \frac{1}{N}\sum_{n=1}^{N} Revenue\_China_{i,n} \tag{12}$$

where N indexes the number of suppliers firm i has. As illustrated by Panel A of Fig. 4, U.S. firm A has three U.S. suppliers, among which firms B and C have Chinese firms as customers. Given that retaliation from China would reduce firm B's and firm C's sales to Chinese

[49] As discussed above, the regulation only requires firms to disclose the revenue share of their major customers; in a large proportion of the supply-chain relationships, no information is given on the associated revenue derived from the major customers. We thus treat all customers equally and construct the simple average measure for research purposes.

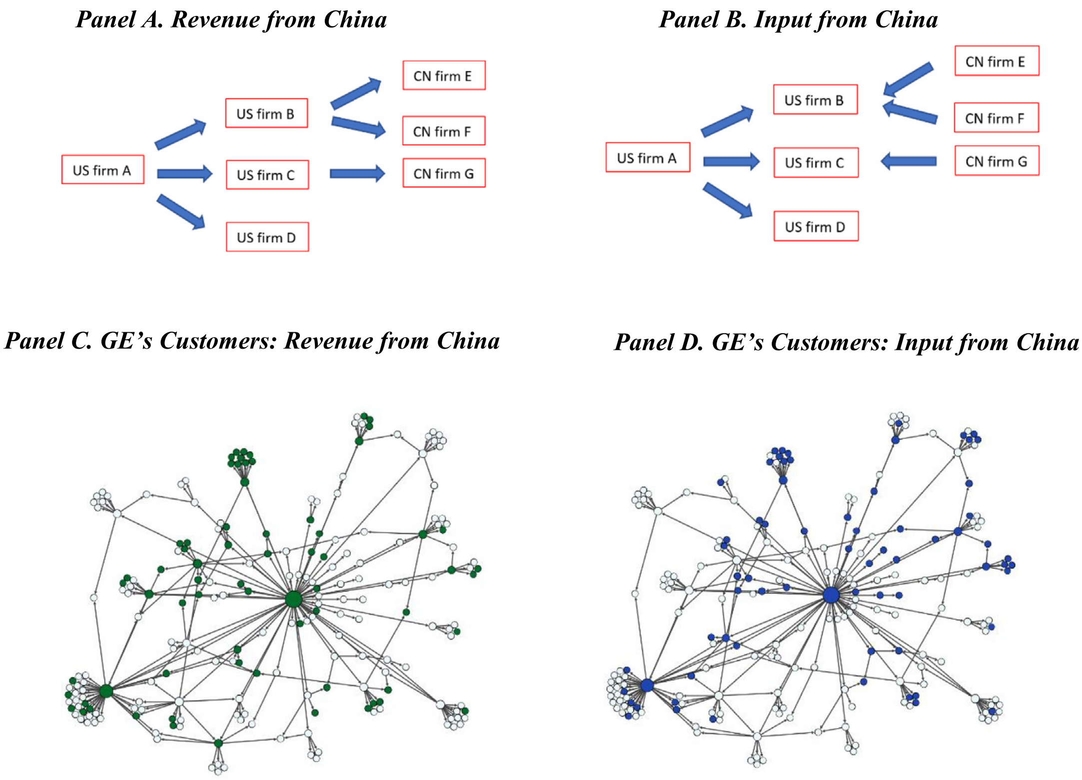

Fig. 3. Firm production networks: customer side.
Notes: This figure illustrates the firm production networks from the customers' perspectives. In Panels A and B, the direction of the arrows indicates the trade flow. Specifically, in Panel A, the U.S. firm B purchases from firm A and Chinese firm E purchases from U.S. firm B. Similarly, in Panel B, U.S. firm B purchases from U.S. firm A and Chinese firms E and F. Panel C presents the network of the customers of General Electric as an example. The graph only contains two layers of customers. Each node represents a firm and the size of the node represents the number of supply chain links of a firm. The node in the center of the graph is General Electric. Green nodes indicate firms that have revenue from China and white nodes indicate firms with zero revenue from China. The direction of the link also shows the trade flow. Panel D shows the same network of customers of General Electric. Here, the blue nodes indicate firms with input from China and white nodes indicate firms without input from China.

firms, firms B and C may downsize their production, and the accompanying adverse performance shocks could be transmitted to firm A. As a further illustration, Panel C shows the two-layer supplier network of Boeing, with the green nodes indicating firms with some revenue from China and white nodes denoting firms without any revenue from China.

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

$$Input\_China\_Suppliers_i = \frac{1}{N}\sum_{n=1}^{N} Input\_China_{i,n} \tag{13}$$

where $Input\_China_{i,n}$ is the share of estimated import value from China for supplier n. Panel B of Fig. 4 illustrates the construction process. U.S. firm A has three U.S. suppliers, among which firms B and C have Chinese firms as suppliers. Tariff hikes increase the cost of Chinese inputs for firms B and C, leading them to increase their product prices. As a result, the production costs of firm A increase. In other words, firm A suffers from tariff-induced cost increases due to cost pass-through. In Panel D, we plot the two-layer supplier network of Boeing, as in Panel C of Fig. 4. The blue nodes indicate firms that purchase inputs from China, and the white nodes indicate firms without inputs from China.

It is worth noting that not all firms have a public customer or a public supplier. For such cases, we assign a value of zero to the indirect measures defined above. As shown in Table 1, the average revenue from China across a firm's customers (suppliers) is 1.6% (2.4%). On average, the average share of input from China across a firm's customers (suppliers) is 9.6% (10.5%).

Appendix 8 offers additional statistics. Panel A of Appendix 8 shows the distributions of the numbers of customers and suppliers in firms' production network. Consistent with the literature (e.g., Atalay et al., 2011), both distributions are highly skewed. The firms with the largest numbers of customers in our sample are Microsoft, GE, IBM, Apple, and Oracle, while those with the largest numbers of suppliers are GE, Walmart, Boeing, Microsoft, and Amazon. Panel B presents

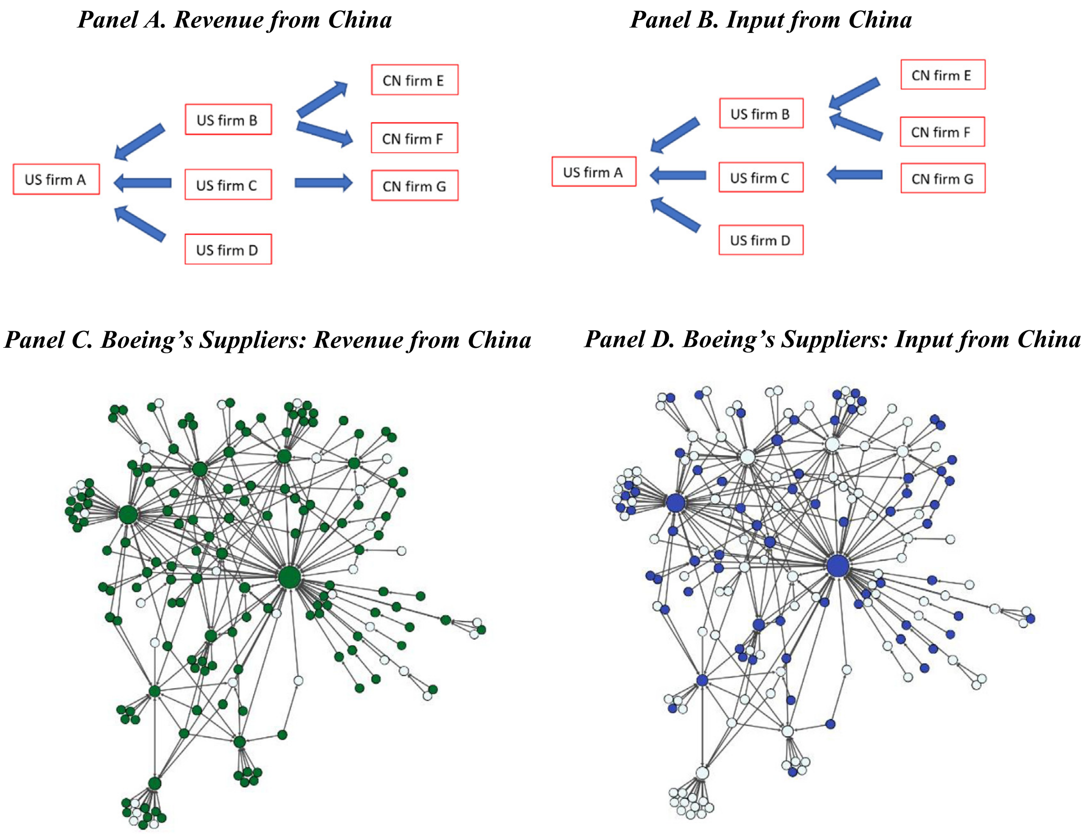

Fig. 4. Firm production networks: supplier side.
Notes: This figure illustrates the firm production networks from the suppliers' perspectives. In Panels A and B, the direction of the arrows indicates the trade flows. Specifically, in Panel A, the U.S. firm B sells products to U.S. firm A and Chinese firms E and F. Similarly, in Panel B, U.S. firm A purchases from U.S. firm B that purchases from Chinese firms E and F. Panel C presents the network of the suppliers of Boeing as an example. The graph only contains two layers of suppliers. Each node represents a firm and the size of the node represents the number of supply chain links of a firm. The largest node is Boeing. Green nodes indicate firms that have revenue from China and white nodes indicate firms with zero revenue from China. The direction of the link also shows the trade flow. Panel D shows the same network of the suppliers of Boeing. Here, the blue nodes indicate firms with input from China and white nodes indicate firms without input from China.

descriptive statistics for the indirect measure in the two samples. Panel B.1 is based on the baseline sample of 2309 firms. On average, a sample firm has 2.4 listed customers and 2.4 listed suppliers. Panel B.2 shows summary statistics for the variable without ascribing zero to firms without listed customers or listed suppliers. For instance, the average share of revenue from China among listed customers is about 3.4%, and the average share of input from China their U.S. customers is about 20.1%.

We next estimate the effects of indirect exposure together with the direct exposure measures included in the baseline regression. Table 5 shows the effect originating from Chinese revenue among a firm's customers and suppliers. The univariate analysis in Panel A indicates that firms with domestic customers that derive revenue from China experience 1% lower stock returns (as measured by *CRR*) than firms without. Meanwhile, firms with domestic suppliers that derive revenue from China experience 1.1% lower stock returns than firms without such suppliers. The regression results reported in Panel B suggest that when including direct exposure to exports to China in the regression, the effects of the average revenue share from China across a firm's domestic customers and suppliers are both statistically and economically significant. Specifically, column (1) shows that a 10% increase in indirect sales exposure through customers (*Revenue_China_Customer*) is associated with a 0.98% lower *CRR* over the three days centered on March 22, 2018. Column (2) shows that a 10% increase in indirect sales exposure through suppliers (*Revenue_China_Supplier*) is associated with a 0.89% lower *CRR*. The effects remain significant when the indirect measures based on customers and suppliers are jointly estimated in the regression model, as shown in column (3), and when industry fixed effects are included, as shown in column (4). Interestingly, column (3) shows that the combined magnitude of the coefficients for the indirect measures (0.083 + 0.079) is significantly larger than the coefficient for the direct measure (0.058). These results suggest that indirect trade exposure through domestic supply chains is quantitatively more important than direct exposure. These results are not surprising, given that supply chains typically contain multiple channels through which the tariff effects can be transmitted (either U.S. or Chinese tariffs), similar to the findings in Dhyne et al., 2021, who use comprehensive firms' network data for Belgian to study direct and indirect exposure to trade shocks.

Table 5
Transmission through domestic production networks: revenue from China.

Panel A. Univariate Analysis

		CRR[−1,+1]	
		N	Mean
Revenue_China_Customer	>median	807	−0.033
	<median	1502	−0.023
	Difference in Means		−0.010***
	p-value		<0.01
Revenue_China_Supplier	>median	999	−0.033
	<median	1310	−0.021
	Difference in Means		−0.011***
	p-value		<0.01

Panel B. Revenue from China

	(1)	(2)	(3)	(4)	(5)	(6)
	CRR [−1,+1]					
Revenue_China	−0.0707***	−0.0746***	−0.0582***	−0.0330*	−0.0568***	−0.0330*
	(−4.60)	(−5.06)	(−3.72)	(−1.85)	(−3.64)	(−1.85)
Revenue_China_Customer	−0.0983***		−0.0832***	−0.0636***		
	(−4.15)		(−3.47)	(−2.65)		
Revenue_China_Supplier		−0.0885***	−0.0788***	−0.0464**	−0.0782***	−0.0470**
		(−4.54)	(−3.99)	(−2.20)	(−3.96)	(−2.23)
Revenue_China_Customer (R&D Low)					−0.0843***	−0.0547**
					(−2.93)	(−1.97)
Revenue_China_Customer (R&D High)					−0.0418*	−0.0358
					(−1.81)	(−1.53)
N	2309	2309	2309	2291	2309	2291
adj. R-sq	0.060	0.062	0.065	0.126	0.066	0.125
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No	Yes

Notes: This table presents the effect of the trade war announcement based on firms' revenue from China and their domestic production networks. *Revenue_China* is the measure of the revenue a firm gains from China. *Revenue_China_Customer* is the simple average revenue from China across a firm's customers. *Revenue_China_Supplier* is the simple average revenue from China across a firm's suppliers. The firm production network is based on all of the supply chain relationships in the three years before the trade war announcement from the Revere database. Panel A shows the univariate analysis results. The regression results are presented in Panel B. *Revenue_China_Customer (R&D Low)* is the mean of *Revenue_China* among firm's customers with R&D intensity below the industry median. *Revenue_China_Customer (R&D High)* is the mean of *Revenue_China* among firm's customers with R&D intensity above the industry median. 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.

We further investigate R&D intensity as a salient characteristic of domestic supply chains. First, we define average exposure to sales in China across a firm's (downstream) U.S. buyers with low R&D intensity:

$$Revenue\_China\_Customers_i(\text{R\&D Low}) = \frac{1}{M}\sum_{m=1}^{M} Revenue\_China_{i,m}^{\text{R\&D Low}} \tag{14}$$

where M indicates the number of firm i's customers, while $Revenue\_China_{i,m}^{\text{R\&D Low}}$ measures firm i's indirect exposure to sales to China through customer m, which has an R&D intensity below the industry median. Similarly, we define average exposure to sales in China across a firm's (downstream) U.S. buyers with high R&D intensity:

$$Revenue\_China\_Customers_i(\text{R\&D High}) = \frac{1}{M}\sum_{m=1}^{M} Revenue\_China_{i,m}^{\text{R\&D High}} \tag{15}$$

where $Revenue\_China_{i,m}^{\text{R\&D High}}$ is constructed using a sample of customers that have an R&D intensity above the industry median. We use the above two measures to replace the original measure, *Revenue_China_Customer*, and present the results in columns (5) and (6) of Table 5. Consistent with our argument in section 5.3, the negative effect is mainly concentrated among domestic customers with low innovative capacity.

Table 6 presents the estimated impact of indirect exposure to Chinese inputs through either domestic customers or suppliers. The univariate analysis in Panel A shows significant differences in stock performance between firms with positive indirect exposure versus firms with zero indirect exposure. Specifically, firms with customers that purchase inputs from China experience, on average, a 1.0% lower three-day return than firms without such customers. Similar differences can be observed between firms with and without suppliers that purchase goods from China. Panel B presents consistent regression results, with the exception of column (4), where industry fixed effects absorb the effect of indirect input exposures. Specifically, column (3) suggests that

Table 6
Transmission through domestic production networks: inputs from China.

Panel A. Univariate Analysis

		CRR[−1,+1]	
		N	Mean
Input_China_Customer	>median	705	−0.033
	<median	1604	−0.023
	Difference in Means		−0.010***
	p-value		<0.01
Input_China_Supplier	>median	738	−0.032
	<median	1571	−0.024
	Difference in Means		−0.008***
	p-value		<0.01

Panel B. Input from China

	(1)	(2)	(3)	(4)	(5)	(6)
	CRR [−1,+1]					
Input_China	−0.0093***	−0.0097***	−0.0093***	−0.0060**	−0.0093***	−0.0059**
	(−3.89)	(−4.03)	(−3.86)	(−2.49)	(−3.87)	(−2.48)
Input_China_Customer	−0.0094***		−0.0086**	−0.0030	−0.0087**	−0.0030
	(−2.75)		(−2.49)	(−0.87)	(−2.51)	(−0.86)
Input_China_Supplier		−0.0071**	−0.0062*	−0.0028		
		(−2.11)	(−1.82)	(−0.83)		
Input_China_Supplier (Differentiated Products)					−0.0075*	−0.0033
					(−1.87)	(−0.85)
Input_China_Supplier (Homogeneous Products)					−0.1000	−0.1040
					(−0.86)	(−0.89)
N	2309	2309	2309	2291	2309	2291
adj. R-sq	0.049	0.049	0.050	0.121	0.050	0.121
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No	Yes

Notes: This table presents the effect of the trade war announcement based on firms' input from China and their domestic production networks. *Input_China* is the ratio defined as the estimated value of imported goods from China over total estimated value of imported goods from the world. It is calculated using product weight from the bill of lading database in 2016 and 2017 and the estimated average unit price per kilogram (kg) from USA Trade Online. *Input_China_Customer* is the simple average input ratio from China across a firm's customers. *Input_China_Supplier* is the simple average input ratio 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. We gauge product differentiation following the practice in Rauch (1999). *Input_China_Supplier (Differentiated Products)* is defined as the average ratio of imported differentiated goods among a firm's suppliers. *Input_China_Supplier (Homogeneous Products)* is defined as the average ratio of imported homogeneous goods among a firm's suppliers. 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.

firms that directly purchase more inputs from China (*Input_China*) experience, on average, a lower return. Indirect input exposure through customers (*Input_China_Customer*) and through suppliers (*Input_China_Supplier*) both demonstrate a significant effect on stock returns, with their combined coefficients having a larger magnitude than that of the direct measure.

We further investigate the type of imported input as another salient characteristic of domestic supply chains. We follow Rauch (1999) in identifying whether a U.S. firm has purchased differentiated products from China. We construct the average exposure to inputs from China across suppliers with differentiated product inputs:

$$Input\_China\_Supplier_i(\text{Differentiated Products}) = \frac{1}{N}\sum_{n=1}^{N} Input\_China_{i,n}^{Differentiated\ Products} \tag{16}$$

where N indicates the number of firm i's suppliers, while $Input\_China_{i,n}^{Differentiated\ Products}$ is the share of estimated value of imported differentiated goods from China over total value of imported goods for supplier n. Similarly, we define the average exposure to inputs from China across suppliers with homogeneous product inputs:

$$Input\_China\_Supplier_i(\text{HomogeneousProducts}) = \frac{1}{N}\sum_{n=1}^{N} Input\_China_{i,n}^{Homogeneous\ Products} \tag{17}$$

where $Input\_China_{i,n}^{Homogeneous\ Products}$ is the share of estimated value of imported homogeneous goods from China over total value of imported goods for supplier n. As shown in column (5) of Table 6, we find that the adverse trade war effect mainly propagates through suppliers buying differentiated products from China.

In sum, the results reported in Tables 5 and 6 collectively show that the structure of a firm's supply network affects perceptions about how tariff hikes will affect the firm, even when it has no direct trade relationship with China. The indirect effect is found to reduce a firm's cash flows due to lower demand from affected customers (downstream portion of the supply chain) and higher input (and hence production) costs for domestic suppliers (upstream portion of the supply chain).

5.5. Product lists

Thus far, we have established the relationship between firms' stock returns and their trade exposure. We intuitively assume that firms that derive a large proportion of their revenue from China or purchase inputs from China, both directly are indirectly, are more affected by the announced tariffs. Now, using the detailed lists of tariffed products, we can conduct an event study at a more disaggregated level and examine whether the heterogeneous effects of the trade war across firms can be attributed to a firm's output/input mix. Our identification hinges on the assumption that investors were uncertain about the products that would be subject to tariff increases in both countries at the time of issuance of the March 22, 2018 presidential memorandum. We later relax this assumption for additional analysis.

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

The Chinese government issued its first product list on March 23, 2018, the day after the presidential memorandum. The list covers 128 products, disaggregated at the HS eight-digit level, with a total value of about $3 billion. Announced by China's Customs Tariff Commission, the list includes 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. According to the Chinese government, the new tariffs were imposed as a retaliation against the U.S. tariffs on imported steel and aluminum. The product on the list with the largest exports to China is aluminum scrap. The retaliatory list provides an opportunity to assess the financial market responses to firms based on information at the firm-product level.

The first empirical challenge of this exercise is to identify the products manufactured by firms. In Compustat and most of the major firm data sets, firms typically report their main industry only. Thus, following the literature (e.g., Hoberg and Phillips, 2016), we conduct a textual analysis of U.S. firms' product descriptions disclosed in their filings with regulators (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 filings and further cleaned to generate a unique list of products manufactured by individual firms. We then combine these two lists with the products included in the Chinese tariff list to construct the 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 9.

Panel A of Table 7 reports the estimation results on the heterogeneous market responses to U.S. firms according to their output mix. Independent of whether the four firm characteristics (column (1)) or industry fixed effects (column (2)) are controlled, we find a negative and statistically significant coefficient on *Output_China_List*, suggesting that the market responds more negatively to firms that have proportionally more of their products tariffed by China and are thus more exposed to the trade war than to other firms. Specifically, a one standard deviation higher *Output_China_List* is associated with an additional 0.19% to 0.22% decline in stock prices between March 22 and March 24, 2018. We also consider the network effects arising from U.S. firms' customers or suppliers. As column (3) of Panel A suggests, the trade war effect is more pronounced when a firm's downstream buyers have export exposure to the product list, consistent with the prediction of our model. This significant effect, however, is weakened when industry fixed effects are included.

The U.S. government issued its first product list on April 3, 2018. Following the March 22 presidential memorandum, the USTR published a provisional list of imports that would be subject to new duties in retaliation for “the forced transfer of American technology and intellectual property.” The list covers about 1300 Chinese products (at the HS eight-digit level), accounting for approximately $50 billion of U.S. imports from China. The products, which include raw materials, construction machinery, aerospace and agricultural equipment, electronics, medical devices, and consumer products, were chosen based on the target sectors mentioned in the “Made in China 2025” plan. Using product-level trade data, we find that automatic data processing machines and machinery accessories are among the products most imported by the U.S. from China.

We define the variable *Input_US_List* as the fraction of a firm's products purchased from China that are covered by the April 3 tariff list issued by the U.S. government.[51] As shown in columns (1) to (4) of Panel B in Table 7, U.S. firms with more inputs

[50] 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.

[51] To be consistent with analysis above, we match the lading database with the product list using four-digit HS codes. The results are similar but noisier when using six-digit HS codes in the matching process.

Table 7
Firms' heterogeneous responses to the announcement of product lists.

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

	(1)	(2)	(3)	(4)
	CRR [−1,+1], Mar 23			
Output_China_List	−0.1192**	−0.1385**	−0.1203**	−0.1387**
	(−2.25)	(−2.55)	(−2.27)	(−2.56)
Output_China_List_Customer			−0.1189**	−0.0732
			(−2.37)	(−1.41)
Output_China_List_Supplier			−0.0226	−0.0773
			(−0.42)	(−1.37)
N	2309	2291	2309	2291
adj. R-sq	0.014	0.032	0.015	0.033
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes

Panel B. Firms' Responses to the U.S. Product List issued on April 3, 2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CRR [−1,+1], Apr 3							
Input_US_List	−0.0061**	−0.0058*	−0.0057*	−0.0058*				
	(−2.05)	(−1.79)	(−1.93)	(−1.77)				
Input_US_List_Customer			−0.0060	−0.0017				
			(−1.58)	(−0.43)				
Input_US_List_Supplier			0.0025	0.0012				
			(0.61)	(0.27)				
Tariff_Change					−0.0013***	−0.0008*	−0.0013***	−0.0008
					(−2.98)	(−1.66)	(−2.86)	(−1.64)
Tariff_Change_Customer							−0.0006	0.0004
							(−0.79)	(0.53)
Tariff_Change_Supplier							0.0001	0.0004
							(0.13)	(0.43)
N	2305	2287	2305	2287	544	536	544	536
adj. R-sq	0.004	0.033	0.004	0.032	0.016	0.066	0.014	0.063
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel C. Firms' Responses to the U.S. Product List issued on April 3, 2018, excluding firms with trade tension expectations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CRR [−1,+1], Apr 3							
Input_US_List	−0.0093**	−0.0099**	−0.0092**	−0.0100**				
	(−2.48)	(−2.37)	(−2.44)	(−2.38)				
Input_US_List_Customer			−0.0036	0.0011				
			(−0.89)	(0.26)				
Input_US_List_Supplier			0.0030	0.0019				
			(0.65)	(0.40)				
Tariff_Change					−0.0020***	−0.0016***	−0.0020***	−0.0017***
					(−3.58)	(−2.60)	(−3.46)	(−2.64)
Tariff_Change_Customer							−0.0004	0.0009
							(−0.48)	(0.94)
Tariff_Change_Supplier							−0.0003	0.0002
							(−0.32)	(0.20)
N	1886	1873	1886	1873	382	377	382	377
adj. R-sq	0.005	0.034	0.005	0.033	0.028	0.070	0.024	0.067
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: This table presents U.S. firms' responses to the product lists announced by the U.S. and China. We consider two product lists, the first Chinese product list released on March 23, 2018, and the first U.S. product list released on April 3, 2018. Panel A presents the U.S. firms' responses to the Chinese product list. The dependent variables are the three-day cumulative raw returns centered on the corresponding event dates. *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 9. The variable is a proxy for U.S. firms' exposure to the Chinese product list in terms of revenue losses. *Output_China_List_Customer* is the average *Output_China_List* among a US firm's customers. *Output_China_List_Supplier* is the average *Output_China_List* among a US firm's suppliers. Panel B presents firms' responses to the first product list announced by the U.S. government on April 3, 2018. *Input_US_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. *Input_US_List_Customer* is the average *Input_US_List* among a US firm's customers. *Input_US_List_Supplier* is the average *Input_US_List* among a US firm's suppliers. *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. The sample only consists of firms that have imports from China according to the lading database. *Tariff_Change_Customer* is the average *Tariff_Change* among a US firm's customers. *Tariff_Change_Supplier* is the average *Tariff_Change* among a US firm's suppliers. In Panel C, we reproduce the results in Panel B using a sample of firms with low level of trade tension expectations. We quantify the trade tension expectations by calculating the number of trade-related news articles for individual firms issued between March 22 and April 2, as in this period, the public started to be aware of the trade tensions. The data on the news articles is retrieved from RavenPack Database. We exclude firms with news articles with any of the trade-related keywords ("trade", "tariff", and "China") in this period and present the results in Panel C. 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.

covered by the U.S. tariff list experience larger negative returns in the three-day window centered on April 3. Specifically, a one-standard-deviation increase in *Input_China_List* is associated with an additional 0.15% (when firm characteristics are controlled for; column (1)) decline in stock prices between April 2 and April 4. We do not find significant indirect network effects, as shown in columns (3) and (4).[52]

We further explore the variation in tariff hikes across products. Specifically, for each product, we compare the planned (post-hike) tariff rate to the pre-event tariff rate. We first calculate the difference between the new rate (according to the tariff list) and the original rate at the HS level and then match with the transactions of firms' imports from China. *Tariff_Change* is defined as the value-weighted average import tariff increase, using transaction quantities as weights. The findings in columns (5) to (8) of Panel B in Table 7 suggest that a 10 percentage-point increase in a firm's average tariff rate results in a 1.3% (when firm characteristics are controlled for; column (5)) to 0.8% (when industry fixed effects are also controlled for; column (6)) reduction in stock returns.

The previous analysis assumes that the public was not clear about the firm-level exposures to tariff hikes. Yet, it is likely that after trade war was announced on March 18, 2018, investors started to form expectations on the trade tensions. To tease out the effect of the unexpected tariff hikes, we use news article discussions to capture firm's trade exposure perceived by the public before the product list was issued on April 3, 2018. To this end, we retrieve the huge amount data on news articles covering our sample listed firms from RavenPack Database. On average, there are 94 thousand news articles per date for our sample firms. Roughly 41 news articles per day were issued for each of our sample firms. We downloaded and cleaned the data to quantify the media mentions regarding trade tensions between US and China around our event dates including Trump's Memorandum on March 18, 2018 and the announcement of US tariff list on April 3. The frequency of the news articles is shown in Fig. 2 of the Online Appendix. We identify firms that were covered by news articles with trade related keywords in the titles, including "trade", "tariff", and "China". In Fig. 5, we show the time-series of the article counts for each of the keywords for our sample firms. The number of trade tension related articles peaked on the date of presidential memorandum March 22, 2018, and the date when U.S. Product List was issued on April 3, 2018. This time-series pattern confirms that the news article mentions are a valid measure for trade expectations for firms being covered.

We calculate the number of trade-related news articles for each sample firm issued between March 22 and April 2, as in this period, the public started to be aware of the trade tensions. More trade-related discussions regarding a firm in this period indicate the firm is likely to be subject to tariff costs imposed by the follow-up tariff lists with the uncertainty taken into account. We exclude firms with news articles with any of the trade-related keywords ("trade", "tariff", and "China") in this period and construct a sample of firms without clear trade-related expectations. We re-estimate the effect of the US product list issued on April 3 and show the results in Table 7 Panel C. US firms with imports mentioned in the product list experience significantly negative performance, with a magnitude larger than that using the full sample of firms with mixed trade-related expectations. For example, when firm characteristics are controlled for, the effect of 10% increase in tariff rate increases from 1.3% to 2% and remains significant when industry fixed effects are included.

We also explore the heterogeneous effect of the product list announcement among industries with more trade-related discussions vs. ones with few trade-related discussions. In Online Appendix Fig. 3, we present the distribution of the news articles mentions across Fama-French 50 classifications with each of the trade-related keywords ("trade", "tariff", and "China"), respectively. Clearly, there are some industries with more media discussions while the majority of industries with few mentions in the news articles. We count the total number of trade mentions at the industry level and perform a subsample analysis. As shown in the Online Appendix Table 1, the effect is only significant among industries with low trade tension expectations, a pattern consistent with our finding in Table 7 Panel C.

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

5.6. The reverse experiment

We have already offered evidence that the heterogeneous effects of tariff announcements are not transitory but persist in the medium term. Meanwhile, several unanticipated events in 2018 and 2019 appeared to send positive signals in terms of the trade war possibly being settled, alleviated, or delayed. In this subsection, we exploit one such event as a reverse experiment to further confirm our baseline results.

On January 9, 2019, U.S. and Chinese officials concluded three days of trade talks in Beijing. At the end of the talks, the Commerce Ministry of China issued an extensive statement to provide a foundation for resolving the two countries' concerns. In a further positive sign, President Trump tweeted that the "Talks with China are going very well!" The fact that the trade talks lasted one day longer than had been previously announced also led market analysts to believe the discussions had made progress. Fig. 6

[52] The lack of the indirect effects of the announcement of the US tariff list on US companies can be because of firms' partial adjustment of supply chains when the tariff hikes were initially announced in March. In addition, the efficient market hypothesis implies that the investors might already expect the potential effect through supply-chain exposure when the trade war event was first announced, implying weaker effects of any subsequent announcements.

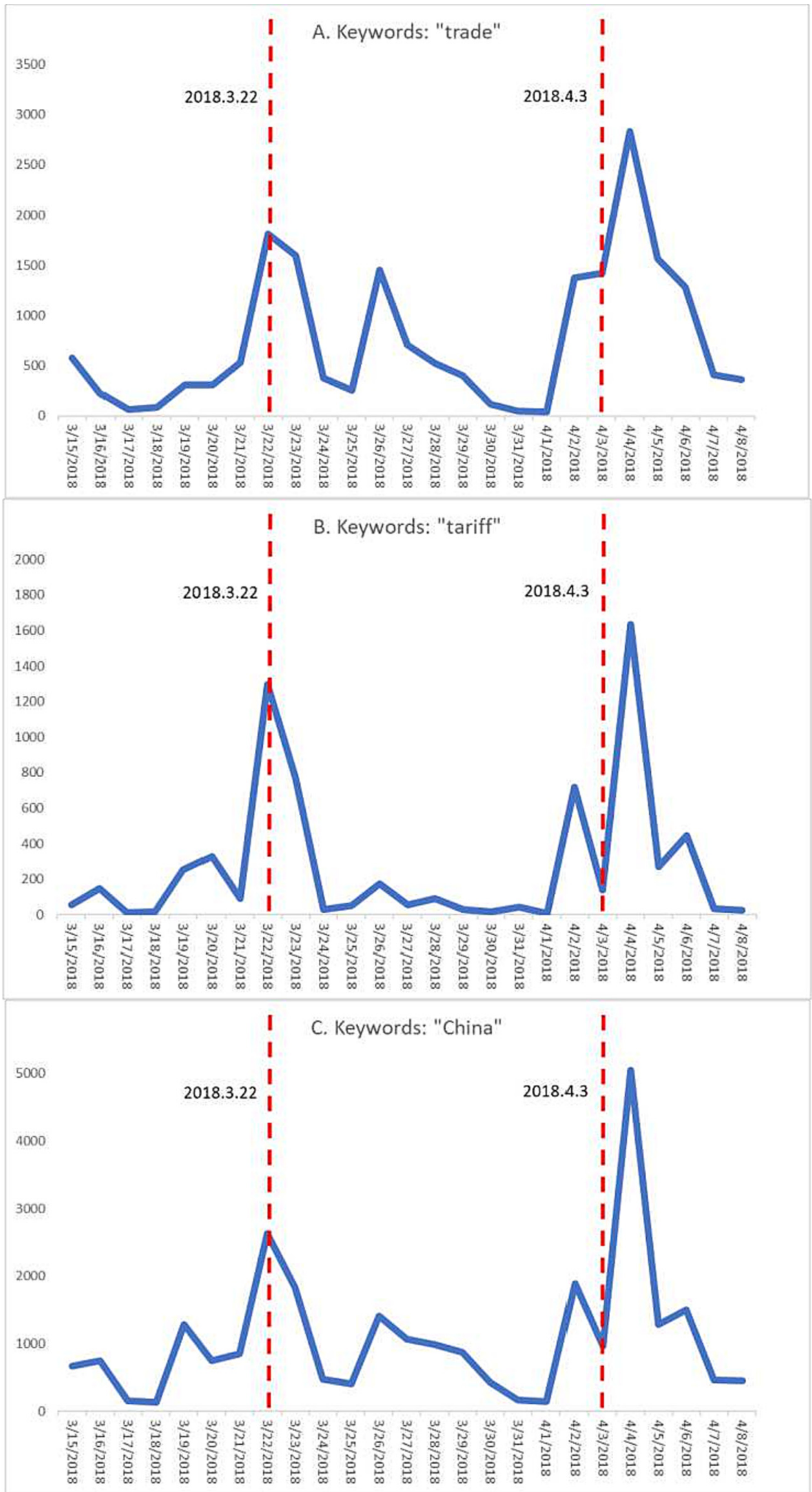

Fig. 5. News articles around the events.

Notes: This figure presents the time-series of the number of news articles covering the sample firms with three keywords. Panel A shows the number of news articles with the keyword "trade". Panel B shows the number of news articles with the keyword "tariff". Panel C shows the number of news articles with the keyword "China". The data on the news articles is retrieved from RavenPack Database.

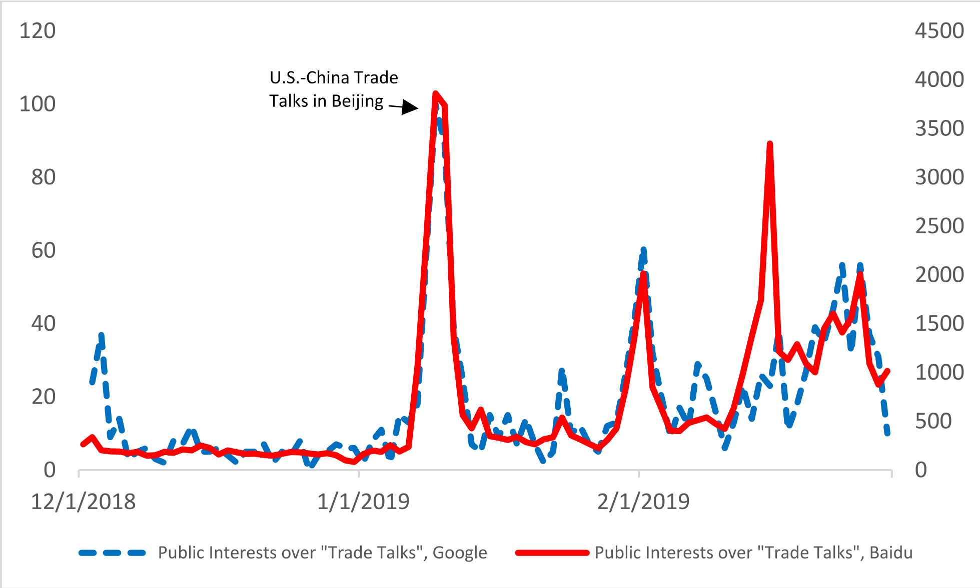

Fig. 6. Public interest in the U.S.-China trade talks.
Notes: This figure presents the time-series of the public interest in “U.S.-China trade talks.” The blue dashed line denotes the public interest in “trade talks” as measured by Google Trends (left scale). The red solid line indicates the public interest in the trade war as measured by the Baidu Index (right scale), the Chinese counterpart of Google.

plots the trajectory of searches on “trade talks” and shows that public interest in the talks peaked on January 9, 2019, as indicated by search engines in both countries. We evaluate firms' stock price responses around this event, which are expected to reverse the adverse effects of the trade war.

The results are reported in Table 8. Panel A presents the univariate analysis. Due to the passage of time, we construct the trade exposure measures using data available to the end of 2018. In the three-day window around the event date, firms that are more dependent on sales to China (having a China revenue share above the median) experience a 0.6% larger gain in raw returns relative to firms that are less dependent on sales to China. Firms that source inputs from China experience a 0.7% larger gain in returns relative to firms without inputs from China. The effects of the direct trade exposures remain significant in the regression as shown in column 4 of Panel B. The effects through the domestic supply chain networks are positive as expected but not significant.

5.7. Stock return reactions of Chinese firms

Thus far, we have examined market reactions to the tariff hike announcement of March 22, 2018 using a sample of U.S. publicly listed firms. The U.S. tariff hikes (and their announcement) should also have affected the export sales, and thus the stock returns, of Chinese firms in the U.S.[53] Therefore, we conduct a similar set of event study analyses from the perspective of Chinese publicly listed firms. We use a unique China customs database that contains detailed firm-level information on imports and exports to measure firms' trading activities with the U.S. The most updated version of the customs database is for 2016. We merge the customs database with the Chinese counterpart of Compustat, the China Stock Market & Accounting Research (CSMAR) database, based on firm names. We first use a fuzzy matching algorithm to filter the firm names in the China customs database with similar firm names from the CSMAR database. We then manually check the accuracy of the matches to generate the final matches between the two databases. We construct two variables for Chinese listed firms: *Revenue_US*, which is a firm's value of exports to the U.S. divided by the firm's total revenue in 2016; and *Input_US*, which is the value of imports from the U.S. over the total import value in 2016.

[53] Carpenter and Whitelaw (2017) and Carpenter et al. (2021) suggest that the stock price informativeness of China's market has become comparable to that of the U.S. market in recent years.

Table 8
Trade talks as a reverse experiment.

Panel A. Univariate Analysis

		CRR[−1,+1], Jan 9	
		N	Mean
Revenue_China	>median	813	0.03
	<median	1314	0.024
	Difference in Means		0.006***
	p-value		<0.01
Input_China	>median	356	0.032
	<median	1771	0.025
	Difference in Means		0.007**
	p-value		0.015

Panel B. Regression Estimation

	(1)	(2)	(3)	(4)	(5)	(6)
	CRR [−1,+1], Jan 9					
Revenue_China	0.0457***		0.0448***	0.0292*	0.0355**	0.0234
	(3.23)		(3.18)	(1.76)	(2.25)	(1.36)
Input_China		0.0059*	0.0055	0.0060*	0.0052	0.0058
		(1.72)	(1.62)	(1.65)	(1.53)	(1.60)
Revenue_China_Customer					0.0418	0.0218
					(1.57)	(0.81)
Revenue_China_Supplier					0.0275	0.0341
					(0.89)	(1.05)
N	2127	2127	2127	2112	2127	2112
adj. R-sq	0.011	0.008	0.011	0.023	0.011	0.023
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes	No	Yes

Notes: This table shows U.S. firms' responses to the U.S.-China trade talks held in Beijing from January 7–9, 2019. We consider the last day of the trade talks as the event day as it conveys the positive signal to the market. *CRR [−1,+1], Jan 9* is the three-day cumulative raw returns centered on January 9, 2019. Panel A presents the univariate analysis results. Panel B presents the regression results. *Revenue_China* is the revenue from China scaled by total revenue using data as updated in Factset Revere database. *Input_China* is the ratio defined as the estimated value of imported goods from China over total estimated value of imported goods from the world. It is calculated using product weight from the bill of lading database updated in 2018 and the estimated average unit price per kilogram (kg) from USA Trade Online. *Revenue_China_Customer* is the average *Revenue_China* among a US firm's customers. *Revenue_China_Supplier* is the average *Revenue_China* among a US firm's suppliers. 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.

Table 9 presents the results for the Chinese market. Panel A offers summary statistics for a sample of 2588 Chinese publicly listed firms.[54] The average *CRR[−1,+1]* around the March 22, 2018 announcement is −4.1%, with a standard deviation of 4.7%. The median firm in the Chinese sample does not import from or export to the U.S. The mean share of exports to the U.S. in total sales is 0.9%,[55] and on average Chinese firms offshore 5.6% of their input from the U.S. Panel B of Table 9 shows the univariate analysis around the time of the announcement. Chinese firms that export to the U.S. suffer an average 0.7% additional negative return relative to firms that do not. Similarly, Chinese firms that purchase inputs from the U.S. experience an average 0.5% additional negative return relative to firms that do not.

Panel C of Table 9 shows the regression results of the event study, which confirm the findings of the univariate analysis. Controlling for firm-level characteristics, we find that the stock prices of Chinese listed firms that are more exposed to exports to the U.S. react more negatively to the announcement. Specifically, a 10% increase in a firm's share of sales in the U.S. (*Revenue_US*) is associated with a 1.3% larger drop in stock price (column (1) in Panel C). The *CRR* for firms with inputs from the U.S. becomes insignificant when firm characteristics are included largely because of the small number of Chinese listed firms that purchase procurements from the U.S. The effect of revenue from the U.S. remains significant when industry fixed effects are included as regressors.[56]

To explore the network effects using the Chinese sample, we collect the required information from companies' annual reports, as Chinese listed firms are required to disclose their top five customers and suppliers.[57] We thus match the disclosed names of suppliers and customers with the names of Chinese listed firms. The estimation results shown in Panel D of Table 9 indicate that the indirect effect arising from revenue exposure to the U.S. in domestic production networks is significant, especially among a Chinese firm's customers.

[54] We do not winsorize variables based on stock returns in China as stocks in China are subject to 10% daily price limits. Other winsorizing practice follows the convention in the US sample.

[55] 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.

[56] We define industries using the 2012 classification by the China Securities Regulatory Commission (CSRC). There are 74 industries in our sample.

[57] The disclosure quality of Chinese firms is inferior to that of U.S. firms. Chinese firms are only required to disclose the total revenue derived from each of the top five customers and the total value of purchases from each of the top five suppliers. In addition, a large number of firms do not disclose the names of the customers or suppliers. We define *Revenue_US_Customer* (*Revenue_US_Supplier*) as the average of *Revenue_US* among customers (suppliers) disclosed in firm's statements.

Table 9
Responses of Chinese firms.

Panel A. Summary Statistics

Variable	N	Mean	S.D.	P25	Median	P75
CRR[−1,+1]	2588	−0.041	0.047	−0.067	−0.046	−0.021
Revenue_US	2588	0.009	0.035	0.000	0.000	0.000
Input_US	2588	0.056	0.180	0.000	0.000	0.000
SIZE	2588	22.217	1.287	21.320	22.096	22.943
MTB	2588	3.039	2.643	1.230	2.297	3.984
LEV	2588	0.410	0.206	0.245	0.391	0.562
ROA	2588	0.043	0.057	0.014	0.039	0.072

Panel B. Univariate Analysis

		CRR[−1,+1]	
		N	Mean
Revenue_US	>median	734	−0.045
	<median	1854	−0.039
	Difference in Means		−0.007***
	p-value		<0.01
Input_US	>median	672	−0.044
	<median	1916	−0.039
	Difference in Means		−0.005**
	p-value		0.021

Panel C. Regression Analysis

	(1)	(2)	(3)	(4)
	CRR[−1,+1]			
Revenue_US	−0.1266***		−0.1296***	−0.0979***
	(−5.79)		(−5.80)	(−4.42)
Input_US		−0.0004	0.0036	0.0029
		(−0.08)	(0.74)	(0.58)
N	2588	2588	2588	2588
adj. R-sq	0.012	0.003	0.012	0.090
Controls	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes

Panel D. Network Effects

	(1)	(2)
	CRR [−1,+1]	
Revenue_US	−0.1274***	−0.0965***
	(−5.68)	(−4.33)
Revenue_US_Customer	−0.8938***	−0.8543***
	(−3.75)	(−2.92)
Revenue_US_Supplier	−0.1544***	−0.0974
	(−3.37)	(−1.35)
Input_US	0.0037	0.0030
	(0.77)	(0.61)
N	2588	2588
adj. R-sq	0.013	0.092
Controls	Yes	Yes
Industry FE	No	Yes

Panel E. Reverse Experiment of the Trade Talks

	(1)	(2)	(3)	(4)
	CRR [−1,+1], Jan 9			
Revenue_US	0.0820***		0.0847***	0.0649**
	(3.03)		(3.12)	(2.32)
Input_US		−0.0006	−0.0033	−0.0032
		(−0.21)	(−1.10)	(−1.03)
N	2582	2582	2582	2582
adj. R-sq	0.016	0.008	0.016	0.046

Table 9 *(continued)*

Panel E. Reverse Experiment of the Trade Talks				
	(1)	(2)	(3)	(4)
		CRR [−1,+1], Jan 9		
Controls	Yes	Yes	Yes	Yes
Industry FE	No	No	No	Yes

Notes: This table presents the effect of the declaration of the trade war on Chinese firms. The sample consists of 2588 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 the value of imported goods from the US over total value of imported goods from the world using data from 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). 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 from the China Securities Regulatory Commission (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 the network effects based on the supply chains coded from firm's financial reports. *Revenue_US_Customer* is the average revenue from the US over total revenue (*Revenue_US*) across its customers as disclosed in the financial statements. *Revenue_US_Supplier* is the average revenue from the US over total revenue (*Revenue_US*) across its suppliers. Panel E 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 a 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.

We conduct the same reverse experiment exploiting the U.S.-China trade talks in January 2019. Panel E of Table 9 suggests that the talks have an offsetting positive effect. Taken together, the evidence based on Chinese listed firms presented here indicates similar patterns of response to the trade war, especially for firms exposed to exports rather than imports.

6. Conclusion

In this paper, we examine the financial market implications of the tariff hikes during the U.S.-China trade war in 2018–2019 for companies connected in global supply chains. Using an event study approach, we find heterogeneous market responses to the Trump administration's presidential memorandum of March 22, 2018, which proposed new and significant tariffs on Chinese imports, across listed firms in both countries. The responses vary according to the degree of firms' direct and indirect exposure to U.S.-China trade. We find that U.S. firms that are more dependent on exports to and imports from China have lower stock prices and higher default risks in the short window around the time of the announcement.

We find that U.S. firms that invest more in research and development (R&D) suffer a smaller decline in stock returns on average, while those that rely on differentiated inputs from China tend to experience a larger decline in stock returns. These findings suggest that product substitutability and thus switching costs in the supply chains are important determinants of the impacts of trade policy shocks on firms' outcomes.

As additional events, we exploit the dates when the Chinese authorities announced the first wave of retaliatory tariffs, when both countries' governments issued the detailed lists of products that are tariffed, and when a constructive trade talk took place in early 2019 that reverted market sentiment. Similar patterns are also observed for Chinese listed firms with respect to their trade relationships with the U.S. The results are robust to using different asset pricing models, alternative model specifications, an alternative sample construction, longer event windows, and a matching strategy.

We document that the expectation of weakened Chinese import competition due to U.S. tariffs plays a statistically significant but economically minimal role. In contrast, we find that U.S. firms' indirect exposure to trade with China through domestic supply chains plays an economically large role, with indirect exposure having a larger negative impact on stock returns than direct exposure. These findings indicate that complex global trade networks play a crucial role in financial markets.

Our findings show that the winners and losers in the bilateral U.S.-China trade relationship are determined by their position (upstream or downstream) and extent of participation in supply chains shared by the two countries.

Data availability

Research Data (Reference data) (data files and documents)

Declaration of Competing Interest

We have no particular conflict of interest or financial interest to declare for this research.

Acknowledgment

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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 Dhyne et al., 2021. However, we will abstract from the recursive feature of the global value chains, focusing on both the partial- and general-equilibrium insights from the model to guide our reduced-form empirical analysis.[58]

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 τ_F for all products imported from Home. Relaxing this assumption by making τ_F product-specific is trivial but offers little additional insight.

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.[59] 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

[58] 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.

[59] Dhyne et al., 2021 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.

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.

3. Market and network structure

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

$$q_i = q_{iH} + q_{iF} + \sum\nolimits_{j \in \Phi_i} m_{ji}$$

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 (Dhyne et al., 2021). 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

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

4. Firm sales and profits

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

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

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

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

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

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

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

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

Proof:

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

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

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

We will empirically examine the magnitude of these effects by assessing the coefficient on the firm's exporting variable 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 variable.

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 variable, 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.

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

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

Notes: This table summarizes the firms' responses in terms of stock returns to the key events considered in this paper. We report the average stock returns for our sample U.S. firms and sample Chinese firms. (1) March 22, 2018: The Trump administration issues a presidential memorandum in reference to Section 301 of the Investigation of China's Laws, Policies, Practices, or Actions that proposes to impose tariffs on up to $50 billion of Chinese imports as a response to China's alleged theft of U.S. intellectual property 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. We present the value-weighted average returns using the market value as weights.

		(1) Event Date (US Time)	(2)
	Event Windows	2018-03-22	2019-01-09
US Firms	1-day [0]	−2.24%	0.64%
	3-day [−1,+1]	−4.02%	2.36%
	5-day [−2,+2]	−1.51%	3.66%
Chinese Firms	1-day [0]	−4.44%	0.55%
	3-day [−1,+1]	−3.86%	0.25%
	5-day [−2,+2]	−2.36%	2.66%

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
EPS Forecasts	The forecasted earnings per share made by an individual analyst. Source: I/B/E/S
Measures of Exposure	
Revenue_China	The share of revenue from China in 2016. Source: Factset Revere
Revenue_China_Customer	Revenue_China_Customer is the average revenue from China in 2016 across a firm's 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	A ratio defined as the estimated value of imported goods from China over total estimated value of imported goods from the world. It is calculated using product weight from the bill of lading database in 2016 and 2017 and the estimated average unit price per kilogram (kg) from USA Trade Online. Source: the U.S. Bill of Lading database & USA Trade Online
Input_China_Customer	The average share of inputs from China among a firm's listed customers. Source: the U.S. bill of lading database and Factset Revere
Input_China_Supplier	The average share of inputs from China 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. This measure is defined for Chinese firms. Source: China Customs Database & CSMAR
Input_US	The share of the value a firm imports goods from the U.S. against the total import value from the world as indicated by the China customs database in 2016. This measure is defined for Chinese firms. Source: China Customs Database & CSMAR
Revenue_US_Customer	Revenue_US_Customer is the average revenue from the US over total revenue (Revenue_US) across its customers as disclosed in the financial statements. This measure is defined for Chinese firms. Source: China Customs Database & CSMAR
Revenue_US_Supplier	Revenue_US_Supplier is the average revenue from the US over total revenue (Revenue_US) across its suppliers as disclosed in the financial statements. This measure is defined for Chinese firms. 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 9. Source: Textual Analysis and United States trade representative
Input_US_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). The measure is aggregated at the firm level using the primary NAICS for across firm's segments. Source: Peter Schott, US Census Bureau, Compustat Segments
Industry_Export	The NAICS industry total exports to China (in 2017) scaled by the shipment value (in 2016). The measure is aggregated at the firm level using the primary NAICS for across firm's segments. Source: Peter Schott, US Census Bureau, Compustat Segments
Other Firm-level Characteristics	
SIZE	Log of total assets in 2016. Source: Compustat
MTB	Market-to-book ratio in 2016 defined as market value of assets over book value of assets. Source: Compustat
LEV	Financial leverage ratio in 2016 defined as long term debt plus debt in current liabilities, divided by assets. Source: Compustat
ROA	Return-on-assets in 2016 defined as operating income before depreciation divided by assets. Source: Compustat
R&D	R&D expenditures scaled by total assets. Source: Compustat

Appendix 4. Robustness checks

Notes: This table shows the robustness checks. Panel A shows the results using cumulative returns adjusted by alternative asset pricing models. *CAR [−1,+1]* is the three-day cumulative abnormal returns around the event date estimated using the standard one-factor market model. *CAR [−1,+1], FF 3-factor* is the three-day cumulative abnormal returns adjusted by the Fama-French three-factor model. Panel B shows results considering several confounding events. Columns (1) and (2) control for firm's past reactions to Federal Open Market Committee (FOMC) announcements. We identify 144 FOMC announcements between 2000 and 2017. We calculate a firm's stock return over the 3-day window centered on each of the event dates, the corresponding market return over the 3-day window. We regress the firm's 3-day returns on the market return for each stock respectively using the sample of all 144 events between 2000 and 2017 and retrieve the estimated coefficient (beta) for each stock. This firm level coefficient is defined as *FOMC Beta*. Columns (3) to (6) show the results based on a sample excluding firms in military related industries and a sample excluding firms in steel and aluminum related industries. Panel C presents the results controlling for the trade exposure to other regions. *Revenue Share Geopolitically Weighted* is a measure that captures the effect of a firm's revenue source countries considering their geopolitical relationships with China. We first construct a firm's revenue share from different countries using the data from Factset Revere. As defined in the text, we calculate the weighted average at the firm level using a bilateral distance measure proposed in Bailey et al. (2017) as a weight. Bailey et al. (2017) use United Nations (UN) General Assembly votes to quantify bilateral policy preference distance between two countries. This measure involves geopolitical considerations that a longer distance between two countries indicate they are more ideologically different. We calculate the weighted average of revenue share combining this geopolitical distance measure. A higher value of this measure indicates a firm has revenue from countries geopolitically distant from China and thus less prone to China related trade conflicts. *Revenue from Middle East* is the firm's revenue from countries in Middle East. *Revenue from EU* is the firm's revenue from countries in European Union. *Revenue from Africa* is the firm's revenue from African countries. Panel D presents the results for the effect on US firms with Chinese subsidiaries. We collect detailed information on US firm's subsidiaries from WRDS Company Subsidiary Database. Subsidiary Number is defined as the number of subsidiaries in China. We consider the interaction between sales to China and the number of Chinese subsidiaries. Panel E presents the results based on regression models weighted by firm size. 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. Alternative Variable Definitions

	(1)	(2)	(3)	(4)
	CAR [−1,+1]		CAR [−1,+1], FF 3-factor	
Revenue_China	−0.0909***	−0.0472**	−0.0834***	−0.0397*
	(−6.01)	(−2.51)	(−5.13)	(−1.92)
Input_China	−0.0083***	−0.0059**	−0.0089***	−0.0058**
	(−3.34)	(−2.36)	(−3.36)	(−2.19)
N	2309	2291	2309	2291
adj. R-sq	0.053	0.121	0.033	0.111
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes

Panel B. Confounding Events

	(1)	(2)	(3)	(4)	(5)	(6)
	CRR [−1,+1]					
			Excluding military related industries		Excluding steel and aluminum related industries	
Revenue_China	−0.0929***	−0.0451**	−0.0881***	−0.0457***	−0.0911***	−0.0478***
	(−6.34)	(−2.46)	(−6.12)	(−2.61)	(−6.31)	(−2.72)
Input_China	−0.0075***	−0.0053**	−0.0082***	−0.0052**	−0.0083***	−0.0054**
	(−3.09)	(−2.18)	(−3.40)	(−2.16)	(−3.44)	(−2.24)
FOMC Beta	0.0091	0.0103				
	(1.01)	(1.11)				
N	2060	2044	2292	2275	2279	2261
adj. R-sq	0.072	0.138	0.058	0.123	0.058	0.122
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes

Panel C. Trade Exposure to Other Places

	(1)	(2)	(3)	(4)
	CRR [−1,+1]			
Revenue Share Geopolitically Weighted	0.0034*	−0.0017		
	(1.72)	(−0.81)		
Revenue from Middle East			0.0558	0.0985
			(0.67)	(1.25)
Revenue from EU			−0.0154	−0.0018
			(−1.63)	(−0.18)
Revenue from Africa			−0.0393	−0.0896
			(−0.25)	(−0.64)
Revenue_China	−0.0759***	−0.0494***	−0.0811***	−0.0484***
	(−4.83)	(−2.76)	(−4.96)	(−2.62)
Input_China	−0.0082***	−0.0058**	−0.0084***	−0.0057**
	(−3.41)	(−2.41)	(−3.52)	(−2.37)
N	2309	2291	2309	2291
adj. R-sq	0.060	0.123	0.059	0.123
Controls	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes

Panel D. US Firms with Chinese Subsidiaries

	(1)	(2)	(3)	(4)
	CRR [−1,+1]			
Revenue_China	−0.0731***	−0.0784***	−0.0399**	−0.0416**
	(−4.92)	(−5.07)	(−2.28)	(−2.29)
Subsidiary Number	−0.0010***	−0.0013***	−0.0006***	−0.0007**
	(−4.72)	(−4.58)	(−2.87)	(−2.42)
Revenue_China × Subsidiary Number		0.0040**		0.0012
		(2.29)		(0.74)
Input_China	−0.0080***	−0.0080***	−0.0055**	−0.0056**
	(−3.33)	(−3.33)	(−2.31)	(−2.32)
N	2309	2309	2291	2291
adj. R-sq	0.062	0.062	0.124	0.124
Controls	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes

Panel E. Weighting Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighting by Firm Size					
	CRR [−1,+1]					
Revenue_China	−0.1071***	−0.0546***	−0.0734***	−0.0437***		
	(−8.20)	(−3.61)	(−5.02)	(−2.77)		
Revenue_China_Customer			−0.0816***	−0.0529**		
			(−3.47)	(−2.28)		
Revenue_China_Supplier			−0.0920***	−0.0508***		
			(−5.16)	(−2.70)		
Input_China	−0.0089***	−0.0054**			−0.0101***	−0.0058***
	(−4.09)	(−2.52)			(−4.56)	(−2.71)
Input_China_Customer					−0.0079**	−0.0011
					(−2.42)	(−0.36)
Input_China_Supplier					−0.0077**	−0.0035
					(−2.36)	(−1.14)
N	2309	2291	2309	2291	2309	2291
adj. R-sq	0.070	0.172	0.079	0.174	0.053	0.168
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes

Appendix 5. Split instrumental variable regressions

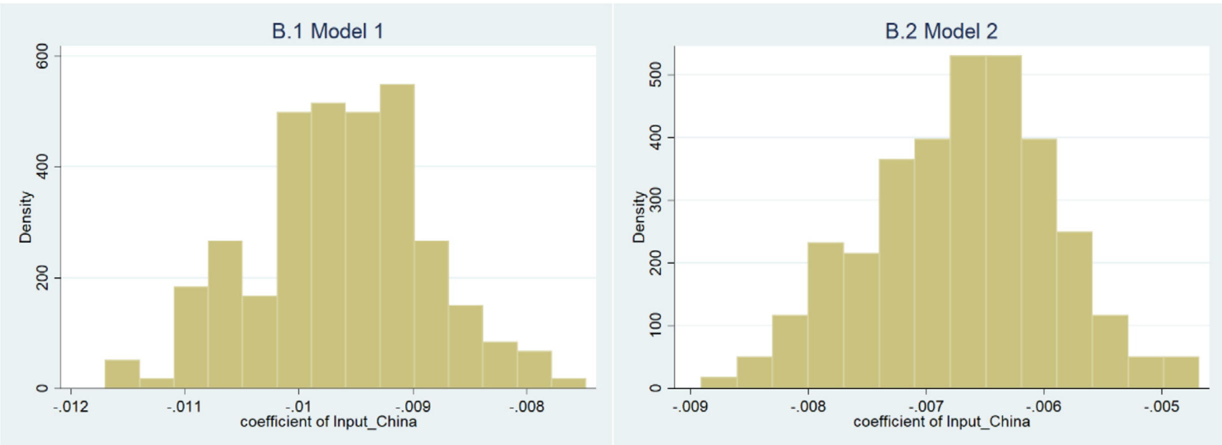
Notes: This table presents the results based on split instrumental variable estimation. Following Farber et al. (2021), we randomly divide the input purchase transaction data by firm and define *Input_China* separately at the firm level using the two constructed samples. We then regress one variable *Input_China* on the other. The instrumented variable is thus included in the baseline estimation model. We repeat this practice for 200 times and report the summary of the estimated coefficient of the instrumented *Input_China* in Panel A and Panel B. Panel A shows the mean of the estimated coefficients and corresponding standard errors and t-values in our baseline model with and without industry fixed effects. Panel B shows the distributions of the coefficients in two models. The left figure of Panel B shows the distribution of the coefficient of the model without industry fixed effects. The right figure of Panel B shows the distribution of the coefficient of the model including industry fixed effects.

Panel A. Summary of the Estimated Coefficients

	(1)	(2)
	CRR [−1,+1]	
Instrumented Input_China		
Mean of coefficient	−0.0096	−0.0067
Mean of SE	0.0028	0.0028
Mean of t-value	−3.4780	−2.3952

(continued on next page)

Panel B. Histograms of the Estimated Coefficients



Appendix 6. Robustness checks using matched samples

Notes: This table presents the results based on samples matched on firm characteristics. The propensity score matching method is used to match the firms with greater exposure to the trade frictions to control firms according to the firm-level variables including firm size, market-to-book ratio, leverage, and ROA. Panels A and B show the results for U.S. firms according to their revenue from China and inputs from China, respectively. Columns (1) and (2) show the means of the variable for treated firms and control firms, respectively. Column (3) shows the difference in the means 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	−0.020	−0.013***	−5.26	<0.01
SIZE	6.902	6.931	−0.029	−0.22	0.829
MTB	2.083	1.968	0.115	1.23	0.218
LEV	0.259	0.258	0.000	0.01	0.991
ROA	0.070	0.073	−0.003	−0.34	0.734

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]	−0.034	−0.027	−0.008**	−2.51	0.01
SIZE	6.979	7.007	−0.027	−0.17	0.87
MTB	1.967	2.119	−0.152	−1.25	0.21
LEV	0.255	0.263	−0.008	−0.43	0.67
ROA	0.077	0.082	−0.005	−0.29	0.77

Appendix 7. Medium-term impacts

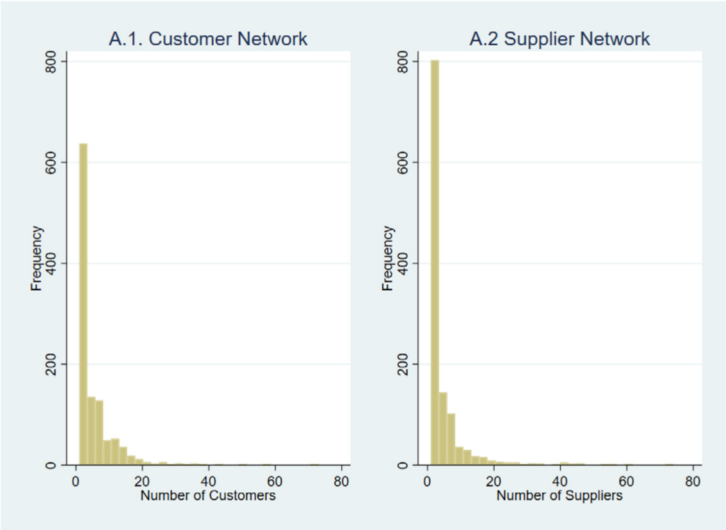
Notes: This table presents the results for medium-term effects of the trade war announcement. The dependent variable is buy-and-hold abnormal returns (*BHAR*) over different event windows. Specifically, *BHAR [−1,+X]* is the buy-and-hold abnormal returns around the event window *[−1,+X]* with zero indicating March 22 adjusted by the market benchmark. The firm-level controls include size, market-to-book ratio, leverage, and ROA. The definitions of the other variables are in Appendix 3. The *t*-statistics based on robust 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	−0.2264***	−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	−0.0187***	−0.0287***	−0.0268*	−0.0428***
	(−2.80)	(−2.59)	(−1.88)	(−2.69)
N	2281	2253	2244	2214
adj. R-sq	0.032	0.012	0.024	0.035
Controls	Yes	Yes	Yes	Yes

Appendix 8. The description of the revere database

Notes: This table shows the description of the Factset 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	0.096	0.205	0.000	0.000	0.084
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	0.105	0.220	0.000	0.000	0.099
B.2 Sample only including firms with listed firms as customers or supplier						
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	0.201	0.259	0.000	0.110	0.304
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	0.202	0.272	0.000	0.075	0.309

Appendix 9. Procedure for the textual analysis

1. We first retrieve the complete list of HS codes from the World Bank website.[60] 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***.

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

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.

Appendix 10. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jinteco.2023.103811.

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