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Journal of International Money and Finance

journal homepage: www.elsevier.com/locate/jimf

The effects of Trump's trade war on U.S. financial markets

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ARTICLE INFO

Article history:

Available online 30 March 2023

JEL classification:

C22
F10
G12

Keywords:

Trade war
Financial markets
Identification by heteroscedasticity
Global value chain

ABSTRACT

We study the impact of President Trump's trade war on U.S. financial markets by integrating trade war-related news into a single "trade war shock," based on a structural vector autoregressive model identified via event-day heteroscedasticity. We find that the identified trade war shock not only significantly affects financial variables such as stock prices and Treasury yields but also explains at least 30% of their variation on impact. The main channels through which the trade war shock affects the S&P 500 index and 10-year Treasury yields are the growth news channel, through which the trade war shock changes investors' growth expectations, and the risk premium channel, through which the trade war shock generates shifts in risk appetite or economic uncertainty. Additional analyses that employ stock prices in the S&P 500 index to explore the role of firms' global value chain exposure during the trade war reveal that firms with high output exposure to China's market suffer significantly more from the trade war, while input exposure does not cause a persistent significant difference.

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1. Introduction

During 2018–2019, traders and investment managers navigated turbulent markets following the Trump administration's trade war with most of the United States' trading partners, involving tariffs on steel and aluminum and a full-blown trade conflict with China over intellectual property. These protectionist measures and associated risks were feared to have serious economic consequences, including increased inflation, reduced consumer spending, and disruptions in global trade. In particular, the trade war was identified as the biggest tail risk 20 times from March 2018 to December 2019, according to the Bank of America/Merrill Lynch monthly fund manager survey. Despite the signing of a Phase One trade agreement between the U.S. and China in January 2020, most tariffs remain in place, and trade tensions persist. Therefore, a comprehensive investigation of the trade war's impact is needed to inform future economic and financial decisions.

Inspired by the work of [Rigobon \(2003\)](#) and [Rigobon and Sack \(2003, 2004, 2005\)](#), we use a structural vector autoregressive (VAR) model identified via event-day heteroscedasticity to study the impact of President Trump's trade war on various U.S. financial variables. Specifically, we select a set of days on which trade war-related news significantly alters investors' views of the likely severity and extent of trade tensions, assuming that on these days, trade war-related news generates particularly high variance in asset returns, but otherwise, there is nothing unusual. We then identify the effects of the trade

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war-related news by comparing the variance-covariance matrices of the VAR residuals on these and other days. For simplicity, as in [Rigobon and Sack \(2005\)](#), we integrate trade war-related news into a single “trade war” factor (shock), which is orthogonal to any other important economic shocks, although news about President Trump’s trade war has many dimensions, including changes in the scale and scope of tariffs and the probability of a trade deal.

We conduct the analysis in two steps. In the first step, we identify the trade war shock and examine its impact on U.S. financial markets. The empirical results indicate that the identified trade war shock leads to declines in equity prices and Treasury yields, a widening of the BAA corporate spread, a drop in oil futures price, an appreciation of the U.S. dollar against the Chinese yuan, and an increase in the price of gold. In particular, a positive trade war shock significantly lowers the S&P 500 index by around 0.45% on impact, representing a loss of around \$104 billion in wealth based on the average \$23 trillion market capitalization of the S&P 500 during the sample period. In addition to the substantial impact effects, the identified trade war shock accounts for a sizable portion of the fluctuations in several financial variables. For example, the forecast error variance decomposition (FEVD) results indicate that the trade war shock can explain up to 38% of the variance in the S&P 500 index. However, the importance of the trade war shock varies remarkably over time. Although the U.S. stock market experiences a sharp sell-off in December 2018, the historical decomposition (HD) results suggest that the trade war shock does not contribute much to the market turbulence at that time.

In the second step, we investigate transmission channels through which the trade war shock affects financial markets, especially the stock market. Utilizing economic common shocks derived by [Cieslak and Pang \(2021\)](#) from stock returns and Treasury yield changes, we find that the trade war shock affects the S&P 500 index and 10-year Treasury yields via two major channels: the growth news channel, through which the trade war shock changes investors’ growth expectations, and the risk premium channel, through which the trade war shock generates shifts in the risk appetite or economic uncertainty. The growth news channel is more decisive in the first half of 2019, when several rounds of trade negotiations are scheduled, and the risk premium channel is more dominant during the second half of 2018, when the trade talks between the U.S. and China break down. In addition, using disaggregated firm-level data, we further explore the role of firms’ global value chain (GVC) structures in transmitting trade war shocks to stock prices. The trade war could affect firms’ value in several ways through their GVC exposure to foreign countries. For example, after an escalation in trade tensions, exporting firms might suffer decreases in offshore output sales, while firms that import intermediate inputs might be hurt by increases in production costs. The results suggest that the greater a firm’s output (export) exposure to China, the greater the extent to which the trade war damages its value, while firms’ input (import) exposures cause no persistent significant differences in a firm’s stock prices during the trade war.

Our work adds to the growing body of literature evaluating the consequences of the trade war, one of the major global events since the Great Recession in 2008. Several studies explore the effects of the trade war on economic outcomes, such as [Bekkers and Schroeter \(2020\)](#), who estimate that the trade war leads to a 0.1% decline in the global GDP through direct tariff increases using the World Trade Organization (WTO) Global Trade Model and argue that the biggest impact of the trade conflict comes from increased uncertainty surrounding trade policy. [Amiti et al. \(2019\)](#) and [Fajgelbaum et al. \(2020\)](#) find that the welfare effects of U.S. tariffs are modest in conventional trade models. However, [Waugh \(2019\)](#) demonstrates that the effects of U.S. tariffs could be large, particularly in exposed regions where Chinese retaliation appeared to decrease local consumption.

To investigate the consequences of the trade war, we pursue an alternative perspective based on the reaction of the financial markets. In this regard, this study is closely related to [Amiti et al. \(2020\)](#); [Egger and Zhu \(2020\)](#), and [Huang et al. \(2020\)](#), who apply the event study approach to examine the heterogeneous effects of the Trump administration’s trade war announcement on firms’ stock returns. However, our paper differs from these studies in that instead of relying on abnormal returns based on statistical or economic models for stock markets, we extract the trade war factor (shock) from the structural VAR framework to measure the effects of the trade war on asset prices. While both our method and the event study approach rely on the selection of significant trade war events, our approach possesses an advantage in its ability to incorporate control variables to effectively account for any confounding effects from other events during the event window. Furthermore, the event study approach assumes that the event of interest is unexpected and has not yet been factored into asset prices. However, several important events related to the trade war are anticipated to some extent.¹ Our method does not require this assumption, only that the event can produce large enough changes in second moments of asset returns.

Another advantage of our approach is that it can be easily extended to examine the channels through which events of the trade war affect financial markets. There exists a strand of literature on the impact of trade policy uncertainty (TPU) on economic outcomes. Previous studies by [Pierce and Schott \(2016\)](#) and [Handley and Limão \(2017\)](#) show that, before China joined the WTO in 2001, uncertainty about U.S. trade policy toward Chinese goods seriously affects U.S. imports from China and lowered the welfare of U.S. households. Using firm-level and macroeconomic data, [Caldara et al. \(2020\)](#) observe that increased TPU during the Trump administration’s trade war has a substantial negative impact on investment. In contrast, [Steinberg \(2019\)](#) finds that the effects of uncertainty about Brexit were small. [Alessandria et al. \(2019\)](#) also examine the same TPU episode as [Pierce and Schott \(2016\)](#) and [Handley and Limão \(2017\)](#), but their study suggests a minimal impact of TPU on trade patterns. Using the structural VAR model, our study introduces an alternative approach to assess the impor-

¹ For example, the May 10, 2019, event of the U.S. raising tariffs on \$200 billion of Chinese imports is included in [Amiti et al. \(2020\)](#) event list, but it is not entirely unexpected. As President Trump tweeted about the tariff increase on May 5, and Lighthizer later confirms that the tariff increase will go into effect if no agreement is reached by May 10.

tance of TPU and shows that the uncertainty and expectation channels play roughly equal role in the transmission of the trade war.

We also contribute to the literature that seeks to empirically assess how policy uncertainty is priced into stocks and options (see, e.g., Pastor and Veronesi (2012); Brogaard and Detzel (2015), Kelly et al. (2016); Bali et al. (2017) and Bianconi et al. (2021)). Our study is similar to that of Bianconi et al. (2021), as both studies attempt to overcome the identification issue caused by the endogeneity of policy actions. However, Bianconi et al. (2021) employ the difference-in-difference (DID) design, which identifies only the differential effect of policy uncertainty on the treated firms compared to the untreated firms. Our framework, however, can identify both the differential effect and the “common” effect, which captures how policy uncertainty affects returns by altering factors or variables that are relevant to firms in general and provides a more comprehensive understanding of how policy uncertainty affects returns.

The remainder of this paper is organized as follows. We describe the empirical approach to extracting the trade war shock in Section 2. We present the data and empirical results that reveal the effects of the identified shock in Section 3. We discuss the transmission channels of the trade war shock in Section 4 and conclude in Section 5.

2. Identification and estimation of the structural VAR Model

2.1. The structural VAR model and the identification problem

We model the selected U.S. financial variables (in first difference) $\Delta Y_t \in \mathbb{R}^n$ in time periods $t \in \mathcal{T} = \{1, \dots, T\}$ as a VAR with exogenous variables:

$$\Delta Y_t = c + \sum_{\ell=1}^p B_\ell \Delta Y_{t-\ell} + D_z z_t + \varepsilon_t, \tag{1}$$

where $c \in \mathbb{R}^n$ is a vector, $\{B_\ell\}_{1 \leq \ell \leq p}$ are $n \times n$ autoregressive matrices, and $z_t \in \mathbb{R}^m$ is a set of exogenous variables to control for macroeconomic announcements and monetary policies in the benchmark model². We explain how z_t is constructed and what it includes in SubSection 3.1. D_z is an $n \times m$ matrix, and $\varepsilon_t \in \mathbb{R}^n$ is a residual vector whose variance–covariance matrix is heteroscedastic, as specified below.

We further assume that ΔY_t is driven by n mutually orthogonal zero-mean and independently distributed structural shocks $u_t \in \mathbb{R}^n$, and ε_t are linear combinations of u_t :

$$\varepsilon_t = A u_t, \tag{2}$$

where A is an $n \times n$ structural matrix that captures the contemporaneous effect of u_t on ΔY_t . Identifying all or a subset of the structural shocks amounts to finding the A matrix or some column(s) of it. Without loss of generality, we order the trade war shock u_t^w the first in u_t . Therefore, identifying u_t^w amounts to finding the first column of A , which we label a_1 .

2.2. Identification through heteroscedasticity

To identify the trade war shock u_t^w , we employ the “identification through heteroscedasticity” methodology proposed by Rigobon (2003) and extended by Wright (2012). Specifically, we split the full sample \mathcal{T} into two subsamples, \mathcal{T}_0 and \mathcal{T}_1 , where $t \in \mathcal{T}_0$ is the “trade war days” with important trade war-related news, and $t \in \mathcal{T}_1$ is the other days. We assume the heteroscedasticity of the structural shocks u_t across the two subsamples:

$$\Omega_s := \mathbb{E}[u_t u_t'] = \begin{cases} \Omega_0, & t \in \mathcal{T}_0 \\ \Omega_1, & t \in \mathcal{T}_1 \end{cases}. \tag{3}$$

In addition, we assume that only the variances of the trade war shock change between \mathcal{T}_0 and \mathcal{T}_1 , and all the other structural shocks are identically distributed with zero mean and unit variance throughout the sample period. In other words, the heteroscedasticity of u_t is driven solely by the heteroscedasticity of u_t^w :

$$\Omega_0 - \Omega_1 = \left(\sigma_{w,0}^2 - \sigma_{w,1}^2 \right) e_1 e_1' = \sigma_w^2 e_1 e_1' \neq 0, \tag{4}$$

where $\sigma_{w,0}^2$ and $\sigma_{w,1}^2$ are the variance of the trade war shock ($\mathbb{E}[u_t^w]^2$) on \mathcal{T}_0 and \mathcal{T}_1 , respectively, and e_i is the i -th column of the n -dimensional identity matrix I_n . With the heteroscedasticity assumption, $\sigma_w^2 := \sigma_{w,0}^2 - \sigma_{w,1}^2 > 0$.

The heteroscedasticity of the trade war shock then transmits to the VAR residuals. To see this, define Σ_0 and Σ_1 as the reduced-form variance–covariance matrices of the VAR on \mathcal{T}_0 and \mathcal{T}_1 , respectively. Then, from Eq. (2) and Eq. (3), the relationship between Σ_s and $\Omega_s, s \in \{0, 1\}$ is given by

$$\Sigma_s = A \Omega_s A'. \tag{5}$$

² We consider additional control variables derived from Cieslak and Pang (2021) when we examine transmission channels of the trade war shock in Section 4.

Combining Eq. (4) and Eq. (5), we can derive the following heteroscedasticity condition of ε_t :

$$\Sigma_0 - \Sigma_1 = \sigma_w^2 a_1 a_1' = \tilde{a}_1 \tilde{a}_1' \tag{6}$$

Eq. (6) is the identification constraint in the empirical study to pin down $\tilde{a}_1 := \sigma_w a_1$. Note that \tilde{a}_1 is only the “contemporaneous relative impulse response,” as in Wright (2012), and we further use \tilde{a}_1 and the variance–covariance matrix of the full sample Σ to solve for the “contemporaneous absolute impulse response,” a_1 . With a_1 , we can extract the series of trade war shock and construct statistics for the structural analysis, such as the impulse response functions, variance decomposition, and historical decomposition.

In the empirical exercise, we first estimate the VAR model in Eq. (1) to obtain the reduced-form variance–covariance matrices on $\mathcal{F}_0 (\hat{\Sigma}_0)$ and $\mathcal{F}_1 (\hat{\Sigma}_1)$, respectively³. Then, we estimate \tilde{a}_1 through the identification constraint in Eq. (6). As Eq. (6) offers $n(n + 1)/2$ moment conditions to estimate an n -dimensional vector \tilde{a}_1 , to utilize all the moment conditions, we adopt the generalized method of moments to find the unique $\hat{\tilde{a}}_1$, following Wright (2012):

$$\hat{\tilde{a}}_1 = \arg \min_{\tilde{a}_1} \left[\text{vech}(\hat{\Sigma}_0 - \hat{\Sigma}_1 - \tilde{a}_1 \tilde{a}_1') \right]' \left[\hat{V}_0 + \hat{V}_1 \right]^{-1} \left[\text{vech}(\hat{\Sigma}_0 - \hat{\Sigma}_1 - \tilde{a}_1 \tilde{a}_1') \right], \tag{7}$$

where $\text{vech}(\cdot)$ is the half-vectorized operator obtained by vectorizing only the lower triangular part of some symmetric matrix, and $\hat{V}_s, s \in \{0, 1\}$ are estimates of the variance–covariance matrices of $\text{vech}(\hat{\Sigma}_s), s \in \{0, 1\}$. Finally, we use $\hat{\tilde{a}}_1$ and the variance–covariance matrix of the full sample $\hat{\Sigma}$ to solve for \hat{a}_1 , and all the subsequent structural analysis can then be traced out.

2.3. Two specification tests

In addition to estimating the VAR and identifying the trade war shock, we run two specification tests to verify the identification assumptions⁴, as proposed by Wright (2012). First, we test the null hypothesis that the variance–covariance matrices of the VAR in Eq. (1) do not differ between \mathcal{F}_0 and \mathcal{F}_1 ; i.e., $\mathbf{H}_0^1 : \Sigma_0 = \Sigma_1$. Rejecting \mathbf{H}_0^1 verifies the heteroscedasticity of the structural shocks. The test statistic is as follows:

$$W_1 = \left[\text{vech}(\hat{\Sigma}_0 - \hat{\Sigma}_1) \right]' \left[\hat{V}_0 + \hat{V}_1 \right]^{-1} \left[\text{vech}(\hat{\Sigma}_0 - \hat{\Sigma}_1) \right]. \tag{8}$$

Because the VAR residual ε_t is not necessarily normally distributed, we use bootstrap hypothesis testing and compare W_1 with a bootstrap distribution in which the trade war days and the other days are randomly scrambled to obtain the bootstrap p value.

Second, we test the null hypothesis that the difference between the two reduced-form variance–covariance matrices Σ_0 and Σ_1 can be uniquely characterized by a single structural shock; i.e., $\mathbf{H}_0^2 : \Sigma_0 - \Sigma_1 = \tilde{a}_1 \tilde{a}_1'$. Accepting \mathbf{H}_0^2 verifies that a single trade war shock can drive the heteroscedasticity of the variance–covariance of the VAR. We do the test by comparing the statistic,

$$W_2 = \left[\text{vech}(\hat{\Sigma}_0 - \hat{\Sigma}_1 - \hat{\tilde{a}}_1 \hat{\tilde{a}}_1') \right]' \left[\hat{V}_0 + \hat{V}_1 \right]^{-1} \left[\text{vech}(\hat{\Sigma}_0 - \hat{\Sigma}_1 - \hat{\tilde{a}}_1 \hat{\tilde{a}}_1') \right], \tag{9}$$

with the bootstrap distribution. Specifically, we bootstrap the distribution using the two-step bias-adjusted bootstrap method (Kilian, 1998) with the stationary bootstrap approach (Politis and Romano, 1994), which resamples blocks of residuals at a length of 10 days to preserve any potential residual autocorrelation and volatility clustering. Let $\hat{\Sigma}_0^*, \hat{\Sigma}_1^*, \hat{V}_0^*, \hat{V}_1^*$, and $\hat{\tilde{a}}_1^*$ be the bootstrapped analogs of the original statistics. Then, the bootstrap distribution of the second statistic is

$$W_2^* = \xi' \left[\hat{V}_0^* + \hat{V}_1^* \right]^{-1} \xi, \tag{10}$$

where $\xi := \text{vech}(\hat{\Sigma}_0^* - \hat{\Sigma}_1^* - \hat{\tilde{a}}_1^* \hat{\tilde{a}}_1^{*'}) - \text{vech}(\hat{\Sigma}_0 - \hat{\Sigma}_1 - \hat{\tilde{a}}_1 \hat{\tilde{a}}_1')$.

³ We use Kilian (1998) bias-adjusted method when estimating the autoregressive matrices $\{B_t\}_{1 \leq t \leq p}$ to mitigate any possible small sample bias.

⁴ The two specification tests provide necessary but not sufficient conditions for identifying the trade war shock. In the remainder of the paper, we further ensure that the identified shock is indeed the trade war shock by carefully selecting trade war events, explicitly controlling for some known important shocks, and comparing our identified shock with other significant macroeconomic and financial shocks.

3. Data and results

3.1. Events, Data, and Model specification

Identifying significant trade war-related events and defining trade war days are essential steps when applying the heteroscedasticity-based method. From newspapers and various financial market commentaries, we collect a list of 49 days mainly related to tariff hikes and trade negotiations from March 1, 2018, to January 15, 2020⁵, on which trade war-related events appear to be the primary determinant of asset price movements. Specifically, we first construct a timeline of the trade war by combining several external sources, such as [Bown and Kolb \(2021\)](#) from the Peterson Institute for International Economics, Reuters⁶, and China Briefing⁷. We then read Zacks' daily stock market news⁸, including a headline story in which the editorial staff discuss important events during the day. Events in the timeline are eliminated if they are not mentioned in Zacks' daily stock market news or their effects on asset markets are significantly altered by other important market drivers. For example, we exclude those events that occur on the same day as any important event on U.S. monetary policies to ensure the identified trade war shock does not correlate with the U.S. monetary policy shock. The first statistic described in Section 2.3 is used to test whether the variance in the selected dates is sufficiently high to identify the trade war shock.

These 49 trade war days are listed in [Table A.1](#). The first and second columns of [Table A.1](#), labeled "Date" and "Event," record the day on which the event is reported in the news and the description of the event, respectively. The last column, labeled "After hours," indicates whether an event occurs on a weekend/stock market holiday or after the stock market closed. Events for which the news is released after hours are categorized on the next business day. Of the 49 trade war days, 37 days are marked in bold. These days are highly related to tariff decisions and seem especially important. If these important trade war days are only about trade conflicts between the United States and China, they are also marked with an asterisk (31 events).

To examine the effects of the trade war events on U.S. financial markets, in the benchmark empirical exercise, we use daily data on six U.S. financial variables, including the S&P 500 index, the BAA corporate yield spread, 10-year Treasury yields, the gold price, the West Texas Intermediate oil futures price, and the exchange rate between the United States and China, as endogenous variables Y_t . All the data are collected from the Federal Reserve Economic Data. As for the exogenous variables Z_t , to correct for macroeconomic announcements, we follow [Andersen et al. \(2007\)](#) and include the unexpected component of the 10 most relevant U.S. macroeconomic indicators, measured as the difference between the actual announcement and its median expectation from the Bloomberg consensus forecasts⁹. To control for monetary policies, we also include monetary policy surprise series, constructed as in [Kuttner \(2001\)](#). Then, a VAR model with one lag selected by the Bayesian information criterion and the Hannan–Quinn criterion is confronted with the data. As the trade war lasts for a relatively short period, following [Wright \(2012\)](#), we estimate the VAR parameters in Eq. (1) from January 4, 2016¹⁰, to January 15, 2020, and we estimate Σ_0 over $\mathcal{T}_0 = 49$ trade war days and Σ_1 over other days starting on March 1, 2018. Then, we solve the generalized method of moments problem, Eq. (7), to estimate \hat{a}_1 and construct a_1 . The results of the two specification tests are summarized in [Table 1](#). For the benchmark model, the p value of the first test is 0.003. Thus, the null hypothesis H_0^1 is rejected, which confirms the heteroscedasticity of the structural shocks. The p value of the second test is 0.781. Thus, the null hypothesis H_0^2 is not rejected, which indicates that the data can be well characterized by a single trade war shock.

3.2. Effects of Trump's trade war

3.2.1. Impulse responses

We trace the dynamic responses of asset prices to the identified trade war shock using [Jordà \(2005\)](#) local projection approach by regressing accumulative asset returns or yield changes across horizons on the trade war shock series:

$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h u_t^w + \Psi_h Z_t + \epsilon_{t+h}, \quad h = 0, \dots, H, \quad (11)$$

⁵ We treat March 1, 2018, as the start of the trade war, when President Trump announces that he will place a 25% tariff on steel and 10% on aluminum. The sample ends after the United States and China formally sign the "Phase One" deal.

⁶ <https://www.reuters.com/article/us-usa-trade-china-timeline-idUSKBN1ZE1AA> (accessed February 2023).

⁷ <https://www.china-briefing.com/news/the-us-china-trade-war-a-timeline> (accessed February 2023).

⁸ <https://www.zacks.com/blog/archive.php?g=59> (accessed February 2023). Zacks Investment Research, founded in 1978, is a firm based in the United States that specializes in offering financial information and analysis to professional investors. Zacks data is trusted by almost all major financial data and media companies. Specifically, Zacks has gained recognition for its comprehensive collection of consensus earnings-per-share (EPS) estimates, which are widely used in academic research. Zacks' daily stock market news summarizes the major events of each day, which discusses not only stock market movements but also fluctuations in other markets, such as oil and bonds.

⁹ The data are obtained from Bloomberg through the Economic Calendars (ECO), which contain the predictions made by a panel of market participants as well as realized values. Bloomberg surveys economists during the weeks before the release of each macroeconomic indicator to obtain a consensus estimate. The macroeconomic indicators we consider include the NAPM/ISM index of purchasing managers, consumer confidence, non-farm payroll employment, industrial production, retail sales, consumer price index, housing start, preliminary GDP, advance GDP, and final GDP releases.

¹⁰ We start in 2016, the presidential election year, as Trump's policy is a crucial factor in the trade war. An alternative starting date is also considered for robustness.

Table 1
Specification tests.

Hypothesis	<i>p</i> value
Benchmark VAR: all trade war event days	
$H_0^1: \Sigma_0 = \Sigma_1$	0.003
$H_0^2: \Sigma_0 - \Sigma_1 = \bar{a}_1 \bar{a}_1'$	0.781
Alternative VAR with four lags	
$H_0^1: \Sigma_0 = \Sigma_1$	0.005
$H_0^2: \Sigma_0 - \Sigma_1 = \bar{a}_1 \bar{a}_1'$	0.632
Alternative VAR with AAA spreads	
$H_0^1: \Sigma_0 = \Sigma_1$	0.001
$H_0^2: \Sigma_0 - \Sigma_1 = \bar{a}_1 \bar{a}_1'$	0.709
Alternative VAR with five endogenous variables	
$H_0^1: \Sigma_0 = \Sigma_1$	0.002
$H_0^2: \Sigma_0 - \Sigma_1 = \bar{a}_1 \bar{a}_1'$	0.695
Alternative VAR with a longer sample	
$H_0^1: \Sigma_0 = \Sigma_1$	0.005
$H_0^2: \Sigma_0 - \Sigma_1 = \bar{a}_1 \bar{a}_1'$	0.756
Benchmark VAR: 37 important trade war event days	
$H_0^1: \Sigma_0 = \Sigma_1$	0.005
$H_0^2: \Sigma_0 - \Sigma_1 = \bar{a}_1 \bar{a}_1'$	0.914
Benchmark VAR: 31 important trade war event days related to China	
$H_0^1: \Sigma_0 = \Sigma_1$	0.012
$H_0^2: \Sigma_0 - \Sigma_1 = \bar{a}_1 \bar{a}_1'$	0.746

Note: This table reports the bootstrap *p* values of the two specification tests of the hypotheses H_0^1 and H_0^2 .

where the coefficient β_h as a function of horizon h measures the accumulative effect of a one-standard-deviation trade war shock u_t^w on asset prices y_t , and the control variables in Z_t include one lag of the shock and the dependent variable.¹¹ We choose the local projection approach because it is well-known that estimating the mean reversion in asset prices with VAR models is plagued with econometrics issues. The local projection method is more robust to model miss-specification and allows us to explore the persistence of the effects of the trade war without specifying the full VAR dynamics.¹² Moreover, with the local projection method, we can examine additional financial variables of interest that are not included in the benchmark VAR model.

Fig. 1 depicts the impulse response functions (IRFs) of the trade war shock to the six benchmark VAR variables for a horizon of 60 days. The solid lines are the mean responses via ordinary least square (OLS) estimates, and the dash-dotted and dotted lines are the boundaries of the 68% and 90% error bands, respectively, calculated with Newey–West standard errors. Fig. 1 shows that all the financial variables in the benchmark model are significantly affected by the trade war shock at the 90% confidence level, except the price of gold. The positive trade war shock persistently lowers the prices of risky assets in U. S. financial markets. In particular, the S&P 500 index falls by around 0.45%, and the BAA yield spread rises by 1 basis point significantly on impact. The trade war shock pushes down 10-year Treasury yields by about 2.1 basis points and makes the dollar appreciate against the Chinese yuan by around 0.2%. Finally, the oil futures price falls after a positive trade war shock, which, with the effects on the stock and bond markets, indicates that the prospect of the trade war poses a downside risk to the U.S. economy.

To further examine the effects of the trade war shock, Fig. 2 shows the IRFs of eight additional financial variables.¹³ Most notably, a positive trade war shock generates a large and significant increase in the VIX, which is widely used as a measure of uncertainty. As changes in risk aversion can also induce variations in the VIX, we also consider two components decomposed from the VIX based on Bekaert et al. (2021): a proxy for risk aversion and a “purified” proxy for uncertainty. The bottom row of Fig. 2 shows that the effect of the trade war shock on risk aversion is around twice as large as the effect on uncertainty on impact, but is much less persistent.¹⁴ Moreover, the NASDAQ Composite index declines more than the S&P 500 index, possibly because the trade tensions between the United States and China focus on unfair trade practices related to technology transfer and intellectual property. The appreciation of the Japanese yen, which is considered a safe haven asset, might indicate that the trade war shock changes investors’ risk appetite and generates a flight to safety by withdrawing liquidity from the stock market for safer assets. However, as another safe haven asset, the price of gold is not significantly affected by the trade war shock, as shown in Fig. 1, which perhaps can be explained by the appreciation of the U.S. dollar.

A sharp increase in the VIX volatility index together with a decrease in inflation expectations proxied by 5-year break-even inflation rates after a positive trade war shock provides some hints regarding the possible transmission channels of the estimated shock. We argue that the estimated shock is not like a supply shock that reflects changes in costs by tariffs,

¹¹ Excluding control variables in Z_t leads to almost identical results.

¹² The equivalence between impulse responses from local projections and VARs is discussed in Plagborg-Møller and Wolf (2021). The impulse response functions estimated directly from the benchmark SVAR model are shown in Fig. D.1.

¹³ All the data are collected from the Federal Reserve Economic Data except for the decomposed components of the VIX, which are constructed by a dynamic no-arbitrage asset pricing model for equities and corporate bonds from Bekaert et al. (2021).

¹⁴ The results are robust if we use alternative measures of risk aversion and uncertainty from Bekaert and Hoerova (2014).

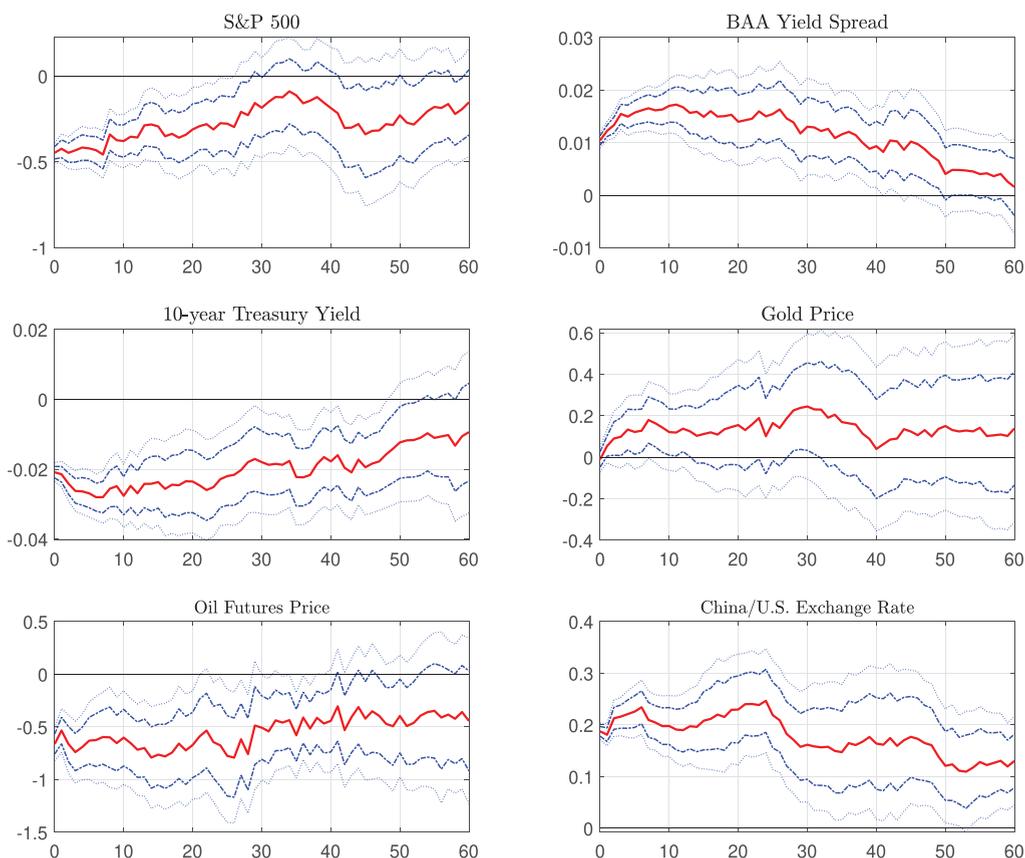


Fig. 1. Local projection impulse responses of the benchmark VAR variables to the trade war shock. Notes: The solid lines are the mean responses via OLS estimates; the dash-dotted and dotted lines are the boundaries of the 68% and 90% error bands, respectively, calculated with Newey–West adjusted standard errors. All the variables are reported in percentages, which means that a response of 1 would be interpreted as a 1% increase due to a one-standard-deviation increase in the shock.

as such shock will produce cost-push inflation and therefore induce an increase in inflation expectations. As a positive trade war shock raises the volatility index, pushes up the price of safe haven assets such as the Japanese Yen and gold, and pushes down the 10-year Treasury yield, the estimated trade war shock may be more like a risk premium shock, which affects financial markets through changes in uncertainty or risk aversion brought about by the greater concern about the intensity of the trade dispute between the United States and China, or the greater likelihood that the trade war will last for a long period.¹⁵ Additionally, the identified trade war shock tends to move long-term yields more than short-term yields, which is in line with the effect of the risk premium shock illustrated in the literature, such as Cieslak and Povala (2015) and Duffee (2018). The transmission channels of the identified trade war shock are discussed further in Section 4.

3.2.2. Variance decomposition

Table 2 reports the results of the FEVD, which measures the average proportion of the h -step ahead forecast error of asset prices attributes to the trade war shock. We calculate the FEVDs of the variables of interest using the methodology proposed by Gorodnichenko and Lee (2020), which is based on the R^2 of the local projection.¹⁶

Table 2 shows that the trade war shock explains a sizable fraction of the fluctuations for most variables of interest. In particular, the variation of the VIX is evidently driven by trade tensions, which also emphasizes the importance of the risk premium channel related to risk aversion and economic uncertainty. Moreover, for the two components of the VIX decomposition, the trade war shock explains more of the variation in the uncertainty part than that of the risk aversion part. The trade war shock also accounts for about 31% of the variation in the S&P 500 index on impact, with a peak contribution of no more than 40% over 60 days. To further explore the importance of the trade war shock, we compute historical decomposi-

¹⁵ For example, Leduc and Liu (2016) show that an increase in uncertainty resembles the effects of a negative aggregate demand shock, which lowers inflation and reduces the long-term interest rates.

¹⁶ The FEVD directly estimated from the benchmark SVAR model is shown in Fig. D.2, which shows similar contributions on impact as shown in Table 2.

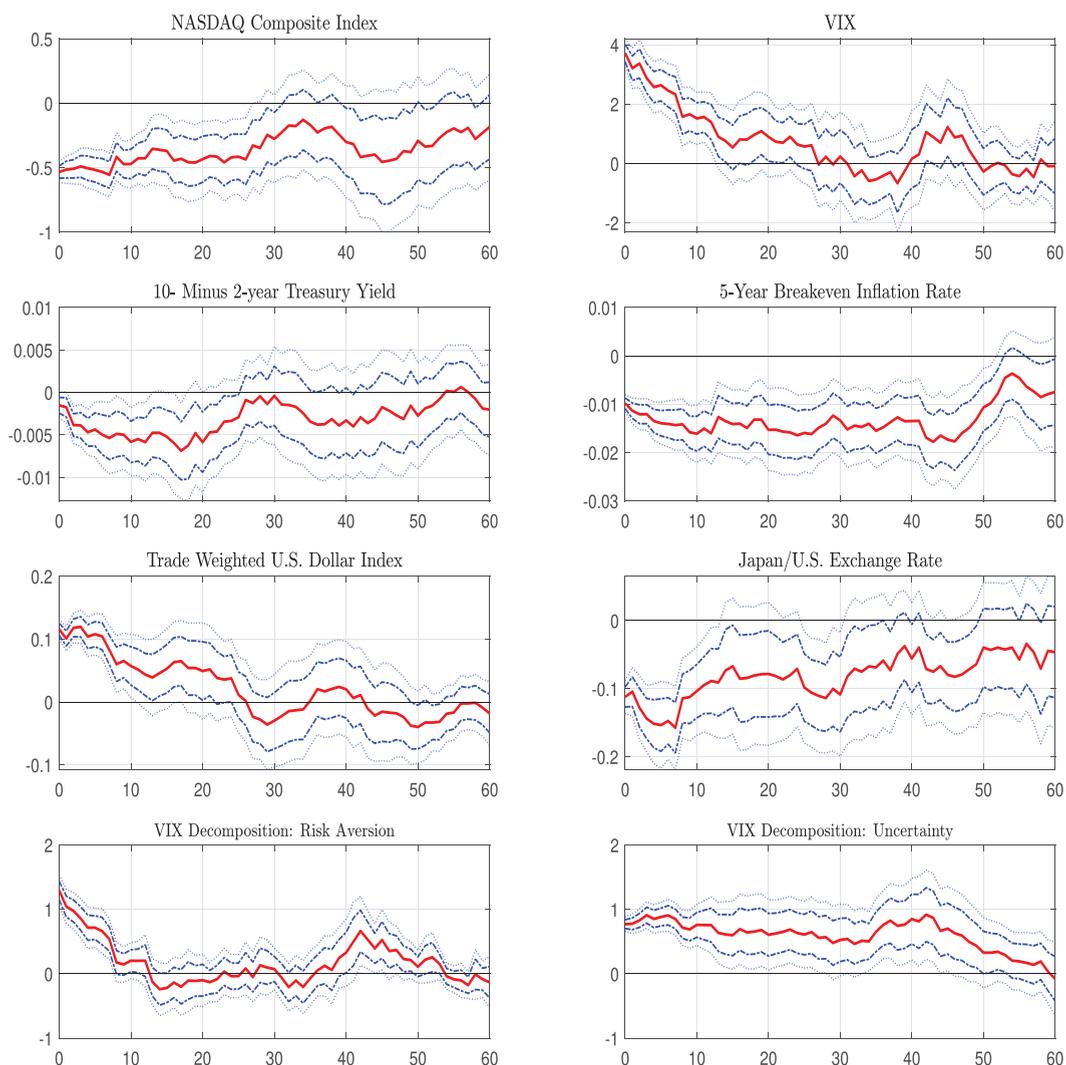


Fig. 2. Local projection impulse response of the additional variables to the trade war shocks. Note: See Fig. 1.

Table 2
Local projection variance decomposition due to the trade war shock.

Variables	Horizons					
	0	4	8	20	40	60
The benchmark variables						
S&P 500	31.00	35.22	38.87	38.36	27.47	22.62
BAA Yield Spread	33.75	42.41	46.70	41.58	32.36	23.49
10-year Treasury Yield	34.17	47.51	49.69	41.39	24.24	13.95
Gold Price	0.05	1.91	2.80	2.18	2.12	1.18
Oil Futures Price	12.21	17.51	19.49	26.23	27.79	26.01
China/U.S. Exchange Rate	61.30	63.26	68.99	67.11	69.66	68.65
The additional variables						
NASDAQ Composite Index	27.95	31.78	36.16	37.41	26.41	22.29
VIX	29.12	35.43	39.66	40.48	32.44	27.37
10- Minus 2-year Treasury Yield	0.39	6.24	13.94	31.13	38.65	44.68
5-Year Breakeven Inflation Rate	15.58	37.88	47.93	58.50	62.07	58.55
Trade Weighted U.S. Dollar Index	29.26	29.49	34.31	40.34	43.25	57.13
Japan/U.S. Exchange Rate	13.55	21.66	24.55	16.12	13.04	8.82
VIX Decomposition: Risk Aversion	25.33	21.66	25.13	25.52	30.65	32.84
VIX Decomposition: Uncertainty	35.26	39.75	44.21	36.58	36.44	35.31

Note: Median shares (in %) of forecast error variance for financial variables of interest due to the trade war shock.

tions in Section 3.2.3, which describe the cumulative contribution of the trade war shock to the financial variables of interest at every given point in time instead of the average movements described by the FEVD.

3.2.3. Historical decomposition

The HD allows us to approximate asset returns or yield changes in ΔY_t as the summation of structural shocks weighted by the impulse response coefficients:

$$r_t = \Delta Y_t = \sum_{h=0}^{t-1} \Theta_h u_{t-h}, \tag{12}$$

where u_t is the vector of structural shocks, and Θ_h is the matrix of impulse response coefficients at horizon h . Denote $r_t^i(u_t^w)$ as the contribution of the trade war shock (u_t^w) to the i -th element of r_t :

$$r_t^i(u_t^w) = \sum_{h=0}^{t-1} \theta_{i,h}^w u_{t-h}^w, \tag{13}$$

where $\theta_{i,h}^w$ is the impulse response of the trade war shock to the i -th element in r_t at time h . We rely on Eq. (13) to analyze the sources of asset prices' movements in certain subperiods.

Fig. 3 reports the historical counterfactuals of the S&P 500 index and 10-year Treasury yields for the entire sample period. In each graph, the black solid line is the actual data series, and the blue solid line is the counterfactual series, indicating the evolution of the variable of interest if we had replaced all the realizations of the trade war shocks with zero while preserving the remaining structural shocks in the model.¹⁷ The vertical distance between the actual and counterfactual series is related to the historical decomposition of the trade war shock, illustrating the effect of the trade war shock on the variable of interest at any given point in time. For the S&P 500 index, Fig. 3 shows that the trade war shock has significant and sizable negative cumulative effects on the stock market right before the United States and China agreed to a temporary truce after the G20 meeting in December 2018. If there is no trade war shock, the S&P 500 index would be 7.4% higher, which is sizable compared with the 4.2% increase in the S&P 500 index from March to December 2018. After several rounds of successful trade negotiations, those negative effects fall, especially after Trump delays the tariff increase at the end of February 2019, which stirs up optimistic expectations that the two countries could strike a final trade deal. However, the trade talks break down at the beginning of May 2019, and the gap between the actual and counterfactual series of the S&P 500 index quickly widens to more than 8.7% at the end of May 2019. The United States and China restart talks at the G20 summit in Osaka in June 2019, which helps reduce the negative effects of the trade war shock until August 1, 2019, when Trump abruptly escalates the trade war by announcing additional tariffs. In the end, the actual and counterfactual series start to converge after mid-October 2019, when Trump cancels some tariffs with China. Similar patterns can be found in the graph for 10-year Treasury yields. For example, in May and August 2019, as in the stock market index, the trade war shock also generates large changes in 10-year Treasury yields.

An interesting observation from Fig. 3 is that the trade war shock does not contribute much to the variants in the S&P 500 index during December 2018, when the U.S. stock market experiences a steep sell-off, as the difference between the actual and counterfactual series does not change significantly. To better analyze the sources of asset price movement in any subperiod of interest, following Kilian and Lee (2014), we express the cumulative change in r_t^i between any dates T_1 and T_2 contributed by the trade war shock (u_t^w) as

$$r_{T_1, T_2}^i(u_t^w) = \sum_{t=T_1}^{T_2} \sum_{h=0}^{t-1} \theta_{i,h}^w u_{t-h}^w. \tag{14}$$

Based on Eq. (14), we find that the trade war shock generates a decrease of only 64 points in the S&P 500 index that sees a very large monthly drop of around 284 points in December 2018. For comparison, the S&P 500 index closes around 172 points lower in May 2019, when the trade war intensifies after President Trump abruptly increases the 10% tariff on \$200 billion of imports from China to 25%, and the trade war shock itself lowers the S&P 500 index by 183 points during this period. Plenty of major news on the trade tension between the United States and China generate turbulence in financial markets during December 2018. For example, only a few days after the G20 meeting in Buenos Aires, Canada announces that Huawei's chief financial officer has been arrested at the request of the United States, which is a major surprise to the financial markets. However, these trade war events does not become the main driver of the U.S. market in December 2018. Instead, domestic factors seem to play a more important role. For example, because of rapid increases in Treasury yields, there are growing concerns about the U.S. monetary policy and the risk of high interest rates. In addition, turbulence in the repurchase agreement market contributes to the high volatility in financial markets at the end of 2018.

Eq. (14) can be extended to calculate the cumulative changes in stock prices due to trade tensions within event windows around trade war events, as in Amiti et al. (2020); Egger and Zhu (2020), and Huang et al. (2020), which rely on the event

¹⁷ We first compute $r_t^i - r_t^i(u_t^w)$ and then accumulate these returns or changes over time as the actual data series are presented in levels.

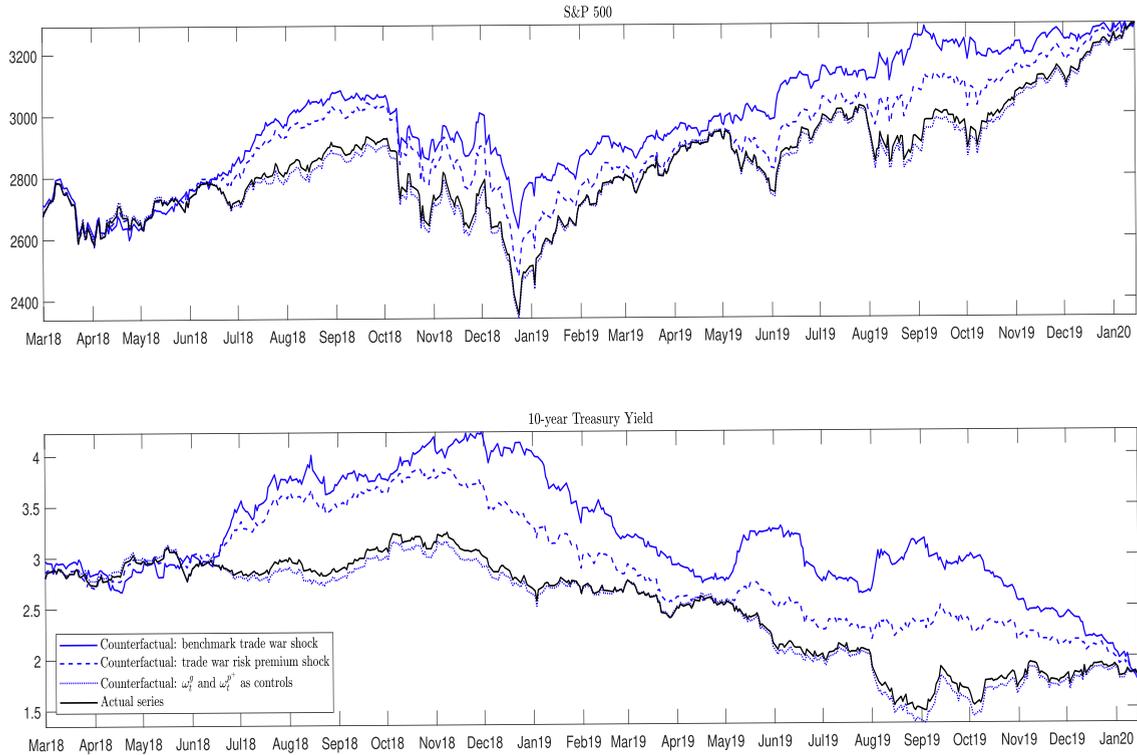


Fig. 3. Historical decomposition of the selected variables. *Notes:* The solid black lines are the actual data series. The blue lines are the counterfactual series. The blue solid lines are the counterfactual series based on the benchmark trade war shock, the blue dashed lines are the counterfactual series based on the trade war risk premium shock estimated via Eq. (16), and the blue dotted lines are the counterfactual series based on the shock estimated via eliminating both the first- and second-moment effects, which are detailed in Section 4. A counterfactual above the actual means that the trade war shock decreases the selected variables, and a counterfactual below the actual series means that the trade war shock increases the selected variables.

study approach. The accumulated contribution of the trade war shock on firm f 's stock return r_t^f over the event window from day $t_0 - 1$ to day $t_0 + T$ can be calculated as

$$r_{t_0-1, t_0+T}^f(u_t^w) = \sum_{t=t_0-1}^{t_0+T} \sum_{h=0}^{t-1} \theta_{f,h}^w u_{t-h}^w, \tag{15}$$

where the impulse response coefficient $\theta_{f,h}^w$ measures the effect of a one-standard-deviation trade war shock on a h -day stock return.¹⁸ Although both our method and the event study approach rely on important trade war events, our method differs from the event study approach in its underlying assumptions. Specifically, our methodology hinges on the assumption that the event of interest is capable of generating significant changes in the second moments of asset returns. In contrast, the event study approach relies on several assumptions, such as the unexpectedness of the event and the absence of any concurrent events affecting the market. Based on Eq. (15), we calculate the accumulated contribution of the trade war shock u_t^w on the S&P 500 index over the 7-day event window for seven events listed in Amiti et al. (2020).¹⁹ The results are listed in Table 3.

Our results are in line with those from Amiti et al. (2020) for certain events, although noticeable differences exist.²⁰ For instance, we disagree with Amiti et al. (2020) regarding the effect of the event on March 22, 2018. Although the total changes in

¹⁸ The impulse response coefficient $\theta_{f,h}^w$ can be calculated with a VAR model or a local projection regression.
¹⁹ In addition to the difference in methods, the S&P 500 index includes only the 500 largest companies listed on stock exchanges in the United States with a market capitalization of around \$23 trillion, while Amiti et al. (2020) investigate approximately 3,000 listed firms from the COMPUSTAT database with a total market capitalization of \$28 trillion, which consists of not only large firms in the S&P 500 index but also many small firms. In addition, Amiti et al. (2020) calculated the effects of trade war events on the firm's rate of return first and then derived the weighted average based on market capitalization, while our calculation is based directly on the S&P 500 index.
²⁰ The total changes in actual market returns are larger in our calculation, possibly because our sample includes larger firms that tend to have higher exposure to international trade and suffer more from the trade war.

Table 3
Comparison between Amiti et al. (2020) results and the HD results

Event	Amity et al. (2020) results		HD Results	
	Market return	Event effect	Market return	Event effect
01Mar18	0.28	1.16	-0.19	-1.30
22Mar18	-2.70	-2.66	-2.80	-0.31
02Apr18	-0.39	-0.43	0.31	0.35
15Jun18	-0.53	-0.23	-0.75	-2.87
17Sep18	0.32	-0.34	0.52	0.53
10May19	-0.70	-2.98	-0.76	-3.09
23Aug19	0.03	-0.5	0.07	-2.04
Total	-2.93	-5.97	-3.59	-8.74

Note: Results are in percentages.

the actual market returns are similar in both studies, our event effect is considerably smaller than that of Amiti et al. (2020). The different results might be attributed to potential deviations from the underlying assumptions of the event study methodology during the March 22, 2018, event: First, the Federal Open Market Committee (FOMC) holds a scheduled meeting on March 20–21, 2018, which could also influence stock prices during the event window of March 22, 2018. Although the Fed's quarter-point rate hike is anticipated, the central bank also raises its GDP projection for 2018, which paves the way for future rate hikes and adds to the pressure on stock markets. Second, the announcement by President Trump on March 22, 2018, is somewhat expected by market watchers. In addition to Bloomberg's report on March 7, 2018, President Trump tweets on the same day that the White House will request that Beijing cut the deficit by \$100 billion. Moreover, on March 14, 2018, Reuters reports that President Trump is seeking to impose tariffs on up to \$60 billion of Chinese imports associated with an investigation into intellectual property theft and will target the technology and telecommunications sectors. The stock prices of companies like the Boeing Company have already fallen significantly days before March 22, 2018, due to fears that they might be the primary targets of Chinese retaliation.

3.3. Estimated trade war shock series

Fig. 4 illustrates the dynamics of the trade war shock over time by graphing its cumulative path. The evolution of the trade war shock is generally in line with the actual trade war process and matches many important turning points. The first sharp increase in the cumulative trade shock occurs on May 29, 2018, when the White House surprisingly reinstates its \$50 billion tariff plan. The escalation of trade tensions makes the series peak at the beginning of January 2019, right before the United States and China agree to resume trade talks, when both sides are eager for a compromise. The level of trade conflicts steadily decreases until May 2019, when President Trump abruptly announces that the United States will increase the 10% tariff on \$200 billion of imports from China to 25%. The trade tension reaches the highest level after Trump announces 10% tariffs on almost all remaining imports from China in August 2019, and then gradually decreases as the United States and China approach the Phase One trade deal.

As the empirical results indicate a possible link between the estimated shock and uncertainty, Fig. 4 also plots the identified trade war shock against Caldara et al. (2020) TPU index, which is based on automated text searches of newspaper articles related to trade policy uncertainty. Both series are normalized by their respective standard deviations and are further modified by setting values equal to zero if the corresponding series values are less than one standard deviation in absolute value and equal to the series values otherwise. Comparing this estimated shock series with the TPU index, clear differences exist, although some parts look similar. The TPU index does not capture the important events mentioned above well. For example, the breakup on May 29, 2018, is a key turning point in the trade war between the United States and China, which indicated that simply increasing purchases of agricultural products from China cannot solve the trade disputes between the two countries. However, the TPU index has large positive spikes only several days later, when the United States moves forward with its steel and aluminum tariffs on the European Union (EU), Canada, and Mexico.²¹

3.4. Robustness checks

In this subsection, we report the results of several robustness checks. The first robustness check is related to the benchmark VAR specifications, and we consider four alternatives. First, we change the lag of the VAR to four, according to the Akaike information criterion. Second, we consider different specifications for the set of endogenous variables included in the VAR. For example, we replace the BAA corporate spread with the AAA spread. Third, we change the number of endogenous variables in the VAR. For example, we estimate a smaller-scale five-variable VAR, including the S&P 500 index, the BAA corporate yield spread, 10-year Treasury yields, the gold price, and the exchange rate between the United States and China.

²¹ More details related to the estimated trade war shock series are provided in B.

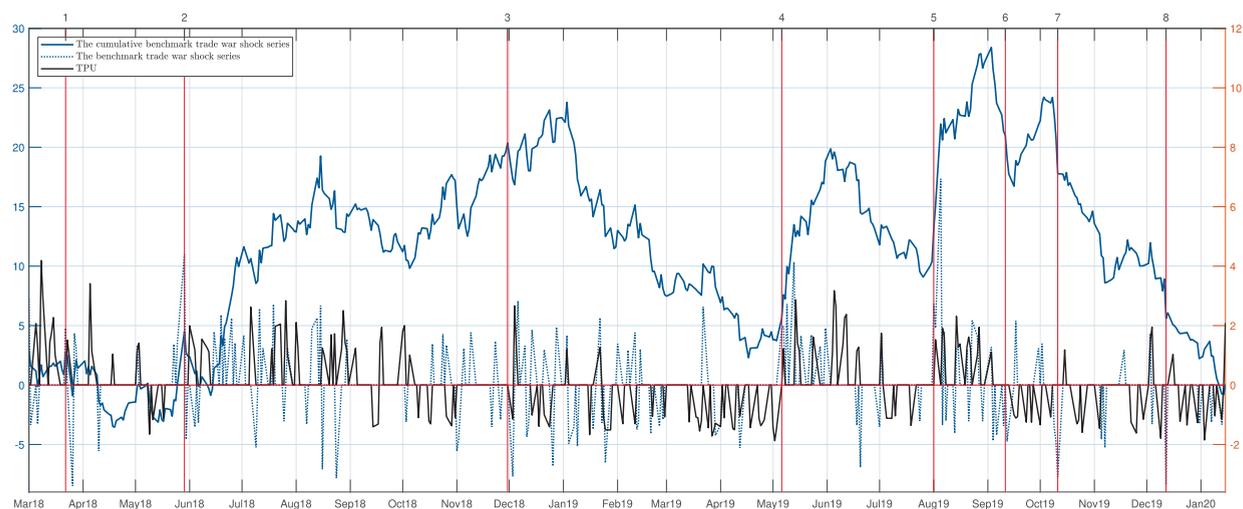


Fig. 4. The benchmark trade war shock series against [Caldara et al. \(2020\)](#) TPU index. *Notes:* The blue solid line is the accumulated trade war shock, the blue dotted line is the trade war shock, and the black solid line is the TPU index. The vertical lines are associated with the following events: (1) 3/22/2018: Section 301 report; (2) 5/29/2018: The United States reinstates tariff plans after a brief truce; (3) 11/30/2018: The US-Mexico-Canada Agreement (USMCA) is signed to replace NAFTA; (4) 5/5/2019: Trump tweets that the United States will increase the 10% tariff on \$200 billion of imports from China to 25%; (5) 8/1/2019: Trump abruptly announces 10% tariffs on almost all remaining imports from China; (6) 9/11/2019: China removes a few tariffs, and Trump delays his tariff increase; (7) 10/11/2019: Trump cancels the October 15 tariff increase; (8) 12/12/2019: Trump tweets that the United States and China are nearing a “big deal”.

Finally, we estimate the benchmark VAR over a longer sample period, starting from October 2014, when the Fed ends its monthly asset purchases program (QE3) to control unconventional monetary policies.

The second robustness check is related to the choice of trade war days. Although [Rigobon and Sack \(2005\)](#) show that the identification through heteroscedasticity methodology is robust to small misspecifications in the determination of trade war days, to illustrate that the main results are robust to the trade war days specification, we estimate the benchmark VAR model and identify the trade war shock using two alternative sets of the trade war days, i.e., trade war days marked in bold, which are highly related to tariff decisions, and trade war days marked with an asterisk, which are important but are associated only with trade conflicts between the United States and China, as shown in [Table A.1](#).

The IRF, FEVD, and HD results for each robustness check do not deviate significantly from those of the baseline specification and are not shown here to save space. As the identified trade war shock plays an important role in our analysis, [Fig. D.3](#) presents scatter plots of the benchmark trade war shock (on the x-axis) against alternative shocks extracted via different robustness checks (on the y-axis), together with fitted lines (in blue) and 45-degree lines (in red). The slope coefficients of all the fitted lines are close to 1. The six alternative shocks and the benchmark trade war shock are situated intensely and closely along the 45-degree line. All the evidence indicates that the alternative shocks in the robustness checks are highly correlated with the benchmark trade war shock and behave similarly. In addition, [Table 1](#) shows the results of the tests of the hypotheses that $\Sigma_0 = \Sigma_1$ and $\Sigma_0 - \Sigma_1 = \tilde{a}_1 \tilde{a}_1'$. In all the alternative settings, the first hypothesis is rejected, while the second hypothesis is accepted.

4. Transmission channels of the trade war shock

4.1. The role of the risk premium and expectations

The reactions of financial variables such as the VIX to the benchmark trade war shock indicate that the changes in the risk premium arising from changes in risk appetite or economic uncertainty are possibly an important channel through which the trade war affects asset markets. However, as shown in [Baker and Bloom \(2013\)](#) and [Piffer and Podstawski \(2018\)](#), changes in investors' expectations for the growth news of fundamentals, such as cash flows in the economy, are usually observed in combination with variations in uncertainty, which have similar effects on the VIX as changes in the risk premium. Therefore, the trade war shock may impact asset markets through a combination of the risk premium and investor expectations channels, underscoring the importance of distinguishing between these two channels.

To examine the relative importance of the risk premium and expectations channel, we first explore the information content of the benchmark trade war shock with the help of “common shocks” derived by [Cieslak and Pang \(2021\)](#). [Cieslak and Pang \(2021\)](#) extract four common shocks from stock returns and Treasury yield changes, which allows us to investigate the drivers of asset prices at daily frequency. The four shocks are the growth news shock (ω_t^g), which is defined as “a shock to investors' expectations about the growth rate of fundamentals (cash flows) in the economy”; the monetary policy shock

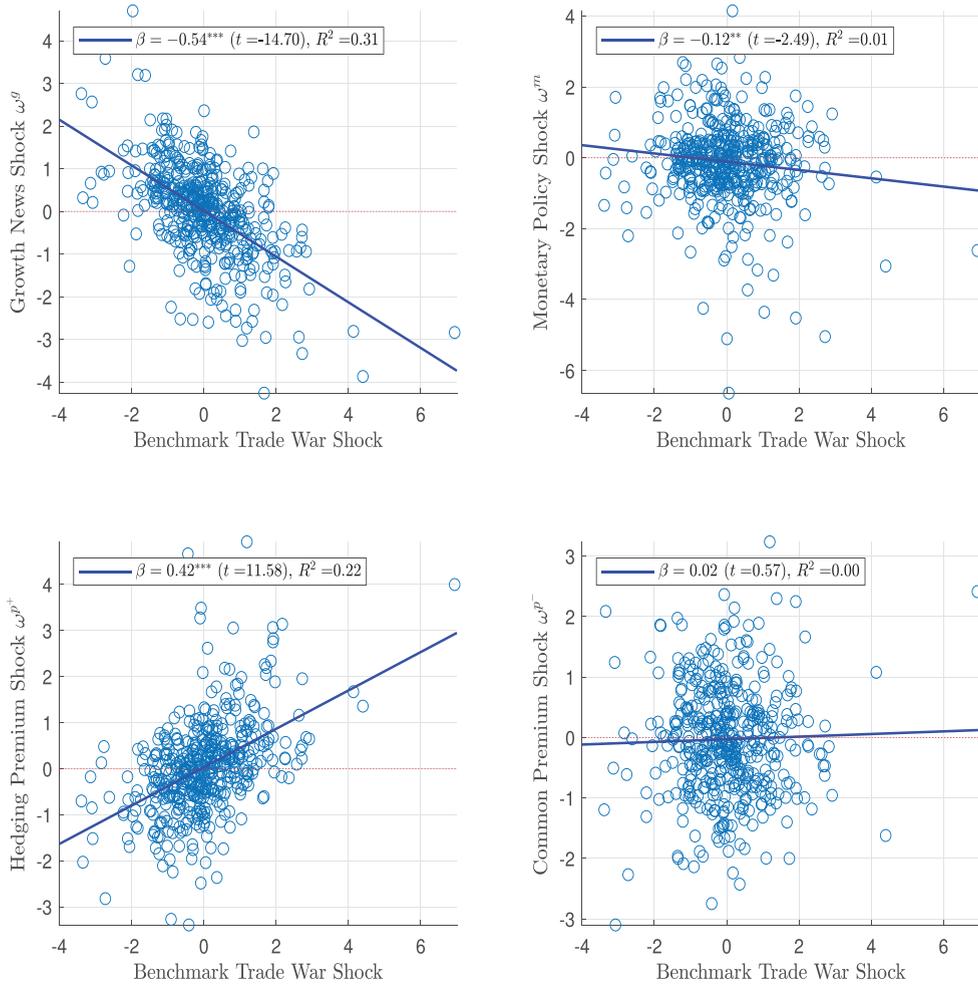


Fig. 5. Benchmark trade war shock vs. four common shocks. *Notes:* The figure presents scatter plots of the benchmark trade war shock (on the x-axis) against the four common shocks extracted via Cieslak and Pang (2021) (on the y-axis) as well as fitted lines (in blue) with the corresponding regression coefficient, t statistic, and R^2 .

(ω_t^m), which is defined as “an exogenous shock to the short-term risk-free rate, or its expected path, that is orthogonal to other state variables driving the short rate”; and two risk premium shocks, the hedging premium shock ($\omega_t^{p^+}$), which is defined as a shock to the cash-flow risk premium arising from shifts in the risk appetite or a shock to the cash-flow uncertainty that drives stock and bond premiums in opposite directions, and the common premium shock ($\omega_t^{p^-}$), which is defined as a shock to “the discount-rate risk premium that drives the common component in compensation required by stock and bond investors due to being exposed to pure discount rate shocks.”²² Fig. 5 presents scatter plots of the benchmark trade war shock against each of the four common shocks, as well as fitted lines. The benchmark trade war shock is negatively correlated with the growth news shock, with the regression coefficient $\beta = -0.54$ and $R^2 = 0.31$, and positively correlated with the hedging premium shock, with the regression coefficient $\beta = 0.42$ and $R^2 = 0.22$. The monetary policy shock and the common premium shock, with insignificant regression coefficients and very low R^2 , do not explain much of the variation in the benchmark trade war shock. Therefore, Fig. 5 indicates that the benchmark trade war shock is mainly a mixture of the growth news shock related to investors’ expectations and the hedging premium shock arising from shifts in uncertainty or risk aversion.

As the benchmark trade war shock is related not only to changes in the risk premium but also shifts in expectations, to evaluate the importance of the risk premium channel, we further use ω_t^g as an additional control variable to eliminate the expectation (first moment) effect and estimate the following VAR:

$$\Delta Y_t = c + B_1 \Delta Y_{t-1} + \delta \omega_t^g + D_z z_t + \varepsilon_t. \tag{16}$$

²² Details of deriving the four common shocks are shown in C.

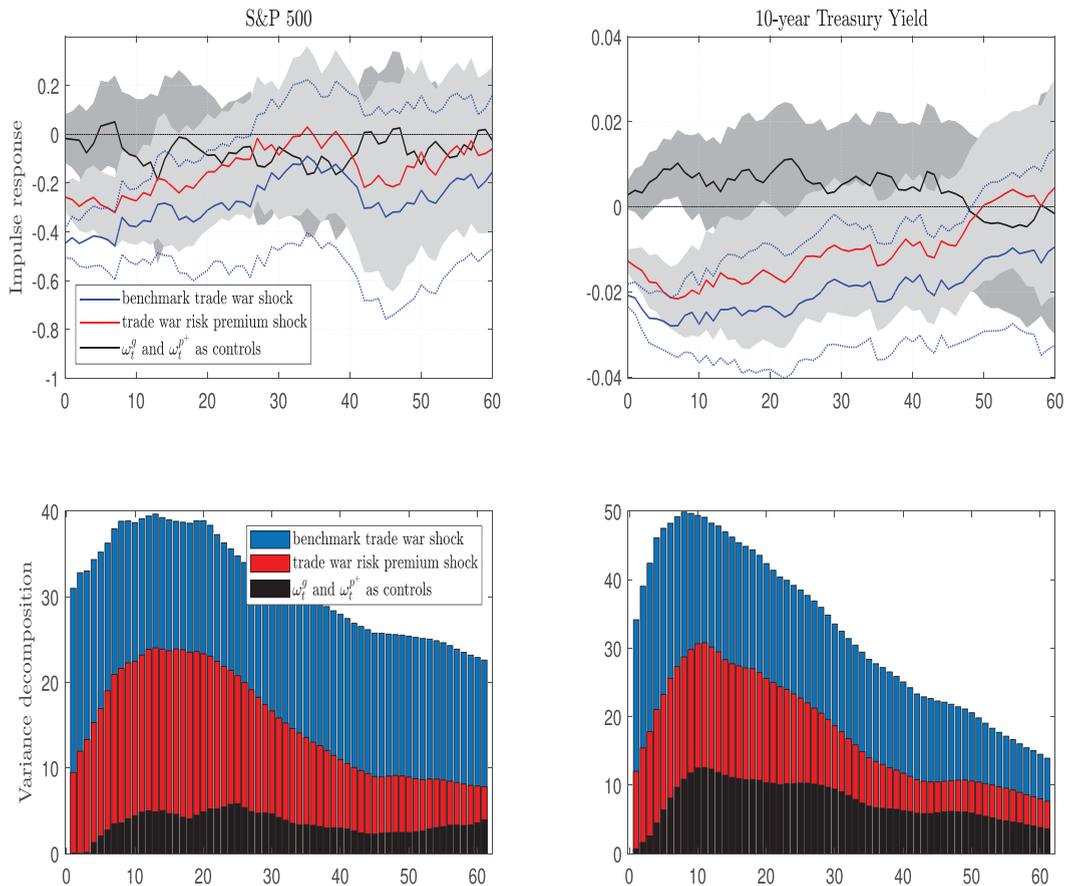


Fig. 6. Local projection IRFs and FEVDs for selected variables, benchmark trade war shock vs. trade war risk premium shock estimated via Eq. (16) vs. shock estimated with ω_t^e and ω_t^p as control variables. *Notes:* The top two graphs are IRFs. The blue solid lines are IRFs of the benchmark trade war shock, and the blue dotted lines are the corresponding 90% error bands. The red solid lines are IRFs of the trade war risk premium shock, with the light gray area covering the 90% error bands. The black solid lines are IRFs of the shock estimated with ω_t^e and ω_t^p as control variables, with the dark gray area covering the 90% error bands. The bottom two graphs are FEVDs. The blue bars are FEVDs of the benchmark trade war shock, the red bars are FEVDs of the trade war risk premium shock, and the black bars are FEVDs of the shock estimated with ω_t^e and ω_t^p as control variables. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

For simplicity, we denote the shock series estimated via Eq. (16) as the “trade war risk premium shock”.²³ Fig. 6 reports the IRFs and FEVDs of the estimated trade war risk premium shock on the S&P 500 index and the 10-year Treasury yields. In the IRF results, the trade war risk premium shock (the red line) has a significant negative but quantitatively smaller effect on the S&P 500 index and the 10-year Treasury yields compared to the benchmark trade war shock (the blue line), which indicates that the role of investors’ expectations in the benchmark trade war shock is not negligible. In particular, the impact effect of the trade war risk premium shock on the S&P 500 index is slightly larger than half of the effect caused by the benchmark trade war shock. From the FEVD results, the trade war risk premium shock provides around half of the explanatory power as the benchmark trade war shock in variants of the asset prices. It contributes approximately 10% of the fluctuations in the S&P 500 index and the 10-year Treasury yields on impact, and its explanatory power gradually reaches more than 20% within 20 days.²⁴ We also compute the HD to explore the importance of the trade war risk-premium shock in certain subperiods. The blue dashed lines in Fig. 3 are the counterfactual series based on the trade war risk premium shock. Notably, the importance of the trade war risk premium shock varies significantly over time. For example, the explanatory power of the trade war risk premium shock on the S&P 500 index is large during the second half of 2018, when no trade talks are formally scheduled between the United States and China,

²³ The p values of the first and second specification tests are 0.025 and 0.763, respectively.

²⁴ As a robustness check, we regress the benchmark trade war shock on the growth expectation shock ω_t^e to get rid of the expectation effect,

$$u_t^w = \alpha + \beta \omega_t^e + e_t,$$

and consider the estimated residual e_t as a proxy for the risk premium part of the trade war shock. The resulting IRFs and FEVDs are qualitatively the same as in Fig. 6.

while the influence of the trade war risk premium shock decreases significantly during the first half of 2019, when several rounds of trade negotiations were scheduled.

Finally, we use ω_t^e and ω_t^{p+} as additional control variables to eliminate both the expectation (first moment) effect and risk premium (second moment) effect. The p value of the first specification test becomes 0.054, indicating that the reduced-form variance–covariance matrix on the trade war days is no longer significantly different from that on the other days at the 5% level. The alternative shock using ω_t^e and ω_t^{p+} as additional control variables also does not play an important role in the financial markets. Fig. 6 reports the IRFs and FEVDs of the shock estimated from this exercise on the S&P 500 index and the 10-year Treasury yields. Compared with the results for the benchmark trade war shock and the trade war risk premium shock, the alternative shock has much smaller effects. In addition, the blue dash-dotted lines in Fig. 3 are the counterfactual series based on the alternative shock, and they almost overlap with the actual data series. In short, all the empirical evidence suggests that the risk premium and expectation channels are the main channels through which the benchmark trade war shock influences financial markets.

4.2. GVC exposure

Using disaggregated firm-level data, we further explore the role of firms' GVC structures in transmitting trade war shocks to stock prices. There are several potential mechanisms by which the trade war can affect U.S. firms' value through their GVC exposure to foreign countries. For example, firms that rely more on sales to foreign markets may suffer more because of realized tariffs and fears about the possibility that the trade barriers on their products in foreign countries could increase. However, firms that import intermediate inputs might also worry that changes in domestic trade barriers could affect their production costs. In addition, firms without any direct connection to international trade might be negatively impacted by "common" (or general equilibrium) effects. For instance, an economic slowdown brought on by a trade conflict may result in lower demand for goods and services in all industries, which can affect these firms, despite not being directly involved in international trade.

With the identified trade war shock, we compute the dynamic responses of stock prices using the local projection similar to Eq. (11), which can easily accommodate state dependence. Specifically, we estimate the following panel regression model:

$$y_{i,t+h} - y_{i,t-1} = \sum_j I_j \left(\alpha_{i,h}^j + \beta_h^j u_t^w + \Psi_h^j Z_{i,t} \right) + \epsilon_{i,t+h}, \quad h = 0, \dots, H, \tag{17}$$

where $y_{i,t+h}$ is the log of firm i 's stock prices at time $t+h$, $\alpha_{i,h}^j$ is a firm-specific fixed effect, u_t^w is the benchmark trade war shock series, and $I_j, j \in \{L, M, H\}$ are indicator functions. As the trade war is mainly related to the United States and China, exposure to China is considered. Therefore, I_L is the indicator of low GVC exposure to China, I_H is the indicator of high GVC exposure to China, and I_M is the indicator of other firms. The difference between the effects for firms with high and low GVC exposure to China is given by $\beta_h^H - \beta_h^L$. Control variables in $Z_{i,t}$ include one lag of the shock and the dependent variable. We consider firms in the S&P 500 index²⁵, and the daily stock prices data are from Compustat. The main issue associated with the local projection method is the serial correlation in the error terms due to the successive leading of the dependent variable. In the analysis, we use the heteroscedasticity and autocorrelation robust standard errors proposed by Driscoll and Kraay (1998), which are suitable in panel regressions as they also consider cross-sectional dependence.

To measure firms' exposure to China's market, we follow Hoberg and Moon (2017), who use the Securities and Exchange Commission's EDGAR 10-K filings to construct dynamically updated text-based measures of the offshore sales of outputs and purchases of inputs for firms. Specifically, two variables for 2017 in the Hoberg-Moon Offshoring Repository are used to construct the indicators in Eq. (17): Offshore Output, which is the number of times a firm mentions selling outputs to a country in its 10-K filings, and Offshore Input, which is the number of times a firm mentions purchasing inputs from a country. Firms with the top 35% of mentions related to China are classified as firms with high exposure, while firms with zero mentions related to China are treated as firms with low exposure.²⁶ We also exclude firms with no foreign exposure from the sample to ensure that firms with no exposure to China's market are not those without any connections to foreign markets. The results summarized under specification I in Table 4 show that firms with high exposure to China's market suffer significantly more from the trade war, regardless of whether they rely on sales to China or import intermediate inputs from there. For example, a positive trade war shock lowers the stock returns of firms with high input or output exposure by 0.51% on impact, compared to a 0.34% reduction for firms with low input and output exposure. This demonstrates that firms with higher exposure to China's market are more significantly impacted by the trade war. Moreover, since firms with zero mentions related to China in their 10-K filings are likely to have no direct trade relations with China, the effect on low-exposed firms can be largely attributed to changes in factors that are relevant to firms in general (the "common" effect). The sizeable impact on low-exposed firms is consistent with the findings of Amiti et al. (2020) using the event study approach.

By examining the samples of firms with high exposure to China, we find that many firms belong to the group with high output exposure and the group with high input exposure. There are 156 firms with high input exposure and 154 firms with high output exposure, but 98 are the same firms. To explore which GVC exposure, input exposure or output exposure, is

²⁶ The results are robust if we choose different standards, such as the top 30% and the top 40%, to define firms with high exposure.

Table 4
GVC exposure and the effects of the trade war shock.

	Horizon				# of firms
	Impact	4 days	8 days	12 days	
Specification I					
(1) Firms with high INPUT	-0.0050*** (0.0004)	-0.0052*** (0.0008)	-0.0053*** (0.0010)	-0.0041*** (0.0013)	156
(2) Firms with low INPUT	-0.0041*** (0.0003)	-0.0042*** (0.0007)	-0.0044*** (0.0009)	-0.0035*** (0.0011)	238
Difference between (1) and (2)	-0.0009*** (0.0001)	-0.0009*** (0.0002)	-0.0009** (0.0003)	-0.0006 (0.0004)	
(3) Firms with high OUTPUT	-0.0053*** (0.0004)	-0.0054*** (0.0008)	-0.0056*** (0.0010)	-0.0044*** (0.0013)	154
(4) Firms with low OUTPUT	-0.0035*** (0.0003)	-0.0035*** (0.0006)	-0.0036*** (0.0009)	-0.0028*** (0.0010)	164
Difference between (3) and (4)	-0.0017*** (0.0002)	-0.0019*** (0.0003)	-0.0020*** (0.0004)	-0.0016*** (0.0005)	
(5) Firms with high INPUT or OUTPUT	-0.0051*** (0.0004)	-0.0052*** (0.0008)	-0.0054*** (0.0010)	-0.0043*** (0.0013)	212
(6) Firms with low INPUT and OUTPUT	-0.0034*** (0.0003)	-0.0036*** (0.0006)	-0.0037*** (0.0009)	-0.0030*** (0.0010)	104
Difference between (5) and (6)	-0.0017*** (0.0002)	-0.0016*** (0.0003)	-0.0017*** (0.0004)	-0.0013** (0.0005)	
Specification II					
(7) Firms with high INPUT and high OUTPUT	-0.0053*** (0.0004)	-0.0055*** (0.0008)	-0.0055*** (0.0011)	-0.0043*** (0.0014)	98
(8) Firms with high INPUT and low OUTPUT	-0.0038*** (0.0004)	-0.0034*** (0.0007)	-0.0034*** (0.0009)	-0.0025** (0.0012)	23
(9) Firms with low INPUT and high OUTPUT	-0.0046*** (0.0004)	-0.0049*** (0.0008)	-0.0052*** (0.0009)	-0.0042*** (0.0012)	41
(10) Firms with low INPUT and low OUTPUT	-0.0034*** (0.0003)	-0.0036*** (0.0006)	-0.0037*** (0.0009)	-0.0030*** (0.0010)	104
Difference between (8) and (10)	-0.0004* (0.0002)	0.0002 (0.0004)	0.0003 (0.0005)	0.0005 (0.0007)	
Difference between (9) and (10)	-0.0012*** (0.0002)	-0.0013*** (0.0003)	-0.0015*** (0.0004)	-0.0012** (0.0005)	
Difference between (8) and (9)	0.0009*** (0.0002)	0.0015*** (0.0005)	0.0018*** (0.0005)	0.0017** (0.0007)	

Notes: All the firms are from the S&P 500 index. "INPUT" denotes input exposure from China, and "OUTPUT" denotes output exposure from China, which are from the Hoberg-Moon Offshoring Repository. All the variables are in logs, which means that a response of 0.01 would be interpreted as a 1% increase due to the shock. Standard errors clustered by firm are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

more important, we subdivide the firms into five categories and re-estimate the regression Eq. (17), where j now has five indexes, $j \in \{LL, HH, LH, HL, O\}$, and I_{LL} is the indicator of firms with low input and low output exposure, I_{HH} is the indicator of firms with high input and high output exposure, I_{LH} is the indicator of firms with low input and high output exposure, I_{HL} is the indicator of firms with high input and low input exposure, and I_O is the indicator of all the other firms. The results are summarized under specification II in Table 4. Investors care more about firms' output exposure than about their input exposure. The greater the firm's output exposure to China, the greater the extent to which the trade war lowers the firm's value, while there is no persistent significant difference between the responses of firms with high input exposure and firms with low input exposure during the trade war. This result is intuitive, as the trade war shock make the U.S. dollar appreciate, especially against the Chinese yuan. For firms that import intermediate inputs from foreign countries, increases in their production costs can be partially offset by the appreciation of the U.S. dollar. However, for firms that rely on sales to foreign markets, the strong U.S. dollar worsens the impact of the trade war.

5. Conclusion

This study provides evidence of the effects of Trump's trade war from March 2018 to January 2020, by employing a structural VAR with financial variables at the daily frequency and following the identification method of Rigobon (2003) and Wright (2012). Additionally, the study explores the potential transmission channels of the trade war shock using economic common shocks derived by Cieslak and Pang (2021) and firms' GVC exposures from Hoberg and Moon (2017). This study has three main empirical findings. First, the effects of the trade war on financial markets are notable, but the contribution of the trade war shock to fluctuations in financial variables varies remarkably over time. Second, the risk premium channel and the expectation channel through which the trade war influences financial markets are both vital, which sheds some light on the debate about the importance of trade policy uncertainty. Finally, GVC exposures, especially output exposures, matter in the

transmission of the trade war shock. Furthermore, although the trade war severely decreases the returns of firms exposed to China, it also has a sizable negative impact on returns for firms with little to no connection to China.

Two possible improvements can be made in future work. First, it is better to identify a trade war news shock and a trade war risk premium shock simultaneously, possibly by combining Rigobon (2003) heteroscedasticity-based method and the restrictions in Cieslak and Pang (2021). Second, as an alternative approach to the event study method, Eq. (15) based on historical decompositions, can be further extended to investigate the effect of an event on stock prices or returns.

CRedit authorship contribution statement

Yong Chen: Methodology, Software, Formal-analysis, Investigation, Writing-original-draft, Writing-review-editing. **Jing Fang:** Methodology, Software, Formal-analysis, Investigation, Writing-original-draft, Writing-review-editing. **Dingming Liu:** Conceptualization, Methodology, Formal-analysis, Investigation, Writing-original-draft, Writing-review-editing.

Funding

This research is supported by the National Natural Science Foundation of China (71803154), the Natural Science Foundation of Fujian Province (2022J01045) and the MOE Project of Key Research Institute of Humanities and Social Sciences at Universities “Research on the transmission mechanism of macroeconomic policy based on micro heterogeneity” (Project No. 22JJD790048).

Data availability

Data will be made available on request.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Trade war events

Table A.1
Trade war event dates

Date	Event	After hours
*3/1/2018	Trump says he will impose a 25% tariff on steel and 10% on aluminum.	No
*3/8/2018	Trump issues formal steel and aluminum tariff proclamations effective March 23, 2018, but exempts some countries, including Canada and Mexico.	Yes
*3/22/2018	The Trump administration releases the Section 301 report and proposes imposing tariffs on up to \$60 billion of Chinese imports.	No
*4/1/2018	China imposes tariffs on \$3 billion of U.S. imports in retaliation for U.S. duties on steel and aluminum.	Yes
*4/3/2018	The Trump administration unveils plans for 25% tariffs on \$50 billion of Chinese imports.	Yes
*4/5/2018	Trump instructs trade officials to consider whether an additional \$100 billion of U.S. imports from China should be subject to new tariffs in response to China's retaliatory tariffs.	Yes
*5/20/2018	The United States and China put the trade war on hold.	Yes
*5/29/2018	The United States reinstates tariff plans after a brief truce.	No
5/31/2018	The United States moves forward with its steel and aluminum tariffs on Canada, Mexico, and the EU.	No
*6/15/2018	The USTR releases a two-stage plan to impose 25% tariffs on approximately \$50 billion of Chinese imports, starting July 6, 2018.	No
*6/18/2018	Trump directs the USTR to identify \$200 billion worth of Chinese goods for additional tariffs at the 10% rate after China retaliates.	Yes
*7/6/2018	U.S. tariffs on \$34 billion of Chinese imports go into effect, the first phase of its June 15 \$50 billion list.	No
*7/10/2018	The USTR releases a list of \$200 billion of Chinese imports to be subjected to the new 10% tariffs.	Yes
7/25/2018	The United States and the European Union vow to work toward zero tariffs.	No
*8/1/2018	The USTR confirms that Trump is considering increasing the proposed tariffs on \$200 billion of Chinese imports to 25%, from 10%.	Yes
*8/23/2018	U.S. tariffs on \$16 billion of Chinese imports go into effect, the second phase of its June 15 \$50 billion list.	No
8/27/2018	The United States and Mexico reach a preliminary trade deal that could replace NAFTA.	No
*9/17/2018	The United States finalizes 10% tariffs on \$200 billion of Chinese goods, which goes into effect on September 24 and is planned to increase to 25% on January 1, 2019.	No

(continued on next page)

Table A.1 (continued)

Date	Event	After hours
*9/24/2018	China cancels scheduled trade talks with the United States after U.S. tariffs on \$200 billion of Chinese imports announced on September 17 take effect.	No
10/1/2018	The United States and Canada reach a new trade deal to replace NAFTA.	No
11/30/2018	The United States-Mexico-Canada Agreement is signed to replace NAFTA.	No
*12/1/2018	The United States and China agree to a temporary truce after the G20 meeting in Buenos Aires. However, if no agreement is reached by March 1, 2019, the 10% tariffs on \$200 billion of Chinese imports will be raised to 25%.	Yes
12/5/2018	Canada says that Huawei's chief financial officer has been arrested at the request of the United States.	Yes
12/29/2018	Trump hails "big progress" after a call with Xi.	Yes
1/7/2019	The United States and China resume trade talks, with both eager for a compromise.	No
1/22/2019	The United States cancels preparatory talks with China.	No
1/31/2019	Trump expresses optimism about trade talks with China, announcing that he will meet with Xi "in the near future."	No
2/7/2019	Trump says he will not meet with Xi before the March trade deal deadline.	No
2/15/2019	Xi meets Lighthizer and Mnuchin after trade talks in Beijing and hails progress.	No
*2/22/2019	Trump meets with Liu He on trade talks and later announces that he will delay the tariff increase on \$200 billion of Chinese imports that had been scheduled to go into effect on March 1, 2019.	No
3/28/2019	During talks in Beijing, China is reported to be making unprecedented proposals for a tech transfer.	No
4/3/2019	The United States and China draw closer to a final trade agreement during talks in Washington.	No
*5/5/2019	In a sudden reversal, Trump tweets that the United States will increase the 10% tariff on \$200 billion of imports from China to 25%.	Yes
*5/6/2019	Lighthizer confirms that the tariff will increase on May 10.	Yes
*5/10/2019	The United States increases tariffs after trade talks in Washington fail to produce a breakthrough.	No
5/30/2019	Trump announces new Mexican tariffs in response to migrants.	Yes
6/7/2019	Trump calls off tariffs after the United States-Mexico deal.	Yes
*6/29/2019	Trump and Xi agree to restart the United States-China trade talks at the G20 summit in Osaka.	Yes
*7/16/2019	Trump says that a trade deal between the United States and China is a long way off and threatens to impose additional tariffs on Chinese goods.	No
*8/1/2019	Trump abruptly escalates the trade war and announces 10% tariffs on most remaining imports (around \$300 billion) from China, coming into effect on September 1, 2019.	No
*8/5/2019	The Chinese currency falls to the lowest point since 2008 as the trade war escalates.	No
*8/13/2019	The USTR office decides to delay new tariffs on Chinese goods from September 1 to December 15, imposing 10% tariffs on \$112 billion of imports from China from September 1, 2019, and then \$160 billion on December 15, 2019.	No
*8/23/2019	After China unveils retaliatory tariffs on \$75 billion of U.S. goods, Trump announces more tariffs, imposing a 15% tariff, not 10%, on the \$112 billion list on September 1 and the \$160 billion list on December 15. Trump also says that the current 25% tariff on \$250 billion of Chinese goods will increase to 30%, starting October 1.	No
*9/11/2019	China removes a few tariffs, and Trump delays his tariff increase on \$250 billion of Chinese imports from 25% to 30%.	No
9/20/2019	A Chinese trade delegation calls off a planned visit to farms in Nebraska and heads back to China after Trump says he is not interested in a partial deal with China.	No
*10/11/2019	Trump cancels the October 15 tariff increase on \$250 billion of U.S. imports from China, pointing to "Phase One" of a deal with China.	No
*12/12/2019	Trump tweets that the United States and China are nearing a "big deal" that could avoid the fresh tariff imposition scheduled for December 15 and roll back existing duties (Trump calls off the December 15 tariff increase in anticipation of a deal later).	No
12/19/2019	The U.S. House approves the new trade deal with Canada and Mexico.	No
*1/15/2020	The United States and China sign the Phase One deal.	No

Note: This table lists the "trade war days". Days that are considered especially important are in bold. If these important trade war days are only about trade conflicts between the U.S. and China, they are also marked with an asterisk. The last column, which is labeled After hours, indicates whether an event occurs on a weekend or a stock market holiday, or after the stock market closed.

Appendix B. More on the estimated trade war shock series

Fig. B.1 presents the sample autocorrelation function (ACF) and histogram of the estimated benchmark trade war shock (\hat{u}_t^w), which demonstrates that the trade war shock is approximately Gaussian white noise.

Furthermore, we compare the trade war shock with several measures of macroeconomic shocks (x_t) available from existing literature. We run the following regressions

$$x_t = \alpha + \beta u_t^w + e_t. \quad (\text{B.1})$$

As measures for x_t , since the length of the trade war shock is no more than two years, we must use at least monthly data to ensure a sufficient sample size for the regression. In the existing literature, productivity shocks and fiscal policy shocks are only available on a quarterly basis. Therefore, due to data availability, we consider macroeconomic shocks such as the monetary policy, oil supply, financial, and TPU shocks. We use each shock at the original frequency available in the data set provided by the literature, and aggregate the trade war shock to such frequency when necessary. There are 23 observations for monthly data and 473 observations for daily data.

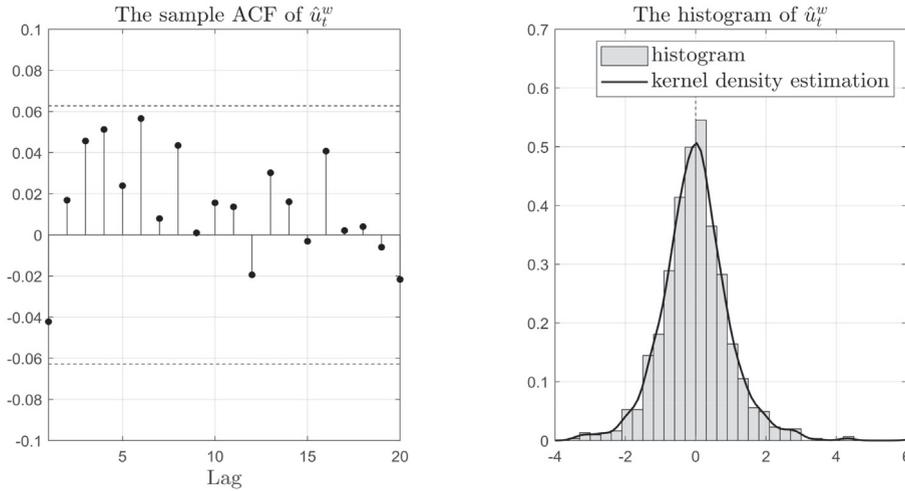


Fig. B.1. The sample ACF and histogram of the benchmark trade war shock. *Note:* In the sample ACF graph, the dash lines are 95% confidence bands based on Bartlett’s formula.

Table B.1
Correlations of the trade war shock with other macroeconomic shocks.

Shock	Source	Obs	β	S.E.	p value
Monetary policy	Bu et al. (2021)	23	0.0234	0.0215	0.2772
Oil supply	Baumeister and Hamilton (2019)	23	1.4636	0.9005	0.1041
Financial	Gilchrist and Zakrajšek (2012)	23	0.0726	0.1052	0.4900
	TED spread	473	-0.0025	0.0046	0.5849
TPU	Baker et al. (2016)	23	0.2529	0.3172	0.4253
	Caldara et al. (2020)	473	0.0399**	0.0174	0.0219

Notes: Reported standard errors are Newey-west standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The results, reported in Table B.1, indicate that the benchmark trade war shock is orthogonal to the monetary policy shock, the oil supply shock, and two financial shocks, which ensures that the trade war shock does not erroneously include information from other important macroeconomic structural shocks. The trade war shock is uncorrelated with the monthly TPU series from Baker et al. (2016) but is significantly correlated with the daily TPU shock from Caldara et al. (2020). In addition, using the Granger causality test, we find that the benchmark trade war shock Granger-causes the daily TPU shock from Caldara et al. (2020) at the 10% level but not vice versa, which indicates that the trade war shock contains relevant information about the future values of the daily TPU indices.

Appendix C. Common shocks from Cieslak and Pang (2021)

To extract the four common shocks (factors) $\omega_t := (\omega_t^g, \omega_t^m, \omega_t^{p^+}, \omega_t^{p^-})'$, described in SubSection 4.1 from stock returns and Treasury yield changes, following Cieslak and Pang (2021), we first estimate a four-variable VAR in first differences with one lag including (log of) stock market returns on S&P 500 price index (pd_t), the 2- ($y_t^{(2)}$), 5- ($y_t^{(5)}$) and 10- ($y_t^{(10)}$) year Treasury yields with data during the sample period (January 2016 to January 2020). Denoting $Y_t = (y_t^{(2)}, y_t^{(5)}, y_t^{(10)}, pd_t)'$, we estimate the following VAR(1) on ΔY_t :

$$\Delta Y_t = c + B_1 \Delta Y_{t-1} + \varepsilon_t, \quad \mathbb{E}[\varepsilon_t \varepsilon_t'] = \Sigma. \tag{C.1}$$

Then, we can recover ω_t through

$$\varepsilon_t = A \omega_t, \tag{C.2}$$

where the structural matrix A is

$$A = \begin{bmatrix} A_g^{(2)} & A_m^{(2)} & A_{p^+}^{(2)} & A_{p^-}^{(2)} \\ A_g^{(5)} & A_m^{(5)} & A_{p^+}^{(5)} & A_{p^-}^{(5)} \\ A_g^{(10)} & A_m^{(10)} & A_{p^+}^{(10)} & A_{p^-}^{(10)} \\ A_g^s & A_m^s & A_{p^+}^s & A_{p^-}^s \end{bmatrix}. \tag{C.3}$$

Identifying ω_t amounts to estimating A , and we achieve identification through the same sign restrictions as those specified in Cieslak and Pang (2021). Specifically, we impose three types of restrictions on the elements of A to identify ω_t :

(i) Sign restrictions that determine the direction in which a shock moves innovations to stocks and yields. We assume that the growth news shock (ω_t^g) and the hedge premium shock (ω_t^p) move stocks and yields in the same direction, and the monetary policy shock (ω_t^m) and the common premium shock (ω_t^c) move stocks and yields in the opposite direction. Therefore, we impose the following sign restrictions on A

$$A = \begin{bmatrix} + & + & - & + \\ + & + & - & + \\ + & + & - & + \\ + & - & - & - \end{bmatrix}. \tag{C.4}$$

(ii) The between-asset restrictions that determine the relative effects of a shock on different elements of Y_t . We assume that the growth news shock (ω_t^g) and the monetary policy shock (ω_t^m) drive the short end of the yield curve more than its long end. For ω_t^g , we assume that $|A_m^{(2)}| > |A_m^{(10)}|$, and $|A_g^{(2)}| > |A_g^{(10)}|$, reflecting the fact that the growth news shock affects short-rate expectations and is mean-reverting, albeit it can be persistent. We do not constrain the relationship between $A_m^{(2)}$ and $A_m^{(5)}$ based on the evidence that growth news can exert a non-monotonic effect at short and intermediate maturities. For ω_t^m , we assume that $|A_m^{(2)}| > |A_m^{(5)}| > |A_m^{(10)}|$. The opposite restrictions hold for the two risk premium shocks ($\omega_t^{p^+}$ and $\omega_t^{p^-}$): $|A_{p^+}^{(2)}| < |A_{p^+}^{(5)}| < |A_{p^+}^{(10)}|$ and $|A_{p^-}^{(2)}| < |A_{p^-}^{(5)}| < |A_{p^-}^{(10)}|$.

(iii) The within-asset restrictions that determine the relative importance of different shocks for a given element $Y_{i,t}$, which constrain the relative contributions of different shocks to the conditional variances of yields. We assume that the conditional variance of the 10-year yield is largely determined by the risk premium shock rather than by shocks to short-rate expectations (growth news and monetary policy shocks) and, conversely, by the conditional variance of the 2-year yield. Specifically, for the 10-year yield, we have

$$\left(A_m^{(10)}\right)^2 + \left(A_g^{(10)}\right)^2 < \left(A_{p^+}^{(10)}\right)^2 + \left(A_{p^-}^{(10)}\right)^2, \tag{C.5}$$

and for the 2-year yield, we have

$$\left(A_m^{(2)}\right)^2 + \left(A_g^{(2)}\right)^2 > \left(A_{p^+}^{(2)}\right)^2 + \left(A_{p^-}^{(2)}\right)^2. \tag{C.6}$$

We use Bayesian estimation to obtain n_1 admissible draws (which satisfy the identification restrictions) of A from its posterior distribution $\left\{A^{(i)}\right\}_{i=1}^{n_1}$. To circumvent the problem of model multiplicity, we select the median target (MT) solution among n_1 draws, for which the impact responses of asset prices to structural shocks are the closest to the median response. For each draw $A^{(i)}$, we first vectorize it by $\theta^{(i)} = \text{vec}\left(A^{(i)}\right)$ and then standardize each $\theta^{(i)}$, by subtracting the element-wise median ($\text{median}\left(\theta^{(i)}\right)$) and dividing by the standard deviation ($\text{std}\left(\theta^{(i)}\right)$). Finally, we solve θ^{MT} through

$$\theta^{MT} = \min_{1 \leq i \leq n_1} \left[\frac{\theta^{(i)} - \text{median}\left(\theta^{(i)}\right)}{\text{std}\left(\theta^{(i)}\right)} \right]' \left[\frac{\theta^{(i)} - \text{median}\left(\theta^{(i)}\right)}{\text{std}\left(\theta^{(i)}\right)} \right]. \tag{C.7}$$

With θ^{MT} and ε_t^{MT} , we can construct the common shock series through $\omega_t^{MT} = \left(A^{MT}\right)^{-1} \varepsilon_t^{MT}$.

Appendix D. Additional Figures

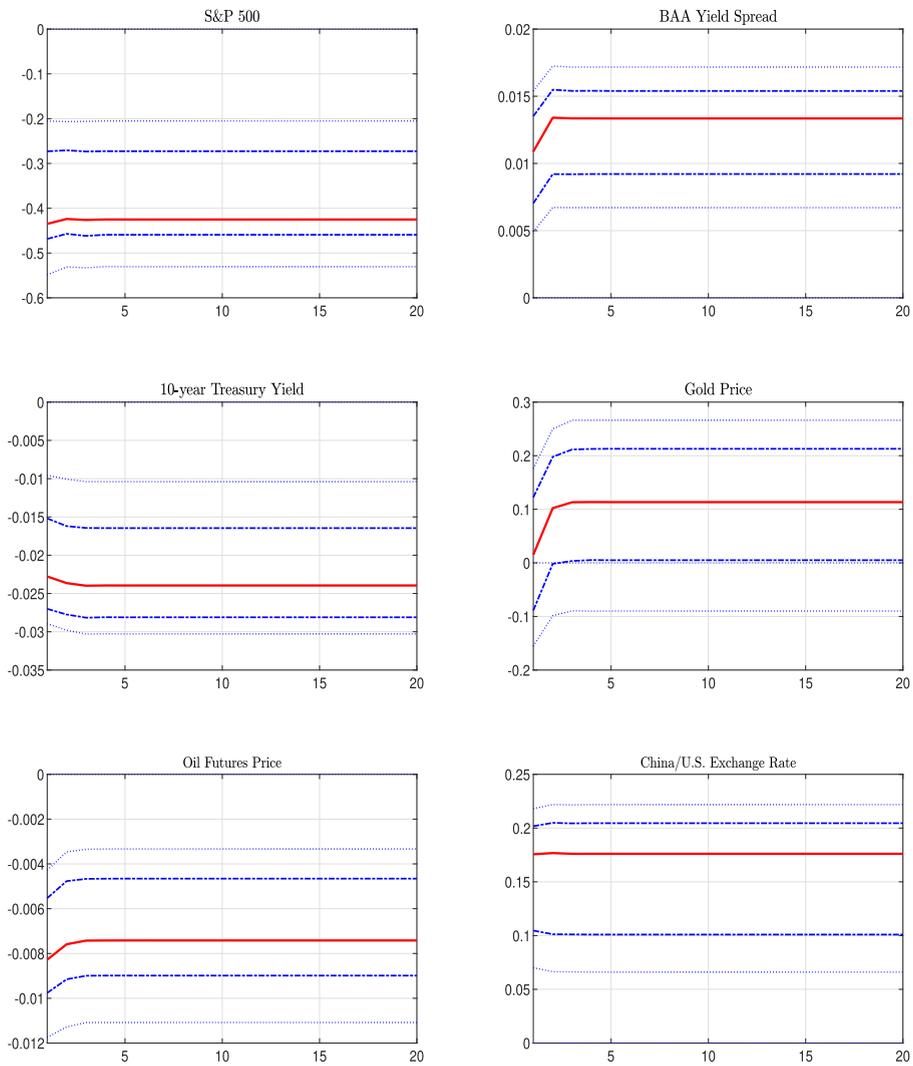


Fig. D.1. SVAR impulse responses of the benchmark trade war shock. *Notes:* Solid lines are the OLS response; dash-dotted lines and dotted lines are the boundaries of the 68% and 90% bootstrap confidence intervals, respectively. Except interest rates, which are in levels, all the variables are in logs and the corresponding responses are scaled by 100, which means that a response of 1 would be interpreted as a 1% increase due to a one-standard-deviation increase in the shock.

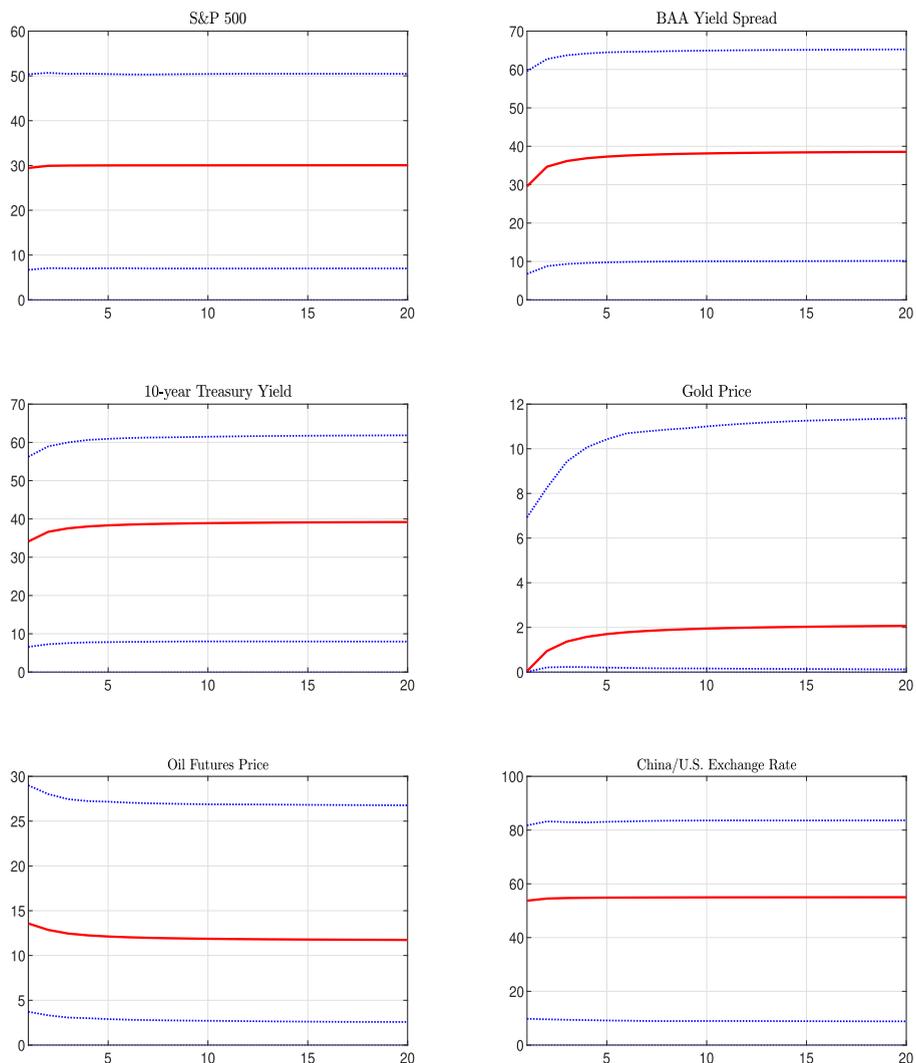


Fig. D.2. SVAR forecast error variance decomposition of the benchmark trade war shock. *Notes:* Solid lines are the OLS result; dotted lines are the boundary of the 90% confidence intervals.

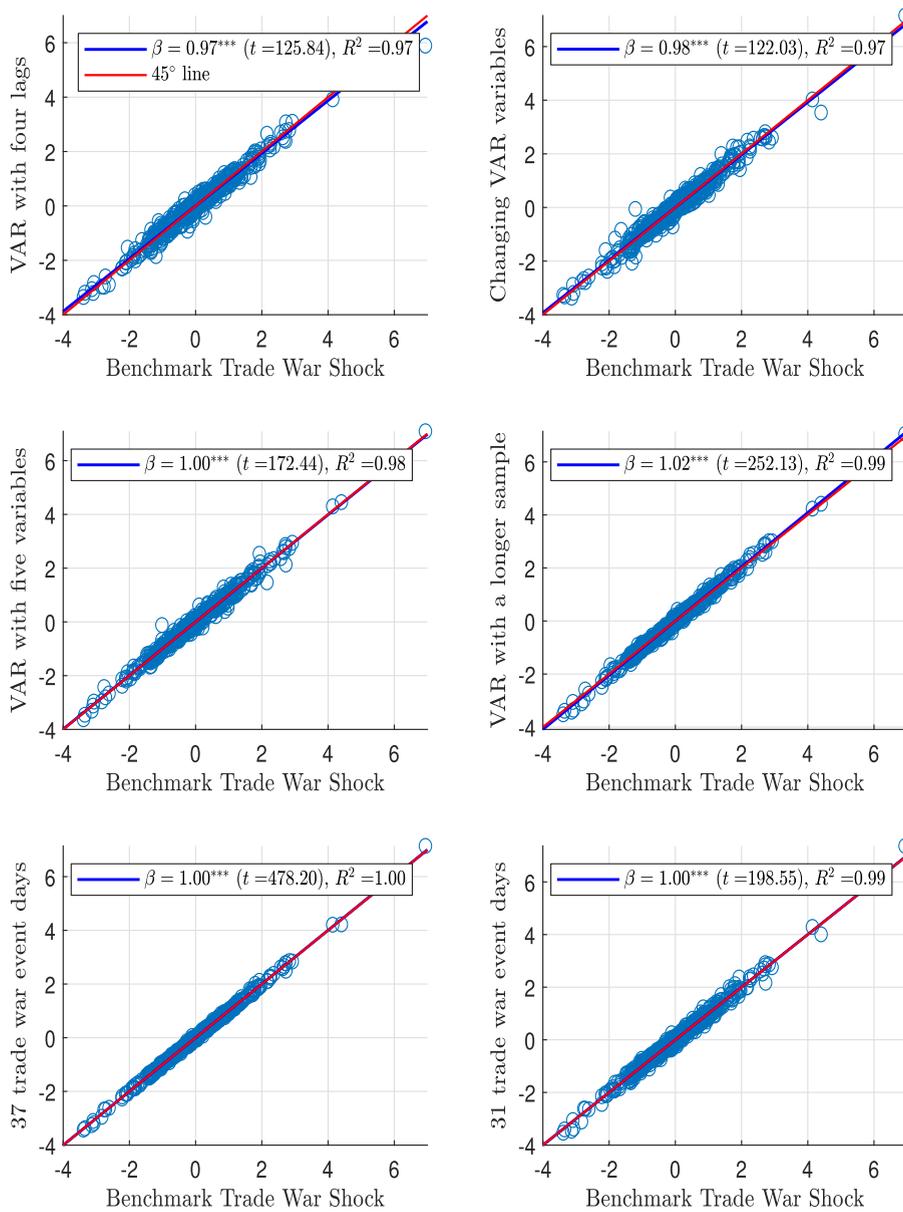


Fig. D.3. Benchmark trade war shocks vs. robustness checks. *Notes:* The figure presents scatter plots of the benchmark trade war shock (on the x-axis) against alternative shocks extracted via different robustness checks (on the y-axis). Each graph contains a fitted line (in blue) and a 45-degree line (in red), and reports the slope coefficient, *t*-statistic, and *R*² of the fitted line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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