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RESEARCH ARTICLE

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# The multifaceted impact of US trade policy on financial markets

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**Summary**

We study the multifaceted effects of trade policy shocks on financial markets using a structural vector autoregression identified via event day heteroskedasticity. We find that restrictive US trade policy shocks affect US and international stock prices heterogeneously, but generally negatively. They increase market uncertainty, lower US interest rates, and lead to an appreciation of the US dollar. The effects are significant for several weeks or quarters. Decomposing the trade policy shocks further suggests that trade policy uncertainty dominates tariff level effects. Chinese trade policy shocks against the United States further hurt US stocks.

## 1 | INTRODUCTION

Threats of a more restrictive trade policy are seen among the major risks for the course of the world economy. Average US tariffs on goods from China, for example, increased from 3.1% in January 2018 to 21.0% at the end of 2019 (Bown, 2020b), covering about two-thirds of these imports (Amiti et al., 2020). Many observers are afraid of a trade war due to retaliation by other countries, especially China, which may increase the intensity far beyond the existing level. Even if such a scenario does not materialize, the US administration practiced one-sided trade policy initiatives during our sample period (2017 until early 2020), thus bringing this instrument back into international economic policy.

In this paper, we use a structural vector autoregression (SVAR) model to analyze the impact of this trade policy on financial markets. Our aim is twofold: First, we want to estimate the importance and persistence of unexpected trade policy interventions. Second, we want to shed light on the potential heterogeneity of trade policy shocks and their effects across firms, industries, and countries. Specifically, our analysis applies an SVAR for the daily frequency identified through heteroskedasticity surrounding trade policy events, adapting the approach of Wright (2012), who studies unconventional monetary policy. The resulting time series of trade policy shocks, evolving from the empirical model, is based economically on the days where important information on US trade policy (with a focus on China) becomes public. The approach allows for precise identification of the impulse responses to structural trade policy shocks based on mild econometric assumptions, while at the same time it facilitates an assessment of their effects at macroeconomically relevant horizons.[1]

The identification strategy singles out days on which the variance of latent trade policy shocks is particularly high between 2017 and 2020. These are days of important announcements by US (or Chinese) authorities that alter the views of market participants about the likelihood and direction of trade policy interventions. The heteroskedasticity approach assumes that the structural macro-financial relations in our SVAR remain constant over the sample while one structural shock changes its variance on the set of event days, that is, it occurs on average with a relatively larger size on these days. We denote this shock as the structural trade policy shock. All other shocks are assumed to have an unchanged variance on the set of event days compared with the remaining sample. Importantly, this strategy allows for the possibility that other structural shocks occur on event days. It does not require exclusion restrictions, which might be problematic in a model of high-frequency financial market variables. Moreover, it avoids the difficulty of measuring market expectations and their dispersion, or of quantifying what investors have learned from the announcements. It is only necessary to identify days on which important announcements reached financial markets and to find an asset price that is highly responsive to such news. For the latter, we compute a stock price index ("China Exposure Stock Index") for the S&P 500 firms with the highest trade exposure to China according to their 10-K filings.

We find heterogeneous effects of restrictive trade policy shocks on stock prices of firms, industries, and countries. Overall, there is a decline of stock prices, an increase in volatility, and a significant impact on other financial markets. These results are derived from an SVAR model with six variables, where just one type of trade policy shock is assumed. Due to its characteristics, in particular the volatility increase and the US-dollar appreciation (at least in part due to increased demand for a safe asset), we further classify this shock as a "trade policy uncertainty shock," reflecting the uncertainty created by the many and inconsistent trade policy announcements by the US government between 2017 and 2020.

Considering major US trade policy announcements, our estimates suggest that a positive trade policy uncertainty shock leads, on average, to an immediate increase in general uncertainty, proxied by the VIX. Market volatility returns to pre-shock levels after 2 weeks. US stock market indices for a broad set of firms (i.e. the Russell 2000 index) and for firms being heavily exposed to trade with China suffer a drop of about 0.6% and 1%, respectively. This decline is statistically significant for about 2–3 months. Moreover, we find that shorter and longer-term interest rates fall significantly for several months. Importantly, the US dollar appreciates significantly, consistent with safe haven net demand. Furthermore, the identified shock series has a significant contemporaneous positive correlation with external measures of trade policy uncertainty, and there is some evidence that it leads the alternative measures. Due to the series' forward-looking character, it is not really related to the more sluggish measures of actual tariff changes, and due to its focus on trade policy, it is not significantly related to general measures of economic uncertainty. Extending the SVAR to specific assets, we see that more than 90% of S&P 500 firms' stock prices and nine of the 11 S&P 500 sector indices are significantly negatively affected. The more internationally oriented sectors of the US economy, that is, IT and materials, suffer the most.

Regarding 49 considered international stock markets, we find that 44 of them decline significantly following positive US trade policy uncertainty shocks. We observe a clear pattern whereby Latin-American countries are affected most negatively, followed by the United States, China, and European, other Asian, and, finally, African countries. Likewise, increased stock market volatility is not merely a US phenomenon. Volatility indices for Chinese and emerging stock markets increase significantly. Finally, we find evidence that restrictive trade policy shocks by China also hurt the US economy.

As we cannot rule out entirely that there may be more than one type of trade policy shock, we later on relax the assumption that only one shock occurs with larger magnitude on the set of event dates and thus follow the standard approach in Rigobon (2003). This model permits the identification of different types of trade policy shocks by allowing all shock variances to change over time so that we can find more than one shock with high variance on trade policy announcement days. We confirm the existence of one dominating trade policy shock, which is quite similar (as assessed by the impulse responses) to the trade policy uncertainty shock in the main model. In addition, there is potentially a second type of trade policy shock that has characteristics of a level shock, that is, announcements of future tariff changes, as the VIX does not respond significantly to this shock but stock prices of firms being particularly

[1]Identification through heteroskedasticity is developed in Rigobon (2003) and is applied thereafter, for example, by Rigobon and Sack (2004) analyzing monetary policy effects and by Hébert and Schreger (2017) analyzing the impact of respective news on default costs of Argentina. We use the specific implementation proposed by Wright (2012).

engaged with China fall stronger than the market. Variance decompositions show that the trade policy uncertainty shock accounts for about 10%–20% of the unexpected variability in the VIX (depending on horizon), but less than 10% of the variability in the stock indices. In contrast, the trade policy level shock accounts for 25%–40% of the forecast errors of the "China Exposure Stock Index" and for 10%–20% of the variation in the Russell 2000, a broader US stock market index. Overall, these multifaceted results suggest a new perspective on the impact of US trade policy: Trade policy uncertainty affects mainly stock price volatility and related financial market variables such as treasury yields, as well as the exchange rate, whereas the effect on the level of stock prices is muted. Tariff changes on the other hand have a muted effect on financial market volatility and interest rates but a stronger effect on the level of stock prices.

Our study relates to the field of trade policy—more specifically, to the effects of tariff policy during the recent US–Chinese trade dispute. We relate to and differ from three lines of related studies. First, regarding the literature using empirical or quantitative-theoretical trade models (e.g., Amiti et al., 2019, 2020; Fajgelbaum et al., 2020), we share with these studies the ambition to capture the consequences of trade restrictions for the whole economy.[2] However, we use a different approach, as our SVAR considers major interdependencies between financial markets, operates at a higher frequency, and allows for the existence of trade policy uncertainty and level shocks.

Second, we also connect with high-frequency event studies that analyze trade policy effects on stock markets (e.g., Breinlich, 2014; Egger & Zhu, 2020; Huang et al., 2019; Moser & Rose, 2014).[3] Our SVAR approach shares with these papers the sharp identification using high-frequency data, while still yielding a longer-term and comprehensive view on how the effects come to pass. Moreover, our econometric assumptions are weaker in that we allow for other shocks on event days.

Third, several papers examine the impact of trade-related uncertainty on economic outcomes, such as Baker et al. (2016), Pierce and Schott (2016), Handley and Limão (2017), and Caldara et al. (2020).[4] Although we also show that trade policy announcements have strong uncertainty effects, we apply high-frequency financial data to identify a series of structural trade policy shocks. Moreover, we do not need to assume that trade policy uncertainty is exogenous with respect to the macroeconomy; we only need to assume that the variance of trade policy shocks is higher on event days.

Overall, we believe that our combination of high-frequency identification (and data) with the longer-term perspective of a SVAR-approach is unique in this literature and allows for complementing insights. In particular, this approach provides a multifaceted picture regarding the impact and persistence of trade policy shocks on financial markets, a result that is rare.

The remaining paper is organized in five more sections. Section 2 characterizes the SVAR model, describes the data, and shows specification tests. Sections 3 and 4 contain core and extended results for the impact of US–China trade shocks on financial markets, respectively. Section 5 documents robustness tests, and Section 6 concludes.

## 2 | METHOD AND DATA

In this section, we first discuss the SVAR model (Section 2.1), then we introduce and describe the data (Section 2.2), and, finally, we show the appropriateness of our model with specification tests (Section 2.3).

[2]Amiti et al. (2019) estimate the annual reaction of import prices and quantities to tariff changes for detailed product categories and infer the welfare effects within a partial-equilibrium international trade model (Amiti et al., 2020, provide an extension). Fajgelbaum et al. (2020) estimate trade elasticities on monthly observations and apply them in a full-blown general-equilibrium model to find small negative short-run welfare implications for the US. Tariffs are almost completely passed through (see also Cavallo et al., 2021, or Flaaen et al., 2020).

[3]Huang et al. (2019) show in their event study that US tariff announcements have larger negative effects on firms that are more dependent on trade with China. Egger and Zhu (2020) find that US tariff announcements and changes also have negative effects on international stock markets; these are larger for domestic than for Chinese firms. Inference covers a few days around the events in each study.

[4]Pierce and Schott (2016) as well as Handley and Limão (2017) study reductions in trade policy uncertainty due to China's entry into the World Trade Organization (WTO) while US tariffs did not change. This reduced uncertainty makes respective Chinese exports more attractive and leads to larger employment declines in the competing US manufacturing industries. Baker et al. (2016) measure the relative occurrence of news articles featuring economic policy uncertainty related to trade policy. Caldara et al. (2020) construct a similar monthly trade policy uncertainty index based on the relative coverage in seven US newspapers. In line with Baker et al. (2016), the authors find significant decreases in investment when their uncertainty indices rise.

## 2.1 | The SVAR model

The reduced form VAR is represented as

$$\boldsymbol{A}(\boldsymbol{L})\boldsymbol{Y}_t = \boldsymbol{\mu} + \boldsymbol{u}_t, \tag{1}$$

where $Y_t$ is a $kx1$ vector with $k$ variables of interest and $\mu$ a vector of constants. $A(L)$ denotes the parameter matrix polynomial in a lag operator, and $u_t$ are the reduced form errors. In analyzing the impact of trade policy shocks on financial markets, the core financial market is the United States. Thus, the variables in $Y_t$ in the baseline model refer to US markets.

The stock markets are represented by three indices. First, we construct a stock price index for large listed US firms, a subset of S&P 500 constituents, with a high trade exposure to the Chinese market through imports and exports. We explain the construction of the index in detail below. The index is crucial for identification as this asset price is highly responsive to announcements about trade policy. Second, we include the Russell 2000 index, which covers the firms ranking in between 1000 and 3000 regarding their size; size is here proxied by stock market capitalization. The index represents approximately 8% of the total market capitalization of the United States with an average market capitalization per firm of around US$ 2.3 billion. These smaller firms are often more domestically oriented than S&P 500 firms. Third, we include the VIX, measuring expected volatility of the S&P 500 over the next 30 days, to consider uncertainty in this financial market (and the economy).

To paint a more comprehensive picture of US financial markets, we add further variables to our VAR. We include two kinds of interest rates. The 1-year treasury rate reflects expectations about monetary policy actions. The 10-year rate rather reflects expectations on growth and inflation as well as demand for safe assets. Another important group of financial markets for an open economy is foreign exchange markets, which we capture by relying on the US-dollar effective exchange rate, that is, the value of the dollar measured against a basket of other currencies. It improves characterization of the nature of the identified trade policy shocks as it reflects both relative growth expectations and safe haven demand.

All variables enter the model in levels, and we take logarithms of the exchange rate, the VIX, and the stock price indices. Therefore, we follow most of the literature, which relies on similar kinds of VARs (e.g., Wright, 2012). Kilian and Lütkepohl (2017, Section 2.3.5) show that the least-squares reduced form estimates are consistent and asymptotically normal when estimating a level VAR for integrated variables.

The structural VAR model is identified via heteroskedasticity, following the approach in Wright (2012). The author analyzes the effects of US monetary policy shocks on interest rates at the zero lower bound. Wright identifies days on which the Federal Open Market Committee (FOMC) meets as dates when monetary policy shocks have especially high variance. In our case, the event dates include major announcements of US trade policy changes.

The identification strategy works as follows. The reduced form errors $u_t$ from Equation (1) are related to the structural shocks $\varepsilon_t$ via the linear transformation $u_t = B\varepsilon_t = \sum_{i=1}^{k} b_i \varepsilon_{t,i}$. The structural shocks are uncorrelated, implying a diagonal covariance matrix. The approach does not rely on a Cholesky decomposition, and, hence, without loss of generality, we order the trade policy shock first within $\varepsilon_t$. We are only interested in this shock (i.e., $\varepsilon_{t,1}$) and do not try to identify the remaining shocks for now. We do so later in a generalization of the identification strategy (see Section 3.2). $b_1$ represents the first column of $B$ and, thereby, the contemporaneous effect of the trade policy shock on the endogenous variables in $Y_t$. The approach assumes that the trade policy shock has mean zero and variance $\sigma_1^2$ and $\sigma_0^2$ on announcement days and non-announcement days, respectively, whereas the impact effects are assumed to be constant. The variances $\sigma_1^2$ and $\sigma_0^2$ are assumed to be significantly different, providing the first identifying assumption. All other shocks, $\varepsilon_{t,2}, \ldots, \varepsilon_{t,k}$, have unit variances on all dates—our second identifying assumption. We test the two assumptions in Section 2.3, which shows that they are supported by the data.

Then, the reduced form covariance matrix for announcement dates is

$$\boldsymbol{\Sigma}_1 = \mathrm{E}\left(\boldsymbol{u}_t \boldsymbol{u}_t'\right) = \mathrm{E}\left(\boldsymbol{B}\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t' \boldsymbol{B}'\right) = \boldsymbol{B}\mathrm{E}\left(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t'\right)\boldsymbol{B}' = \boldsymbol{b}_1 \boldsymbol{b}_1' \boldsymbol{\sigma}_1^2 + \sum\nolimits_{i=2}^{k} \boldsymbol{b}_i \boldsymbol{b}_i{}'. \tag{2}$$

Subtracting $\Sigma_0$ from this term yields

$$\boldsymbol{\Sigma_1} - \boldsymbol{\Sigma_0} = \boldsymbol{b_1 b_1' \sigma_1^2} - \boldsymbol{b_1 b_1' \sigma_0^2} = \boldsymbol{b_1 b_1'} \left(\boldsymbol{\sigma_1^2} - \boldsymbol{\sigma_0^2}\right). \tag{3}$$

To solve for the elements in $b_1$, the difference in variances $\left(\sigma_1^2 - \sigma_0^2\right)$ is normalized to 1. Following Wright (2012), we solve for $b_1$ via GMM and, hence, minimize the following objective:

$$\boldsymbol{J_W(b_1)} = \boldsymbol{vech}\left(\widehat{\boldsymbol{\Sigma_1}} - \widehat{\boldsymbol{\Sigma_0}} - \boldsymbol{b_1 b_1'}\right)' \left(\frac{\widehat{\boldsymbol{V_0}}}{\boldsymbol{T_0}} + \frac{\widehat{\boldsymbol{V_1}}}{\boldsymbol{T_1}}\right)^{-1} \boldsymbol{vech}\left(\widehat{\boldsymbol{\Sigma_1}} - \widehat{\boldsymbol{\Sigma_0}} - \boldsymbol{b_1 b_1'}\right) \tag{4}$$

with respect to $b_1$. $\widehat{V_i}$ is the estimate of the variance–covariance matrix of the reduced form variance on announcement or non-announcement dates. It can be calculated via

$$\widehat{\boldsymbol{V_i}} = \frac{\boldsymbol{1}}{\boldsymbol{T_i}} \sum_{\boldsymbol{T_i}} \boldsymbol{vech}\left(\widehat{\boldsymbol{u}}_t \widehat{\boldsymbol{u}}_t{}' - \overline{\widehat{\boldsymbol{u}}\widehat{\boldsymbol{u}}'}\right) \boldsymbol{vech}\left(\widehat{\boldsymbol{u}}_t \widehat{\boldsymbol{u}}_t{}' - \overline{\widehat{\boldsymbol{u}}\widehat{\boldsymbol{u}}'}\right)' \tag{5}$$

(Kilian & Lütkepohl, 2017, chapter 14.3.1). The identification conditions for $b_1$ are based on economic reasoning through the choice of the set of announcement dates $t \in T_1$.

Finally, if the impact vector $b_1$, the reduced form errors $u_t$, and the reduced form covariance matrix over the whole sample $\Sigma_u$ are given, the first structural shock can be obtained as

$$\boldsymbol{\varepsilon_{1t}} = \boldsymbol{b_1}' \boldsymbol{\Sigma_u}^{-1} \boldsymbol{u_t} / \left(\boldsymbol{b_1}' \boldsymbol{\Sigma_u}^{-1} \boldsymbol{b_1}\right) \tag{6}$$

(see Stock & Watson, 2018, footnote 6, p.933).

The main advantages of the identification strategy are that it allows for other shocks on trade event days and that some of its main assumptions are testable. At the same time, it assumes that the impact effects $b_1$ are constant across volatility regimes, which is untestable in our setup. However, this assumption does not seem particularly strong, given the daily frequency of the data and our definition of regimes, which together imply that we only assume that the impact effects of trade policy shocks do not change within a day when switching from non-announcement days to announcement days. Moreover, the identification strategy requires a specification of the heteroskedasticity, that is, a definition of the event windows and the number of volatility regimes. We could potentially misspecify both. However, Rigobon (2003) shows that the estimates, while being less precise, would nevertheless be consistent.

There are potential alternative identification strategies. For example, one can use exclusion restrictions to identify relative price effects by treating statuary tariff changes as exogenous (e.g., Amiti et al., 2019). In contrast, the literature on trade policy uncertainty treats this uncertainty as contemporaneously unaffected by other variables, such as tariff changes (e.g., Caldara et al., 2020). Although these assumptions might be plausible when working with macroeconomic data, they are unlikely to hold for asset prices that respond to each other in nearly continuous time. Sign restrictions, on the other hand, allow for contemporaneous responses of all variables to trade policy shocks. However, theory provides contradicting predictions for the signs of key effects (e.g., Caldara et al., 2020, show that tariff uncertainty may induce a decrease in the policy rate, whereas Lindé & Pescatori, 2019, show that the increased prices may induce a rise in the policy rate), and it is precisely our aim to determine them empirically.

## 2.2 | Data

Our baseline model uses daily financial data from Bloomberg from January 2, 2017, through January 17, 2020, inclusive. We start in 2017 to reduce the risk of structural breaks due to the start of a new US administration during January 2017. In the sensitivity analysis, we show that our results are robust to starting the sample earlier. Our sample ends in January 2020 before the Covid-19 pandemic started.

We construct a China-exposure US stock price index. The stock prices of firms with high imports from and/or exports to China are expected to be more sensitive to trade announcements than other firms. The high responsiveness of the index to new information on trade policy helps identification as the variance of the index is particularly high on announcement days. The index draws from the Hoberg and Moon (2017, 2019) offshoring database. This database is a firm-nation-year network that extracts publicly traded US firms' disclosures from their annual 10-K filings. For each year, the database lists the number of times each firm mentions selling or purchasing goods from a given nation. We explicitly look for S&P 500 firms that either mention using inputs from China or exporting to China in 2017.

To create an index of firms especially exposed to trade with China, we only include firms with a substantial number of export and import mentions in our index. For 2017, we find that 248 of the S&P 500 firms display some entries concerning trade with China. The mean number of mentions is 5.2. For our index, we only keep those firms that have disclosed a number of mentions that lies more than one standard deviation above the mean, that is, these firms mentioned trade relations with China more than 15 times in their 10-K filings for 2017. This yields a list of 47 S&P 500 firms with especially strong exposure to the Chinese market. The final index is an equally weighted mean of these 47 firms' stock prices.

Table A2 in the Supporting Information contains a list of these firms including a short business description and the industry. According to the S&P Global Industry Classification Standard, 16 firms operate in the consumer discretionary sector, 10 in IT, six in materials, five in health care, five in industrials, two in consumer staples, and one firm each in communication services, energy and real estate. According to the North American Industry Classification, 38 of the 47 firms are manufacturing firms.

In further analyses, we use stock prices for all S&P 500 companies and the S&P 500 sector indices. We also consider MSCI country stock price indices for 49 countries and volatility indices like the VIX for 13 international stock price indices.

We obtain the event dates from an outside source: the Peterson Institute for International Economics (PIIE), which is an established US economic policy think tank. Bown and Kolb (2020) from the PIIE have published a list called "Trump's Trade War Timeline: An Up-to-Date Guide," which provides an overview of US trade dispute events. Our baseline specification takes policy announcements concerning trade with China from their list of "Battle #2: Steel and Aluminum as National Security Threats" and "Battle #3: Unfair Trade Practices for Technology, Intellectual Property." Choosing these two battles, which contain the largest tariff changes to the largest volumes of US imports from China, we obtain 32 announcement dates. The smaller samples of policy dates used in event studies like Egger and Zhu (2020) and Huang et al. (2019) are mostly included within these 32 dates. In robustness checks, we also add Battle #1 or delete Battle #2; neither substantially alters our findings. For the baseline case, we do not include the other three PIIE categories (Battles 4, 5 and 6), which pertain to the EU, Mexico, and specific Chinese telecommunications firms.

Note that we merely choose dates on which a change in US trade policy is announced or displayed for the first time to the public. We do not include dates on which trade policy is altered when the change has been announced or become public knowledge beforehand. Asset prices should immediately respond to new information such that an eventual imposition of tariffs does not result in a further significant response of prices. Table A1 lists all 32 announcement dates from the PIIE and briefly describes these measures. The first two took place in April 2017, when the United States started investigations concerning a threat to national security via steel and aluminum imports. At the last event in our sample, on January 15, 2020, China and the United States signed the so-called "Phase One Deal," whereby China agreed to adhere to prespecified export targets with the United States over the next 2 years while most tariffs remained in effect. Appendix S1 contains a detailed account of the trade disputes of the US during our sample period. Changes in the "China Exposure Stock Index" on event dates show that it is *ex ante* not always clear whether we can speak of a restrictive or easing trade policy shock when tariff lists are altered or policy changes announced. This supports our heteroskedasticity identification where we do not make any assumptions about the sign of the shock on event dates.

To cleanly identify trade policy shocks, it is important to ensure that the event dates do not systematically mix with other major macroeconomic events that affect financial markets. We explicitly consider a potential impact from monetary policy. Regarding the initial 32 dates, we find one FOMC statement (August 1, 2018, without a change in the forecasted federal funds rate) and two further statements by chairman Jerome Powell (March 1, 2018, and August 23, 2019). We discard the three dates to obtain a baseline specification with 29 event dates. Four events (March 1, 2018, August 1, 2018, December 1, 2018, and August 1, 2019) fall together with releases of the ISM Manufacturing Index, arguably the most important US index of expected business conditions. In a robustness check, we show that the results remain largely unaltered when we add events of Fed information or discard ISM releases (see Section 5).

When the event takes place over the weekend (four occasions), we specify the following Monday as the event day. When the policy announcement takes place in the evening after 4 pm Eastern Time when the New York stock exchange has closed, we specify the following day as the event day. The resulting 29 event dates seem to be scattered randomly across weekdays (five on Mondays, six on Tuesdays, two on Wednesdays, nine on Thursdays, and seven on Fridays) and do not follow an obvious pattern. This further bolsters the assumption of an unchanged variance for the remaining shocks.

At first sight, the assumption of zero-mean trade policy shocks over the sample period from 2017 to 2020 might be seen as unrealistic. However, these shocks measure the unexpected part of trade policy, not the systematic stance. To see whether the stance of trade policy matters, we extend the sample back to 2008 in a robustness analysis to give further room for easing trade policy (see Figure B10 in the Supporting Information).

## 2.3 | Specification tests

We estimate the reduced form VAR in Equation (1) with six variables in (log-) levels with a lag length of 5 (trading) days and obtain a stable VAR(5) process. Moreover, we follow Wright (2012) in testing the two major identifying assumptions of our model. First, we test the hypothesis that there exists no difference between announcement and non-announcement date residuals, namely, $H_0: \Sigma_1 = \Sigma_0$. This is tested via the test statistic

$$\mathbf{vech}\left(\widehat{\boldsymbol{\Sigma}_1} - \widehat{\boldsymbol{\Sigma}_0}\right)'\left(\frac{\widehat{\boldsymbol{V}_0}}{\boldsymbol{T}_0} + \frac{\widehat{\boldsymbol{V}_1}}{\boldsymbol{T}_1}\right)^{-1}\mathbf{vech}\left(\widehat{\boldsymbol{\Sigma}_1} - \widehat{\boldsymbol{\Sigma}_0}\right). \tag{7}$$

The null hypothesis assumes equal covariances, and, thus, for this test, we set $\widehat{V_0} = \widehat{V_1} = \widehat{V}$, the covariance over all residuals in the full sample. We compare this test statistic to a distribution obtained from a bootstrap sample where announcement and non-announcement dates are randomly scattered while retaining the total number of announcement dates. By construction, this should give equal variance–covariance matrices for the two sets of dates in the bootstrap sample. The resulting bootstrap $p$-value is the fraction of bootstrap test statistics that exceed the Wald statistic in Equation (7).

The second model assumption states that there exists a single trade policy shock. In other words, the assumption postulates that only one shock changes its variance on event dates. We apply the moving-block bootstrap from Jentsch and Lunsford (2019). We arrange the residuals in blocks of equal length from which we draw with replacement to join the draws end-to-end. We follow the authors' rule of thumb $l = 5.03T^{1/4}$ and thus select a residual block size of 27. The assumed heteroskedasticity is maintained in each bootstrap sample even though the total number of event dates might slightly change across samples. Brüggemann et al. (2016) show that this bootstrap ensures high asymptotic coverage accuracy of impulse responses that, for instance, the residual wild bootstrap might lack in the presence of conditional heteroskedasticity. Apart from testing the second model assumption, we use this bootstrap to construct confidence intervals for impulse responses.

To test the assumption of a single trade policy shock, given by $\Sigma_1 - \Sigma_0 = b_1 b_1'$, we use the test statistic in Equation (4), that is, the GMM objective function to estimate $b_1$. The null hypothesis is $\Sigma_1 - \Sigma_0 - b_1 b_1' = 0$. The alternative is $\Sigma_1 - \Sigma_0 - b_1 b_1' < 0$. We compare the Wald statistic one-sided to its distribution in the bootstrap sample with the maintained heteroskedasticity assumption. The $p$-value is the fraction of bootstrapped $J_W^*(b_1)$s that exceed $J_W(b_1)$.[5] A rejection of this null hypothesis would imply that our identification of a single trade policy shock is not valid, that is, that there is more than one distinct change in the shock variances.

Table 1 displays the $p$-values of the two identification tests. Using our baseline specification with 29 announcement dates (i.e., all 32 dates without monetary policy announcements), we can reject the null hypothesis of equal announcement and non-announcement dates; we cannot reject the hypothesis of a single identified trade policy shock. The first test indicates an even stronger change in variances for all 32 dates and a slightly weaker change for the specification without ISM release dates. The second assumption of a single trade policy shock is never rejected across specifications.

[5]Formally, the bootstrap simulates the distribution of

$\boldsymbol{vech}\left(\left(\widehat{\boldsymbol{\Sigma}_1} - \widehat{\boldsymbol{\Sigma}_0} - \widehat{\boldsymbol{b}_1}\widehat{\boldsymbol{b}_1}'\right) - \left(\widehat{\boldsymbol{\Sigma}_1^*} - \widehat{\boldsymbol{\Sigma}_0^*} - \widehat{\boldsymbol{b}_1^*}\widehat{\boldsymbol{b}_1^*}'\right)\right)'\left(\frac{\widehat{V_0^*}}{T_0} + \frac{\widehat{V_1^*}}{T_1}\right)^{-1}\boldsymbol{vech}\left(\left(\widehat{\boldsymbol{\Sigma}_1} - \widehat{\boldsymbol{\Sigma}_0} - \widehat{\boldsymbol{b}_1}\widehat{\boldsymbol{b}_1}'\right) - \left(\widehat{\boldsymbol{\Sigma}_1^*} - \widehat{\boldsymbol{\Sigma}_0^*} - \widehat{\boldsymbol{b}_1^*}\widehat{\boldsymbol{b}_1^*}'\right)\right)$ where variables with stars denote the bootstrap sample analogues of the estimated objects in the original sample (Wright, 2012).

**TABLE 1** Specification tests

| Hypothesis | Wald statistic | Bootstrap *p*-value |
|---|---|---|
| 29 baseline events | | |
| $\Sigma_0 = \Sigma_1$ | 76.66 | 0.002 |
| $\Sigma_1 - \Sigma_0 = b_1 b_1'$ | 70.02 | 0.976 |
| 27 dates: no ISM releases | | |
| $\Sigma_0 = \Sigma_1$ | 65.13 | 0.003 |
| $\Sigma_1 - \Sigma_0 = b_1 b_1'$ | 66.72 | 0.988 |
| 32 event dates | | |
| $\Sigma_0 = \Sigma_1$ | 81.43 | 0.001 |
| $\Sigma_1 - \Sigma_0 = b_1 b_1'$ | 61.95 | 0.981 |

*Notes*: Wald statistic 1 displayed in Equation (7). In each sample, the variance–covariance matrix is calculated over all observations. The moving-block bootstrap uses 1000 draws to obtain the *p*-values. Wald statistic 2 is displayed in Equation (4). All VAR models use five lags.

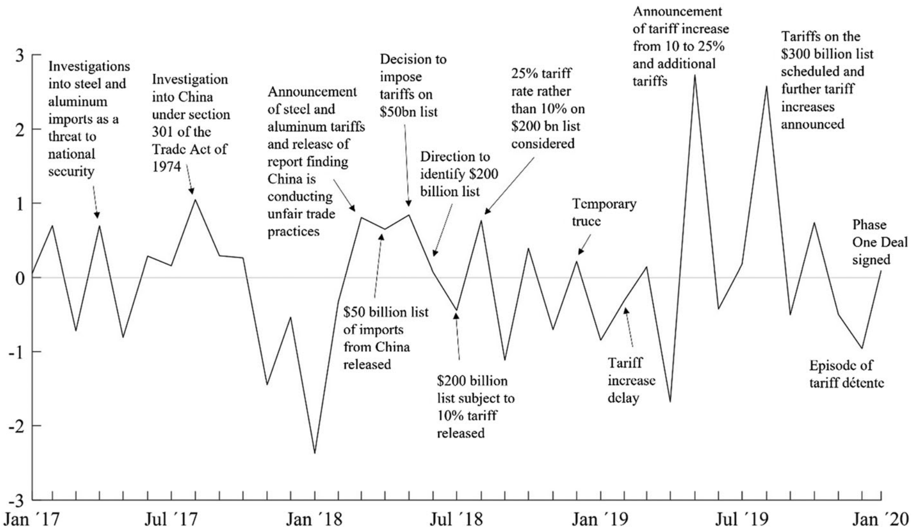


**FIGURE 1** Monthly aggregated and standardized US trade policy shock series

## 3 | RESULTS

We present results in this section in two steps. First, we take the indication for the existence of a single trade policy shock from the Wald test at face value and discuss impulse responses for the baseline six-variable model in Section 3.1. Then, we relax the assumption of a single shock in Section 3.2 and allow for multiple shocks with higher variance on event days to see whether there are more dimensions that can be disentangled.

### 3.1 | Main model

Before we show the estimated responses to trade policy shocks, we first discuss the estimated structural shocks. How well do they match the narrative account of the US–China trade dispute? Figure 1 provides a graphical representation of our shock series, which has mean zero in line with the model approach and is aggregated at the monthly level to provide a clearer picture. Looking at the spikes and troughs, that is, large positive and negative cumulated shocks, the figure shows that the shock series is closely related to important events of US–China trade policy, as described in Table A1. An example is the spike in March 2018, occurring when the US Department of Commerce releases its report finding that China is conducting unfair trade practices and announcing tariffs on steel and aluminum. The maximum peak occurs in May 2019 when the US government unexpectedly announces to increase tariffs on $200 billion of Chinese imports from 10% to 25% and indicates further tariffs on goods not yet targeted. The month with the second largest accumulated restrictive shocks is August 2019. During that month, the US government first announces a 10% tariff on additional $300 billion of imports from China, then revises the level to 15% instead, and additionally announces a future tariff increase on already taxed goods from China.

Regarding the signs of the impact effects, we expect that restrictive trade policy shocks affect the overall economy, represented by stock price indices, negatively. Moreover, those firms actively trading with China are expected to lose more than those firms that are more domestically oriented. Results are provided in Figure 2, which shows the estimated dynamic impact of a trade policy shock on the endogenous variables, together with 90% confidence bands. The impact effects correspond to the estimated $b_1$.

We look at positive shocks that increase the VIX on impact. We interpret such a shock as being restrictive. This interpretation is supported by an analysis of the estimated trade policy shocks on event days (see Table A1). For example, we identify large restrictive shocks on March 22, 2018, when the administration released a report on China conducting unfair trade practices, and on May 29, 2018, when the White House stated that it will impose tariffs of $50 billion on Chinese goods. In contrast, we identify a large easing shock on October 11, 2019, when the US President postponed announced tariff hikes and indicated negotiations over a phase one deal (Figure A1 and the accompanying table in the Supporting Information show the daily shock series and list the largest daily shocks, of which about 80% can be linked to trade news).

Indeed, concerning the effect on values of firms being exposed to trade with China, the shock leads to an instantaneous decline of their stock price index of about 1.1%, which remains significantly negative for nearly 3 months. The impact on relatively smaller firms covered by the Russell 2000 is smaller, with a size of about −0.6% but also holds for several months. Comparing the two stock index responses, the shock seems to affect operations of firms that are heavily involved in international trade more strongly than domestically operating firms. Moreover, there is an increase in uncertainty by 6.2%, which remains significantly above trend for about 2 weeks. This increase in volatility in the markets raises risk premia, which contributes to depressed stock prices.

Additionally, for 1-year treasuries, interest rates fall over time and persistently by about 2 basis points. They do not fall significantly on impact, indicating that monetary policy does not react directly to this trade policy shock. This result

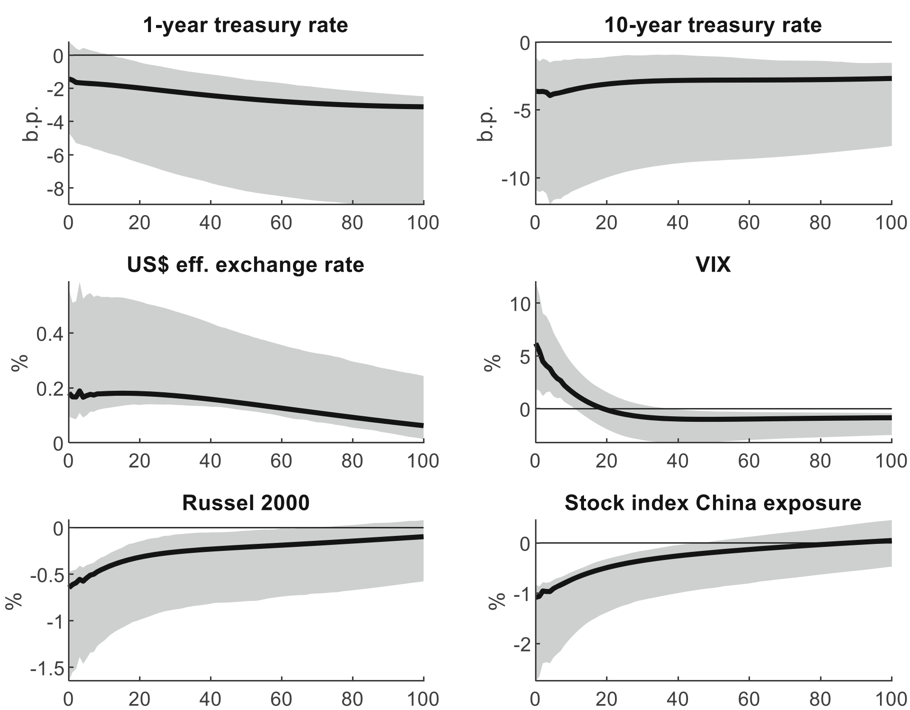


**FIGURE 2** Estimated impulse responses to US trade policy shock in baseline model. *Notes*: The figure shows impulse responses to a restrictive US trade policy and 90% moving-block bootstrap confidence intervals from a bootstrap sample size 1000. An increase in the US$ eff. exchange rate denotes an appreciation of the US$.

is in line with the stance of the Federal Reserve (and other central banks) that it does not respond to one-time events, such as an expected tariff increase. But then, the short-term rate falls persistently below trend. This could reflect an endogenous response on monetary policy to elevated uncertainty (Bekaert et al., 2013). Additionally, 10-year treasuries decline by about 3 basis points, reacting significantly on impact. This seems to reflect the depressed economic outlook.

Finally, the US dollar appreciates by 0.2% instantaneously and then falls back over the next year, remaining above trend significantly for at least 5 months. This conflicts with decreased interest rates that make the US dollar, ceteris paribus, less attractive and suggests that other channels might dominate the exchange rate response. In principle, the appreciation is consistent with increased import restrictions (consequently increased competitiveness) that create US-dollar net demand and increase the uncertainty underlying demand for safe assets, such as the US dollar. These effects seem to dominate the interest rate effect on the US dollar. Thus, overall, the trade policy shocks appear to be dominated by the characteristics of an uncertainty shock, that is, the strong increase of the VIX, the significant decline in interest rates, and the US-dollar appreciation. We shed further light on the different dimensions of the announcements in the next section, where we allow for multiple shocks changing their variance on event dates.

## 3.2 | A model with multiple shocks

Although the former model (see Section 3.1) was estimated under the assumption of a single trade policy shock, we now relax this assumption. We use the exact same inputs (variables, event dates, and lags) but consider the possibility of multiple types of structural shocks related to the event dates by allowing all shock variances to change. In other words, we lift the two identifying assumptions of the baseline model that one structural variance changes while the others stay constant to see how restrictive they are.

To identify the model, we decompose the reduced form covariance matrices on non-announcement and announcement days, $\Sigma_0$ and $\Sigma_1$, respectively, as follows:

$$\boldsymbol{\Sigma_0} = \boldsymbol{BB'} \text{ and } \boldsymbol{\Sigma_1} = \boldsymbol{B\Lambda B'}, \tag{8}$$

where $\Lambda = \text{diag}(\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6)$ is a diagonal matrix with the (positive) structural shock variances on the main diagonal and otherwise zeros. $B$ is the constant matrix of impact effects, as before. The decomposition relies on the normalization that the structural shock variances on non-announcement days have unit variance. The diagonal elements of $\Lambda$ are the eigenvalues of the matrix $\Sigma_1 \Sigma_0{}^{-1}$ (Lütkepohl et al., 2021). Note that $\Sigma_1 \Sigma_0{}^{-1} = B\Lambda B'(BB')^{-1} = B\Lambda(B')^{-1}$, which has the form of an eigendecomposition where $b_i$, the columns of $B$, are the corresponding eigenvectors. Estimating $\widehat{\Sigma_1 \Sigma_0{}^{-1}}$, the impact vectors $\widehat{b_i}$ and variance changes $\widehat{\lambda}_i$,for $i = 1, \ldots, k$ can be calculated as eigenvectors and eigenvalues, respectively.

Lanne et al. (2010) show that if the $\lambda_i$s are distinct, then the decomposition in Equation (8) is unique up to changes in the signs of the shocks and corresponding orderings of the columns of $B$ and $\Lambda$. In other words, the full model is point-identified if the $\lambda_j$ are all different. As these elements can be interpreted as the variance shifts of the structural shocks relative to non-announcement days, identification requires that the volatility shifts on announcement days are not the same for all shocks. This assumption can be tested after estimation, which is an advantage over more conventional just-identifying assumptions that cannot be assessed. If only some of the variance shifts are significantly different, the model is partially identified. But an analysis of the shocks associated with the distinct $\lambda_j$s may still be informative.

Table 2 shows the point estimates of the relative variances, ordered from largest to smallest, along with their 68% and 90% intervals based on 1000 draws from the moving-block bootstrap. There is one shock with clearly higher

**TABLE 2** Estimated shock variances of the multiple-shocks model

| | $\widehat{\lambda}_1$ | $\widehat{\lambda}_2$ | $\widehat{\lambda}_3$ | $\widehat{\lambda}_4$ | $\widehat{\lambda}_5$ | $\widehat{\lambda}_6$ |
|---|---|---|---|---|---|---|
| 5% | 3.28 | 1.72 | 1.10 | 0.59 | 0.29 | 0.13 |
| 16% | 3.84 | 1.92 | 1.28 | 0.70 | 0.37 | 0.19 |
| Point | 4.74 | 1.97 | 1.56 | 1.50 | 0.56 | 0.45 |
| 84% | 6.47 | 2.77 | 1.93 | 1.31 | 0.62 | 0.37 |
| 95% | 7.73 | 3.22 | 2.16 | 1.48 | 0.70 | 0.43 |

*Note*: Point estimators for the different $\widehat{\lambda}_i$ and the bootstrap quantile estimates from the moving-block bootstrap with 1000 draws.

estimated variance on announcement days. The point estimate is $\widehat{\lambda_1} = 4.74$ and significantly larger than 1 according to the 90% confidence bands. There is another shock with higher variance $(\widehat{\lambda_2} = 1.97)$ for which the confidence bands do not cover 1. For the other four shocks, the estimated variance increases $(\widehat{\lambda_3} = 1.56, \widehat{\lambda_4} = 1.50)$ or decreases $(\widehat{\lambda_5} = 0.56, \widehat{\lambda_6} = 0.45)$. The 90% confidence bands suggest that the variance change is distinct for Shocks 1 and 2 as the bands do not touch each other. Shocks 2 and 3 are difficult to separate, as the 68% bands of the variance change of these shocks slightly overlap. Together, this informal evidence suggests that in this model, there are two candidate structural trade policy shocks with higher variance on announcement days, but that the second of these is difficult to separate statistically from the remaining four shocks.

To test for statistical identification formally, we perform the Wald-type test proposed by Lütkepohl et al. (2021). We use the estimated $\widehat{\lambda_j}$s together with the share of event days ($\tau = 0.037$) in the total number of observations ($T = 790$) in the following test statistic:

$$\boldsymbol{Q_r} = \boldsymbol{c}(\boldsymbol{\kappa_1}, \boldsymbol{\kappa_2}, \boldsymbol{\tau})^2 \left[ -\boldsymbol{T} \sum_{k=s+1}^{s+r} \boldsymbol{log}\left(\widehat{\lambda_k}\right) + \boldsymbol{T}\, \boldsymbol{r}\, \boldsymbol{log}\left( \frac{1}{r} \sum_{k=s+1}^{s+r} \widehat{\lambda_k} \right) \right], \tag{9}$$

where $\boldsymbol{c}(\kappa_1, \kappa_2, \tau)^2 = \left(\frac{1+\kappa_1}{\tau} + \frac{1+\kappa_2}{1-\tau}\right)^{-1}$, $r$ is the number of restrictions, $s \in \{0, 1\}$, and the kurtosis parameters $\kappa_1$ and $\kappa_2$ are set to zero in line with the conditional Gaussianity assumption. The null hypothesis is that the shock variances are equal. Under the null, the asymptotic distribution of $Q_r$ is $\chi^2$ with $\frac{1}{2}r(r+2)(r-1)$ degrees of freedom.

Table 3 shows the results of four tests that follow the procedure outlined in Lütkepohl et al. (2021). The data clearly reject the assumption that all relative variances are equal. The test statistic is 50.52 and the associated $p$-value 0.002. The test does not reject the equality of $\lambda_1$, $\lambda_2$, $\lambda_3$, and $\lambda_4$ but rejects the equality of $\lambda_1$, $\lambda_2$, and $\lambda_3$ at the 10% level. Importantly, the assumption $\lambda_1 = \lambda_2$ obtains a $p$-value of 0.0731. In sum, the variance heterogeneity provides evidence that Shock 1 can be separated from Shocks 2 and 3, but Shocks 2 and 3 cannot be disentangled. Considering the informal inspection of the shock variances and also the relatively small event-date-share $\tau$, we conclude that there is some evidence for two types of trade policy shocks with higher variances on announcement days but that only the first one can be identified while the second is a borderline case.

Figure 3 shows the impulse responses to the two shocks, together with the impulse responses derived from the main model (Section 3.1) and the 90% bootstrap confidence bands for the main model. The two trade-policy news related shocks are of size $+1 \bullet \sqrt{\lambda_i}$, their standard deviation on event dates. One can see that the impulse responses of Shock 1, that is, the dashed lines in Figure 3, follow the pattern of the impulse responses of the main model. The main difference is a smaller and shorter-lived impact on the two stock market indices. By contrast, the impact responses to Shock 2, presented by the dotted lines in Figure 3, are different. The change in the VIX, in the US dollar and in interest rates is almost zero. However, there is a common feature of Shock 2 with the shock of the main model, that is, the negative and somewhat persistent impact on stock markets.

The comparison shows that the two shocks capture different dimensions of trade policy. The responses to Shock 1 suggest an interpretation as a trade policy uncertainty shock. Such a shock increases volatility and raises risk premia in financial markets. Increased uncertainty causes a worse economic development that contributes to lower interest rates and increases net demand for safe assets, such as US treasuries and the US dollar (see also Erceg et al., 2018). Despite the strong increase in aggregate market volatility, it is unlikely that Shock 1 captures general macroeconomic uncertainty, given the identification strategy that singles out days with systematically higher information flows related to trade policy. Inversely, it seems plausible that higher trade policy uncertainty raises aggregate uncertainty, given the important changes in trade policy in the sample.

In contrast, the responses to Shock 2 suggest an interpretation as a level or tariff change announcement shock. Such a shock will primarily affect trade-oriented firms, that is, we expect here a decline in the China Exposure Stock Index.

**TABLE 3** Identification tests for the multiple-shocks model

| Hypothesis | $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6$ | $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5$ | $\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4$ | $\lambda_1 = \lambda_2 = \lambda_3$ | $\lambda_1 = \lambda_2$ | $\lambda_2 = \lambda_3$ |
|---|---|---|---|---|---|---|
| $\chi^2$ | 50.52 | 31.49 | 13.59 | 10.12 | 5.23 | 0.3664 |
| df | 20 | 14 | 9 | 5 | 2 | 2 |
| $p$-values | 0.0002 | 0.0047 | 0.1378 | 0.0719 | 0.0731 | 0.8326 |

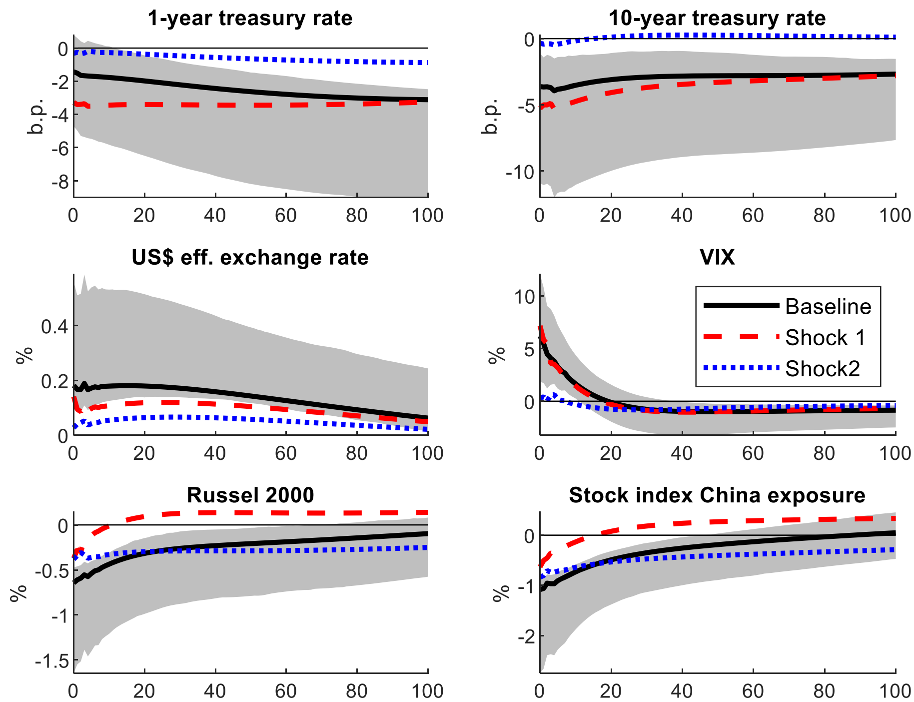


FIGURE 3 Estimated impulse responses to restrictive US trade policy shocks. *Notes*: The figure shows the baseline impulse responses with 90% moving-block bootstrap confidence bands and the point estimates of the first two shocks on event dates from the multiple-shocks model. To obtain event-date shocks, the point estimates in the $B$ matrix are multiplied by the square root of the associated $\widehat{\lambda}_i$. An increase in the US$ effective exchange rate denotes an appreciation of the US$.

TABLE 4 Forecast error variance decomposition for the multiple-shocks model

| | 1-year Treasury | 10-year Treasury | US$ eff. exchange rate | VIX | Russel 2000 | Stock Index Chn. Exp. |
|---|---|---|---|---|---|---|
| Horizon = 1 | | | | | | |
| Shock 1 | 58.0 | 44.6 | 4.9 | 18.8 | 3.3 | 9.1 |
| Shock 2 | 1.3 | 0.5 | 0.4 | 0.1 | 8.3 | 38.1 |
| Horizon = 100 | | | | | | |
| Shock 1 | 52.0 | 27.9 | 6.0 | 10.9 | 1.5 | 5.8 |
| Shock 2 | 4.4 | 0.2 | 4.0 | 3.9 | 16.8 | 39.6 |
| Horizon = 500 | | | | | | |
| Shock 1 | 33.6 | 20.7 | 5.5 | 11.5 | 4.8 | 11.0 |
| Shock 2 | 5.0 | 2.6 | 5.1 | 5.4 | 19.1 | 24.4 |

Different from an uncertainty shock, volatility will not change much. This is exactly what we find. In particular, stock prices of firms with larger trade with China fall significantly because importers face higher input costs in the future and exporters are likely to be negatively affected by retaliation tariffs.

To formally evaluate the relation between the different shocks, we perform a projection of the baseline shock on Shock 1 and Shock 2 from the multiple-shocks model. In combination, Shock 1 and Shock 2 account for more than 85% of the variation of the shocks from the main model. In a rolling-window regression, the resulting "loadings" on these two shocks are rather invariant over time (see Figure A2).

The interpretation of Shocks 1 and 2 as a trade policy uncertainty shock and a trade policy level shock, respectively, is supported by a forecast error variance decomposition. Table 4 shows the average economic importance of the two shocks (in rows) to the variability of the endogenous variables (in columns). Shock 1 accounts for about 18.8% of the variation in the VIX at Horizon 1 and for slightly more than 10% at all other horizons. Moreover, it has a 1%–5% impact (depending on horizon) on the Russell 2000, a 3%–10% impact on the China Exporter Stock Index, a roughly 5% impact on the US dollar, and high impact on interest rates with one-third to two-thirds for the short-term rate and still 20%–45% for the 10-year Treasury. In contrast, Shock 2 explains hardly anything of the forecast errors for the VIX, and much less than Shock 1 of the other variables, except for the stock market indices: Here it explains 24%–40% of the China Index and still 8%–19% of the Russell 2000.

## 4 | DISAGGREGATED RESULTS FOR FIRMS, INDUSTRIES, AND COUNTRIES

After having characterized the overall importance and nature of the identified trade policy shocks, we next turn to a disaggregated analysis of their impact. Throughout the following, we use our daily trade policy shock measure from the main model with 29 event dates (Section 3.1) and estimate the potentially heterogeneous impact of trade policy shocks on individual firms, industries, and countries. Finally, we compare the shock time series to other measures proposed in the literature and conduct a special case study for China. Given that the impacts of the single trade policy shock in the main model largely resemble those of Shock 1 in the second model (allowing for multiple shocks), and the shock series are correlated with 0.74, we interpret the following findings mainly as responses to a trade policy uncertainty shock.

For the disaggregated analysis, we use asset prices for the firms included in the S&P 500 index, the industry sectors of the S&P 500 as classified by Standard and Poor's, stock market indices of many larger countries in the world economy, and, finally, volatility indices for a range of international stock market indices. We regress the return of the variable of interest $\boldsymbol{r_{Y_t}}$ on a constant, the trade policy shock $\boldsymbol{\varepsilon_t}$ as well as one lag of the dependent variable and the shock:

$$\boldsymbol{r_{Y_t}} = \boldsymbol{\alpha} + \boldsymbol{\beta}\boldsymbol{\varepsilon_t} + \boldsymbol{\gamma}\boldsymbol{r_{Y_{t-1}}} + \boldsymbol{\delta}\boldsymbol{\varepsilon_{t-1}} + \boldsymbol{\nu_t}, \tag{10}$$

where $\nu_t$ is an error term. We report the point estimate for the coefficient of interest $\beta$ with autocorrelation and heteroskedasticity robust standard errors. The magnitude of the estimated $\beta$ coefficients is directly comparable to the impact effects contained in $b_1$.

### 4.1 | Firms

We run the described analysis for 482 firms in the index for which Bloomberg provides data over the sample horizon January 2017 to January 2020. The restrictive trade policy shocks affect stock prices negatively on average. The shocks lead to declining stock prices for 454 or 94% of firms, of which 426 decline significantly at the 1% level. Merely 28 firms in the sample see their valuations increase (see Figure A3). None of these increase by more than 0.3% on impact. Of the 28 firms that do not lose from trade policy shocks, 19 are identified as utilities and the remaining nine as real estate and rental and leasing firms by the North American Industry Classification System (NAICS).

On the left side of the distribution, 13 firms' stock prices decrease by more than 1.5%, with 10 of these firms belonging to the manufacturing industry. Specifically, nine are in the semiconductor manufacturing industry according to the NAICS. Overall, semiconductor manufacturing firms seem to be hit hardest, with 10 out of the 11 firms that lose most when hit by a US trade policy shock belonging to that category (compare Bown, 2020a, for a qualitative analysis of the role of semiconductor firms in the US–China trade dispute). The S&P industry classification assigns all semiconductor firms to the IT sector. In sum, the estimates indicate that a large part of the US economy is negatively affected.

### 4.2 | Industries

For the next analysis, we use the standard classification of the S&P 500 firms into 11 industry sectors to identify which industries are most affected by trade policy shocks, expecting that export orientation plays a role. Figure 4 shows for all industries, except for utilities and real estate, that the point estimates are negative and statistically significant at the 1% level. The most negatively affected industries are IT, materials, financials, and industrials, which are all internationally oriented industries. Out of the negatively hit industries, consumer staples is the least affected industry. The

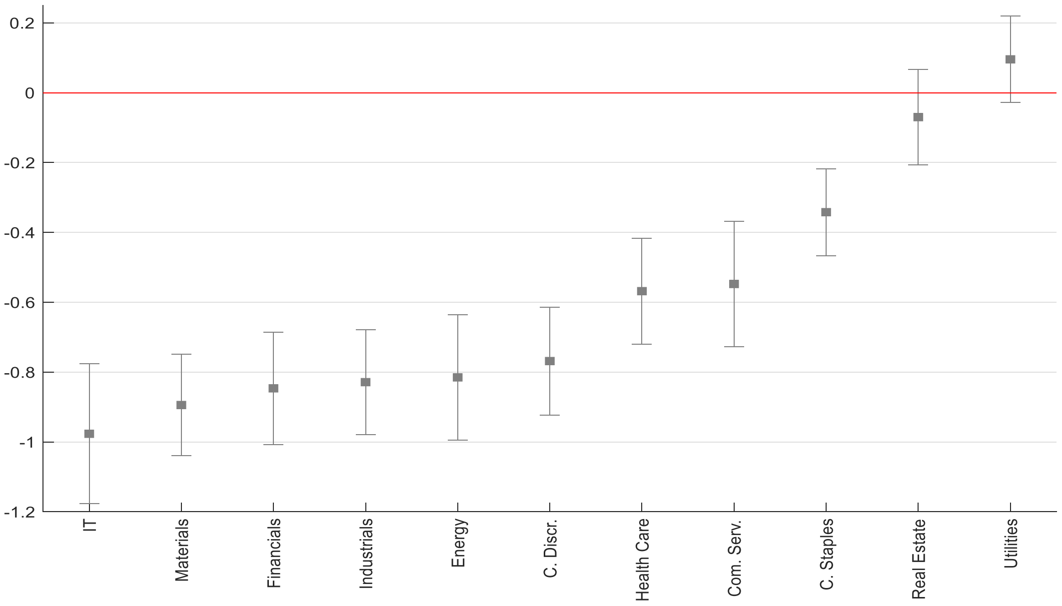


**FIGURE 4** Impact responses of S&P sector indices to a US trade policy shock. *Notes*: C. Discr. is consumer discretionary, Com. Serv. are communication services and C. Staples are consumer staples. 99% HAC standard error confidence bands.

United States was hesitant to tariff essential goods like food, household, and personal products that belong to this sector. In general, this pattern seems to fit to the observation that uncertainty about relative price changes due to tariffs affects industries differently: Internationally oriented industries and those with closer ties to China, such as industrials, lose more value than domestically oriented industries.

## 4.3 | Country returns

Next, we focus on the impact of trade policy shocks on countries other than the United States. In a globalized world, one would expect that most other countries are also negatively affected by restrictive US trade policy shocks. We take the full universe of 49 MSCI country indices for our calculations, and the results in Figure 5 do indeed conform to our expectation. The effect for 46 of 49 countries is negative, and for 44 countries, it is statistically significant at the 1% level.

Looking at regional country groups, the Latin-American stock markets seem to be hardest hit. The next countries, that is, those hit somewhat less, are dominated by European economies. Even less hit are most Asian countries, whereas African countries are hardly affected at all. This country pattern is largely consistent with the idea that geographical proximity to the United States (and thus tentatively closer economic relations) leads to stronger negative impacts. Interestingly, the MSCI China index decreases by around 0.62%, and thus somewhat less than US stocks. The index captures 701 large and mid-cap companies, covering about 85% of China's stock market capitalization. Overall, the country patterns make sense as the identified trade policy shocks mostly refer to US–China tensions.

## 4.4 | Country volatilities

Now, we regard further volatility indices to judge if stock market indices of other countries experience a similar rise in volatility. Figure 6 shows that all 13 indices rise on impact. The two indices representative for China, the China ETF (exchange-traded fund) volatility index, and the Hang Seng volatility index, measuring volatility of the Hang Seng, the leading Hong Kong stock exchange, both increase significantly by around 3.2% and 1.3%, respectively. Moreover, volatility of emerging market stock prices (measured by the EM ETF) increases most by around 4.5%. Thus, US trade policy shocks increase volatility also outside the United States and China.

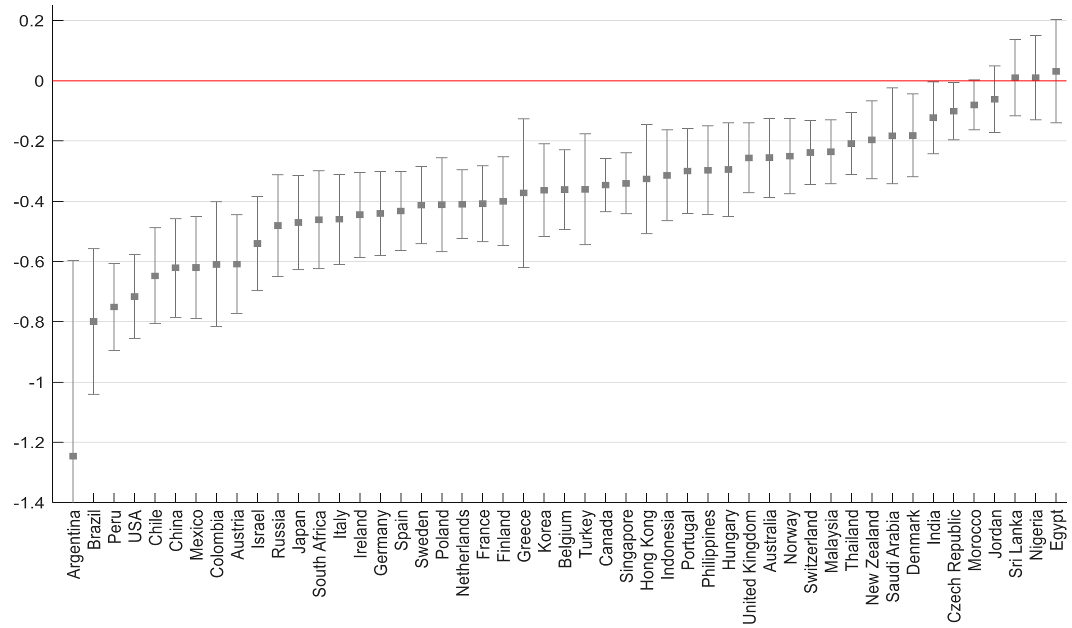


**FIGURE 5** Impact responses of MSCI country indices to a US trade policy shock. *Note*: 99% HAC standard error confidence bands.

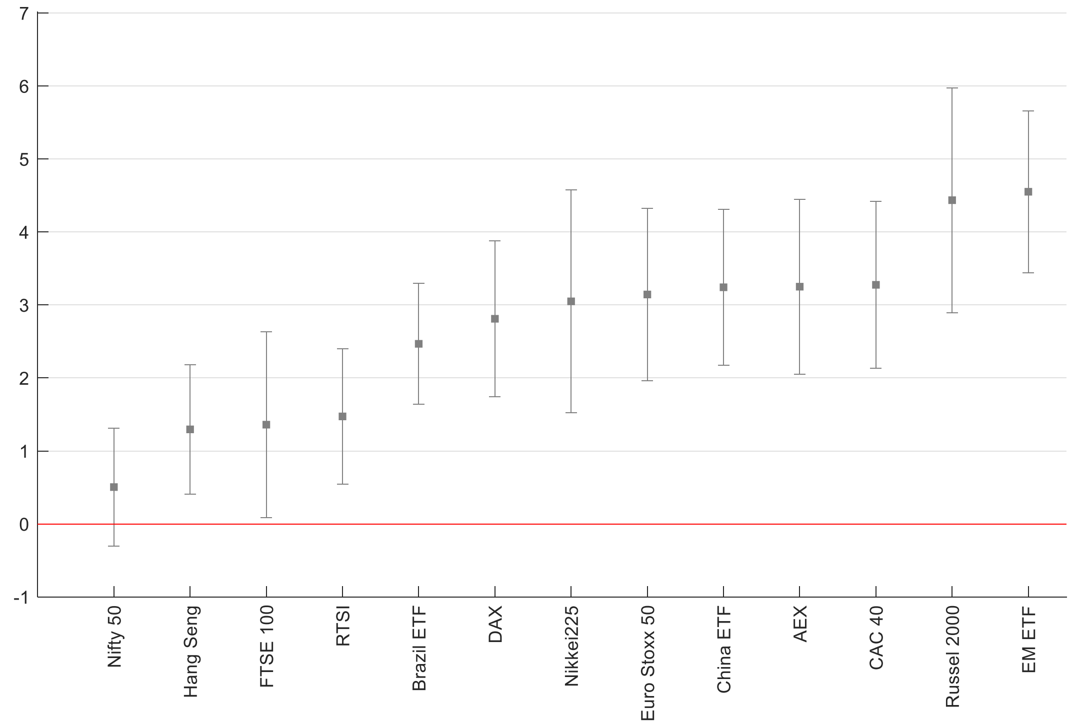


**FIGURE 6** Impact responses of various volatility indices to a US trade policy shock. *Note*: 99% HAC standard error confidence bands.

## 4.5 | Comparison of estimated trade policy shocks with other measures

Another way to inform about our shocks, shown in Figure 1, is to compare them to other series capturing related information. We draw on external data for changes in tariff levels, in general economic uncertainty, and in trade policy uncertainty. For each, we gather two or three series. For the tariff-level comparison, we use the monthly US tariff

**TABLE 5** Pairwise correlation between trade policy shocks, tariff rates, and uncertainty measures

| Lags | Monthly US tariff change on Chinese goods | Quarterly US aver. tariff rate change | Economic policy uncertainty (BBD) |
|---|---|---|---|
| −1 | 0.0225 (0.8978) | 0.1042 (0.7605) | 0.2185 (0.2074) |
| 0 | 0.2088 (0.2217) | 0.1185 (0.7138) | 0.0701 (0.6846) |
| 1 | 0.0591 (0.7359) | −0.3958 (0.2282) | −0.0729 (0.6775) |

*Notes*: Pairwise correlations and $p$-values of the aggregated shocks series with monthly changes in US tariffs on Chinese goods, quarterly changes in average US tariff rates on all goods, and various newspaper-based economic policy uncertainty and equity market volatility indices at various lags. BBD refers to Baker et al. (2016), BBDK to Baker et al. (2019), and CIMPR to Caldara et al. (2020). Lag −1 shows the correlation of the trade policy shock series lagged 1 month with the other series. Coefficients are labeled according to significance.
$^{*}p < 0.1$. $^{**}p < 0.05$. $^{***}p < 0.01$.

changes on Chinese goods of Bown (2020b) and compute the change in the average quarterly US tariff rate across all goods as the ratio of US customs duties over US imports of goods.[6]

Table 5 shows that the contemporaneous connection between the two tariff-change series and the estimated shocks is small, either because the shocks capture mainly announcement dates and implementations often happen later or because they are mainly related to uncertainty and not to level effects. The result is similar if we consider measures of economic policy uncertainty (Baker et al., 2016) or equity market volatility (Baker et al., 2019). Again, there are positive but rather small correlations with our shocks.

The picture changes if we take measures of uncertainty about trade policy, that is, the updated trade policy uncertainty (TPU) index of Baker et al. (2016), the TPU index of Caldara et al. (2020), and the measure of equity market volatility related to trade policy by Baker et al. (2019). All these indices result from counting newspaper article occurrences using search terms related to the economy, trade policy, and uncertainty. Our shocks have consistently positive contemporaneous correlations with these series, and the coefficients are highly significant. If there is a lag structure, our series tends to lead the others by 1 month although the lagged coefficients are insignificant. The lead appears plausible as asset prices are likely to respond quicker to new information than daily or weekly newspapers. From a policy perspective, the tentatively leading properties of our shock measure can be useful for policy makers to respond to economic shocks faster.

### 4.6 | Impact from China

Due to the special role of China, we further examine this case. It is known that China does not passively accept US trade policy shocks but responds with its own measures. We collect, from the same database as above, the 14 Chinese announcements that target the United States (see Table A3 for a list of the events). We identify Chinese trade policy shocks using the model and the identification strategy outlined in Section 2. Figure 7 demonstrates that a restrictive Chinese trade policy shock also has significant negative effects on the US economy. They appear slightly larger than those of US trade policy shocks while the shape is comparable. The impact on stock prices is more persistent when looking at the statistical significance, but this might also reflect fewer Chinese retaliation events that are, on average, of larger significance.

## 5 | ROBUSTNESS

We perform many robustness tests, showing that our results are invariant to changes in trade policy battles, the selection of event dates, the bootstrap method, the sample size, the lag length in the SVAR, the use of a Minnesota prior, and the inclusion of day-of-week dummies in the VAR. Results are shown in Appendix S2.

[6]US Customs duties (i.e., proceeds from tariffs) data are taken from the US Bureau of Economic Analysis and imports data from the U.S. Census Bureau's U.S. International Trade and Goods and Services report (FT900). Both series are seasonally adjusted.

**TABLE 5** (Continued)

| Lags | Equity market volatility (BBDK) | Trade policy uncertainty (BBD) | Trade policy uncertainty (CIMPR) | Equity market volatility—trade policy (BBDK) |
|---|---|---|---|---|
| −1 | −0.2481 (0.1508) | 0.2678 (0.1199) | 0.2072 (0.2322) | 0.0634 (0.7176) |
| 0 | 0.0587 (0.7337) | 0.3301 (0.0493)** | 0.3701 (0.0263)** | 0.406 (0.0140)** |
| 1 | −0.0896 (0.6089) | 0.0084 (0.9617) | 0.0728 (0.6778) | −0.1152 (0.5100) |

*Notes*: Pairwise correlations and *p*-values of the aggregated shocks series with monthly changes in US tariffs on Chinese goods, quarterly changes in average US tariff rates on all goods, and various newspaper-based economic policy uncertainty and equity market volatility indices at various lags. BBD refers to Baker et al. (2016), BBDK to Baker et al. (2019), and CIMPR to Caldara et al. (2020). Lag −1 shows the correlation of the trade policy shock series lagged 1 month with the other series. Coefficients are labeled according to significance.
*$p < 0.1$. **$p < 0.05$. ***$p < 0.01$.

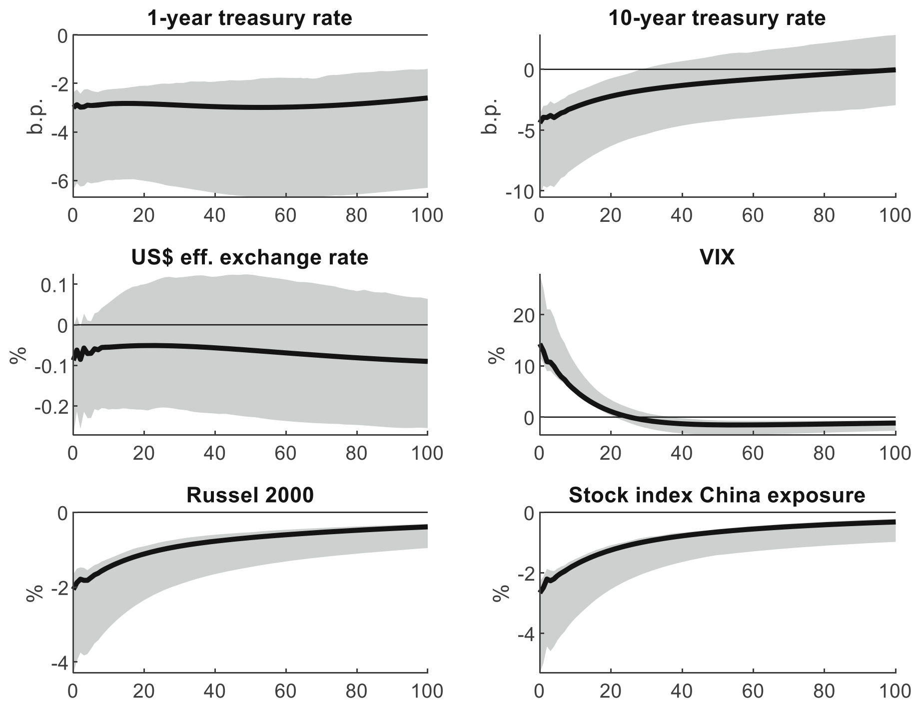


**FIGURE 7** Estimated impulse responses to Chinese trade policy shock. *Notes*: The figure shows impulse responses to a restrictive trade policy shock. Identification of the trade policy shock is based on 14 Chinese announcement dates described in Table A3 in the Supporting Information. The grey areas show 90% moving-block bootstrap confidence intervals with bootstrap sample size 1000.

## 6 | CONCLUSIONS

The US administration used restrictive trade policies, in particular, increased tariffs, as an instrument to support the domestic economy. We propose an SVAR approach identified through heteroskedasticity on trade policy event days to analyze the impact of trade policy shocks on the US economy and the world economy. Our approach uses high-frequency data for a clean identification of the shocks (as event studies) and stretches the analysis over longer horizons (as macro models). Moreover, it seems reasonable to allow for more than one type of structural trade policy shock.

We find that restrictive US trade policy shocks cause a significant increase in uncertainty, a decrease of US stock price indices, a decline of interest rates, and an appreciation of the US dollar. Thus, all considered financial markets react and contribute to a multifaceted picture of rising economic uncertainty and expected output losses, which is not the intention of this policy. The characteristics of the dominating trade policy shock suggest that this is an uncertainty shock; we also reveal that there is potentially a second type of shock, a level shock. However, its effects are dominated by the trade policy uncertainty shock. Disaggregated analyses further show that the significantly negative impact of restrictive shocks applies to more than 90% of S&P 500 firms and to most US industries, such that there is a broadly negative impact on the US economy. Moreover, the shocks also negatively affect most countries of the world economy, by lowering stock market indices and increasing their volatility. Negative effects are further amplified by retaliation measures of China.

Overall, it seems surprising that the US administration is pursuing this policy as the US economy is hit broadly and the economic environment becomes significantly more uncertain. Although these results are not easy to rationalize, it may be possible that those parts of the US economy that remain unaffected or even profit are not covered by our analysis (such as non-listed firms). Longer-term adjustments to these shocks, which are also not covered in our approach, may provide a rationale for these measures. Finally, a rationalization could be that trade policy is a (temporary) tool to realize advantages in other policy areas.

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## CONFLICT OF INTEREST

None.

## OPEN RESEARCH BADGES

This article has been awarded Open Data Badge for making publicly available the digitally-shareable data necessary to reproduce the reported results. Data is available at http://qed.econ.queensu.ca/jae/datasets/boer001/.

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