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The multifaceted impact of US trade policy on financial markets

Lukas Boer, Lukas Menkhoff, and Malte Rieth

Abstract. We study the multifaceted effects and persistence of trade policy shocks on financial markets in a structural vector autoregression. The model is identified via event day heteroskedasticity. We find that restrictive US trade policy shocks affect US and international stock prices heterogeneously, but generally negatively overall, increasing market uncertainty, lowering interest rates, and leading to an appreciation of the US-Dollar. The effects are significant for several weeks or quarters. These effects reveal elements of both relative price shocks and uncertainty shocks of which the latter may be more important. Chinese trade policy shocks against the US further hurt US stocks.

JEL-Classification: F 13 (trade policy); F 51 (international conflicts); G 10 (general financial markets)

Keywords: Trade policy shock; structural VAR; stock prices; exchange rates; interest rates; heteroskedasticity

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1 Introduction

Threats of a more restrictive trade policy are currently seen among the major risks for the course of the world economy. In particular, the US administration is fueling concerns about increasing US import taxes. Average US tariffs on goods from China, for example, have increased from 3.1 percent in January 2018 to 21.0 percent at the end of 2019 (Bown, 2020), covering about two-thirds of these imports (Amiti et al., 2020). Many observers are afraid of a potential 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 is practicing one-sided trade policy initiatives, thus bringing this instrument back into international economic policy.

The effects of this policy are not obvious; nor is the approach to address them. The increase in tariffs changes the relative prices of affected goods and services, which leads to winners and losers in the US economy and globally. This supports approaches that look at the effects of tariff changes either in trade models (e.g., Amiti et al., 2019; Fajgelbaum et al., 2020) or in event studies (e.g., Breinlich, 2014; Egger and Zhu, 2019). At the same time changes in trade policy create uncertainty that negatively affects the economy and is at the focus of empirical macro strategies that investigate the impact of trade policy uncertainty (Caldara et al., 2020).

Indeed, all these approaches are usefully applied in isolation. However, we are not aware of any paper that looks simultaneously at both the relative price effect and the uncertainty effect of changes in trade policy. In this paper, we propose an encompassing model in the form of a structural vector autoregression (SVAR) that accounts for both aspects. Our aim is twofold: first, we want to estimate the importance and persistence of unexpected trade policy interventions. Second, we aim at shedding light on how the effects come to pass. Specifically, our analysis applies a SVAR for the daily frequency identified through heteroskedasticity on

trade policy events, adapting the approach of Wright (2012) who studies unconventional monetary policy. The approach allows for a precise identification of structural trade policy shocks based on mild econometric assumptions, while at the same time facilitates an assessment of their effects at macro-economically relevant horizons.¹

The identification strategy singles out days between 2017 and 2020 on which the variance of latent trade policy shocks is particularly high. 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 change in the covariance matrix of the reduced form VAR residuals on these days relative to other days enables identification of the structural trade policy shocks. Importantly, this strategy allows for the possibility that other structural shocks occur on the same day. Hence, it does not require exclusion restrictions, which might be problematic if asset prices respond to each other instantaneously. 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.

We find heterogeneous effects of restrictive trade policy shocks on stock prices of firms, industries, and countries, overall a decline of stock prices and a significant impact on other financial markets, too. The mechanism of relative price effects becomes obvious in the heterogeneous stock price reactions, uncertainty effects are revealed in the volatility increase and the US-dollar appreciation follows from the tariff increases (in trade models) or from an increased net demand for safe assets (in a finance perspective). Overall, these multifaceted results suggest – in combination with historical and variance decompositions – a new

¹ Identification through heteroskedasticity is developed in Rigobon (2003), and is applied thereafter; for example, by Rigobon and Sack (2004) analyzing monetary policy effects during “normal” times, by Wright (2012) analyzing monetary policy at the zero lower bound, 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).

perspective on the impact of US trade policy, i.e. that the increase of uncertainty may have an even stronger effect on financial markets than the relative price changes.

To be clear, our aim is not to “disentangle” tariff-related relative price shocks and trade uncertainty shocks. Our ambition is more modest. We use a set of minimal assumptions that gives full voice to the data *ex ante*, but still enables sharp identification of the overall impact of specific trade policy interventions. We then look *ex post* whether effects of these shocks are (more) related to the working of relative prices or changes in uncertainty, or both. We do so in several ways throughout this paper. For example, heterogeneous effects on stock prices mainly reflect relative price changes, whereas a change in the VIX (volatility index of US stock prices) is by itself a measure of uncertainty.

Considering major US trade policy announcements, our estimates suggest that an average restrictive trade policy shock leads to an immediate increase in uncertainty, proxied by the VIX. Market volatility returns to pre-shock levels after two weeks. US stock market indices for large and smaller listed firms suffer a drop of about 0.8%. This decline is statistically significant for about three weeks. Moreover, we find that shorter and longer-term interest rates fall significantly. Importantly, the US Dollar appreciates significantly, consistent with increased price competitiveness and safe haven net demand.

We then show that trade policy shocks are an important driver of both stock market volatility and stock prices. The shocks explain a significant share of the long run variance of market volatility over the horizon from 2017 to early 2020 and a smaller, but sizeable, share of the variance of stock price changes over a few weeks. Furthermore, the identified shocks have a significant contemporaneous correlation with external measures of trade policy uncertainty and there is some evidence that they lead the alternative measures. Due to their forward-looking character, they are not really related to the more sluggish measures of tariff changes. Extending the SVAR to specific assets, we see that around a half of S&P 500 firms’ stock prices and 4 of

the 11 S&P 500 sector indices are significantly negatively affected. The more internationally oriented sectors of the US economy, i.e. industrials, financials, materials, and IT, suffer most.

Regarding 48 considered international stock markets, we find that most decline following US trade policy shocks. We do not observe a clear pattern as to which regions are affected most. Chinese stock prices, however, decline significantly on impact and stronger than their US counterparts. Likewise, increased stock market volatility is not merely a US phenomenon. Volatility indices for China and emerging market stocks increase significantly following a US trade policy shock. Finally, we find evidence that trade policy shocks by China also hurt the US economy. Overall, the analysis indicates a negative impact of restrictive US trade policy shocks on the domestic (US) economy and on the world economy through changes in both relative prices and uncertainty, with the latter being more important.

Literature. Our study relates to the field of trade policy. More specifically, to the effects of tariff policy during the recent US-Chinese trade dispute. A large literature shows positive effects of a liberalized trade policy on various dimensions like trade volumes (e.g., Yi, 2003), prices (De Loecker et al., 2016), firms (e.g., Amiti and Konings, 2007), poverty (e.g., Topalova, 2010), and welfare (e.g., Caliendo and Parro, 2015), while the effect on labor markets is rather mixed and often highlights distributional concerns (e.g., Goldberg and Pavcnik, 2005). Several studies concentrate on the restrictive trade policy measures of the Trump administration.

For example, two studies use a trade-based modeling approach. Amiti et al. (2019) estimate the annual reaction of import prices and quantities to tariff changes for detailed product categories and estimate 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. The two studies suggest that tariffs are almost completely passed through to US consumers and firms for most goods (see

also Cavallo et al., 2019, or Flaaen et al., 2020, for analyses of tariff pass-through after recent US trade policies).

We also connect with high-frequency event studies that analyze trade policy effects on stock markets (e.g., Breinlich, 2014; Moser and Rose, 2014). This approach allows for precise identification and detailed cross-sectional analyses of the incidence of tariff changes. Egger and Zhu (2019) find that US tariff changes have negative effects on international stock markets; these are larger for domestic firm valuations than for Chinese firms. Statistical significance is shown for three days following the event, up to a window of 10 days. Thus, this approach remains rather silent on macroeconomic effects and on the uncertainty associated with trade policy shocks. 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.

Lastly, several papers examine the impact of trade-related uncertainty on economic outcomes. Pierce and Schott (2016) study a reduction in trade policy uncertainty due to China's entry into the World Trade Organization (WTO) while US tariffs did not change. Consequently, employment declines more strongly in US manufacturing industries more exposed to the reduced uncertainty. Fan et al. (2018) demonstrate how the reduced uncertainty after the WTO accession led to the exit of less productive Chinese exporters and the entry of Chinese firms supplying higher quality goods at lower prices. 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 addition, the authors build two quarterly measures from public companies' quarterly earnings calls and from estimated import tariff rates. In line with Baker et al. (2016), the authors find significant decreases in investment as their uncertainty indices rise.

The remaining paper is organized in five more sections. Section 2 characterizes the structural VAR 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, while 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 by specification tests (Section 2.3).

2.1 The SVAR model

The reduced form VAR is represented by

$$A(L)Y_t = \mu + u_t, \quad (1)$$

where Y_t is a $k \times 1$ vector with k variables of interest and μ 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 US. Thus, the variables in Y_t in the baseline model refer to US markets. The stock market is represented by a broad index, i.e. the S&P 500. It includes the 500 largest listed US firms with an average market capitalization of around US\$ 46 billion over the sample horizon 2017 to early 2020. It covers approximately 80% of the total US market capitalization. To consider uncertainty in this financial market (and the economy), the VIX is included in our model of the US economy, measuring expected volatility of the S&P 500 over the next 30 days.

Our main research question is how this market is affected by the shock. As the US economy is much broader than these large 500 firms, which are mainly internationally oriented, we also include the Russell 2000 index, which covers the firms ranking in between 1,000 and

3,000 regarding their size; size is here proxied by stock market capitalization. The index represents approximately 8% of the total market capitalization of the US with an average market capitalization per firm of around US\$ 2.3 billion. These relatively smaller firms often are more domestically oriented than S&P 500 firms.

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 one-year treasury rate reflects expectations about monetary policy actions. The ten-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 are foreign exchange markets, which we capture by relying on the US-Dollar effective exchange rate, i.e. 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.

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. He identifies days on which the Federal Open Market Committee meets as dates where monetary policy shocks have especially high variance.

The identification strategy works as follows. The reduced form errors u_t are related to the structural shocks ε_t via the linear transformation $u_t = B \varepsilon_t = \sum_{i=1}^k b_i \varepsilon_{t,i}$. The structural errors are uncorrelated, implying a diagonal covariance matrix. b_1 represents the first column of B . This approach does not rely on a Cholesky decomposition and hence, without loss of generality, we order the trade policy shock first. We are only interested in this shock (the first column of B) and do not try to identify the remaining shocks. The approach assumes that the trade policy shock has mean zero and variance σ_1^2 and σ_0^2 on announcement days and non-announcement days, respectively. These variances are assumed to be significantly different,

thus providing the identifying assumption. All other shocks, $\varepsilon_{t,2}, \dots, \varepsilon_{t,k}$, have unit variances on all dates.² The reduced form covariance matrix for announcement dates is then:

$$\Sigma_1 = E(\mathbf{u}_t \mathbf{u}_t') = E(\mathbf{B} \varepsilon_t \varepsilon_t' \mathbf{B}') = \mathbf{B} E(\varepsilon_t \varepsilon_t') \mathbf{B}' = \mathbf{b}_1 \mathbf{b}_1' \sigma_1^2 + \sum_{i=2}^k \mathbf{b}_i \mathbf{b}_i'. \quad (2)$$

Subtracting Σ_0 from this term yields

$$\Sigma_1 - \Sigma_0 = \mathbf{b}_1 \mathbf{b}_1' \sigma_1^2 - \mathbf{b}_1 \mathbf{b}_1' \sigma_0^2 = \mathbf{b}_1 \mathbf{b}_1' (\sigma_1^2 - \sigma_0^2). \quad (3)$$

To solve for the elements in \mathbf{b}_1 , the difference in variances $\sigma_1^2 - \sigma_0^2$ is normalized to 1. We solve for \mathbf{b}_1 via GMM and, hence, minimize

$$J_W(\mathbf{b}_1) = \text{vech}(\widehat{\Sigma}_1 - \widehat{\Sigma}_0 - \mathbf{b}_1 \mathbf{b}_1')' \left(\frac{\widehat{V}_0}{T_0} + \frac{\widehat{V}_1}{T_1} \right)^{-1} \text{vech}(\widehat{\Sigma}_1 - \widehat{\Sigma}_0 - \mathbf{b}_1 \mathbf{b}_1') \quad (4)$$

with respect to \mathbf{b}_1 . \widehat{V}_t is the estimate of the variance-covariance matrix of the reduced form variance on announcement or non-announcement dates. It can be calculated via

$$\widehat{V}_t = \frac{1}{T_t} \sum_{T_i} \text{vech}(\widehat{\mathbf{u}}_t \widehat{\mathbf{u}}_t' - \overline{\widehat{\mathbf{u}} \widehat{\mathbf{u}}'}) \text{vech}(\widehat{\mathbf{u}}_t \widehat{\mathbf{u}}_t' - \overline{\widehat{\mathbf{u}} \widehat{\mathbf{u}}'})' \quad (5)$$

(Kilian and Lütkepohl, 2017). The identification conditions for \mathbf{b}_1 are based on economic reasoning through the choice of the set of announcement dates $t \in T_1$.

There are several potential alternative identification strategies. For example, one can use exclusion or sign restriction to identify two types of shocks. In fact, the trade literature focusing on the relative price effects treats statutory tariff changes as exogenous with respect to trade policy uncertainty (e.g., Amiti et al., 2019), while 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). While these assumption might be plausible when working with macroeconomic data, they are unlikely to hold for asset prices that respond to each other in

² We also estimate a two variable SVAR that we fully identify, explained in the appendix. The model assumes the same heteroskedasticity pattern of the trade policy shock. The estimated variance for the second shock is equal to 1 for the second regime, implying an unchanged variance on announcement dates for the residual shock.

nearly continuous time. Sign restriction, on the other hand, allow for contemporaneous responses of all variables to trade policy shocks. However, theory gives contradicting predictions for the signs of key effects and it is precisely our aim to determine them empirically. Finally, there are strategies based on instruments that aim at econometrically disentangling news and uncertainty (Piffer and Podstawski, 2018). But these look at general news and uncertainty shocks, yielding a large number of observations and potential shocks, while we are interested specifically in trade policy shocks. The current trade dispute provides arguably too few interventions to disentangle them further.

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 in 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. The included variables in the VAR are 1-year and 10-year US treasury yields, the effective US-Dollar exchange rate, the VIX index, the S&P 500 index, and the Russell 2000 index. 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 48 countries and volatility indices like the VIX for 13 stock price indices. All variables enter the model in levels and we take logarithms of the exchange rate, the VIX, and the stock price indices.

To minimize the degree of discretion, we obtain the event dates on which we assume a higher volatility of trade policy shocks from an outside source: the Peterson Institute for International Economics (PIIE), which is an established US economic policy think tank. Chad P. Bown and Melina Kolb 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 29 announcement dates. In robustness checks, we also add Battle #1 or delete Battle #2 which both does not substantially alter our findings. We do not include the other two PIIE categories (battle 4 and 5) which pertain to the EU and Mexico.

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 1 lists all 29 announcement dates from the PIIE and shortly describes these measures. The first two took place in April 2017, when the US 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 USA signed the so-called “Phase One Deal”; China agreed to purchase an additional \$200 billion US goods while most tariffs remained in effect. The online appendix contains a detailed account of the trade disputes of the US with other countries. The S&P 500 changes on event dates show that it is ex-ante not fully clear whether we can speak of a restrictive or easing trade policy shock when tariff lists are altered, or several policy changes announced. This supports our heteroskedasticity identification where we do not make any assumptions about the sign of the shock on event dates.

<Table 1>

To establish an exogenous effect of trade policy, it is important to ensure that our event dates do not systematically mix trade policy announcements with other major macroeconomic

events that affect financial markets. We explicitly consider a potential impact from monetary policy. Regarding the initial 29 dates, we find one FOMC statement (August 1, 2018, without a change in the forecasted federal funds rate) and two further statements by Fed chair Jerome Powell (March 1, 2018, and August 23, 2019). Three events (March 1, 2018, August 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. As two US trade policy events fall together with Fed events and ISM releases, a total of 4 events is discarded from the 29 initial dates. Impulse responses to trade policy shocks remain largely unaltered when we add events of Fed info or ISM releases (see Section 5).

When the event takes place at the weekend (4 occasions), we specify the following Monday as the event day. When the policy announcement takes place in the evening after 4 pm CET when the New York stock exchange has closed we specify the following day as the event day. The resulting 25 event dates seem to be scattered randomly across weekdays (five on Mondays, six on Tuesdays, two on Wednesdays, six on Thursdays and six on Fridays) and do not follow an obvious pattern. This should further bolster the assumption of an unchanged variance for other shocks, such as regularly scheduled macro announcements (compare footnote 2 in Section 2.1).

2.3 Specification tests

We estimate the reduced form VAR with 6 variables in equation (1) with a lag length of one day, as suggested by the three information criteria: Bayes, Akaike and Hannan-Quinn. We obtain a stable VAR(1) 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 $\Sigma_1 = \Sigma_0$. This is tested via the test statistic

$$\text{vech}(\widehat{\Sigma}_1 - \widehat{\Sigma}_0)' \left(\frac{\widehat{V}_0}{T_0} + \frac{\widehat{V}_1}{T_1} \right)^{-1} \text{vech}(\widehat{\Sigma}_1 - \widehat{\Sigma}_0). \quad (6)$$

We compare this test statistic to a distribution obtained from a bootstrap sample where announcement and non-announcement dates are randomly assigned while retaining the number of announcement dates. By construction, this should give equal variance-covariance matrices for the two sets of dates in the bootstrap sample.

The second model assumption that we test states that there exists a single trade policy shock. We apply a recursive design wild bootstrap to obtain 2,000 samples that retain the given heteroskedasticity structure. This bootstrap multiplies the residuals with iid standard-normally distributed terms. Apart from testing the second model assumption we use this bootstrap to construct confidence intervals for impulse responses. As a robustness check, we also apply the bias-adjusted bootstrap from Neely (2016), which uses a moving block bootstrap of length 10 for non-announcement day residuals and a resampling of announcement dates residuals to maintain the assumed heteroskedasticity.

To test the assumption of a single trade policy shock, given by $\Sigma_1 - \Sigma_0 = b_1 b_1'$, we compare the test statistic on the RHS of (4) to its distribution in the bootstrap sample with maintained heteroskedasticity assumptions. A rejection of this null hypothesis would imply that our identification of a single trade policy shock is not valid. Table 2 displays the p-values of the two identification tests. Using our baseline specification with 25 announcement dates (i.e. all 29 dates without monetary policy announcements or ISM information releases), we can reject the null hypothesis of equal announcement and non-announcement dates and cannot reject the hypothesis of a single identified trade policy shock. The tests yield similar results when we use all 29 events, or exclude either monetary policy or economic data release dates.

<Table 2>

3 Results

We present results in this section in three steps. In the first two, we focus on the model-internal results. Section 3.1 discusses impulse responses for the baseline model and Section 3.2 provides historical and variance decompositions. In Section 3.3, we relate the identified structural shock series to external evidence.

3.1 Main model

Before we show the estimated responses to trade policy shocks, we first discuss the estimated structural shock series and then discuss the expected signs of the impact effects. Regarding the trade policy shocks, we see how well 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, i.e. 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 1. An example is the spike in March 2018, which occurs as the US department of commerce releases its report, finding that China is conducting unfair trade practices and tariffs on steel and aluminum are announced. The maximum peak occurs in August 2019 when the US government first announces a 10 percent tariff on additional \$300 billion of imports from China, then revises the level to 15 percent instead and on top announces a future tariff increase on already taxed goods from China.

<Figure 1>

Regarding the expected signs of the impact effects, we expect that restrictive trade policy shocks affect asset prices in two main ways. First, they are bad news for the US and world economy. Second, they increase uncertainty. The two parts may either reinforce or offset each other, depending on the asset price we look at. We expect that stock market indices are generally

affected negatively by both components. While higher uncertainty is likely to depress all stock prices as risk premia rise, changes in relative prices of international trade may lower large firm stock prices more than those of smaller firms, because they are more likely to operate internationally. Furthermore, pure negative news shocks will depress stock returns but leave the VIX unchanged, while uncertainty will impact predominantly the VIX but also stock prices.

With respect to short-term interest rates, announced tariff increases are likely to increase inflation and inflation expectations, thus prompting a contractionary response of monetary policy, while increases in uncertainty are typically offset by an accommodative reaction by the central bank. Longer-term rates more reflect growth and inflation expectations as well as safe haven demand. As restrictive trade policy news lower growth expectations but increase inflation expectations, their impact on the ten-year Treasury rate is *ex ante* ambiguous. In contrast, increases in uncertainty will unambiguously lower the longer end of the yield curve as investors' seek safety. Finally, news about slower future growth should tentatively weaken the currency, while increased competitiveness (due to tentatively rising tariffs, see also Erceg et al., 2018) and increased uncertainty may support the US-Dollar. *Ex ante* we expect that this tariff level effect and the uncertainty effect dominate the future growth argument.

Figure 2 shows the estimated dynamic impact of a scaled restrictive trade policy shock on the endogenous variables, together with 90% confidence bands.³ There is an immediate increase in uncertainty by 10.4%, which remains significantly above trend for about two weeks. Concerning the level effect on firm values, the shock leads to an instantaneous decline of the

³ As the 6-variable model only provides information about relative and not absolute effects, we need to scale the shock. For this purpose we use a 2-variable-model containing the S&P 500 and the VIX. This model with two variance regimes can be fully identified. We identify both columns of the *B* matrix of instantaneous impulse responses and the variance shifts in the high volatility regime. In the bivariate model, a restrictive event date trade policy shock (equivalent to a 1.4 standard deviations shock as the trade shock has a variance of 2.08 on event dates) increases the VIX by 10.44%. The standard deviation of the VIX is 26%, such that our normalization pertains to less than one half of a standard deviation change in the VIX. Normalizing our 6-variable model to this instantaneous response of the VIX, we get the impulse responses as shown in Figure 1. For details of the bivariate model, see the online appendix.

S&P 500 of about 0.82%, which remains significantly negative for 15 trading days; i.e. three weeks. A quick back-of-the-envelope calculation displays the gravity of this finding. The average S&P 500 market capitalization over our sample horizon is US\$ 23.0 trillion. This yields a wipe out on impact of around US\$ 184 billion after an average restrictive trade policy shock. It is equivalent to more than nine S&P 500 companies for which the median market capitalization is around US\$ 20 billion.

The impact on smaller firms covered by the Russell 2000 is about of the same size (-0.77%) but holds slightly shorter, such that these firms seem to be affected less. Additionally, for one-year treasuries, interest rates fall significantly on impact and persistently by about 2 basis points. This also holds for ten-year treasuries, which decline at impact by about 4 basis points. Finally, the US-Dollar appreciates by 0.3% instantaneously and then falls back over the next year, remaining above trend significantly for roughly six months; this indicates that increased competitiveness creates US-Dollar net demand and increased uncertainty creates demand for safe assets, such as the US-Dollar, which both dominate the decreased interest rates that make the US-Dollar c.p. less attractive. Overall, the trade policy shocks seem to resemble a convolute of relative price shocks and uncertainty shocks. The strong increase of the VIX, the significant decline in interest rates, and the US-dollar appreciation contribute to the picture that the uncertainty shocks may dominate.

<Figure 2>

3.2 Historical and variance decomposition

To further characterize the identified shocks and study their economic importance for specific asset prices during the sample period, we compute historical decompositions. They give the cumulative contribution of the trade policy shock to each variable at each point in time. Figure 3 shows the de-trended evolution of the endogenous variables (thick black line) and their

counterfactual evolution where only trade policy shocks are present (dashed grey line). These shocks explain the VIX quite precisely. Starting in 2018, from where on most policy announcements occur, the counterfactual evolution of the VIX tracks most of the peaks in the actual evolution. Whenever the VIX spikes, the trade policy shock accounts for this to a large extent. Historically, trade policy shocks seem to be the dominant force behind movements in uncertainty.

<Figure 3>

The shocks also contribute substantially to the evolution of stock prices, in particular of larger firms, over the sample horizon and track them closely for the greater part. Interestingly, the shocks contribute to the stock market decline at the end of 2018 but do not explain most of it, as it is the case for uncertainty. Other shocks not identified in our analysis must play an important role here.

For the ten-year rate, the trade policy shocks explain the secular movements during the second half of the sample to some extent, whereas they are largely irrelevant for the one-year rate and for the exchange rate, except for the very end of the sample. The latter observation may reflect offsetting forces, whereby trade policy shocks seem to weaken the outlook for the US economy and, thus, the US-Dollar, but simultaneously improve competitiveness and trigger a flight to safety, revaluing the currency.

While this eye-balling is already suggestive of an important uncertainty component in the shocks, we next quantify precisely their average economic importance. For this, we compute variance decompositions, which tell how much of the forecast error variance at various horizons is accounted for by trade policy shocks. We normalize the size of the trade policy shock to explain 41.6 % of the one day forecast error variance of the VIX. In the forecast error variance decomposition of the bivariate model with just the VIX and the S&P 500, the trade policy shock accounts for 83% of the variance in the one-day ahead forecast of the VIX. Relating this

substantial extent to the historical decomposition and putting it into perspective of our sample horizon for which the US-China trade dispute has been one if not the major determinant, we still opt to choose a more conservative normalization. While the exact degree of normalization is arbitrary, it is reasonable that explained variance will be clearly smaller in a larger model which accounts for other important variables. Thus, we go down from 83% to half of it, to be on the safe side. This methodologically necessary scaling is largely innocuous as we are mainly interested in the relative explanatory power.

Table 3 shows that the shock is important for understanding the high frequency movements of essentially all asset prices in the model. It explains 25.4% of the variance of the one-day ahead forecast of the S&P 500. This share should be judged in light of the 41.6% normalization on the VIX (and would be higher with larger normalization percentages). The share declines to 5.4% for 50 trading days and remains largely at that level. Numbers for the Russell 2000 are similar in their pattern but lower regarding their level. The explanation by trade policy shocks of the forecast error of the VIX remains relatively large and is still at 25% after 100 trading days.

<Table 3>

These numbers seem to reflect that trade disputes, in particular the US-China trade dispute, were one of the dominant themes for stock markets between 2017 and early 2020. Although this topic is still important, the covid-19-virus, with its severe economic consequences, is now dominating the debate. However, trade policy announcements regain attention, as the US government is uttering new tariff threats towards China as a response to China's strategy in dealing with the virus.

The explanatory power for both interest rates is at the same order of magnitude as the short-term one for the S&P 500 and not clearly limited to either short or long horizons. As mentioned above, the strong uncertainty affects the US-Dollar exchange rate whose forecast

error variance is explained to about 25% on the first day of shocks and still to about 16% in the long run. All in all, the results indicate that these shocks have a strong impact on stock prices, but the impact on implied stock market volatility and the consequences on interest rates and the exchange rate are even larger.

3.3 Comparison of estimated trade policy shocks with other measures

Another way to inform about our shocks, shown in Figure 1 above, is to compare them to other series capturing related information. We draw on external data for changes in tariff levels and in trade policy uncertainty. For each, we gather two series. For the tariff level comparison, we use the monthly US tariff changes on Chinese goods of Bown (2020) and the change in the average quarterly US tariff rate across all goods, which we calculate as the quarterly change in US customs duties as a ratio of US imports of goods. There is no apparent connection between the two level series and the estimated shocks (Figure A2), probably because the shocks capture mainly announcement dates.

For the uncertainty comparison, we take the updated trade policy uncertainty (TPU) index of Baker et al. (2016) and the TPU index of Caldara et al. (2020). Both indices result from counting newspaper article occurrences using search terms related to trade and uncertainty. Figure 4 shows two plots of these series, in each case in combination with our shock series. Both plots show a strong co-movement, indicating a positive contemporaneous correlation between the time series.

<Figure 4>

To analyze the relations between these series more formally, Table 4 shows contemporaneous and lead/lag correlations. Our shocks contemporaneously have the highest correlation with the two uncertainty series, and if there is a lag structure, our series tends to lead the others by one month although the lagged coefficients are insignificant. There is also a

consistently positive correlation with the monthly tariff rate, but it is low and far from significant. The sign pattern with the quarterly measure is inconclusive and insignificant.

<Table 4>

As Figure 4 and Table 4 suggest some positive lead of our shock series with respect to the other measures, we test for such a relation using Granger-causality tests. We use bivariate models containing our shock series, either at the monthly or quarterly frequency, and one of the other series at a time since the number of observations is relatively small in all cases. Results in Table 5 corroborate the initial impressions. There is no relation with the monthly tariff changes and a highly significant lead with respect to the quarterly average tariff rate change. But overall, the lead of changes in tariff levels is relatively weak, judged by the F-statistics which usually do not exceed one and the p-values which in five cases are far above any conventional significance levels. In contrast, there is a tighter lead relation with the trade policy uncertainty measures, in particular with respect to the one of Baker, Bloom & Davis (2016). For two lags the hypothesis of no Granger-causation is rejected at the 1% level, and for three lags the test statistic barely misses significance at the 10% level. For the measure of Caldara et al. (2020), the hypothesis is rejected at the 11% level for one lag.

<Table 5>

All in all, the results appear plausible as asset prices are likely to respond quicker to new information than daily or weekly newspapers and since announcements of tariff increases typically lead their implementation. From a policy perspective, the tentatively leading properties of our shock measure can be useful as it allows to detect and respond to economic shocks faster.

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. We build on the model developed above and estimate the potentially heterogeneous impact of trade policy shocks on individual firms, industries, and countries. Finally, we conduct a special case study for China.

Throughout the following, we use our 6-variables model as the basis and exchange the Russell 2000 index for the asset of interest. These asset prices are 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, the leading stock market indices of many larger countries in the world economy, and, finally, volatility indices for a range of stock market indices.

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 quite heterogeneously and negatively on average. The shocks lead to declining stock prices for 77% of firms, of which 46% decline significantly at the 10% level while merely 6% of S&P 500 constituents see their value increase significantly (see Appendix Figure A3). This indicates that the induced changes in relative prices translate into very heterogeneous changes in firms' stock prices, and that – in line with expected welfare losses of restrictive trade policy – most of the economy is negatively affected.

Industries. For the next analysis, we use the standard classification of the S&P 500 firms into 11 industry sectors in order to identify which industries are most affected by trade policy shocks, expecting that export orientation plays a role. For each of the 11 sectors, we run our model again, finding the pattern shown in Figure 5 which again shows quite some heterogeneity. For all 11 industries, the point estimates are negative, for 4 industries the effect is statistically significant. The most negatively affected industries are industrials, financials and materials, which are all internationally oriented industries. Consumer staples is the least

affected industry. The US 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 relative price changes due to increased tariffs affects industries differently: internationally oriented industries and those with closer ties to China, such as industrials, lose more value than domestically oriented industries.

<Figure 5>

Country returns. In the next part of the disaggregated analyses, we focus on the impact of trade policy shocks on other countries than the US. In a globalized world, one would expect that most other countries should also be negatively affected by US trade policy shocks. We take the full universe of 48 MSCI country indices for our calculations and the results in Figure 6 do indeed conform to our expectation. The figure shows results for all countries including the US S&P 500 response, ordered by the size of the point estimates. The effect for 42 of 48 countries is negative, for 19 countries it is statistically significant.

<Figure 6>

Looking at regional country groups, the Latin-American stock markets seem to be hardest hit. Also some close partners of the US are hit, but overall the pattern is much influenced by other country-specific determinants. Interestingly, the MSCI China index decreases by around 1.2%, and thus more than US stocks. This index captures 701 large and mid-cap Chinese companies, covering about 85% of China's stock market capitalization. Overall, the discussed country-related patterns make sense as the identified trade policy shocks mostly refer to US-China tensions.

Country volatilities. The prior analysis has shown that the identified trade policy shock resembles to a large extent an uncertainty shock. Next we regard further volatility indices apart from the VIX to judge if stock market indices of other countries experience a similar rise in volatility. Figure 7 shows that out of the instantaneous impulse responses available for 13

volatility indices all but two indices rise on impact following a US trade policy shock. 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 8% on impact. Moreover, volatility of emerging market stock prices (measured by the EM ETF) and of French stock prices (measured by the CAC 40) increase significantly by around 10% on impact. Thus, US trade policy shocks increase volatility also outside the US and China.

<Figure 7>

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 own measures. We have collected, from the same database as above, the 15 Chinese announcements that target the US, analyzing the impact of these trade policy shocks on the US (see Appendix Table A1 for a list of the events). The limited number of observations does not allow for identifying the shock in a 6-variables model precisely; we need to trim the model to include the two main variables, stock prices and option-implied volatility. Figure 8 demonstrates that a one standard deviation Chinese trade policy shock also has significant negative effect on the US economy, and these effects are precisely estimated. The effects are slightly larger than those of US trade policy shocks while the shape is largely comparable. The impact on stock prices appears more persistent when looking at the statistical significance, but this might also reflect fewer Chinese retaliation events that are on average of larger significance.

<Figure 8>

5 Robustness

We perform several robustness tests which show that our results are invariant to changes in trade policy battles, the selection of event dates, the bootstrap method, the sample size or the lag length in the SVAR. Results are shown in Appendix B.

6 Conclusions

The current US administration uses restrictive trade policies, in particular increased tariffs, as an instrument to support the domestic economy and possibly to assert US positions in general. Thus, unilateral trade policy is an increasingly important instrument. Current analyses of this instrument rely on trade-based models of the economy, on macro-analyses of increased uncertainty, or on short-term event studies. This leaves a gap for an approach that uses high-frequency data for clean identification of the shocks (as event studies), stretches the analysis over longer horizons (as macro models), and allows for two impact channels, i.e. uncertainty and changes in relative prices (as trade-based models). Therefore, 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.

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 output losses, which is not the intention of this policy. Disaggregated analyses further show that the significantly negative impact applies to almost half of S&P 500 firms and to several US industries, such that there is a highly heterogeneous impact on the US economy. We interpret this heterogeneity mainly as consequence of the change in relative prices. Variance decompositions as well as the appreciation of the US-dollar

suggest, however, that the associated increase in uncertainty is a possibly stronger force than the change in relative prices.

Moreover, this policy also negatively affects most countries of the world economy, by lowering stock market indices and increasing their volatility. Negative effects seem to be 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. While these results are not easy to rationalize, it may be possible those parts of the US economy that remain unaffected or even profit are not covered by our analysis (such as non-listed firms). Moreover, longer-term adjustments to these shocks, which are also not covered in our approach, may brighten the picture. One element could be that trade policy is a (temporary) tool to realize advantages in other policy areas.

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Figure 1: Monthly aggregated and standardized US trade policy shock series

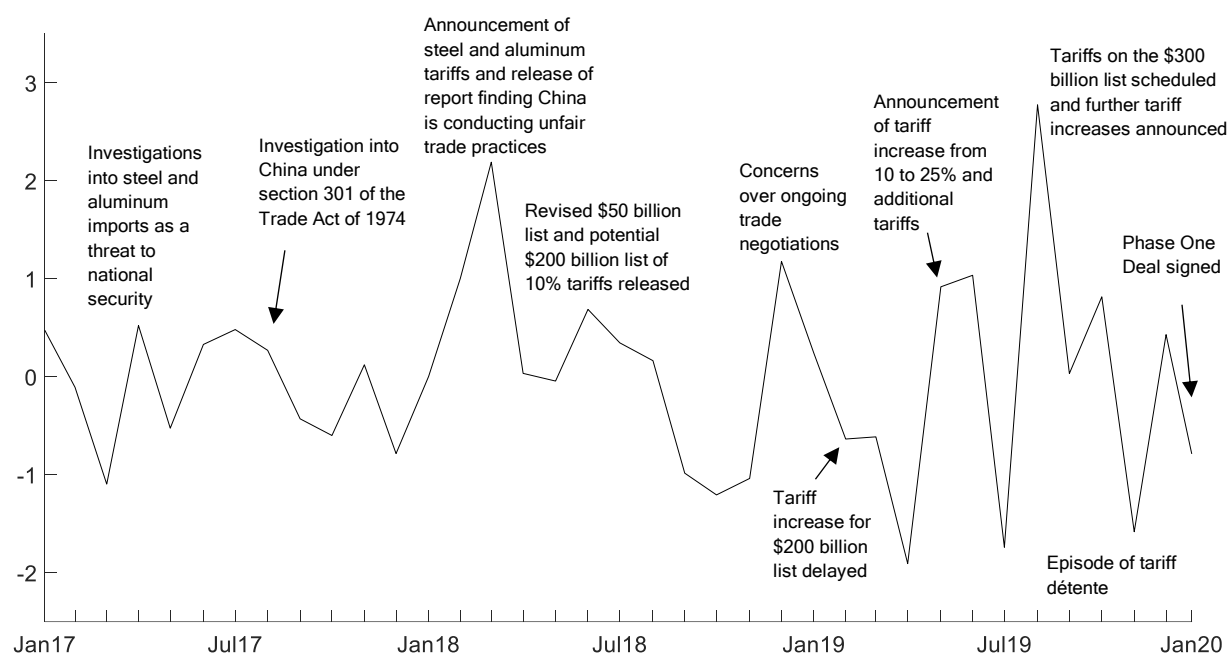
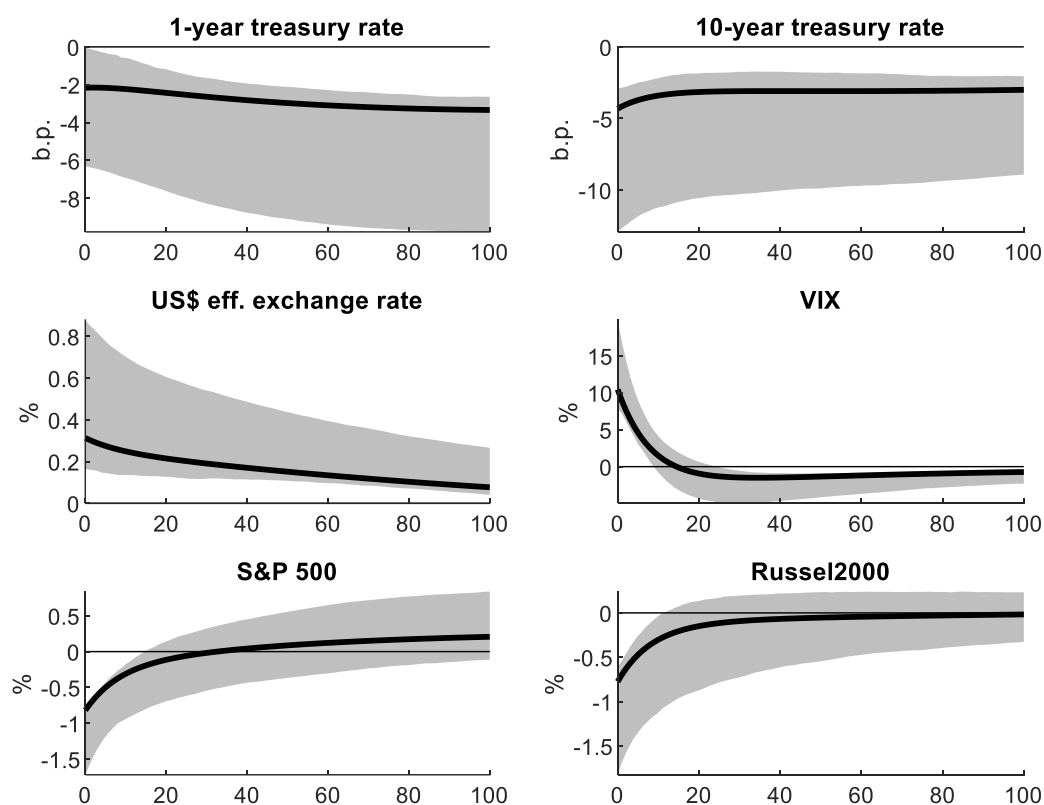
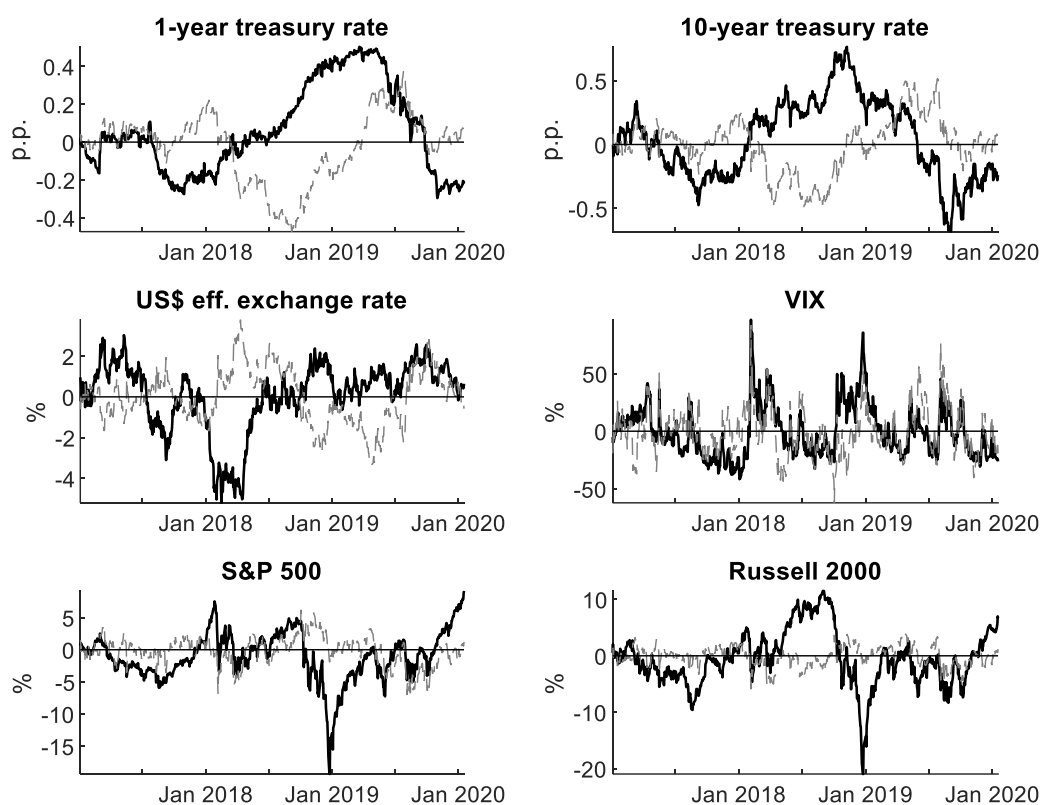


Figure 2: Estimated impulse responses to US trade policy shock in baseline model



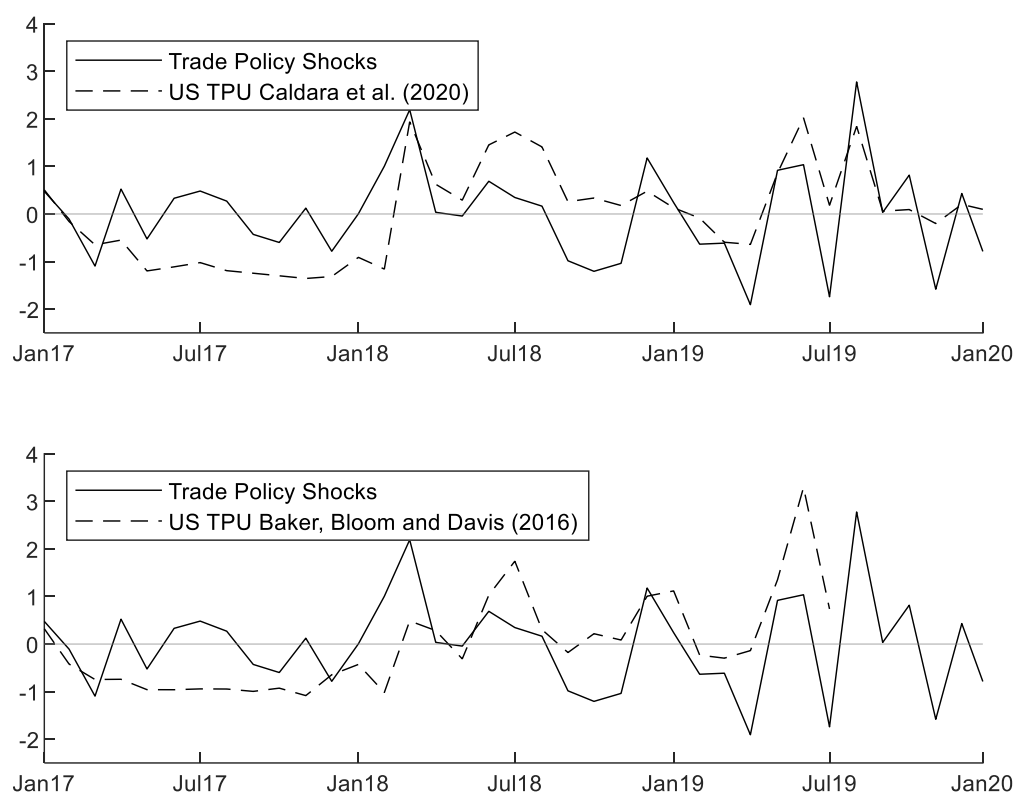
Notes: The figure shows impulse responses to a restrictive US trade policy shock in the high-volatility regime. The event-date shock is normalized to change the VIX by 10.44% as in the bivariate model laid out in the appendix. 90% residual wild bootstrap confidence intervals with sample size 2,000.

Figure 3: Historical decomposition



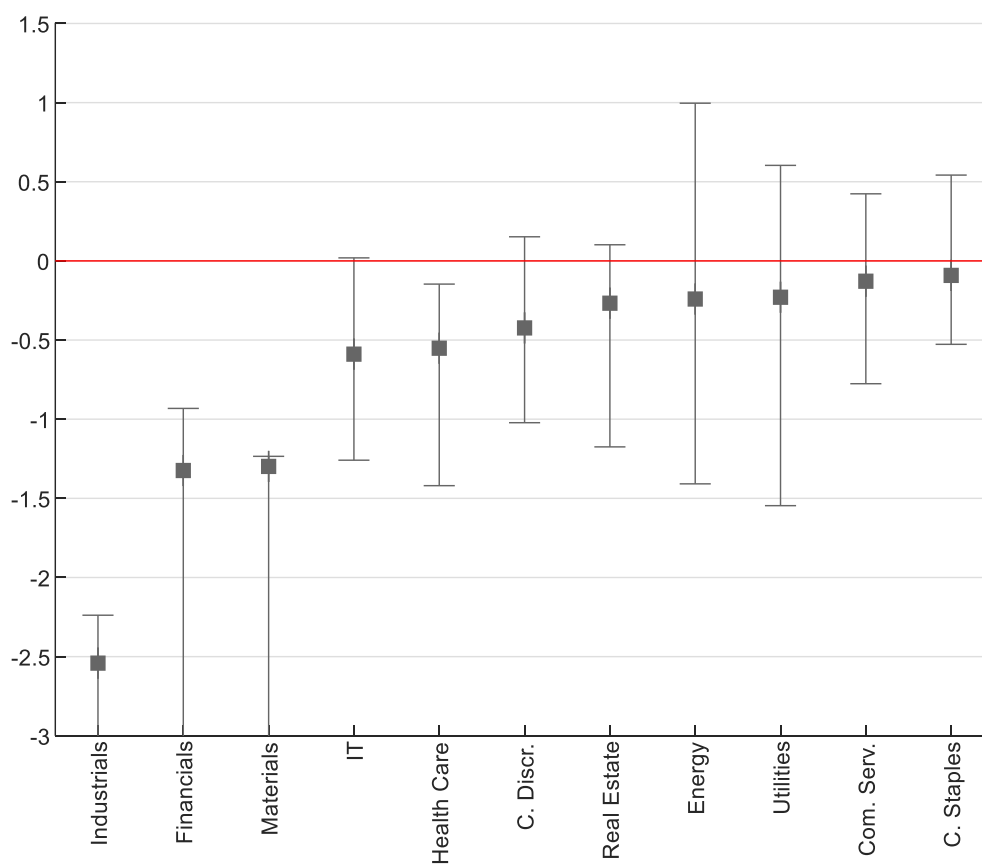
Notes: The thick black line is the actual observed evolution of the non-deterministic part of each variable obtained from its reduced form moving average representation. The y-axis shows the deviation from the deterministic part in levels. The grey dashed line shows the part that is only explained by the trade policy shock obtained from the structural moving average representation where all shocks except the trade policy shock are muted.

Figure 4: Monthly US trade policy shock series and US trade policy uncertainty measures



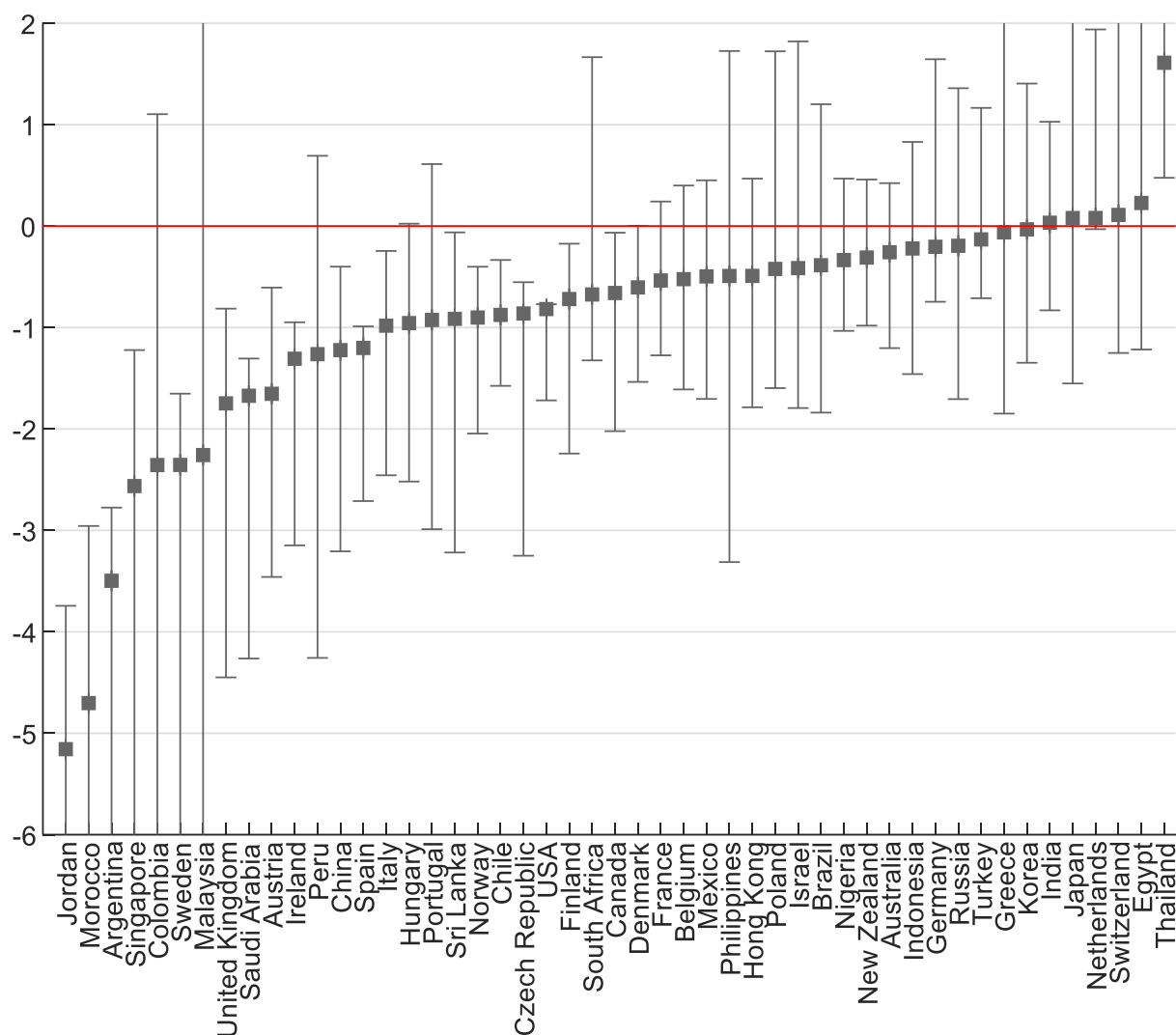
Notes: The dashed lines show monthly standardized measures of US trade policy uncertainty (TPU). Both series are based on daily newspaper coverage frequency. An increase in the series means a relatively increased occurrence of articles concerning trade policy uncertainty. Baker, Bloom and Davis (2016) search for the joint occurrence of words related to economic policy uncertainty and trade policy while Caldara et al. (2020) look for trade policy and uncertainty-related words that are in close range to each other within an article. Baker, Bloom and Davis (2016) use 10 major US newspapers while Caldara et al. (2020) use 7 major US newspapers.

Figure 5: Impact responses of S&P sector indices to a US trade policy shock



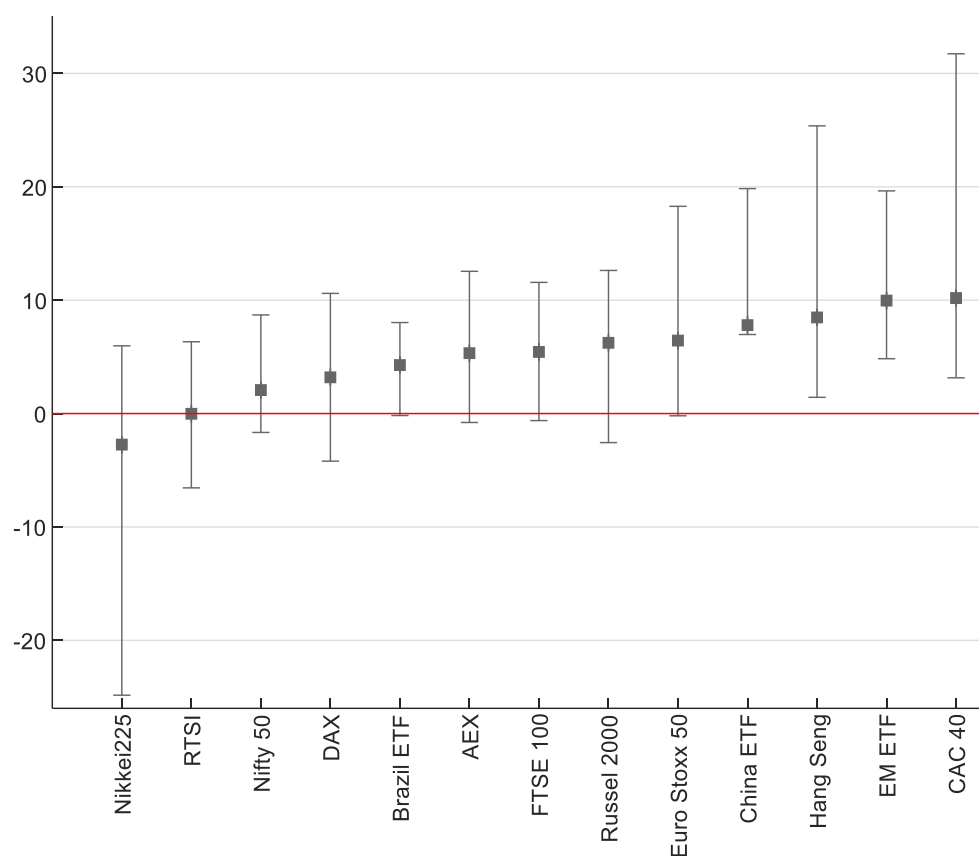
Notes: Estimates are obtained from the 6-variable model where the log Russell 2000 is exchanged for the log S&P 500 sector indices in turn. The response by the VIX is scaled to -10.44% representing an event-day trade policy shock. C. Discr. is consumer discretionary, Com. Serv. are communication services and C. Staples are consumer staples. 25 baseline events and 90% bootstrap confidence intervals are used.

Figure 6: Impact responses of MSCI country indices to a US trade policy shock



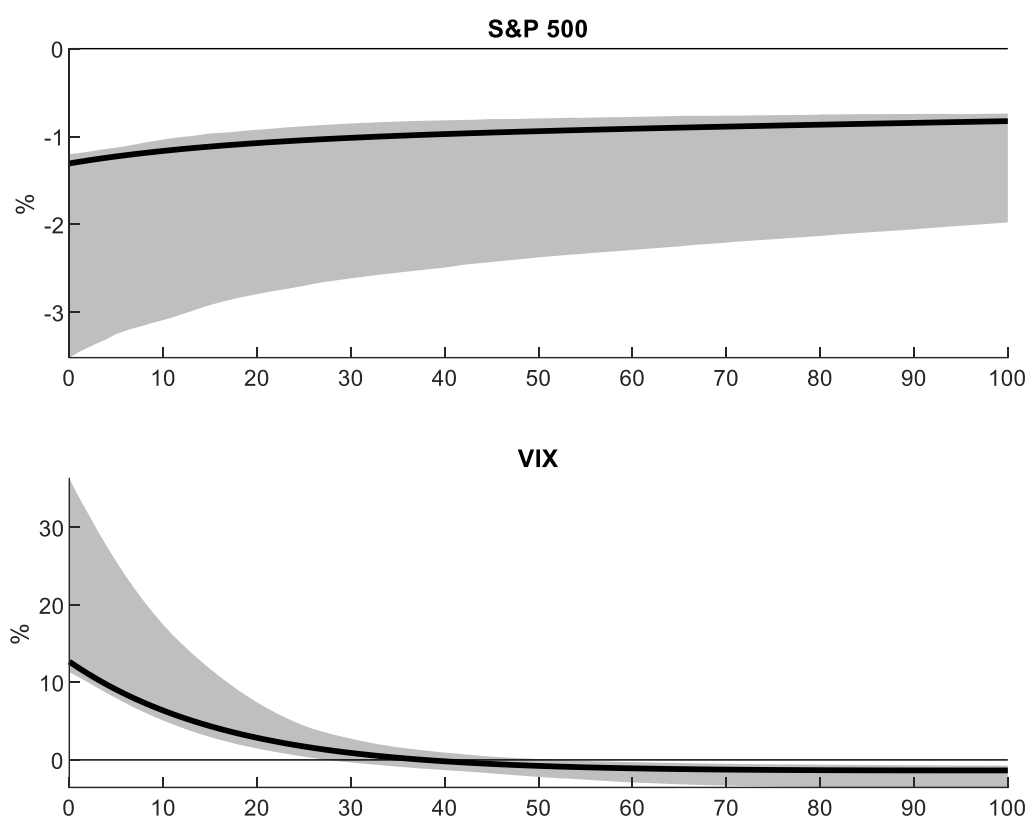
Notes: Estimates are obtained from the 6-variable model where the log Russell 2000 is exchanged for the log MSCI country indices in turn. Due to time differences we specified mid-day US date t events at date $t+1$ for the residuals from the regression of the MSCI country index on the other variables in the VAR for the following countries: India, Indonesia, Korea, Malaysia, Philippines, Sri Lanka, Thailand, China, Hong Kong, Japan, Singapore, New Zealand and Australia. The US response is the S&P 500 response from the baseline model in Figure 1. 25 baseline events are used. 90% bootstrap confidence intervals.

Figure 7: Impact responses of various volatility indices



Notes: Estimates are obtained from the 6-variable model where the log Russell 2000 is exchanged for the log volatility indices in turn. The indices measure the 30-calendar-day expected volatility for the following stock market indices that are ordered by impact size: Nikkei 225 (Japan), RTSI (Russia), Nifty 50 (India), DAX (Germany), Brazil ETF, AEX (Netherlands), FTSE 100 (UK), Russel 2000 (US), Euro Stoxx 50 (Euro Zone), China ETF, Hang Seng (Hong Kong), EM ETF (Emerging Markets), CAC 40 (France). Due to time differences we specified mid-day US date t events at date $t+1$ for the residuals from the volatility regression in the VAR for the following indices: Nikkei 225, Nifty 50, China ETF and Hang Seng. 25 baseline events are used. 90% bootstrap confidence intervals.

Figure 8: Estimated impulse responses to Chinese trade policy shock



Notes: The figure shows impulse responses to a restrictive trade policy shock in the high-volatility regime. Identification of the trade policy shock is based on 15 Chinese announcement dates using the bivariate model described in the appendix. The grey areas show 90% residual wild confidence intervals with sample size 2,000.

Table 1: US trade policy announcement dates

Date	Event	S&P 500 reaction (% change)
4/20/2017	President Trump instructs Commerce Secretary Wilbur Ross to self-initiate an investigation into whether steel imports threaten US national security under Section 232 of the Trade Expansion Act of 1962.	0.76
4/27/2017	President Trump instructs Commerce Secretary Wilbur Ross to self-initiate an investigation into whether aluminum imports threaten US national security.	0.06
8/18/2017	US Trade Representative Robert E. Lighthizer self-initiates an investigation of China under Section 301 of the Trade Act of 1974.	-0.18
2/16/2018	The Department of Commerce releases its reports finding imports of steel and aluminum products threaten US national security under the rarely used Section 232 of the Trade Expansion Act of 1962.	0.04
3/1/2018	President Trump announces forthcoming tariffs on all trading partners of 25% on steel and 10% on aluminum.	-1.33
3/8/2018	President Trump issues formal steel and aluminum tariff proclamations effective March 23, but exempts Canada and Mexico, pending his view of the outcome of the North American Free Trade Agreement (NAFTA) renegotiation talks.	0.45
3/22/2018	The Trump administration releases report finding China is conducting unfair trade practices related to technology transfer, intellectual property, and innovation. Trump indicates forthcoming tariffs.	-2.52
4/3/2018	The Trump administration releases its \$50 billion list of 1,333 Chinese products under consideration for 25% tariffs, which covers \$46.2 billion of US imports.	1.26
4/5/2018	President Trump instructs trade officials to consider whether an additional \$100 billion of US imports from China should be subject to new tariffs.	0.69
5/20/2018	China and the US strike a trade agreement; the US will suspend plans to slap tariffs on up to \$150 billion goods. China will halt the imposition of retaliatory tariffs.	0.74
5/29/2018	The White House releases a statement that it would impose tariffs on the \$50 billion list of goods from China.	-1.16
6/15/2018	The US Trade Representative releases a revised list of products on which it plans to impose 25% tariffs, in two phases, starting July 6, 2018.	-0.10
6/18/2018	In response to China's retaliatory tariffs announced on June 15, 2018, President Trump directs the US Trade Representative to identify an additional \$200 billion worth of Chinese goods for a 10% tariff rate.	-0.21
7/10/2018	Following up on the June 18 request, the US Trade Representative releases a list of \$200 billion of imports from China to be subjected to new 10% tariffs after public hearings in August.	0.35
7/16/2018	The US Trade Representative files separate disputes at the WTO against Canada, China, the EU, Mexico, and Turkey, challenging the tariffs each WTO member imposed in response to US aluminum and steel trade actions meant to protect US national security interests.	-0.10
7/20/2018	In an interview, President Trump says he is ready to impose tariffs on all US imports from China, which totaled \$504 billion in 2017.	-0.09
8/1/2018	The US Trade Representative considers a 25% tariff rate rather than 10% on the \$200 billion list of imports from China.	-0.10
8/7/2018	The US administration releases a revision (removal of 5 products) to the second phase of its \$50 billion list of 25% tariffs effective on August 23.	0.28
9/17/2018	President Trump finalizes the list of products on \$200 billion of imports from China scheduled to be subject to a 10% tariff going into effect on September 24. Trump also announces the rate will increase to 25% on January 1, 2019.	-0.56

12/1/2018	China and US agree to a temporary truce to de-escalate trade tensions; both refrain from increasing tariffs or imposing new tariffs for 90 days.	1.09
2/24/2018	President Trump announces via Twitter that he will delay the tariff increase on \$200 billion of imports from China that had been scheduled for March 1, 2019. The 10% tariffs would have been raised to 25%.	0.12
5/5/2019	President Trump tweets (later officially confirmed) that the US will increase the 10% tariff on \$200 billion of imports from China to 25% on May 10, 2019. He also indicates he will “shortly” impose 25% tariffs on the rest of US imports from China not yet targeted with his Section 301 tariffs.	-0.45
8/1/2019	President Trump says the United States would impose a 10% tariff on an additional \$300 billion of imports from China, going into effect on September 1, 2019.	-0.90
8/13/2019	The Trump administration plans to impose the new 10% tariff on just \$112 billion of imports from China starting September 1, 2019, delaying the additional tariffs on \$160 billion to December 15, 2019.	1.45
8/23/2019	President Trump says he would apply a 15% tariff, not 10%, on the \$112 billion list on September 1 and the \$160 billion list on December 15. He also says the current 25% tariff on \$250 billion of Chinese goods would increase to 30%, starting October 1.	-2.59
9/11/2019	President Trump plans to delay his tariff increase on \$250 billion of Chinese imports from 25 to 30%, originally set out on August 23, 2019, from October 1 to October 15.	0.72
10/11/2019	President Trump announces the October 15 tariff increase on \$250 billion of US imports from China (25% raised to 30%) will not go ahead as planned. He also states negotiations had resulted in a forthcoming “substantial phase one deal” with China, “subject to getting it written.”	1.09
12/13/2019	President Trump calls off the scheduled December 15 tariff increase and indicates his administration and China have reached agreement on the legal text of an 86-page deal that will be signed in January 2020.	0.01
1/15/2020	China and the US sign the “Phase One Deal”. Under the agreement, China agrees to purchase the amount of an additional \$200 billion worth of US exports. Most tariffs remain in effect.	0.19

Notes: Announcement dates from Battles #2 (steel and aluminum as national security threats) and #3 (unfair trade practices for technology, intellectual property (IP)). We selected 29 dates on which the US announces a change in trade policy concerning its trading partner China. The baseline specification uses 25 days, discarding March 1, 2018 (ISM Manufacturing Index (ISMMI) release and FED chair speech), August 1, 2018 (FOMC meeting and ISMMI release), August 1, 2019 (ISMMI) and August 23, 2019 (FED chair speech). Source: Bown and Kolb (2020).

Table 2: Specification tests

Hypothesis	Wald statistic	Bootstrap p-value
25 baseline announcement dates		
$\Sigma_0 = \Sigma_1$	42.80	0.081
$\Sigma_1 - \Sigma_0 = b_1 b_1'$	121.48	0.141
26 dates: no FED announcements		
$\Sigma_0 = \Sigma_1$	48.14	0.048
$\Sigma_1 - \Sigma_0 = b_1 b_1'$	88.89	0.383
26 dates: no ISM releases		
$\Sigma_0 = \Sigma_1$	42.46	0.083
$\Sigma_1 - \Sigma_0 = b_1 b_1'$	111.90	0.199
29 announcement dates		
$\Sigma_0 = \Sigma_1$	49.10	0.039
$\Sigma_1 - \Sigma_0 = b_1 b_1'$	65.55	0.624

Notes: Wald statistic 1 displayed in equation (6). In each sample the variance-covariance matrix is calculated over all observations. The bootstrap uses 2,000 draws. Wald statistic 2 is displayed in equation (4).

Table 3: Forecast Error Variance Decomposition for the 6-variable model

Horizon in days	One Year Treasury	Ten Year Treasury	US\$ eff. Ex. Rate	VIX	S&P 500	Russell 2000
1	24.6	29.7	24.7	41.6	25.4	15.4
5	25.1	28.7	23.1	37.3	21.0	12.0
10	26.0	28.0	21.6	32.5	16.6	9.2
50	35.2	28.6	18.3	24.5	5.4	3.7
100	40.0	29.5	17.3	25.0	4.4	2.9
150	40.0	28.7	16.6	24.4	5.2	2.7
600	30.3	20.5	16.5	23.5	5.9	2.7

Notes: The size of the trade policy shock is normalized to account for 41.6% of the variance of the one-day-ahead forecast of the VIX.

Table 4: 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	Baker, Bloom & Davis (2016)	Caldara et al. (2020)
-1	0.053 (0.762)	0.110 (0.748)	0.185 (0.327)	0.083 (0.635)
0	0.083 (0.632)	-0.207 (0.518)	0.301* (0.099)	0.470*** (0.004)
1	0.068 (0.697)	-0.490 (0.126)	-0.210 (0.264)	-0.137 (0.434)

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 the trade policy uncertainty measures from Baker, Bloom and Davis (2016) and Caldara, Iacoviello, Molliigo, Prestipino and Raffo (2020) at various lags. Lag -1 shows the correlation of the trade policy shock series lagged 1 month with the other four series. Coefficients are labelled according to significance (***p<0.01, **p<0.05, *p<0.1).

Table 5: Granger-causality tests

Granger-caused	Lags	3	2	1
Monthly US tariff change on Chinese goods	F-statistic	0.781	0.885	0.072
	p-value	(0.673)	(0.643)	(0.788)
Quarterly US aver. tariff rate change	F-statistic	13.645***	(0.169)	0.163
	p-value	(0.003)	(0.912)	(0.687)
Baker, Bloom & Davis (2016)	F-statistic	6.000	9.161**	0.073
	p-value	(0.112)	(0.010)	(0.787)
Caldara et al. (2020)	F-statistic	1.542	1.552	2.630
	p-value	(0.673)	(0.460)	(0.105)

Notes: F-statistics and p-values for the test whether our monthly (or quarterly) trade policy shock Granger-causes in bivariate models the monthly changes in US tariffs on Chinese goods, the quarterly changes in average US tariff rates on all goods, the trade policy uncertainty measures from Baker, Bloom and Davis (2016), and the trade policy uncertainty index from Caldara, Iacoviello, Molliigo, Prestipino and Raffo (2020), respectively, at lags 1 to 3. Coefficients are labelled according to significance (***p<0.01, **p<0.05, *p<0.1).

ONLINE APPENDIX

to

The multifaceted impact of US trade policy on financial markets

APPENDIX A

A description of the list of announcements

Table 1 lists all 29 announcement dates from the PIIE. The first two took place in April 2017, when the US started investigations concerning a threat to national security via steel and aluminum imports. It took almost one year, until February 16, 2018, before the Department of Commerce proclaimed that national security was indeed threatened. Subsequently, on March 1, 2018, President Trump announced 25% tariffs on steel and 10% tariffs on aluminum, followed by a formal tariff proclamation the week after. The statement includes the imposition date March 23, 2018, which we do not list as an announcement date here.

The first trade policy reversal directed solely at China was enacted on August 18, 2017, with an investigation of Chinese policies under Section 301 of the Trade Act of 1974. Seven months later, on March 22, 2018, the ensuing report was issued, finding that China is conducting unfair trade practices. This established a first basis for the imposition of tariffs.

At the beginning of April 2018, the US government announced a \$50 billion list of Chinese products on which it was considering a 25% tariff. Moreover, President Trump initiated further investigations to consider tariffs on an additional \$100 billion of imports from China. After a short trade agreement, which held for one week, at the end of May 2018, the US released a revised version of the \$50 billion list that was scheduled to be taxed in two phases, the first starting on July 6, 2018. On June 18, 2018, the US started another investigation concerning an additional \$200 billion of Chinese goods subject to a 10% tariff rate. This list was published on July 7, 2018. Later that month, the US filed cases at the WTO against China and other countries, with President Trump stating in an interview that he was ready to impose tariffs on all imports from China. On August 1, 2018, the US Trade Representative stated that the tariff on the proposed \$200 billion list would be set to 25% instead of the initial 10%. One week later, a

revision to the second phase of the \$50 billion list was made by increasing the tariff for the remaining \$16 billion of goods to 25%. Finally, in mid-September 2018, the \$200 billion list was scheduled to go into effect on September 24 with 10% tariffs; subsequently increasing to 25% effective January 1, 2019. After an agreed truce in December, the US government refrained from increasing tariffs in January. In late February, President Trump declared that the 25% tariff rate would be further postponed.

The trade dispute escalated once more on May 5, 2019, when President Trump tweeted that the tariff rates on the \$200 billion list would increase to 25% effective May 10 and that all other imports from China not yet targeted under Section 301 were to be taxed at 25%. The US government confirmed this tweet on the same day.

The next US trade policy announcement took place on August 1, 2019, when President Trump declared a 10% tariff on an additional \$300 billion list of Chinese goods, starting on September 1, 2019. On August 13, 2019, the US government announced concrete plans for the list with a 10% tariff on \$112 billion of goods starting in September and delaying tariff enactment for the remaining goods to mid-December 2019. Ten days later, on August 23, 2019, President Trump announced to tax the \$300 billion at 15% instead of 10%. Moreover, he declared to increase the 25% tariff on \$250 billion of Chinese goods to 30% on October 1.

After going through with the September tariffs, the trade war began to deescalate on September 11, when President Trump announced to move the October tariff increase two weeks further into the future. Then on October, the tariff increase was canceled, and Trump announced a forthcoming trade agreement, the “Phase One Deal”. Chances of a successful agreement were raised on December 13, 2019 when the US President withdrew the planned mid-December tariffs. The “Phase One Deal” was finally signed on January 15, 2020, the last event day in our sample. China agreed to import additional \$200 billion of US goods and services over the next two years while most existing tariffs remained in place.

A simple bivariate model

Due to the unity normalization of the difference in variances of the trade policy shock between the two regimes (see equation 3), we need to scale the shock. To find a suitable scaling, we estimate a bivariate SVAR model that is fully identified via heteroskedasticity relying on the same split between announcement and non-announcement dates. We estimate the model series on the log S&P 500 and the log VIX. The structural shocks are related to the reduced form shocks as in the 6-variable model via $u_t = B \varepsilon_t$. We assume that the structural shocks have variance 1 on non-announcement dates and variance Λ on announcement dates. This yields the following two variance-covariance matrices for non-announcement and announcement dates, respectively:

$$\Sigma_0 = BB' \text{ and } \Sigma_1 = B\Lambda B' \text{ with } \Lambda = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix},$$

where λ_1 denotes the relative variance of the first shock and λ_2 the relative variance of the second shock on event dates compared to non-event dates for which the variances are normalized to 1. These two systems yield 6 unknowns (four elements in B and λ_1 and λ_2) and 6 knowns (three distinct elements each in Σ_0 and Σ_1). Hence, we can identify the system fully.

We obtain the following parameters:

Parameter	Value
b_1	$\begin{pmatrix} -0.0041 \\ 0.0723 \end{pmatrix}$
$\begin{pmatrix} \lambda_1 \\ \lambda_2 \end{pmatrix}$	$\begin{pmatrix} 2.08 \\ 1.00 \end{pmatrix}$

Using b_1 , $\begin{pmatrix} \lambda_1 \\ \lambda_2 \end{pmatrix}$, and the estimated reduced-form VAR parameters A_j from equation (1) in section 2.1, the response of the variables Y_t to the structural shock can be traced over time using the relations

$$\theta_h = \begin{cases} \Phi_h \sqrt{\Lambda} b_1, & h = 1, 2, \dots \text{ for event date shocks} \\ \Phi_h b_1, & h = 1, 2, \dots \text{ for non - event date shocks} \end{cases} ,$$

where θ_h is a $(K \times 1)$ vector of structural impulse responses for the propagation horizon h . The coefficients $\Phi_i = \sum_{j=1}^i \Phi_{i-j} A_j$ can be computed recursively starting with $\Phi_0 = I_K$ (compare Lütkepohl, 2005, Section 2.1.2).

We normalize the impulse vector for the trade policy shock b_1 in the 6-variable model to affect the VIX by 0.072 as in the bivariate model. Relying on $\lambda_1 = 2.08$, we obtain an instantaneous impact of 0.1044 (10.44%) on the VIX for event days, i.e. the high-volatility regime. The effect on the S&P 500 is then -0.82%, close to the effect in the bivariate model. Figure A1 shows the impulse responses to a restrictive trade policy shock on event dates in the bivariate model.

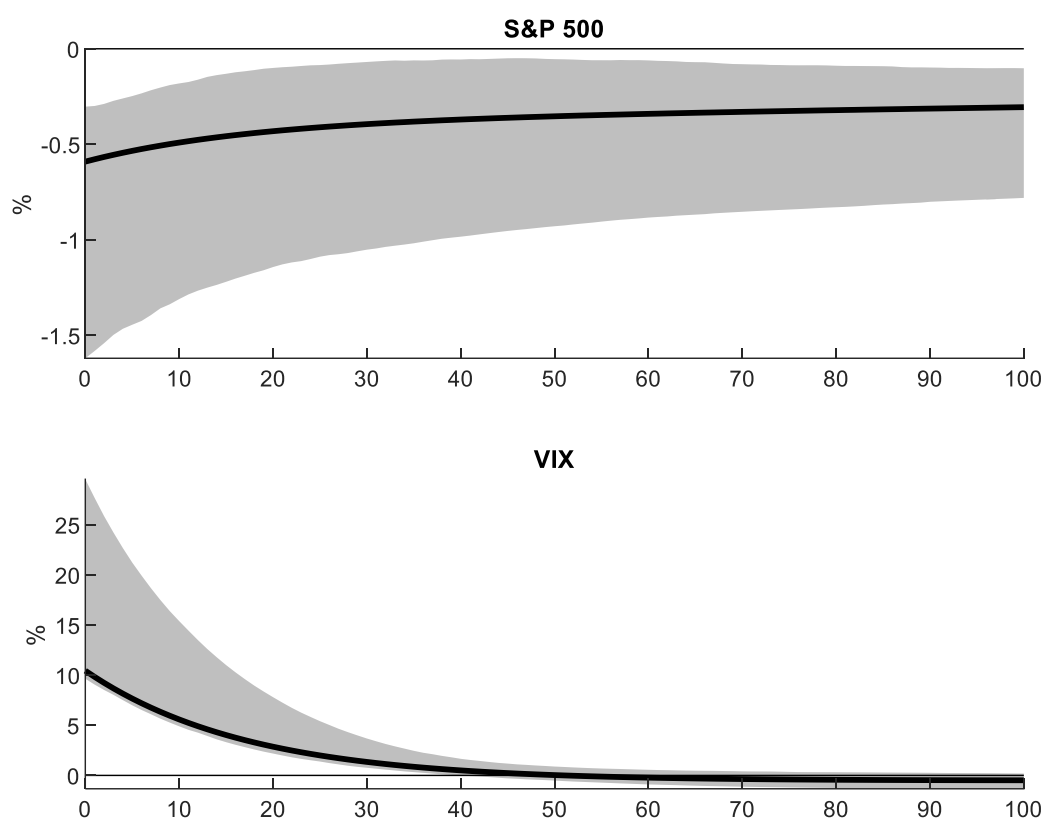
<Figure A1>

Estimating the model on the residual-wild bootstrap sample with maintained heteroskedasticity structure, the mean of λ_2 is 1.01 and the mean of λ_1 is 2.73. This implies that the variance of the second shock does indeed not change. In the six-variable model, we assume that the variances of five residual unidentified shocks do not change on announcement dates.

References

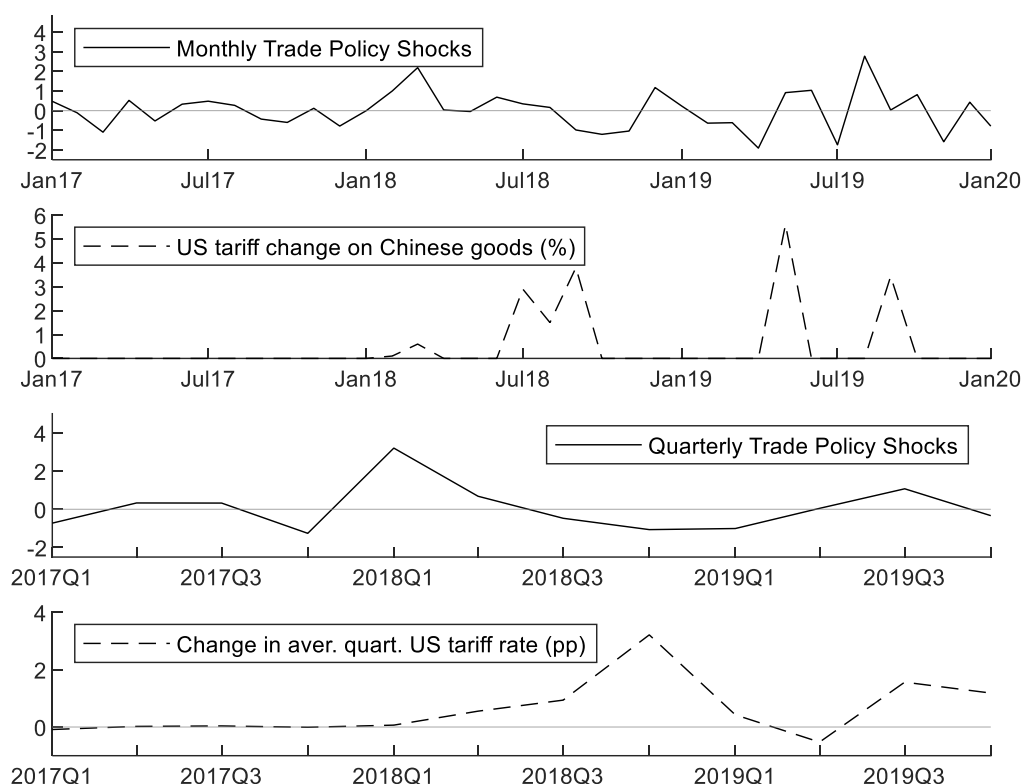
Lütkepohl, Helmut. 2005. New Introduction to Multiple Time Series Analysis. Springer-Verlag, Berlin.

Figure A1: Estimated impulse responses to US trade policy shock in the bivariate model



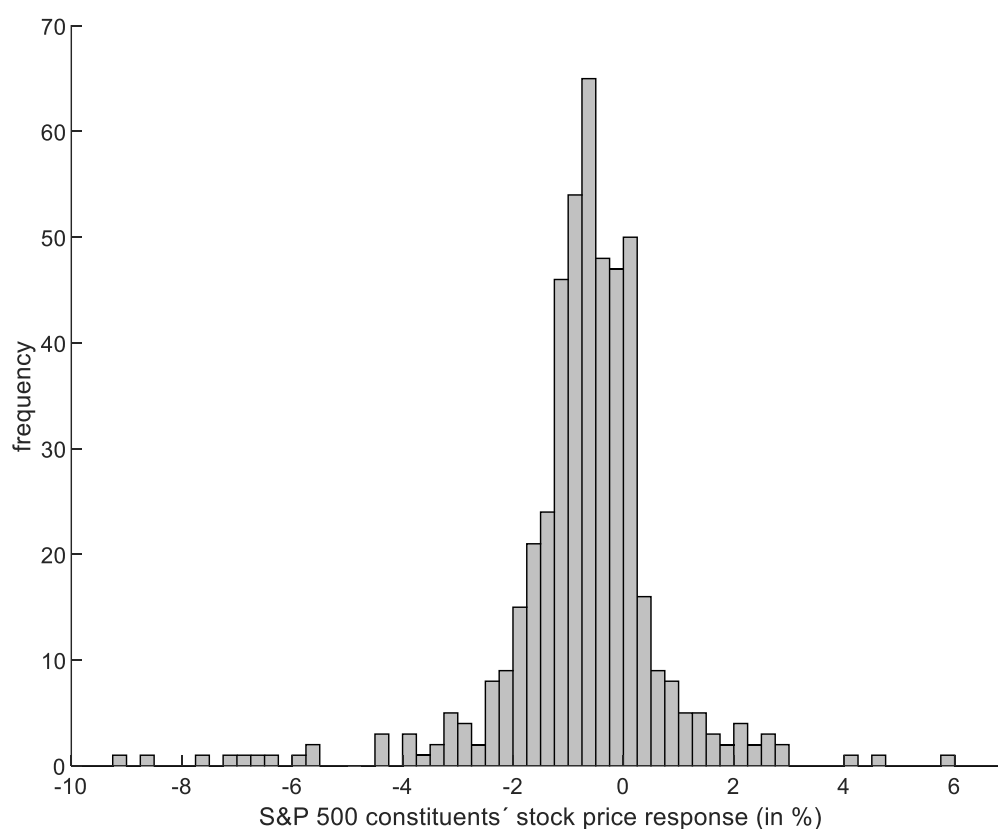
Notes: Trade policy shock in the high-volatility regime (on event dates). Identification is based on 25 announcement dates and 90 % residual-wild bootstrap confidence intervals are used.

Figure A2: US trade policy shock series and US tariff rates



Notes: The solid lines show the trade policy shocks aggregated at monthly and quarterly frequency. The data for monthly US tariff changes on Chinese goods comes from Bown (2020). The change in the average quarterly US tariff rate across all goods is calculated as the quarterly change in US customs duties as a ratio of US imports of goods (CD/IM). Both series are seasonally adjusted. Customs duties data come 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).

Figure A3: Impact responses of S&P 500 stock prices to restrictive US trade policy shock



Notes: Estimates are obtained from the 6-variable model where the log Russell 2000 is exchanged for each log S&P 500 constituent in turn. The response by the VIX is scaled to -10.44% representing an event-day trade policy shock. The number of observations is 482. The mean response over all stock prices is -0.97% with 76.76% negative responses. 242 responses, that is 46.47%, are significantly negative at the 90% level. 6.02% of responses are significantly positive at the 90% level. 3 responses are smaller than -10% and not shown in the graph. 25 baseline events are used.

Table A1: Chinese trade policy announcement dates

Date	Event	S&P 500 reaction (% change)
2/5/2018	The Chinese government self-initiates antidumping and countervailing duty investigations of roughly \$1 billion of US exports of sorghum. While this is not an explicit retaliation linked to Trump's tariffs on solar panels and washing machines, the coincidence of timing suggests a repeat of China's retaliatory response to President Obama's imposition of a safeguard tariff on tires in September 2009.	-4.10
4/2/2018	China imposes retaliatory tariffs on US products, worth \$2.4 billion in export value in 2017. This compares to the US steel and aluminum tariffs covering Chinese exports worth \$2.8 billion in 2017.	-2.23

4/4/2018	China publishes its list of 106 products subject to forthcoming 25% tariffs as retaliation for Trump's Section 301 tariffs, covering \$50 billion of China's imports from the US.	1.16
4/17/2018	The Chinese government announces preliminary antidumping duties of 178.6% on imports from the US of sorghum.	1.07
5/18/2018	China's Commerce Ministry announces end of tariffs on US sorghum during negotiations to resolve trade disputes.	-0.26
6/15/2018	China issues an updated \$50 billion retaliation list of 25% tariffs.	-0.10
8/3/2018	China warns it could add duties of 5 to 25% on \$60 billion of US goods following Trump's threat to raise proposed tariff rates on \$200 billion of Chinese goods from 10 to 25% as well as potentially cover all \$500 billion of imports from China with tariffs.	0.45
8/8/2018	China revises the second tranche of its June 15 list of \$50 billion of imports from the United States with which it planned to impose 25% tariffs.	-0.03
8/14/2018	China's Commerce Ministry announces a formal case alleging that US tariffs have damaged China's trade interests.	0.64
9/18/2018	China announced its plan to place tariffs on \$60 billion of US exports if Trump goes ahead with his recently finalized tariffs on \$200 billion of Chinese exports.	0.54
12/1/2018	China and US agree to a temporary truce to de-escalate trade tensions; both refrain from increasing tariffs or imposing new tariffs for 90 days.	1.09
5/13/2019	In retaliation for President Trump's tariff rate increase on May 10, China announced that on June 1, it intends to increase the tariff rate covering some of the \$60 billion of US exports it had already hit in September.	-2.41
8/23/2019	China releases its plan to retaliate on \$75 billion of US exports, effective September 1 and December 15, 2019, in response to Trump's forthcoming tariffs on \$300 billion of Chinese goods.	-2.59
9/11/2019	China announces it will exclude 16 products (less than \$2 billion of US exports) from its retaliatory tariffs imposed in 2018, such as some animal feeds, chemicals, and petroleum products.	0.72
1/15/2020	China and the US sign the "Phase One Deal". Under the agreement, China agrees to purchase the amount of an additional \$200 billion worth of US exports. Most tariffs remain in effect.	0.19

Notes: Shaded fields are from PIIE Battle #1, the remainder are from Battles #2 and #3.

APPENDIX B: Robustness tests

We show here the results of several robustness tests. They confirm that our main results hold qualitatively when we modify data and methods.

Trade policy battles. A crucial ingredient for identification is the set of event dates. In our baseline choice, we opt for announcement dates from Battles 2 and 3 of the PIIE catalogue of US trade war events. These dates include the most important events for US-China relations, where a total of more than \$500 billion of imports from China is considered. To check whether this decision is critical, we discard the events from Battle 2 “Steel and Aluminum” because these tariffs concerned not merely China. For example, steel exports from China to the US had already been largely restricted by antidumping duties beforehand. The impulse responses from 21 event dates from Battle 3 only look nearly identical to our baseline specification (green dashed line in Figure B1). A further check adds the first battle over solar panels and washing machine imports to the event list. This comprises the event dates October 31, 2017, and November 21, 2017, when the US International Trade Commission announced that imports of the two goods cause serious injury to the domestic industries producing them. The Commission recommended the imposition of tariffs, which President Donald Trump approved on January 22, 2018, yielding an additional event date. The tariffs concern around \$1.8 billion of imported washing machines (which may be imported not mainly from China), and \$8.5 billion of imported solar panels, for which China dominates the global supply. Impulse responses from the structural model with 28 announcement dates, capture by the yellow dash-dotted line in Figure B1, look almost identical to the benchmark specification.

<Figure B1>

Varying event dates. Our baseline specification excludes four events from the 29 policy announcements where either monetary policy news, important economic data releases, or both

reached the market. The red dotted lines in Figure B1 depict the impulse responses to a trade policy shock when we exclude three potentially confounding monetary policy events.⁴ The blue dashed line in Figure B1 depicts the specification where releases of the ISM Purchasing Manager Index are excluded. As further alternative, we include 6 imposition dates. This extends the number of event dates to 31 (green thin solid lines in Figure B1). These exclusions or inclusions do not alter our findings and show largely unchanged impulse responses. The full results including confidence bands for each set of event dates are shown in Figures B2-B6 of the online appendix.

<Figures B2-B6>

Bootstrap method. To test the robustness of our bootstrap method, we specify a more elaborate bootstrap method using a bias-adjusted estimator following Neely (2016). He replicates Wright’s (2012) findings and uses a bias-adjustment for the estimator, which is then also introduced into the bootstrapping for confidence intervals. The residuals are resampled from two sets, i.e. non-announcement and announcement residuals. Non-announcement residuals are sampled with a moving block bootstrap of length 10 while announcement date residuals are simply sampled with replacement. Hence, the assumed heteroskedasticity structure is maintained. A VAR is estimated for each bootstrap, where the bias is calculated as the difference between the average VAR regression parameters over all bootstraps and the VAR parameters of the OLS estimation on the original sample. The bootstrap for the confidence intervals uses the bias-adjusted VAR parameter and the same sampling of residuals to create novel samples. We estimate reduced form VARs on these samples and the instantaneous impulse vector b_1 to create a large set of impulse responses for inference. Figure B7 displays the impulse responses and confidence bands from this bootstrap technique. Results are almost

⁴ On March 1, 2018, Fed chair Jerome Powell testified before the US Senate. On August 1, 2018, a FOMC statement took place communicating an unchanged target range for the federal funds rate. Last, the announcement date August 23, 2019, falls together with a speech by Jerome Powell at Jackson Hole.

unchanged compared to the residual wild bootstrap which adds an iid normally distributed error with mean zero to each residual.

<Figure B7>

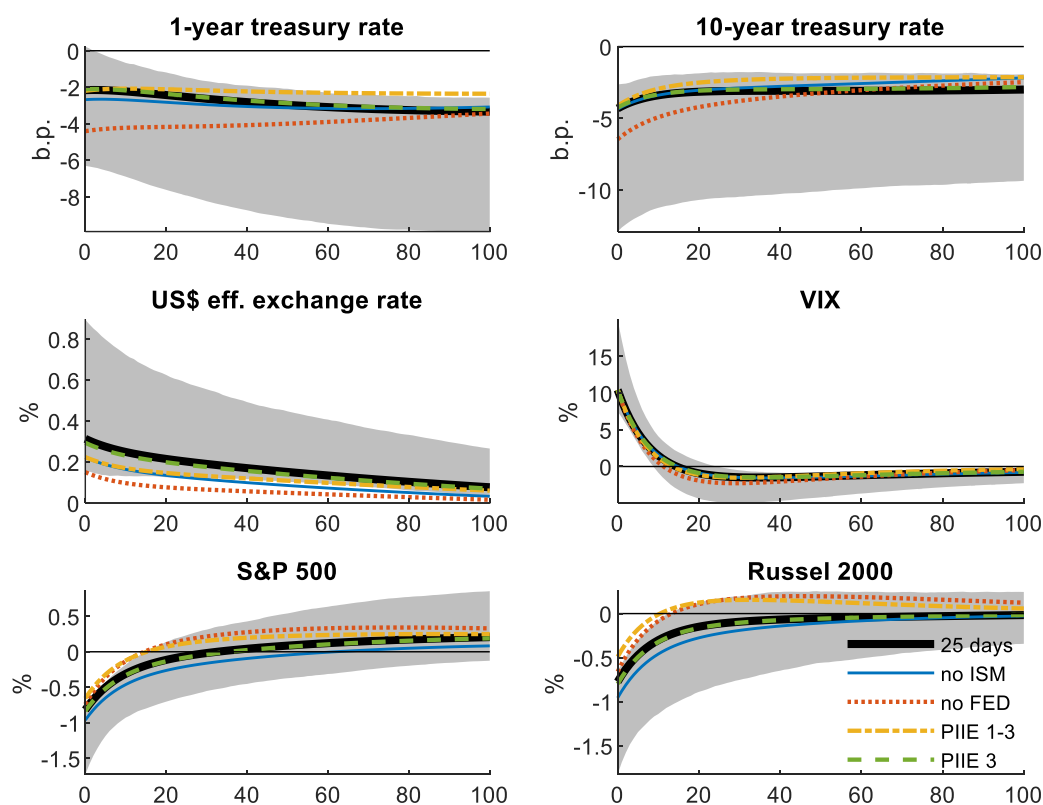
Longer sample. Another robustness analysis extends the sample backwards to start in June 2008. This yields a sample size of 3,033 observations, more than four times as long as our baseline period, starting in 2017. Comparing the impulse responses for the longer sample, shown in Figure B8 to our baseline results, we observe that the effects on impact are quantitatively close but less precisely estimated.

<Figure B8>

Different lag lengths. Finally, we experiment with different lag lengths, although AIC, BIC and HQ suggest one lag. Figure B9 shows the impulse response for one to four lags, which are almost unchanged compared to the baseline estimates.

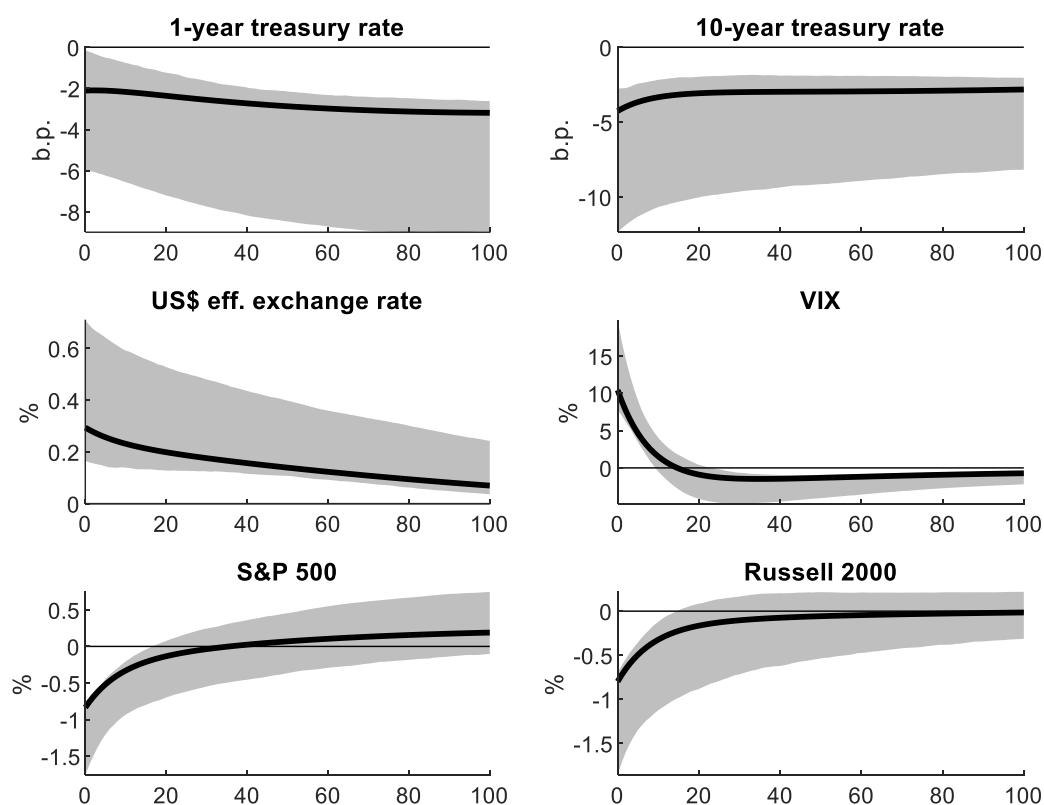
<Figure B9>

Figure B1: Overview of impulse responses from different event date specifications



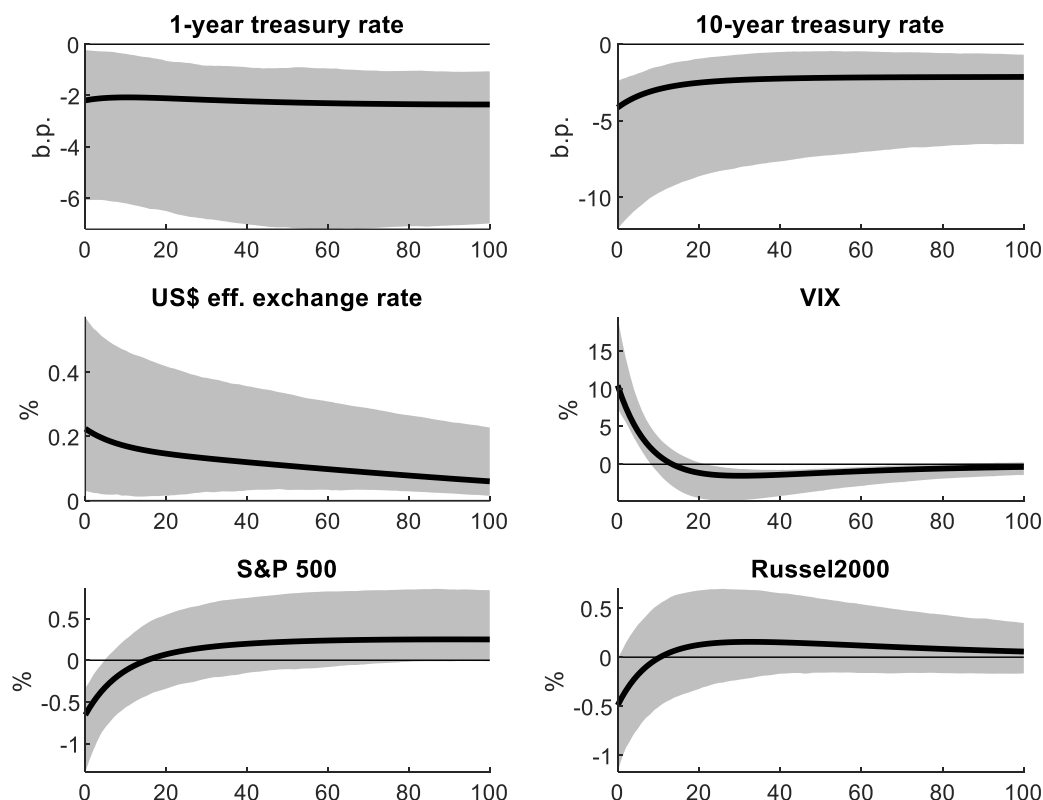
Notes: Impulse responses for the different event day specifications. '25 days' is the baseline specification. 'No ISM' has 26 event dates excluding ISM release dates. 'No FED' has 26 event dates excluding Fed announcement dates. '29 days' uses all 29 event dates from Table 1. 'PIIE 1-3' adds 3 events from PIIE category 1 on solar panels and washing machines to the 25 baseline dates. 'PIIE 3' uses 21 announcements only from PIIE category 3 resulting from 25 baseline events without 4 events from PIIE category 2 ("Steel and Aluminum").

Figure B2: Impulse responses to US trade policy shock using 21 announcement dates from PIIE Battle #3



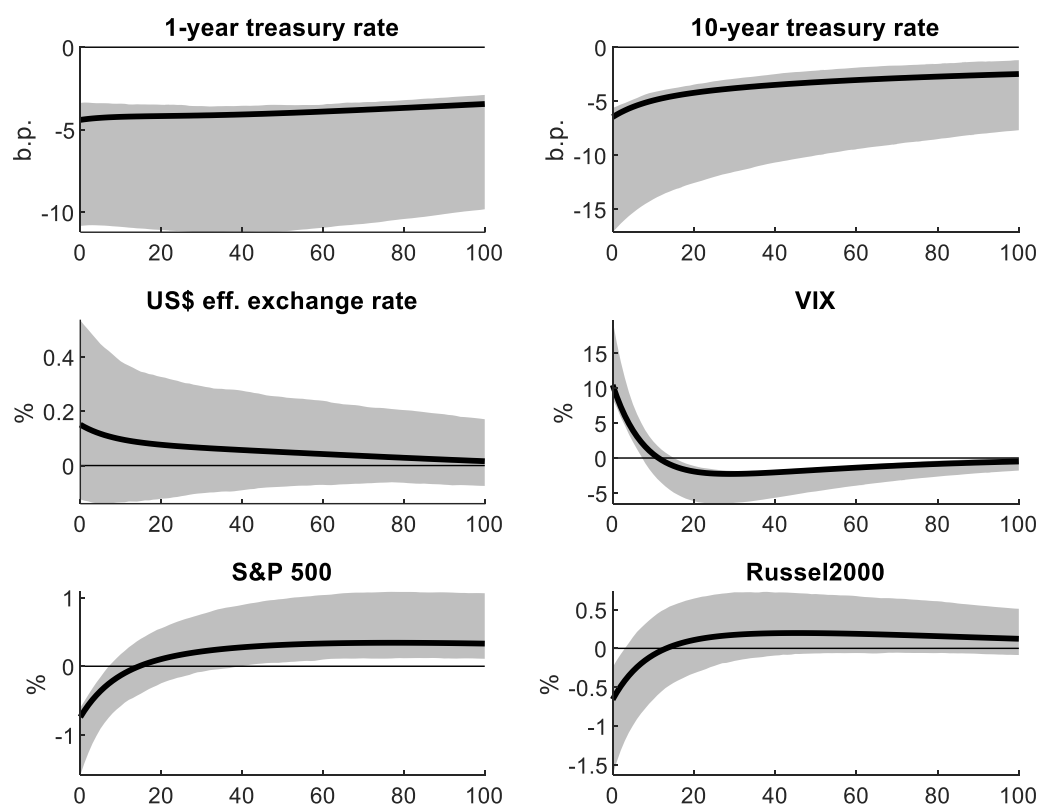
Notes: 21 event dates resulting from 25 baseline events without 4 events from PIIE category 2 (“Steel and Aluminum”). The 4 dates left out are April 20, 2017, April 27, 2017, March 8, 2018 and July 16, 2018. The event-date shock is normalized to change the VIX by 10.44% as in the bivariate model laid out in the appendix. The grey areas show 90% confidence intervals.

Figure B3: Impulse responses to US trade policy shock using 28 announcement dates including PIIE Battle #1



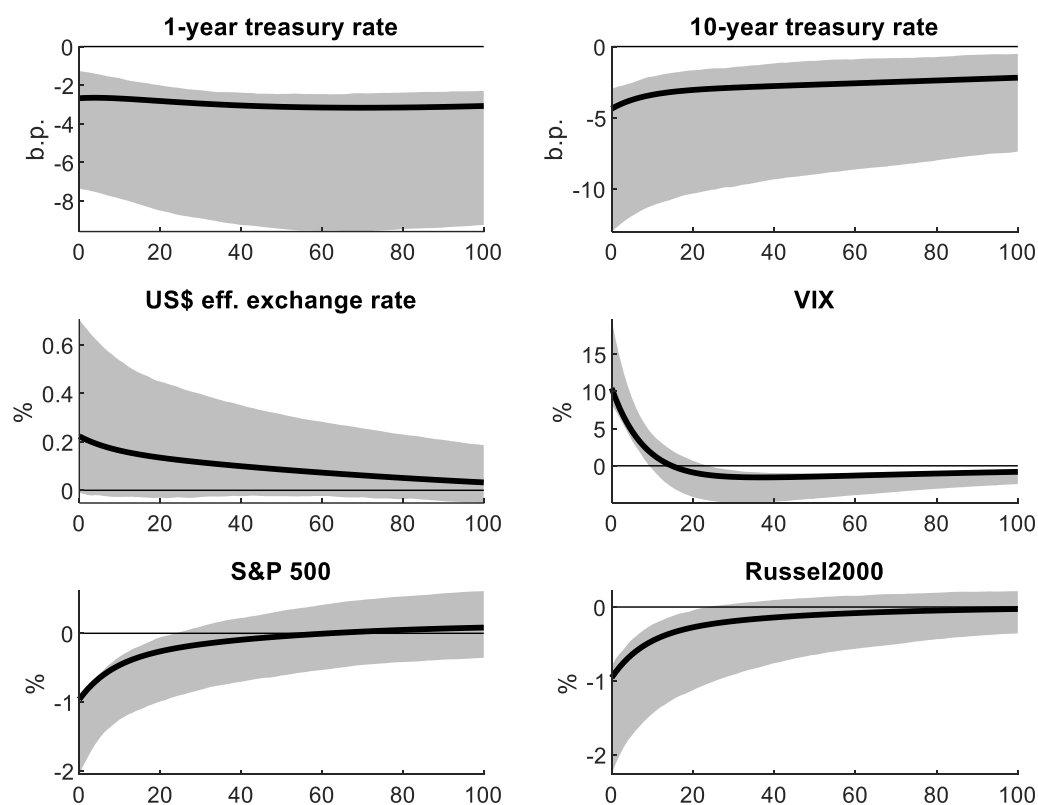
Notes: 25 baseline announcements and 3 US trade policy announcements from PIIE battle #1 “Solar Panel and Washing Machine Imports Injure US Industries”. The dates include October 31, 2017 (US International Trade Commission finds that imports of solar panels have caused injuries to the US solar panel industries and recommends restrictions), November 21, 2017 (US International Trade Commission finds that imports of washing machines have caused injuries to the US washing machines industries and recommends restrictions) and January 22, 2018 (President Trump approves global safeguard tariffs on imports of solar panels and washing machines). The shock is normalized to the VIX in the 2-variable model with 25 announcement dates. The grey areas show 90% confidence intervals.

Figure B4: Impulse responses to US trade policy shock excluding FED announcement dates



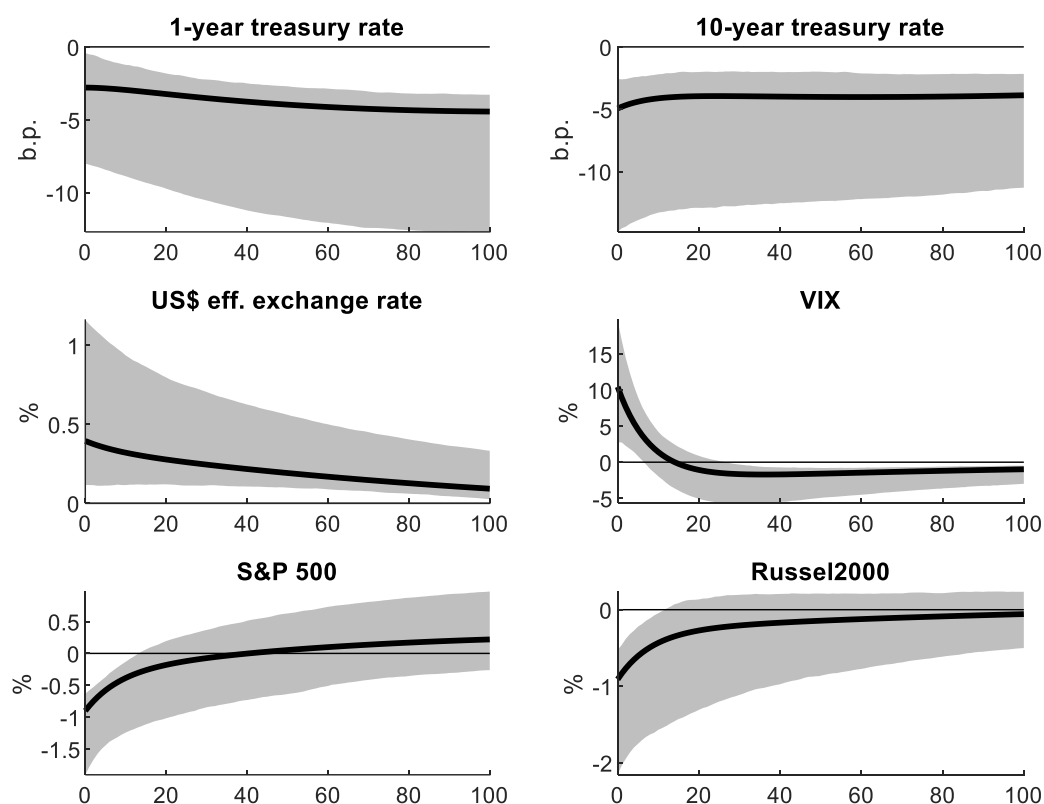
Notes: Event date March 1, 2018 is added to the 25 baseline events. The shock is normalized to the VIX in the 2-variable model with 25 announcement dates. The grey areas show 90% confidence intervals.

Figure B5: Impulse responses to US trade policy shock excluding ISM release dates



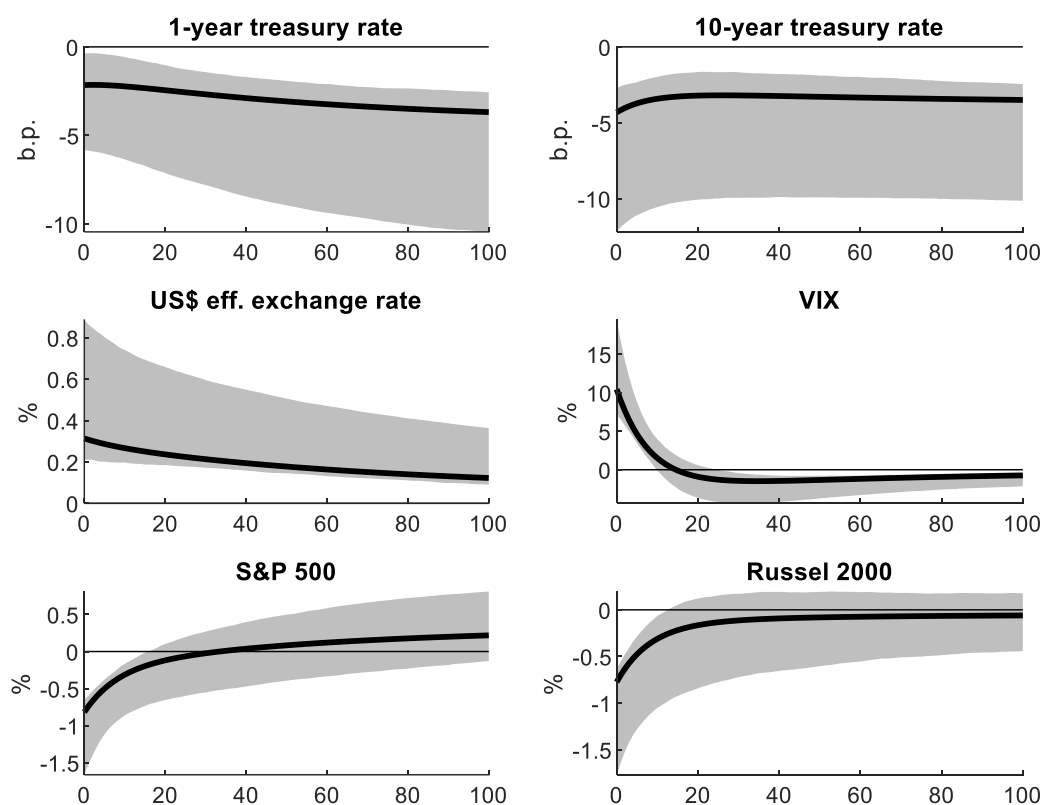
Notes: Event date August 23, 2019 is added to the 25 baseline events. The shock is normalized to the VIX in the 2-variable model with 25 announcement dates. The grey areas show 90% confidence intervals.

Figure B6: Impulse responses to US trade policy shock using 31 event dates including imposition dates



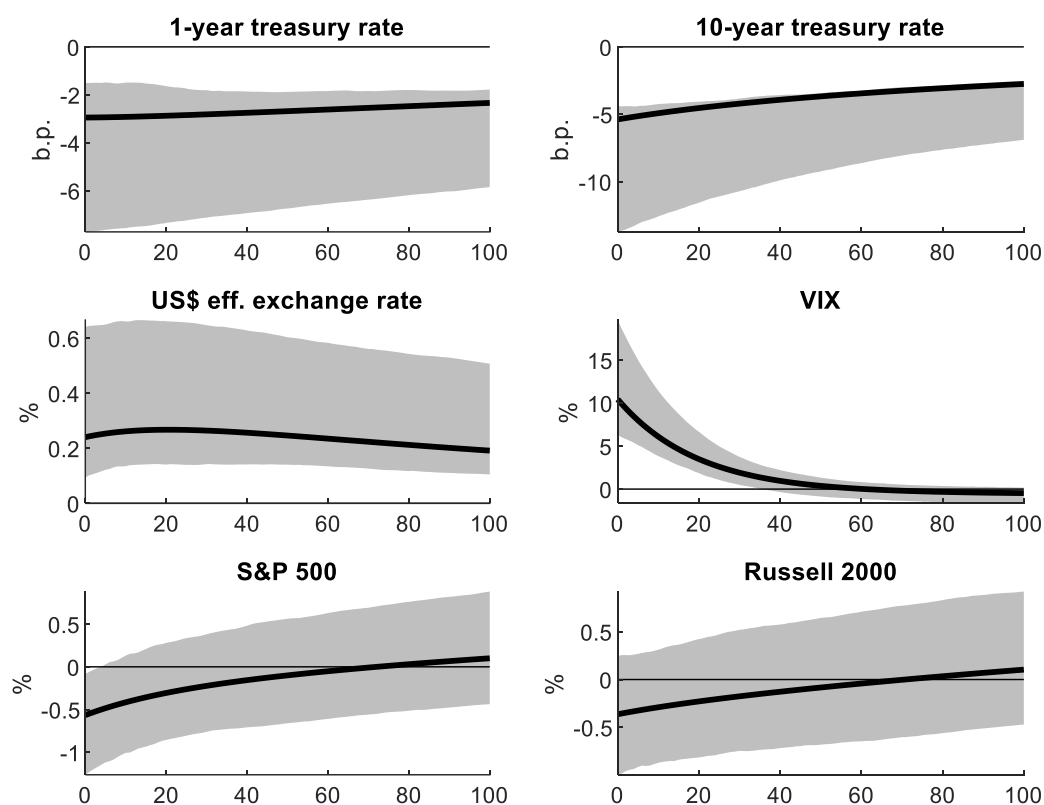
Notes: The following six events with US tariff impositions on Chinese imports are added to the 25 baseline events: March 23, 2018 (steel and aluminum tariffs), July 6, 2018 (25% tariffs on US\$ 34 bn of Chinese imports), August 23, 2018 (25% tariffs on US\$ 16 bn of Chinese imports), September 24, 2018 (10% tariffs on US\$ 200 bn of Chinese imports), May 10, 2019 (rise from 10 to 15% for US\$ 200 bn list) and September 2, 2019 (10% tariffs on US\$ 112 bn of Chinese imports). The shock is normalized to the VIX in the 2-variable model with 25 announcement dates. The grey areas show 90% confidence intervals.

Figure B7: Impulse responses to US trade policy shock using alternative bootstrap



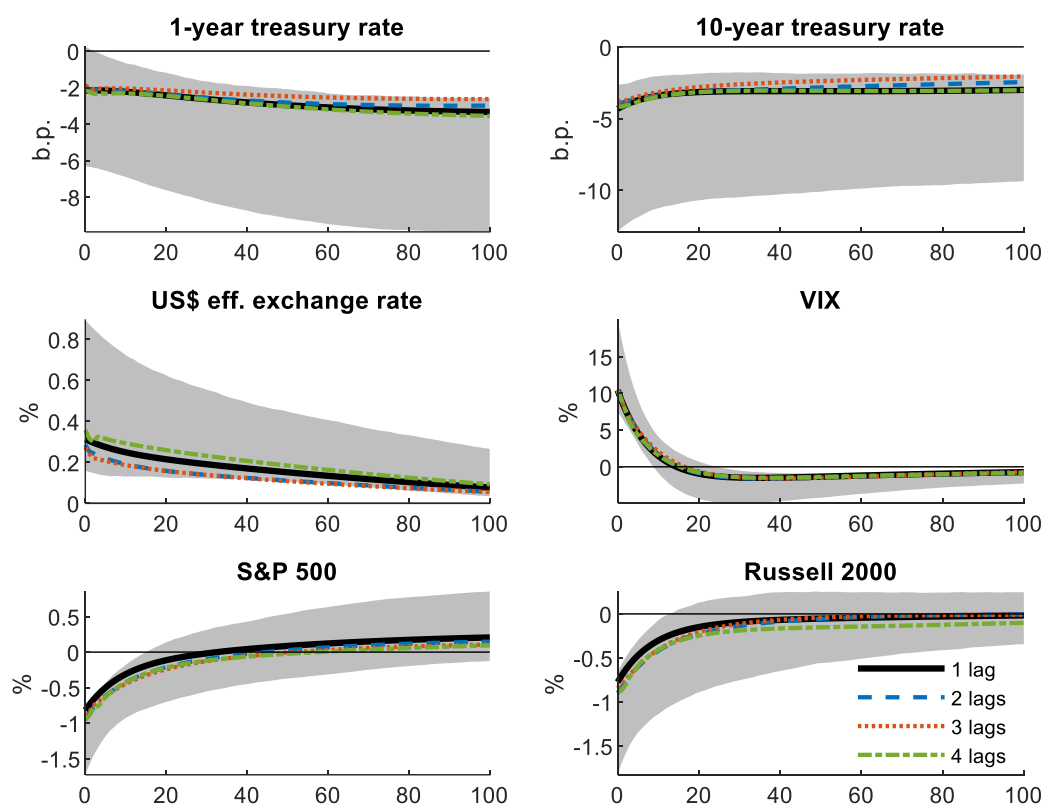
Notes: The estimation uses a bias-adjusted estimator (as in Neely, 2016, with sample size 2000) and 90% bootstrap intervals (sample size 2000) with a moving block bootstrap of length 10 for non-announcement dates and a sampling with replacement from residuals for announcement dates to maintain the assumed heteroskedasticity in the data.

Figure B8: Impulse responses to US trade policy shocks for longer sample



Notes: The sample horizon is June 4, 2008, to January 17, 2020. The shock is normalized to increase the VIX contemporaneously by 10.44% as in the baseline model using the shorter sample. The grey areas show 90% confidence intervals.

Figure B9: Overview of impulse responses with different lag lengths



Notes: Impulse responses for 25 baseline announcement dates using VARs with 1, 2, 3, and 4 lags. The grey areas show 90% confidence intervals for the 1 lag estimator.