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The multifaceted impact of US trade policy on financial markets

Lukas Boer, Lukas Menkhoff, and Malte Rieth

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Abstract. 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 US further hurt US stocks.

JEL-Classification: C 32 (time-series models); 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 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 macro-economically relevant horizons.¹

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).

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, i.e., 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 to 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 6 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 (in the main model) 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 two weeks. US stock market indices for a broad set of firms (Russell 2000) 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 two to three 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 9 of the 11 S&P 500 sector indices are significantly negatively affected. The more internationally oriented sectors of the US economy, i.e., 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 US, China, 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, i.e., announcements of future tariff changes, as the VIX does not respond significantly to this shock but stock prices of firms being particularly engaged with China fall stronger than the market. Variance decompositions show that the trade policy uncertainty shock accounts for about 10% to 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% to 40% of the forecast errors of the “China Exposure Stock Index” and for 10% to 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, while 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; Amiti et al., 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; Moser and Rose, 2014; Egger and Zhu, 2020; Huang et al., 2019).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), Caldara et al. (2020).⁴ While 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.

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 (Amity 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.

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 multi-faceted 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, 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 with specification tests (Section 2.3).

2.1 The SVAR model

The reduced form VAR is represented as

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

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 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 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 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 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.

All variables enter the model in levels and we take logarithms of the exchange rate, the VIX, and the stock price indices. Thereby, 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 ε_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 ε_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 σ_1^2 and σ_0^2 on announcement days and non-announcement days, respectively, while the impact effects are assumed to be constant. The variances σ_1^2 and σ_0^2 are assumed to be significantly different, providing the first identifying assumption. All other shocks, $\varepsilon_{t,2}, \dots, \varepsilon_{t,k}$, 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:

$$\Sigma_1 = E(u_t u_t') = E(B \varepsilon_t \varepsilon_t' B') = B E(\varepsilon_t \varepsilon_t') B' = b_1 b_1' \sigma_1^2 + \sum_{i=2}^k b_i b_i'. \quad (2)$$

Subtracting Σ_0 from this term yields

$$\Sigma_1 - \Sigma_0 = b_1 b_1' \sigma_1^2 - b_1 b_1' \sigma_0^2 = b_1 b_1' (\sigma_1^2 - \sigma_0^2). \quad (3)$$

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

$$J_W(b_1) = \text{vech}(\widehat{\Sigma}_1 - \widehat{\Sigma}_0 - b_1 b_1')' \left(\frac{\widehat{V}_0}{T_0} + \frac{\widehat{V}_1}{T_1} \right)^{-1} \text{vech}(\widehat{\Sigma}_1 - \widehat{\Sigma}_0 - b_1 b_1') \quad (4)$$

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

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

(Kilian and 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 Σ_u are given, the first structural shock can be obtained as

$$\varepsilon_{1t} = b_1' \Sigma_u^{-1} u_t / (b_1' \Sigma_u^{-1} b_1) \quad (6)$$

(see Stock and 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 statutory 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). While 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 while Lindé and 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, i.e., 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 A1 in the online appendix 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, 6 in materials, 5 in health care, 5 in industrials, 2 in consumer staples, and 1 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. Chad 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 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 (battle 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 1 lists all 32 announcement dates from the PIIE and briefly 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;” whereby China agreed to adhere to prespecified export targets with the US over the next two years while most tariffs remained in effect. Online appendix A 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.

Table 1: US trade policy announcement dates

Date	Event	China Exposure Index (% change)	Structural Shock	Bloomberg Economic Calendar
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.	1.21	-0.13	IJC (up), PFMI (down)
4/27/2017	President Trump instructs Commerce Secretary Wilbur Ross to self-initiate an investigation into whether aluminum imports threaten US national security.	0.56	-0.36	CDGO (down), IJC (up), PHS (up)
8/18/2017	US Trade Representative Robert E. Lighthizer self-initiates an investigation of China under Section 301 of the Trade Act of 1974.	-0.48	-0.04	-

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.	-0.54	1.37	BP (up)
3/1/2018	President Trump announces forthcoming tariffs on all trading partners of 25% on steel and 10% on aluminum.	-1.52	0.94	IJC (up), Fed Chair testifies, ISM (up)
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.	0.14	0.53	IJC (down)
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.	-2.67	1.78	IJC (up)
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.	1.54	-0.49	-
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.	0.98	-0.11	IJB (up)
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.	0.76	-0.42	-
5/29/2018	The White House releases a statement that it would impose tariffs on the \$50 billion list of goods from China.	-0.92	2.44	CC (down)
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.	0.08	-0.01	-
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.	-1.32	1.27	BP (down)
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.	-1.87	1.84	PPI (up), COI (down)
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.	-0.39	-0.72	CRS (-), RS (-)
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.	-0.73	-0.77	-
8/1/2018	The US Trade Representative considers a 25% tariff rate rather than 10% on the \$200 billion list of imports from China.	-0.99	0.29	NEC (up), ISM (down), COI (up), FOMC, ffrate (-)
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.	0.54	-0.80	JOLT (down)
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.	0.40	-0.61	-
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.	2.50	-1.38	ISM (up)
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%.	0.66	-0.65	-
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.	-1.23	1.41	-

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.	-1.92	1.54	IJC (up), ISM (down)
8/2/2019	Day after unexpected major tariff announcement. ¹	-1.52	1.34	NP (-), UR (-)
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.	1.35	-0.74	CCPI (up)
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.	-3.86	1.77	Fed Chair Speaks, NHS (down)
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.	0.19	-0.45	CCPI (up), IJC (down)
9/12/2019*	First considerations of interim trade deal. ²	0.08	-1.36	CRS (down), RS (up)
10/10/2019	Trade talks between the US and China with first signs of a temporary deal. ³	1.01	-1.57	CCPI (down), IJC (down)
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.”	2.28	-1.66	-
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.	-0.74	1.02	CRS (down), RS (down)
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.	-0.34	0.49	PPI (down), COI (down)

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 32 dates on which the US announces a change in trade policy concerning its trading partner China. The baseline specification uses 29 days, discarding dates in grey: March 1, 2018 (FED chair speech), August 1, 2018 (FOMC meeting), and August 23, 2019 (FED chair speech). Source: Bown and Kolb (2020). A positive value of the structural shock indicates a restrictive trade policy shock. The structural shock is calculated as in Equation (6) and relies on the 29 event dates baseline specification. * indicates evening or weekend events: Index change and structural shock shows next working day values. Bloomberg Economic Calendar high importance events: ADP Nonfarm Employment Change (NEC), Building Permits (BP), CB Consumer Confidence (CC), Core CPI (CCPI), Core Durable Goods Orders (CDGO), Core Retail Sales (CRS), Crude Oil Inventories (COI), Fed Chair Speech, Fed Interest Rate Decision (ffrate), FOMC meeting (FOMC), Initial Jobless Claims (IJC), ISM Manufacturing PMI (ISM), JOLTs Job Openings (JOLT), New Home Sales (NHS), Nonfarm Payrolls (NP), Pending Home Sales (PHS), Philadelphia Fed Manufacturing Index (PFMI), PPI (Purchasing Price Index), Retail Sales (RS). Up, down and flat (-) refer to actual minus forecast. ¹ <https://finance.yahoo.com/news/stock-market-news-august-2-2019-121309215.html>.

² <https://www.bloomberg.com/news/articles/2019-09-12/trump-says-he-d-consider-an-interim-trade-agreement-with-china>

³ <https://www.bloomberg.com/news/articles/2019-10-09/asian-stocks-set-to-rise-on-trade-talk-optimism-markets-wrap>

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 (4 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 2017-2020 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 online appendix).

2.3 Specification tests

We estimate the reduced form VAR in equation (1) with 6 variables in (log-) levels with a lag length of five (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

$$\text{vech}(\widehat{\Sigma}_1 - \widehat{\Sigma}_0)' \left(\frac{\widehat{V}_0}{T_0} + \frac{\widehat{V}_1}{T_1} \right)^{-1} \text{vech}(\widehat{\Sigma}_1 - \widehat{\Sigma}_0). \quad (7)$$

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 (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 (4), i.e., 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 2 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.

Table 2: 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 1,000 draws to obtain the p-values. Wald statistic 2 is displayed in equation (4). All VAR models use 5 lags.

⁵ Formally, the bootstrap simulates the distribution of $\text{vech}((\widehat{\Sigma}_1 - \widehat{\Sigma}_0 - \widehat{b}_1 \widehat{b}_1') - (\widehat{\Sigma}_1^* - \widehat{\Sigma}_0^* - \widehat{b}_1^* \widehat{b}_1^{*'}))' \left(\frac{\widehat{V}_0^*}{T_0} + \frac{\widehat{V}_1^*}{T_1} \right)^{-1} \text{vech}((\widehat{\Sigma}_1 - \widehat{\Sigma}_0 - \widehat{b}_1 \widehat{b}_1') - (\widehat{\Sigma}_1^* - \widehat{\Sigma}_0^* - \widehat{b}_1^* \widehat{b}_1^{*'}))$ where variables with stars denote the bootstrap sample analogues of the estimated objects in the original sample (Wright, 2012).

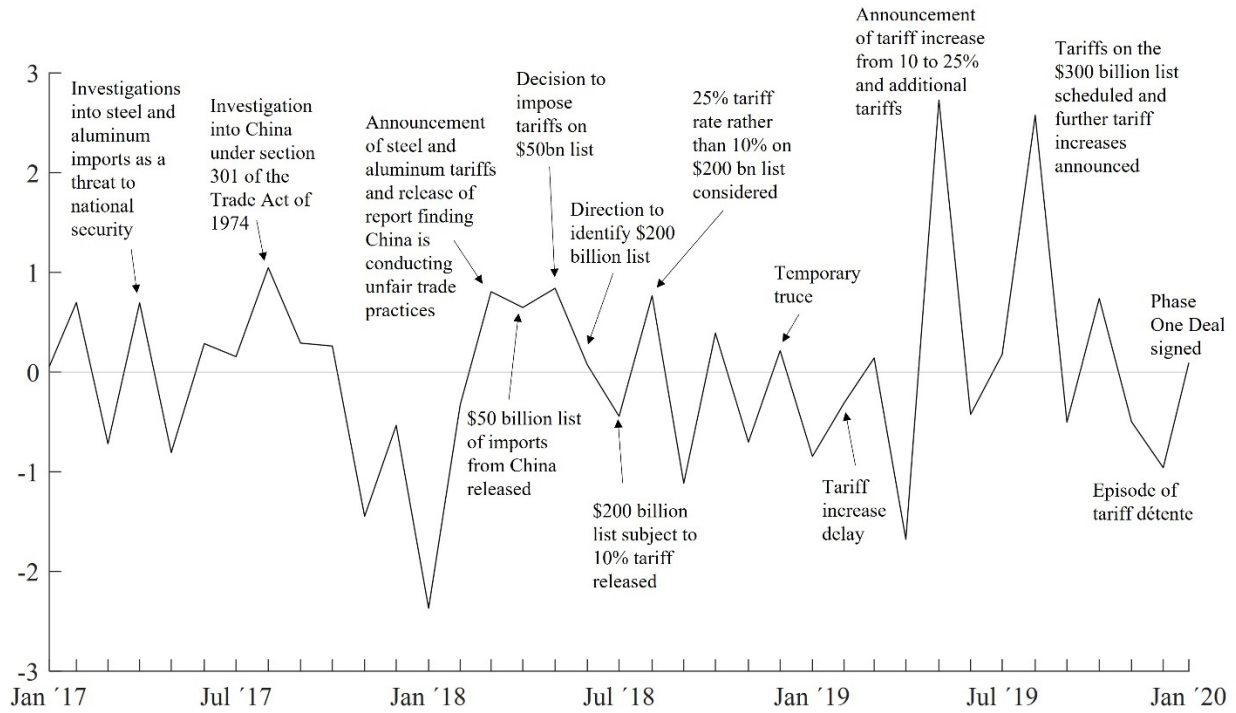
3 Results

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 6-variables 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, 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, 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.

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

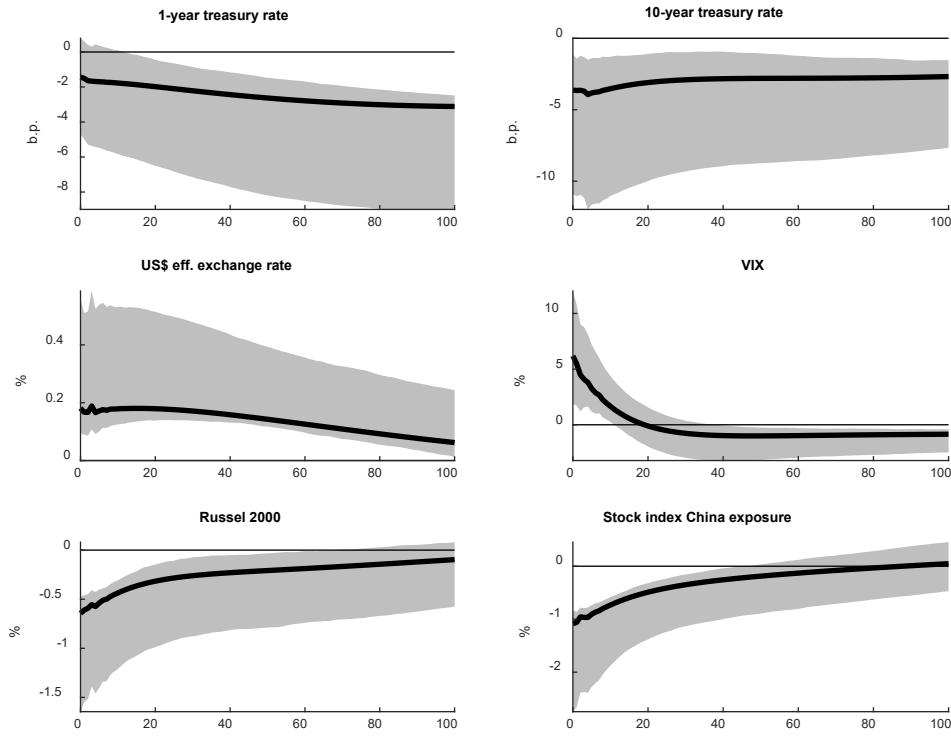


Regarding the signs of the impact effects, we expect that restrictive trade policy shocks affect the overall economy, represented by stock price indices, negatively. Moreover, those firms actively trading with China are expected to lose more than those firms that are more domestically oriented. Results 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 1). 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 online appendix show the daily shock series and list the largest daily shocks of which about 80% can be linked to trade news).

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 1,000. An increase in the US\$ eff. exchange rate denotes an appreciation of the US\$.

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 three 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 two weeks. This increase in volatility in the markets raises risk premia, which contributes to depressed stock prices.

Additionally, for one-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 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, ten-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 five 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, i.e., 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

While 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, Σ_0 and Σ_1 , respectively, as follows:

$$\Sigma_0 = BB' \text{ and } \Sigma_1 = B\Lambda B', \quad (8)$$

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 Λ 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 $i = 1, \dots, k$ can be calculated as eigenvectors and eigenvalues, respectively.

Lanne et al. (2010) show that if the λ_i s are distinct, then the decomposition in (8) is unique up to changes in the signs of the shocks and corresponding orderings of the columns of B and Λ . In other words, the full model is point-identified if the λ_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 to the distinct λ_j s may still be informative.

Table 3 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 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:

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

where $c(\kappa_1, \kappa_2, \tau)^2 = \left(\frac{1+\kappa_1}{\tau} + \frac{1+\kappa_2}{1-\tau} \right)^{-1}$, r is the number of restrictions, $s \in \{0,1\}$, and the kurtosis parameters κ_1 and κ_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 χ^2 with $\frac{1}{2}r(r+2)(r-1)$ degrees of freedom.

Table 3: 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

Notes: Point estimators for the different $\widehat{\lambda}_i$ and the bootstrap quantile estimates from the moving-block bootstrap with 1,000 draws.

Table 4 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 λ_1 , λ_2 , λ_3 , and λ_4 but rejects the equality of λ_1 , λ_2 , and λ_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 τ , 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.

Table 4: Identification tests for the multiple-shocks model

Hypothesis	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5 = \lambda_6$	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = \lambda_5$	$\lambda_1 = \lambda_2 = \lambda_3 = \lambda_4$	$\lambda_1 = \lambda_2 = \lambda_3$	$\lambda_1 = \lambda_2$	$\lambda_2 = \lambda_3$
χ^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

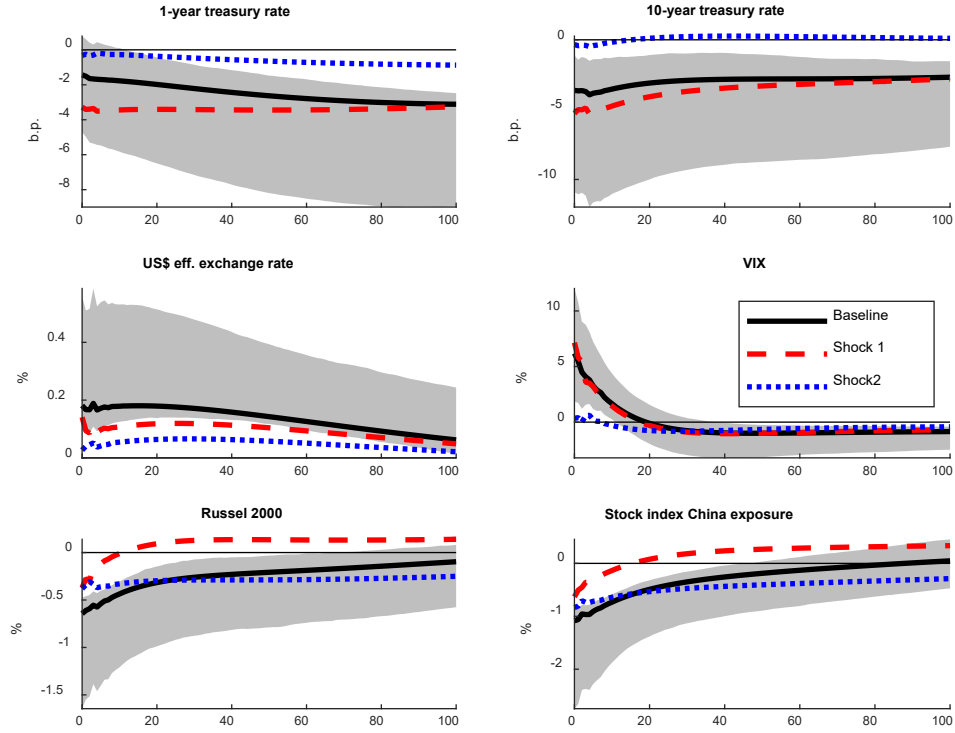
Figure 3 shows the impulse responses to the two shocks, together with the impulse responses derived from the main model (Section 3.1) and the 90% bootstrap confidence bands

for the main model. The two trade-policy news related shocks are of size $+1 \cdot \sqrt{\lambda_i}$, their standard deviation on event dates. One can see that the impulse responses of shock 1, i.e., 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 are almost zero. However, there is a common feature of shock 2 with the shock of the main model, i.e. 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 which 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, i.e., we expect here a decline in the China Exposure Stock Index. 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.

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 $\hat{\lambda}_t$. An increase in the US\$ effective exchange rate denotes an appreciation of the US\$.

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 percent 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 shock 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 5 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% to

5% impact (depending on horizon) on the Russell 2000, a 3% to 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% to 45% for the ten-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% to 40% of the China Index and still 8% to 19% of the Russell 2000.

Table 5: Forecast Error Variance Decomposition for the multiple-shocks model

	One-year Treasury	Ten-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

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 r_{Y_t} on a constant, the trade policy shock ε_t as well as one lag of the dependent variable and the shock:

$$r_{Y_t} = \alpha + \beta \varepsilon_t + \gamma r_{Y_{t-1}} + \delta \varepsilon_{t-1} + v_t, \quad (10)$$

where v_t is an error term. We report the point estimate for the coefficient of interest β with autocorrelation and heteroskedasticity robust standard errors. The magnitude of the estimated β coefficients are directly comparable to the impact effects contained in b_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 Appendix 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 9 as real estate and rental and leasing firms by the North American Industry Classification System (NAICS).

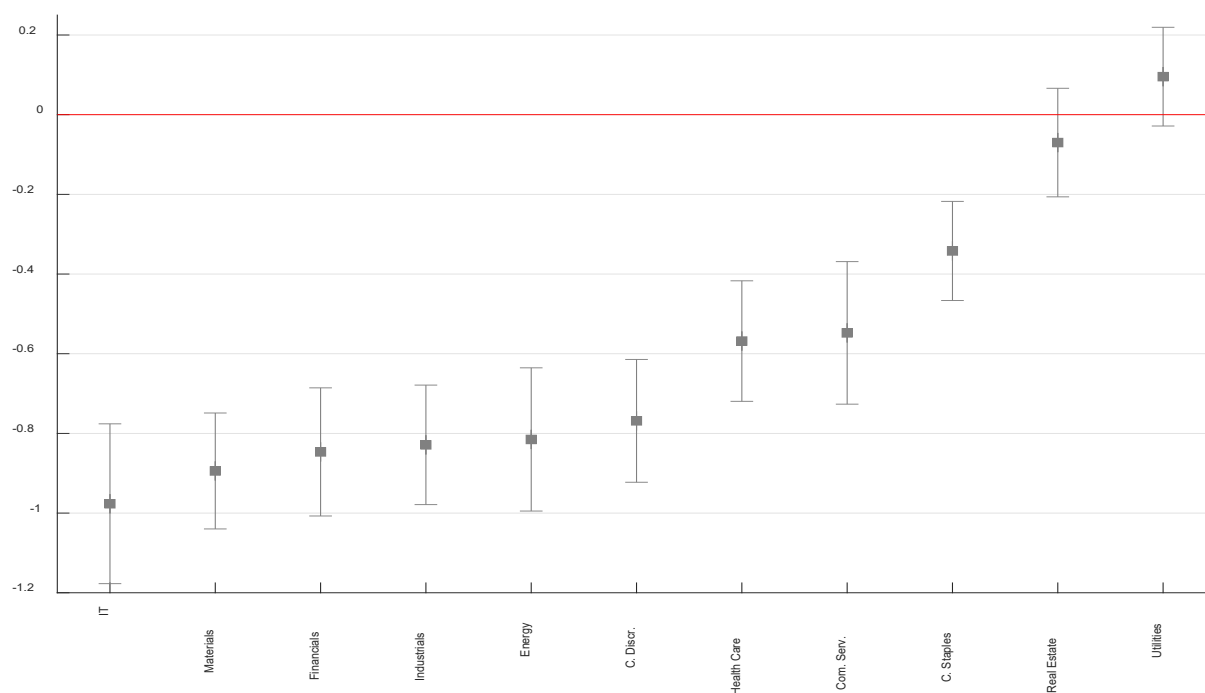
On the left side of the distribution, 13 firms' stock prices decrease by more than 1.5%, with 10 of these firms belonging to the manufacturing industry. Specifically, 9 are in the semiconductor manufacturing industry according to the NAICS. Overall, semiconductor manufacturing firms seem to be hit hardest, with 10 out of the 11 firms that lose most when hit by a US trade policy shock belonging to that category (compare Bown, 2020, 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.

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 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 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.

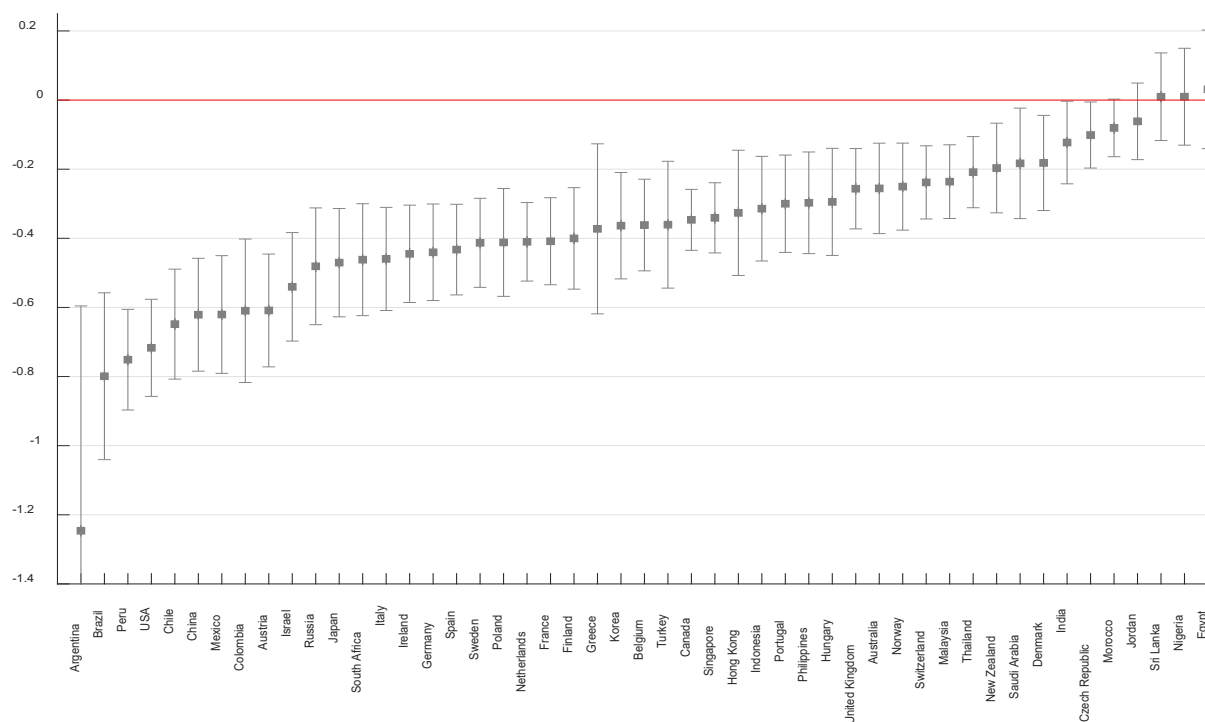
Country returns. Next, we focus on the impact of trade policy shocks on countries other than the US. In a globalized world, one would expect that most other countries are also negatively affected by restrictive US trade policy shocks. We take the full universe of 49 MSCI country indices for our calculations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

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.

Figure 5: Impact responses of MSCI country indices to a US trade policy shock



Notes: 99% HAC standard error confidence bands.

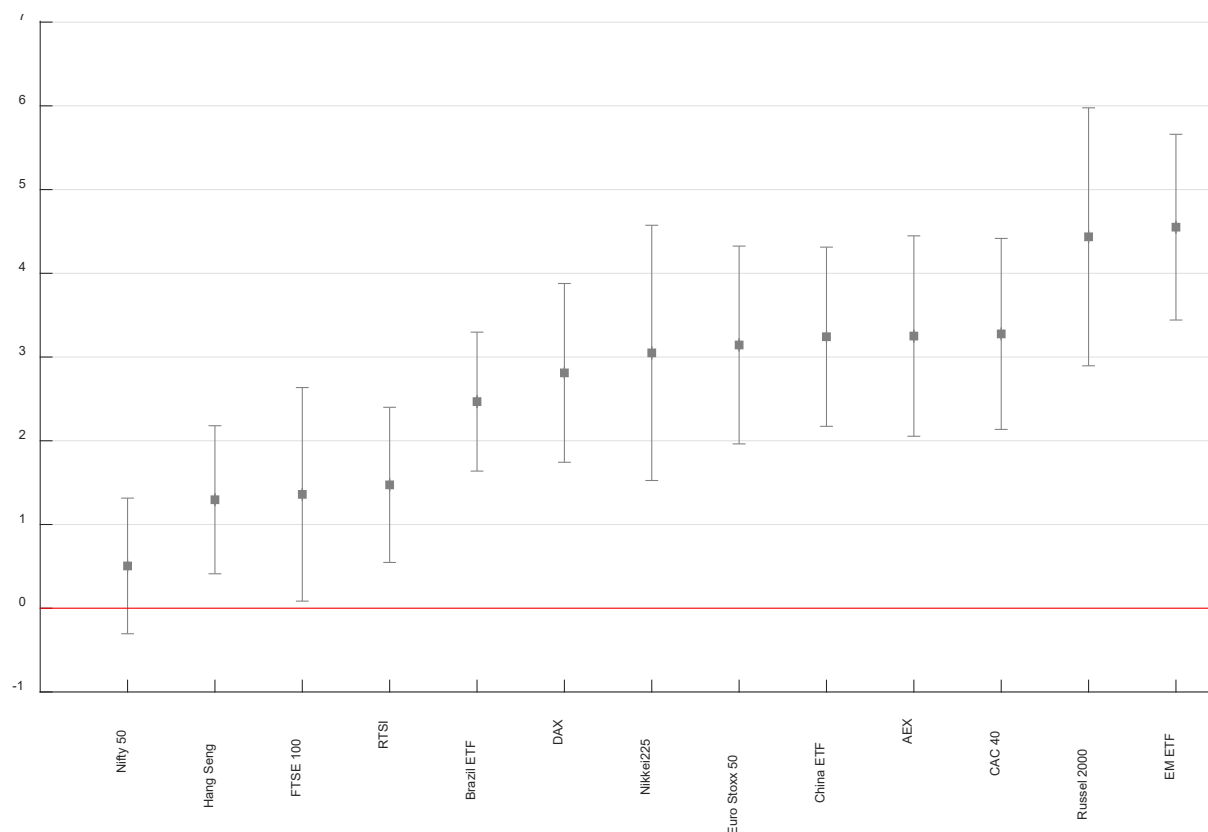
Looking at regional country groups, the Latin-American stock markets seem to be hardest hit. The next countries, i.e., those hit somewhat less, are dominated by European economies. Even less hit are most Asian countries, while African countries are hardly affected at all. This country pattern is largely consistent with the idea that geographical proximity to the US (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.

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 US and China.

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, 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 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

Figure 6: Impact responses of various volatility indices to a US trade policy shock



Notes: 99% HAC standard error confidence bands.

Table 6 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.

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 6: Pairwise correlation between trade policy shocks, tariff rates and uncertainty measures

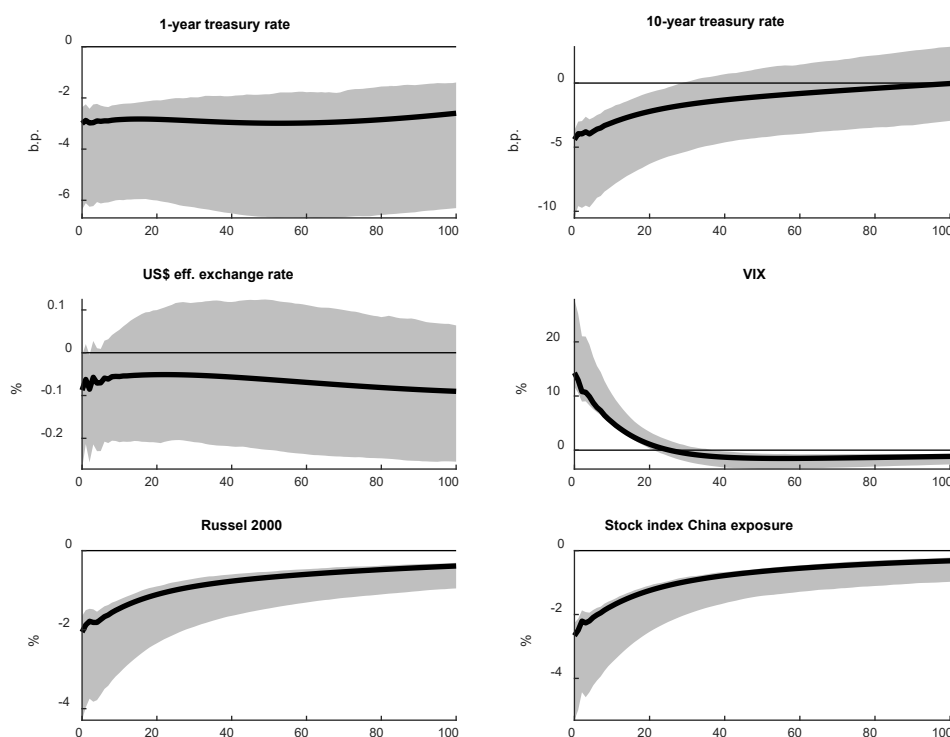
Lags	Monthly US tariff change on Chinese goods	Quarterly US aver. tariff rate change	Economic Policy Uncertainty (BBD)	Equity Market Volatility (BBDK)	Trade Policy Uncertainty (BBD)	Trade Policy Uncertainty (CIMPR)	Equity Market Volatility - Trade Policy (BBDK)
-1	0.0225 (0.8978)	0.1042 (0.7605)	0.2185 (0.2074)	-0.2481 (0.1508)	0.2678 (0.1199)	0.2072 (0.2322)	0.0634 (0.7176)
0	0.2088 (0.2217)	0.1185 (0.7138)	0.0701 (0.6846)	0.0587 (0.7337)	0.3301 (0.0493)**	0.3701 (0.0263)**	0.406 (0.0140)**
1	0.0591 (0.7359)	-0.3958 (0.2282)	-0.0729 (0.6775)	-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, Bloom and Davis (2016), BBDK to Baker, Bloom, Davis and Kost (2019) and CIMPR to Caldara, Iacoviello, Molodtsova, Prestipino and Raffo (2020). Lag -1 shows the correlation of the trade policy shock series lagged 1 month with the other series. Coefficients are labelled according to significance (***) $p < 0.01$, (**) $p < 0.05$, (*) $p < 0.1$.

The picture changes if we take measures of uncertainty about trade policy, i.e., 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 one 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.

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 US (see Appendix Table A2 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.

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 A2 in the appendix. The grey areas show 90% moving-block bootstrap confidence intervals with bootstrap sample size 1,000.

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 Online Appendix B.

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 an 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 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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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. We have added three adjacent event dates (August 2, September 13 and October 10, 2019) to this list to reach a total of 32 dates. These three dates either precede a PIIE event date when first information pertaining to the event reached markets already the day before the PIIE event or we specify a day after the PIIE event when markets still digested the news. No monetary policy announcements took place on these additional dates.

The first two event dates from the final list 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.

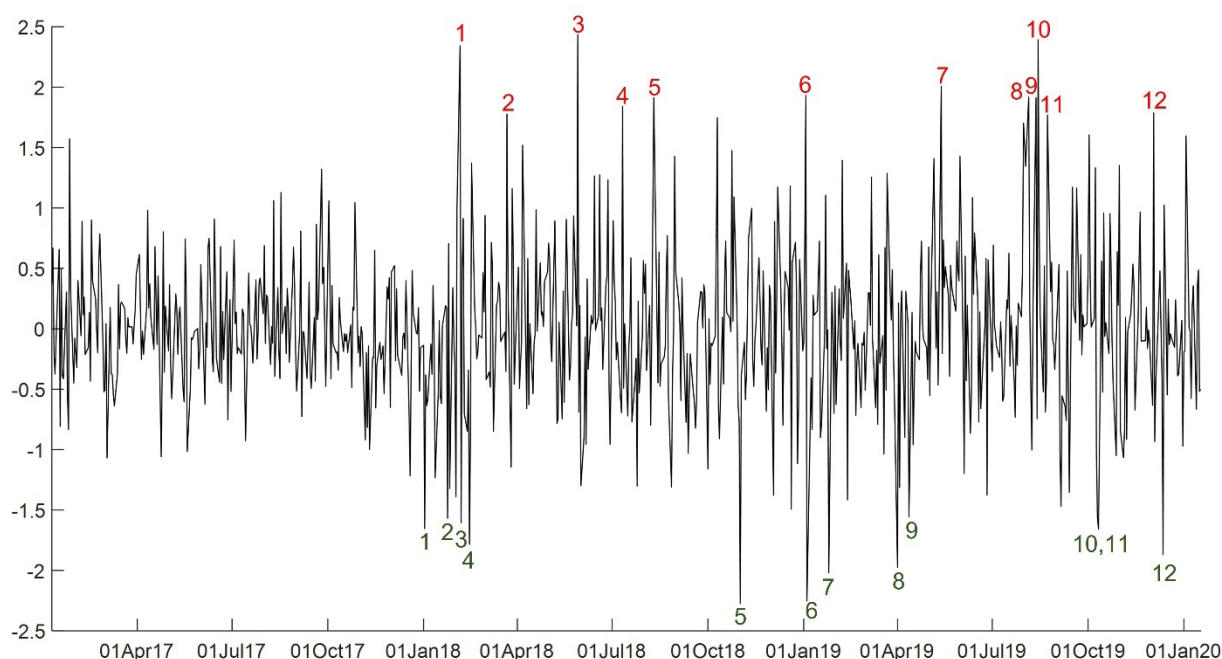
The next US trade policy announcement took place on August 1, 2019, when President Trump declared a 10% tariff on an additional \$300 billion list of Chinese goods, starting on September 1, 2019. This major change in trade policy still rattled markets the following day. On August 13, 2019, the US government 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. First news on an interim trade deal between the US and China reached markets the following day. Then in October, the tariff increase was finally 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.

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Figure A1: Estimated daily US trade policy shock series

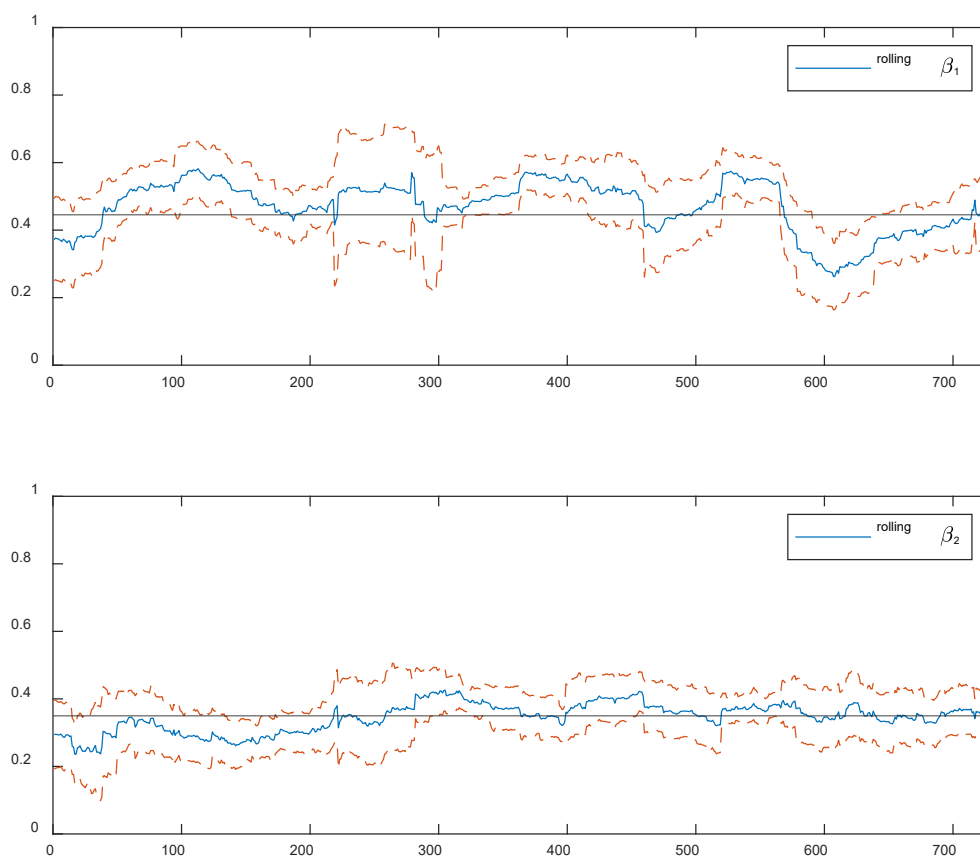


Restrictive trade policy shocks			
#	Date	T1 (PIIE event) / T2 (other trade policy event) / T3 (some trade policy news) / NT (no trade policy news)	Bloomberg Economic Calendar
1	Feb 5, 18	T1: "China investigates US exports of sorghum" (cat. 2)	ISM (up)
2	Mar 22, 18	T1: "Unfair trade practices investigation results" (cat. 3)	IJC (up)
3	May 29, 18	T1: "White House plans tariffs after brief 'hold'" (cat. 3)	CC (down)
4	Jul 11, 18	T1: "USTR announces \$200 billion tariffs on China" (cat. 3)	PPI (up), COI (down)
5	Aug 10, 18	T1: "Higher rates for Turkey" (cat. 2)	CCPI (-)
6	Jan 3, 19	T3: Apple announces revenue warning, Trump's chief economic adviser says Apple would not be the only casualty of the tariff tit-for-tat between the US and China. ²	NEC (up), IJC (up), ISM (down)
7	May 13, 19	T1: "China plans to hike tariff rates" (cat. 3), Monday after PIIE cat. 3: "US raises tariff rate on previous list"	-
8	Aug 5, 19	T1: Monday after "US Announces Tariffs on Almost All Remaining Imports from China" (cat. 3), US declares China currency manipulator ³	ISMN (down)
9	Aug 12, 19	T1: day before: "Trump plans two major rollouts of fall 2019 tariffs" (cat. 3)	-
10	Aug 14, 19	T1: day after: "Trump plans two major rollouts of fall 2019 tariffs" (cat. 3)	COI (up)
11	Aug 23, 19	T1: "China retaliates and Trump announces more tariffs" (cat. 3)	Fed speech, NHS (down)
12	Dec 3, 19	T2: Trump says China trade deal may have to wait ⁴	-
Easing trade policy shocks			
#	Date	T1 (PIIE event) / T2 (other trade policy event) / T3 (some trade policy news) / NT (no trade policy news)	Bloomberg Economic Calendar
1	Jan 2, 18	NT: First trading day of the year, positive investor sentiment, corporate tax cuts month before ⁵	-
2	Jan 24, 18	NT: Positive investor sentiment, tax reform, US government shutdown ended 2 days before ⁶	EHS (down), COI (down)
3	Feb 6, 18	NT: Bounce back after large stock price declines the day before, strong jobs data ⁷	JOLT (down)

4	Feb 14, 18	NT: Positive investor sentiment, stronger than expected inflation ⁸	CCPI (up), CRS (down), RS (down), COI (down)
5	Nov 1, 18	T2: President Trump tweets: ‘long and very good conversation’ with Chinese president Xi Jinping ⁹	IJC (up), ISM (down)
6	Jan 4, 19	T3: Good jobs report and easing monetary policy forward guidance, Friday before trade talks start on Monday after ¹⁰	NP (up), UR (up), Fed speech, COI (up)
7	Jan 25, 19	NT: US government shutdown ended, positive corporate earnings reports ¹¹	-
8	Apr 1, 19	T2: “China [...] to reduce additional tariffs on US autos in order to encourage trade talks” ¹²	CRS (down), RS (down), ISM (up)
9	April 12, 19	T3: Positive corporate earnings reports, some progress on US-China trade talks ¹³	-
10	Oct 10, 19	T1: day before: “Trump cancels October tariffs, points to “Phase One” of deal with China” (cat. 3)	CCPI (down), IJC (down)
11	Oct 11, 19	T1: “Trump cancels October tariffs, points to “Phase One” of deal with China” (cat. 3)	-
12	Dec 12, 19	T1: day before: “Trump calls off December tariffs in anticipation of deal” (cat. 3), Bloomberg reports about deal ¹⁴	IJC (up), PPI (down)

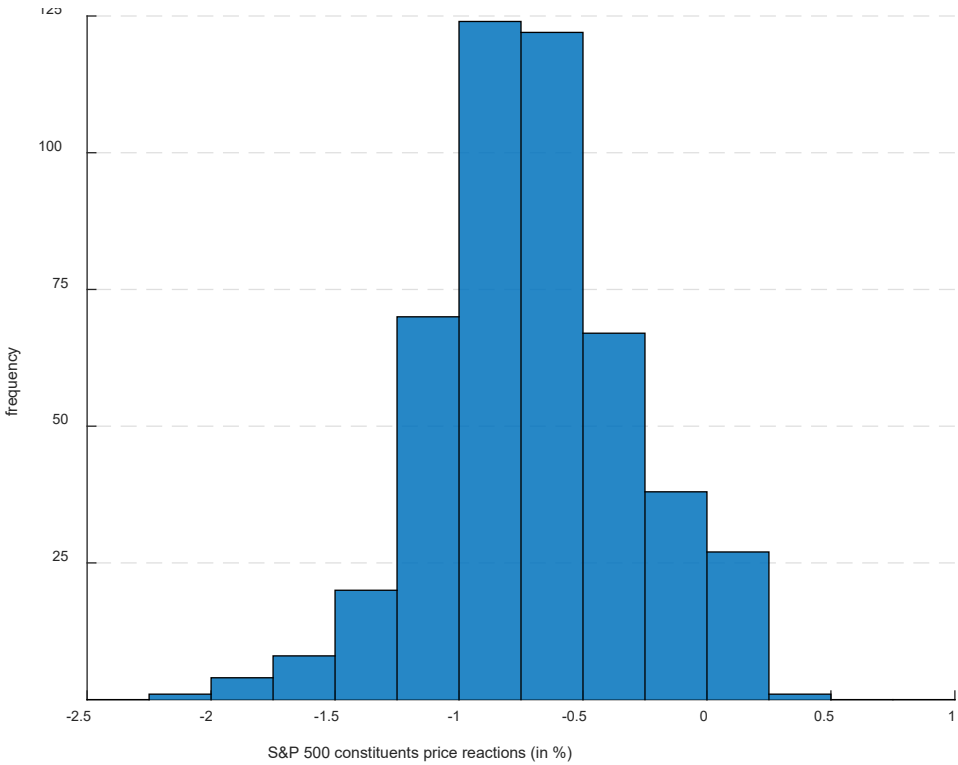
Notes: Daily shock series from baseline 29 event date model with 5 lags. Largest and smallest trade policy shocks are numbered chronologically. PIIE (Peterson Institute for International Economics) events from Bown and Kolb (2020). Category 2 (cat. 2) is to “Steel and Aluminum as National Security Threats”. Category 3 (cat. 3) is “Unfair Trade Practices for Technology, Intellectual Property”. ¹ Yahoo finance (<https://finance.yahoo.com/news/dow-drops-200-points-treasury-yields-move-higher-141746422.html>), ² The Guardian (<https://www.theguardian.com/technology/2019/jan/03/apple-shock-profit-warning-sends-european-shares-sliding>), ³ US Department of the Treasury (<https://home.treasury.gov/news/press-releases/sm751>), ⁴ Reuters (<https://www.reuters.com/article/us-china-trade/trump-says-china-trade-deal-might-have-to-wait-for-2020-election-idUSKBN1Y7134>), ⁵ CNBC (<https://www.cnbc.com/2018/01/02/us-stock-futures-data-dow-tax-politics-on-the-agenda.html>), ⁶ CNBC (<https://www.cnbc.com/2018/01/24/stock-market-off-to-best-start-in-31-years-bodes-well-for-2018.html>), ⁷ Yahoo finance (<https://finance.yahoo.com/news/stock-market-news-feb-7-142502471.html>), ⁸ CNBC (<https://www.cnbc.com/2018/02/14/us-stock-futures-dow-data-earnings-market-sell-off-and-politics-on-the-agenda.html>), ⁹ CNBC (<https://www.cnbc.com/2018/11/01/trump-says-he-and-chinas-xi-exchanged-long-and-very-good-trade-conversation.html>), ¹⁰ CNBC (<https://www.cnbc.com/2019/01/04/stock-market-investors-react-to-us-china-trade-talks.html>), ¹¹ Yahoo finance (<https://finance.yahoo.com/news/stock-market-news-january-25-2019-134156575.html>), ¹² Yahoo finance (<https://finance.yahoo.com/news/stock-market-news-apr-2-132301197.html>), ¹³ CNBC (<https://www.cnbc.com/2019/04/12/stock-market-wall-street-earnings-in-focus-amid-economic-concerns.html>), ¹⁴ Yahoo finance (<https://finance.yahoo.com/news/stock-market-news-december-12-2019-131542591.html>). Bloomberg economic calendar highest importance events. CB Consumer Confidence (CC), Core CPI (CCPI), Crude Oil Inventories (COI), Core Retail Sales (CRS), Existing Home Sales (EHS), Initial Jobless Claims (IJC), ISM Manufacturing PMI (ISM), ISM Non-Manufacturing PMI (ISMN), JOLTs Job Openings (JOLT), ADP Nonfarm Employment Change (NEC), New Home Sales (NHS), Nonfarm Payrolls (NP), Producer Price Index (PPI), Retail Sales (RS), Unemployment Rate (UR). Up, down and flat (-) relate to actual minus forecast.

Figure A2: Regression coefficients for rolling window regressions of the baseline shock on shock 1 and shock 2 from the multiple-shocks model



Notes: Rolling window regression coefficients from regressing the baseline shock series on shock 1 and shock 2 from the multiple-shocks model including 99% heteroskedasticity-robust confidence intervals. The window length is 60 trading days. Black horizontal lines show the single regression coefficients β_1 and β_2 using the whole sample.

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



Notes: Estimates using the returns of the S&P 500 constituents share prices in turn as the dependent variables in equation (10).

Table A1: China exposure stock index constituent firms

Firm	Description	Industry
Agilent Technologies Inc	Agilent Technologies, Inc. provides application focused solutions to the life sciences, diagnostics, and applied chemical markets worldwide.	Health Care
Analog Devices	Analog Devices, Inc. designs, manufactures, tests, and markets integrated circuits (ICs), software, and subsystems that leverage analog, mixed-signal, and digital signal processing technologies.	IT
Albemarle Corp	Albemarle Corporation develops, manufactures, and markets engineered specialty chemicals worldwide. The company operates in three segments: Lithium, Bromine Specialties, and Catalysts.	Materials
Applied Materials Inc	Applied Materials, Inc. provides manufacturing equipment, services, and software to the semiconductor, display, and related industries. It operates through three segments: Semiconductor Systems, Applied Global Services, and Display and Adjacent Markets.	IT
Advanced Micro Devices	Advanced Micro Devices, Inc. operates as a semiconductor company worldwide. The company operates in two segments, Computing and Graphics; and Enterprise, Embedded and Semi-Custom.	IT
Smith (A.O.)	A. O. Smith Corporation manufactures and markets residential and commercial gas and electric water heaters, boilers, tanks, and water treatment products in North America, China, Europe, and India. It operates through two segments, North America and Rest of World.	Industrials
Aptiv PLC	Aptiv PLC designs, manufacturers, and sells vehicle components worldwide. The company provides electrical, electronic, and safety technology solutions to the automotive and commercial vehicle markets.	Consumer Discretionary
Borgwarner Inc	BorgWarner Inc. provides solutions for combustion, hybrid, and electric vehicles worldwide.	Consumer Discretionary
Cardinal Health Inc	Cardinal Health, Inc. operates as an integrated healthcare services and products company in the United States and internationally. It provides customized solutions for hospitals, healthcare systems, pharmacies, ambulatory surgery centers, clinical laboratories, and physician offices.	Health Care
Celanese Corp	Celanese Corporation, a technology and specialty materials company, manufactures and sells high performance engineered polymers in the United States and internationally. The company operates through Engineered Materials, Acetate Tow, and Acetyl Chain segments.	Materials
CF Industries Holdings Inc	CF Industries Holdings, Inc. manufactures and distributes nitrogen fertilizers and other nitrogen products worldwide. Its principal nitrogen fertilizer products include anhydrous ammonia, granular urea, urea ammonium nitrate solution, and ammonium nitrate.	Materials
Conocophillips	ConocoPhillips explores for, produces, transports, and markets crude oil, bitumen, natural gas, liquefied natural gas (LNG), and natural gas liquids worldwide.	Energy
Capri Holdings Ltd	Capri Holdings Limited designs, markets, distributes, and retails branded women's and men's apparel, footwear, and accessories in the United States, Canada, Latin America, Europe, the Middle East, Africa, and Asia.	Consumer Discretionary
Deere & Co	Deere & Company, together with its subsidiaries, manufactures and distributes various equipment worldwide. The company operates through three segments: Agriculture and Turf, Construction and Forestry, and Financial Services.	Industrials

Danaher Corp	Danaher Corporation designs, manufactures, and markets professional, medical, industrial, and commercial products and services worldwide. The company operates through three segments; Life Sciences, Diagnostics, and Environmental & Applied Solutions.	Health Care
Eastman Chemical Co	Eastman Chemical Company operates as an advanced materials and specialty additives company worldwide.	Materials
Ford Motor Co	Ford Motor Company designs, manufactures, markets, and services a range of Ford cars, trucks, sport utility vehicles, electrified vehicles, and Lincoln luxury vehicles worldwide. It operates through three segments: Automotive, Mobility, and Ford Credit.	Consumer Discretionary
Fortune Brands Home & Secur	Fortune Brands Home & Security, Inc., together with its subsidiaries, provides home and security products for residential home repair, remodeling, new construction, and security applications. It operates in three segments: Cabinets, Plumbing, and Doors & Security.	Industrials
Corning Inc	Corning Incorporated engages in display technologies, optical communications, environmental technologies, specialty materials, and life sciences businesses worldwide.	IT
Gap Inc	The Gap, Inc. operates as an apparel retail company worldwide. The company offers apparel, accessories, and personal care products for men, women, and children under the Old Navy, Gap, Banana Republic, Athleta, Intermix, Janie and Jack, and Hill City brands.	Consumer Discretionary
Garmin Ltd	Garmin Ltd. designs, develops, manufactures, markets, and distributes a range of navigation, communication, and information devices worldwide. It operates through five segments: Auto, Aviation, Marine, Outdoor, and Fitness.	Consumer Discretionary
Hasbro Inc	Hasbro, Inc., together with its subsidiaries, operates as a play and entertainment company. The company's U.S.	Consumer Discretionary
Hershey Co	The Hershey Company, together with its subsidiaries, manufactures and sells confectionery products. The company operates through two segments, North America; and International and Other.	Consumer Staples
Ilex Corp	IDEX Corporation, together with its subsidiaries, operates as an applied solutions company worldwide. The company operates through three segments: Fluid & Metering Technologies (FMT), Health & Science Technologies (HST), and Fire & Safety/Diversified Products (FSDP).	Industrials
Intl Flavors & Fragrances	International Flavors & Fragrances Inc., together with its subsidiaries, manufactures flavors and fragrances for use in various consumer products. It operates through two segments, Taste and Scent.	Materials
Ipg Photonics Corp	IPG Photonics Corporation develops and manufactures a range of high-performance fiber lasers, fiber amplifiers, and diode lasers used in various applications primarily in materials processing worldwide.	IT
Kla Corp	KLA Corporation designs, manufactures, and markets process control and yield management solutions for the semiconductor and related nanoelectronics industries worldwide.	IT
L Brands Inc	L Brands, Inc. operates as a specialty retailer of women's intimate and other apparel, personal care, and beauty and home fragrance products. The company operates in three segments: Victoria's Secret, Bath & Body Works, and Victoria's Secret and Bath & Body Works International.	Consumer Discretionary
Leggett & Platt Inc	Leggett & Platt, Incorporated designs and produces various engineered components and products worldwide. It operates	Consumer Discretionary

	through three segments: Bedding Products; Furniture, Flooring & Textile Products; and Specialized Products.	
Mgm Resorts International	MGM Resorts International, through its subsidiaries, owns and operates integrated casino, hotel, and entertainment resorts in the United States and Macau. The company operates through three segments: Las Vegas Strip Resorts, Regional Operations, and MGM China.	Consumer Discretionary
Mosaic Co	The Mosaic Company, through its subsidiaries, produces and markets concentrated phosphate and potash crop nutrients in North America and internationally. The company operates through three segments: Phosphates, Potash, and Mosaic Fertilizantes.	Materials
Mettler-Toledo Intl Inc	Mettler-Toledo International Inc. manufactures and supplies precision instruments and services worldwide. It operates in five segments: U.S. Operations, Swiss Operations, Western European Operations, Chinese Operations, and Other.	Health Care
Nike Inc	NIKE, Inc., together with its subsidiaries, designs, develops, markets, and sells athletic footwear, apparel, equipment, and accessories worldwide. The company offers NIKE brand products in six categories, including running, NIKE basketball, the Jordan brand, football, training, and sportswear.	Consumer Discretionary
Pfizer Inc	Pfizer Inc. develops, manufactures, and sells healthcare products worldwide.	Health Care
PVH Corp	PVH Corp. operates as an apparel company in the United States and internationally.	Consumer Discretionary
Qualcomm Inc	QUALCOMM Incorporated engages in the development and commercialization of foundational technologies and products are used in mobile devices and other wireless products, including network equipment, broadband gateway equipment, consumer electronic devices, and other connected devices worldwide.	IT
Qorvo Inc	Qorvo, Inc. develops and commercializes technologies and products for wireless and wired connectivity worldwide. The company operates in two segments, Mobile Products, and Infrastructure and Defense Products.	IT
Starbucks Corp	Starbucks Corporation, together with its subsidiaries, operates as a roaster, marketer, and retailer of specialty coffee worldwide. The company operates through three segments: Americas, International, and Channel Development.	Consumer Discretionary
Skyworks Solutions Inc	Skyworks Solutions, Inc., together with its subsidiaries, designs, develops, manufactures, and markets proprietary semiconductor products, including intellectual property in the United States, China, South Korea, Taiwan, Europe, the Middle East, Africa, and rest of Asia-Pacific.	IT
Tiffany & Co	Tiffany & Co., through its subsidiaries, designs, manufactures, and retails jewelry and other items. The company offers jewelry collections, engagement rings, and wedding bands. It also sells watches, home and accessories products, and fragrances; and wholesales diamonds and earnings.	Consumer Discretionary
Tapestry Inc	Tapestry, Inc. provides luxury accessories and branded lifestyle products in the United States, Japan, China, Hong Kong, Macau, Taiwan, Europe, Canada, South Korea, Malaysia, Singapore, Australia, and New Zealand.	Consumer Discretionary
Tripadvisor Inc	TripAdvisor, Inc. operates as an online travel company. It operates in two segments, Hotels, Media & Platform; and Experiences & Dining.	Communication Services
Tyson Foods Inc	Tyson Foods, Inc., together with its subsidiaries, operates as a food company worldwide. It operates through four segments: Beef, Pork, Chicken, and Prepared Foods.	Consumer Staples

Western Digital Corp	Western Digital Corporation develops, manufactures, and sells data storage devices and solutions.	IT
Whirlpool Corp	Whirlpool Corporation manufactures and markets home appliances and related products. It operates through four segments: North America; Europe, Middle East and Africa; Latin America; and Asia.	Consumer Discretionary
Waste Management Inc	Waste Management, Inc., through its subsidiaries, provides waste management environmental services to residential, commercial, industrial, and municipal customers in North America.	Industrials
Weyerhaeuser Co	Weyerhaeuser Company, one of the world's largest private owners of timberlands, began operations in 1900. We own or control approximately 11 million acres of timberlands in the U.S. and manage additional timberlands under long-term licenses in Canada.	Real Estate

Notes: S&P 500 constituents with highest frequency of mentioned exports and import activities to/from China in their 2017 10-K disclosures. Firms with a higher number of exports and imports mentions than one standard deviation above the mean number of mentions of 482 S&P 500 firms. Firm descriptions from Compustat.

Table A2: Chinese trade policy announcement dates

Date	Event	China Exp. Index (% change)	Structural Shock	Bloomberg Economic Calendar
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.	-3.90	0.79	ISM (up)
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.	-2.63	0.80	ISM (down)
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.	1.18	-0.02	NEC (up), ISMNM (down), COI (down)
4/17/2018	The Chinese government announces preliminary antidumping duties of 178.6% on imports from the US of sorghum.	1.09	-0.35	BP (up)
5/18/2018	China's Commerce Ministry announces end of tariffs on US sorghum during negotiations to resolve trade disputes.	-0.34	-0.06	-
6/15/2018*	China issues an updated \$50 billion retaliation list of 25% tariffs.	0.05	-0.13	-
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.	0.43	-0.18	ISMNM (down), NP (down), UR (-)
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.	-0.13	0.05	COI (up)
8/14/2018	China files a WTO dispute against US solar panel tariffs.	1.01	-0.36	-
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.	0.40	-0.06	-
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.	2.50	-1.08	ISM (up)
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.	-3.83	1.40	-
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.	-3.86	1.59	Fed Chair speech, NHS (down)
9/11/2019	China announces it will exclude 16 products (less than \$2 billion of US exports) from its retaliatory	1.20	-0.22	PPI (-), COI (down)

	tariffs imposed in 2018, such as some animal feeds, chemicals, and petroleum products.			
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.	-0.34	0.05	PPI (down), COI (down)

Notes: Bown and Kolb (2020). * indicates evening or weekend events: S&P 500 change and structural shock shows next working day values. Date in grey not used due to outlier character. The structural shock is calculated as in equation (6) and relies on the 14 Chinese trade policy events specification. Building Permits (BP), Crude Oil Inventories (COI), ISM Manufacturing PMI (ISM), ISM Non-Manufacturing PMI (ISMNM), ADP Nonfarm Employment Change (NEC), New Home Sales (NHS), Nonfarm Payrolls (NP), Producer Price Index (PPI), Unemployment Rate (UR). Up, down, and flat (-) refer to actual minus forecast.

Table A3: Further PIIE events

Date	Event	China Exp. Index (% change)	Structural shock	Bloomberg Economic Calendar
10/31/2017	PIIE 1: USITC recommends remedies (solar panels)	0.59	-0.06	CC (up)
11/21/2017	PIIE 1: USITC recommends remedies (washing machines)	0.66	-0.25	Fed speech, EHS (up)
1/22/2018	PIIE 1: Trump imposes safeguard tariffs	0.13	0.19	-
3/8/2018	PIIE 2: Steel and aluminum NAFTA tariff exemptions	0.14	0.53	IJC (up)
3/28/2018	PIIE 2: Korea receives permanent exemption for steel, but faces quota	-0.74	0.65	GDPQ4 (up), PHS (up), COI (up)
4/30/2018	PIIE 2: US extends tariff exemptions	-1.06	0.47	PHS (down)
6/1/2018	PIIE 2: US ends tariff exemptions for EU, Canada, and Mexico	1.67	-1.30	NP (up), UR (down), ISM (up)
8/10/2018	PIIE 2: Higher rates for Turkey	-1.14	1.91	CCPI (-)
5/17/2019	PIIE 2: US lifts tariffs on Canada and Mexico	-1.49	0.51	JOLT (up)
8/13/2018	PIIE 3: US passes law on trade and national security	-0.53	0.11	-
5/23/2018*	PIIE 4: Another national security investigation	-0.03	0.13	EHS (down), IJC (up)
8/27/2018	PIIE 4: “Side Letter” on autos reportedly in new US-Mexico trade deal to replace NAFTA	1.08	-1.31	-
11/30/2018	PIIE 4: USMCA is signed with side letters	0.55	0.27	-
5/17/2019	PIIE 4: Trump Delays auto tariff decision	-1.49	0.51	-
5/30/2019*	PIIE 5: Tariffs on Mexico to deter migrants	-1.62	1.43	-
6/7/2019	PIIE 5: Tariffs on Mexico called off	0.89	0.20	NP (down), UR (-)
3/7/2017	PIIE 6: ZTE agrees to settlement	-0.41	-0.37	-
4/16/2018	PIIE 6: US enacts denial order against ZTE	0.88	-0.54	CRS (-), RS (up)
5/13/2018*	PIIE 6: Trump overrules ZTE denial order	0.50	-0.75	-
6/7/2018	PIIE 6: ZTE settlement announced	-0.34	0.41	IJC (down)
7/13/2018	PIIE 6: ZTE denial order lifted	0.09	0.04	Fed report
8/13/2018	PIIE 6: Export Control Reform Act becomes law	-0.53	0.11	-
11/19/2018	PIIE 6: US proposes criteria for essential technologies	-2.34	0.59	-
1/28/2019*	PIIE 6: Department of Justice indicts Huawei	0.23	-0.01	CC (down)
5/15/2019	PIIE 6: Huawei added to entity list	0.11	0.73	COI (up), CRS (down), RS (down)
8/19/2019	PIIE 6: Huawei affiliates added to entity list	1.46	-0.52	-

Notes: Bown and Kolb (2020). * indicates evening or weekend events: S&P 500 change and structural shock shows next working day values. Structural shock from baseline 6-variable model with 5 lags and 29 event dates. Event dates in grey fall together with Fed event dates. They are not used in the analysis. CB Consumer Confidence (CC), Crude Oil Inventories (COI), CCPI (Core CPI), Core Retail Sales (CRS), Existing Home Sales (EHS), Initial Jobless Claims (IJC), JOLTs Job Openings (JOLT), Nonfarm payrolls (NP), Pending Home Sales (PHS), Retail Sales (RS), Unemployment rate (UR). Up, down, and flat (-) concern actual minus forecast.

Table A4: Imposition dates

Date	Event	China exp. Index (% change)	Structural shock	Bloomberg Economic Calendar
1/22/2018	PIIE 1: President Trump approves global safeguard tariffs on solar panels and washing machines	0.3	0.19	-
3/23/2018	PIIE 2: Steel and aluminum tariffs go into effect	-2.25	0.34	CDGO (up), NHS (down)
7/6/2018	PIIE 3: US and China impose first phase of June 15 tariff lists	0.71	-0.19	NP (up), UR (up)
8/23/2018	PIIE 3: US and China impose second phase of \$50 billion tariffs	-0.38	0.77	IJC (down), NHS (down)
9/24/2018	PIIE 3: Next phase of tariffs goes into effect	-0.79	0.31	-
5/10/2019	PIIE 3: US raises tariff rate on previous list	0.16	-0.47	CCPI (down)
9/1/2019*	PIIE 3: Imposition of first part of list 4 (\$112/300bn total), China part of \$75bn	-1.33	0.53	ISM (down)

Notes: Bown and Kolb (2020). Structural shock from baseline 6-variable model with 5 lags and 29 event dates. * indicates evening or weekend events: S&P 500 change and structural shock shows next working day values. Core CPI (CCPI), Core Durable Goods Orders (CDGO), Initial Jobless Claims (IJC), ISM Manufacturing PMI (ISM), New Home Sales (NHS), Nonfarm Payrolls (NP), Unemployment Rate (UR). Up, down, and flat (-) concern actual minus forecast.

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 that address China to a large part. 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 24 event dates from Battle 3 only look nearly identical to our baseline specification (black solid line in Figure B1 and Figure B2). A further check adds event dates from Battles 2 and 3 that do not solely address China as well as the first battle over solar panels and washing machine imports to the event list (see Table A3). Battle 1 comprises the event dates October 31, 2017, and November 21, 2017 (falls together with a Fed chair speech and is thus discarded), 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 36 announcement dates, captured by the red dashed line in Figure B1 and Figure B3, look almost identical to the benchmark specification. In Figure

B1 we have further plotted the impulse responses for all US trade policy events from Battle 1 to 6 of the Peterson trade war timeline (47 event dates). Lastly, we added the imposition dates (see Table A4) which yields a total of 54 event dates.

<Figure B1-B3>

Varying event dates. Our baseline specification excludes three events from the 29 policy announcements where monetary policy news reached the market. The red dashed lines in Figure B4 depicts the impulse responses to a trade policy shock resulting from all 32 event dates while the black dash-dotted lines depict the impulse responses when we exclude releases of the ISM Purchasing Manager Index. As a further alternative, we add 7 imposition dates to the baseline specification (see Table A4 for information on these events). This extends the number of event dates to 35 (thick green dotted lines in Figure B4). These exclusions or inclusions do not alter our qualitative findings and show largely unchanged impulse responses. The full results including confidence bands for each set of event dates are shown in Figures B5-B7 of the online appendix.

<Figures B4-B7>

Bootstrap method. To test the robustness of our bootstrap method, we specify a recursive design wild bootstrap to obtain 1,000 samples that retain the given heteroskedasticity structure in the data generating process. This bootstrap multiplies the residuals with iid standard-normally distributed terms. It retains the mean and, in particular, the time-varying variance of the newly created residuals that are used to create the bootstrap. Through the multiplication with a scalar with mean zero and standard deviation of one, the bootstrap imitates the contemporaneous dependencies in the data, which are then used for identification. It is a common bootstrap for partially identified SVARs (Mertens and Ravn, 2013) as it produces valid inference under heteroskedasticity of unknown form (Gonçalves and Kilian, 2004). Confidence intervals from the residual-wild bootstrap are, however, nearly identical to their

moving-block bootstrap counterparts in Figure 2. Finally, Figure B9 displays the moving-block bootstrap using bias-adjusted VAR reduced form estimates.

<Figure B8-B9>

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. The China exposure US stock index contains 38 out of the original 47 S&P 500 firms over the long horizon. Comparing the impulse responses for the longer sample, shown in Figure B10 to our baseline results, we observe that the effects on impact are quantitatively close. The stock price responses are more persistent while the interest rate responses lose some statistical significance.

<Figure B10>

Different lag lengths. Finally, we experiment with different lag lengths. Figure B11 shows the impulse response for one, five, ten, and 20 lags, which are almost unchanged compared to the baseline estimates.

<Figure B11>

Major event dates. Here, we select event dates according to a statistical criterion. We choose 15, 20, 25 and 30 event dates with the largest absolute change in China exposure stock index on these dates.

<Figure B12>

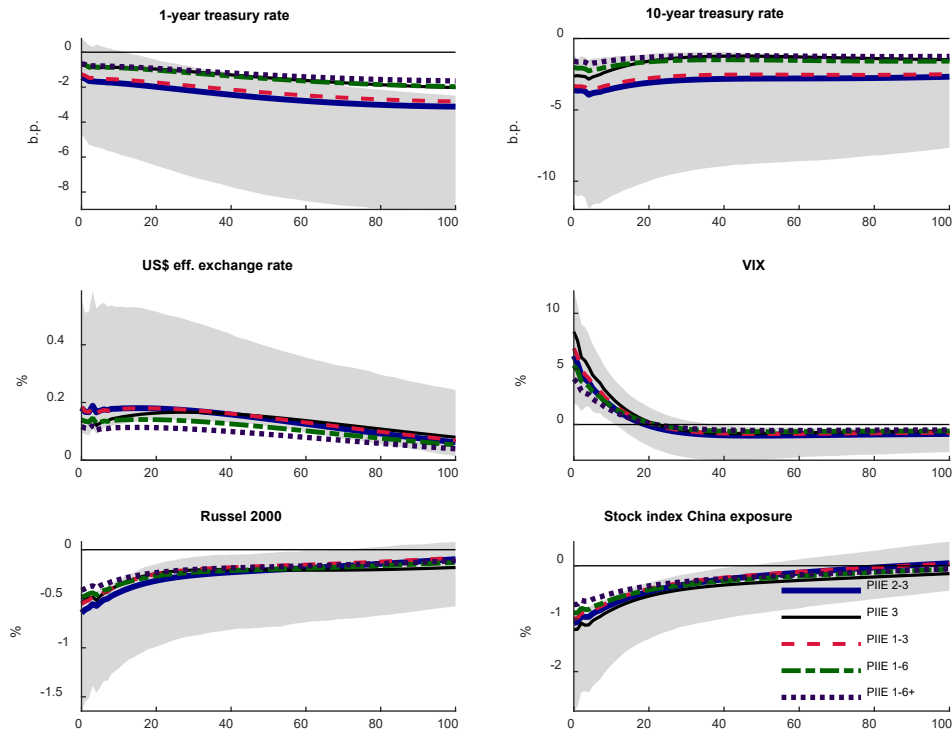
Bayesian VAR estimation. We estimate a Bayesian VAR using a Minnesota prior with standard shrinkage parameters (Doan et al. 1984, Litterman, 1986).

<Figure B13>

Day-of-week dummies. The reduced form VAR is estimated with day-of-week dummies as exogenous regressors.

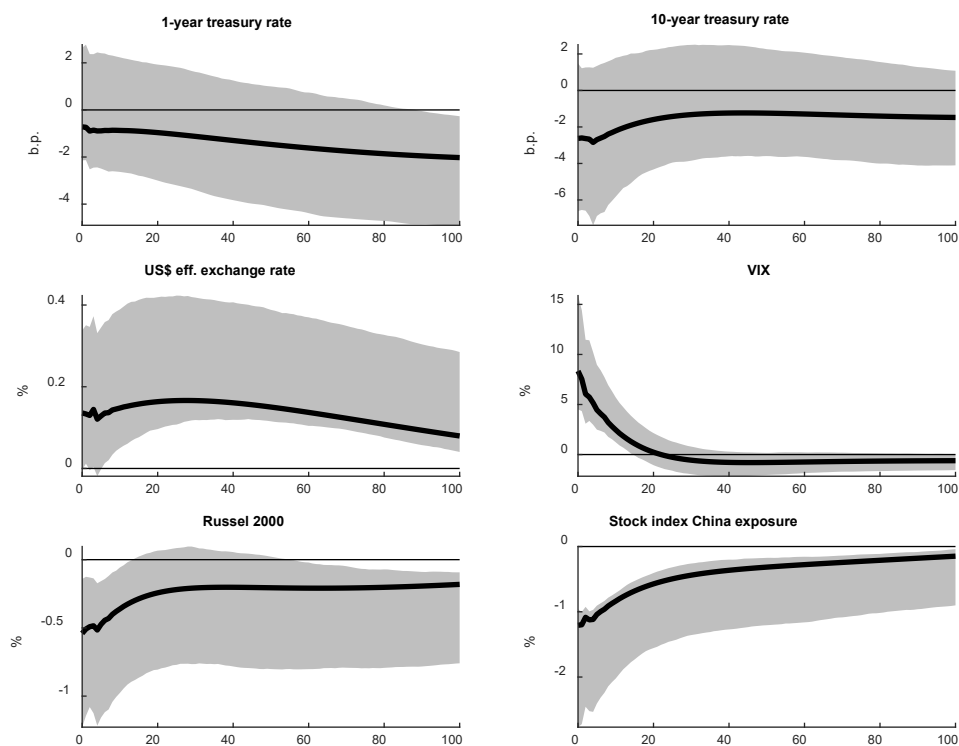
<Figure B14>

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



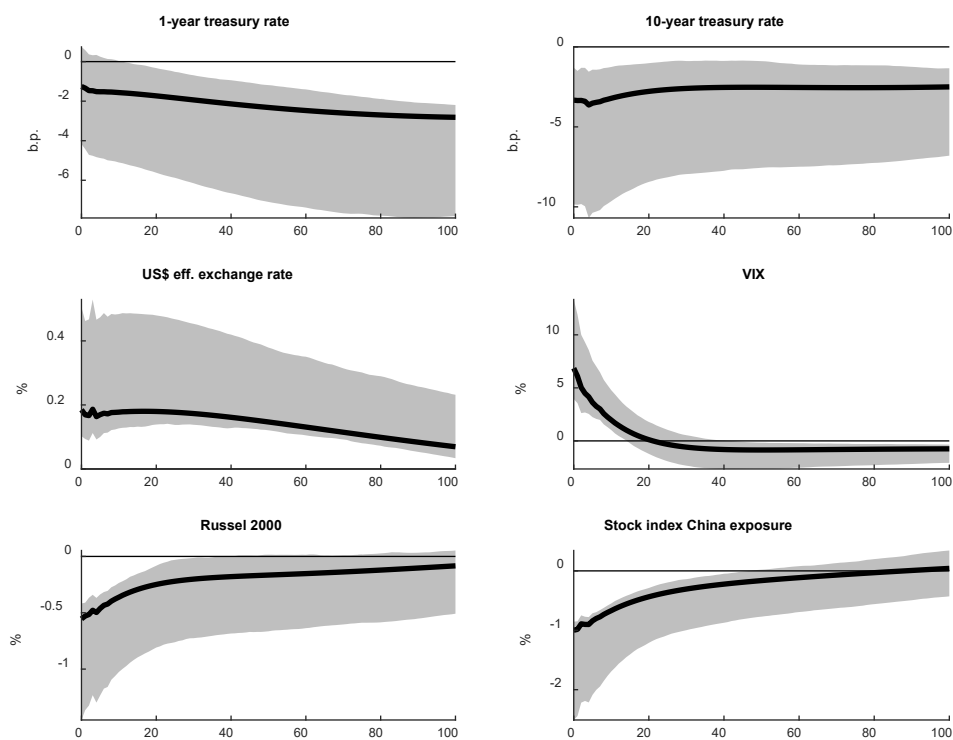
Notes: Impulse responses for the different event day specifications. ‘PIIE 2-3’ is the baseline specification with 29 event dates. ‘PIIE 3’ contains 24 event dates from category 3 (subset of ‘PIIE 2-3’). ‘PIIE 1-3’ contains 36 event dates from categories 1 to 3 including additional category 2 and 3 events that do not concern China (see Table A3). ‘PIIE 1-6’ contains 47 event dates from all 6 categories including events that do not concern China (see Table A3). ‘PIIE 1-6+’ contains 54 event dates. The 47 event dates from ‘PIIE 1-6’ and 7 additional imposition dates from Table A4. 5 lags. The grey areas show 90% confidence intervals for the 29-dates baseline specification.

Figure B2: Impulse responses to US trade policy shock using 24 announcement dates from PIIE Battle #3



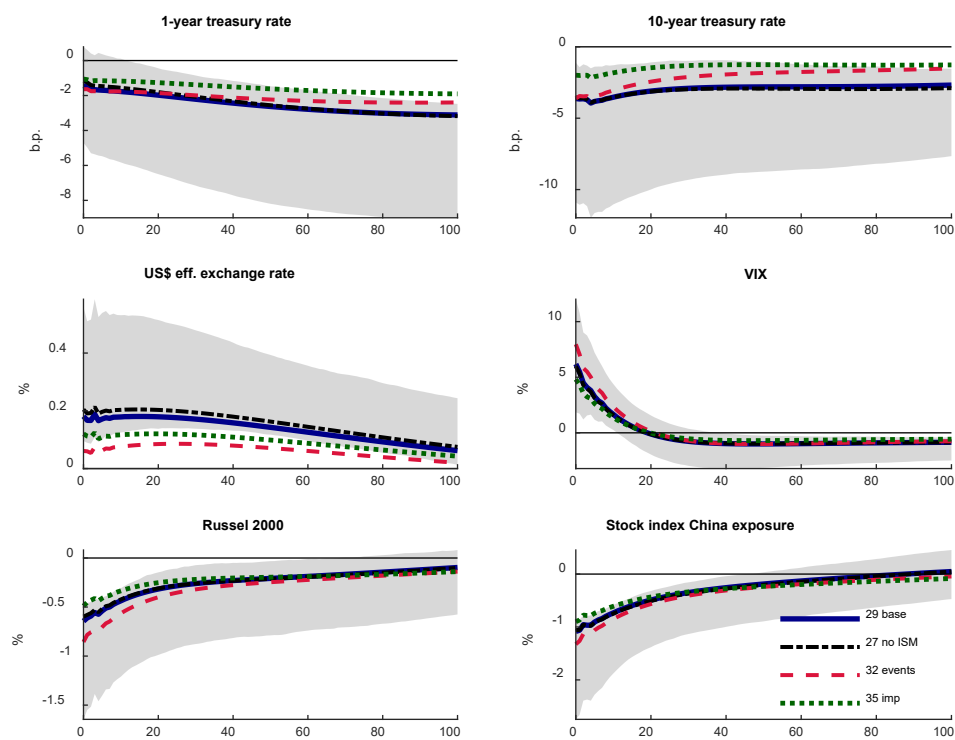
Notes: 24 event dates resulting from 29 baseline events without 5 events from PIIE category 2 (“Steel and Aluminum”). The 5 dates left out are April 20, 2017, April 27, 2017, February 16, 2018, March 8, 2018, and July 16, 2018. The grey areas show 90% confidence intervals.

Figure B3: Impulse responses to US trade policy shock using 36 announcement dates from PIIE Battles #1-3



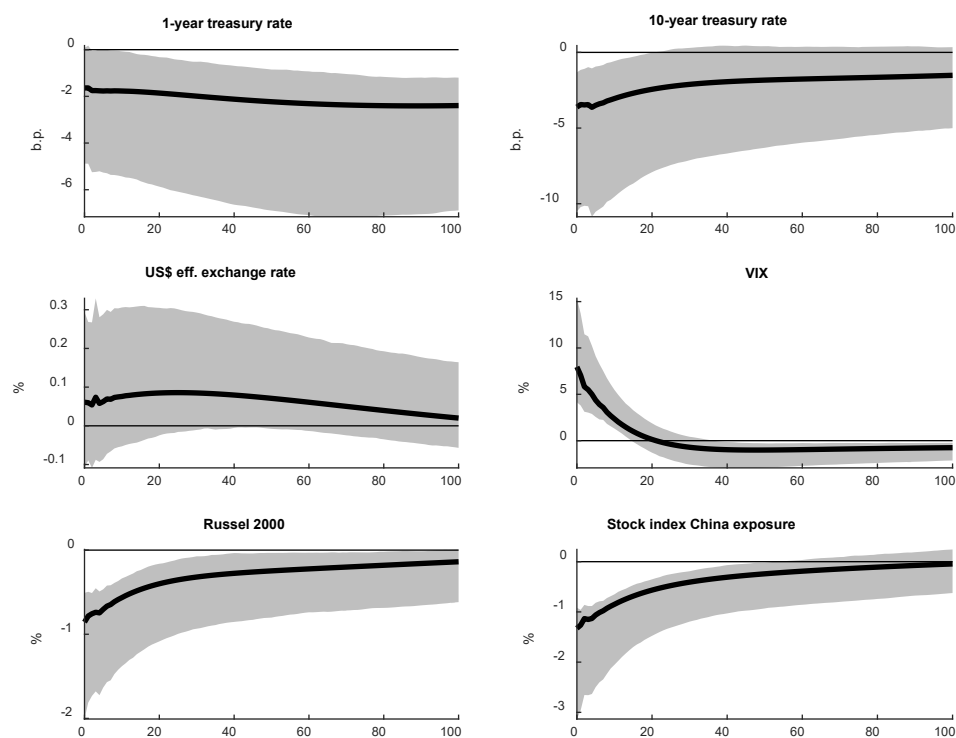
Notes: 36 baseline and additional events from PIIE category 1-3 from Table A3. 5 lags. The grey areas show 90% confidence intervals.

Figure B4: Impulse responses to US trade policy shock using different event date specifications



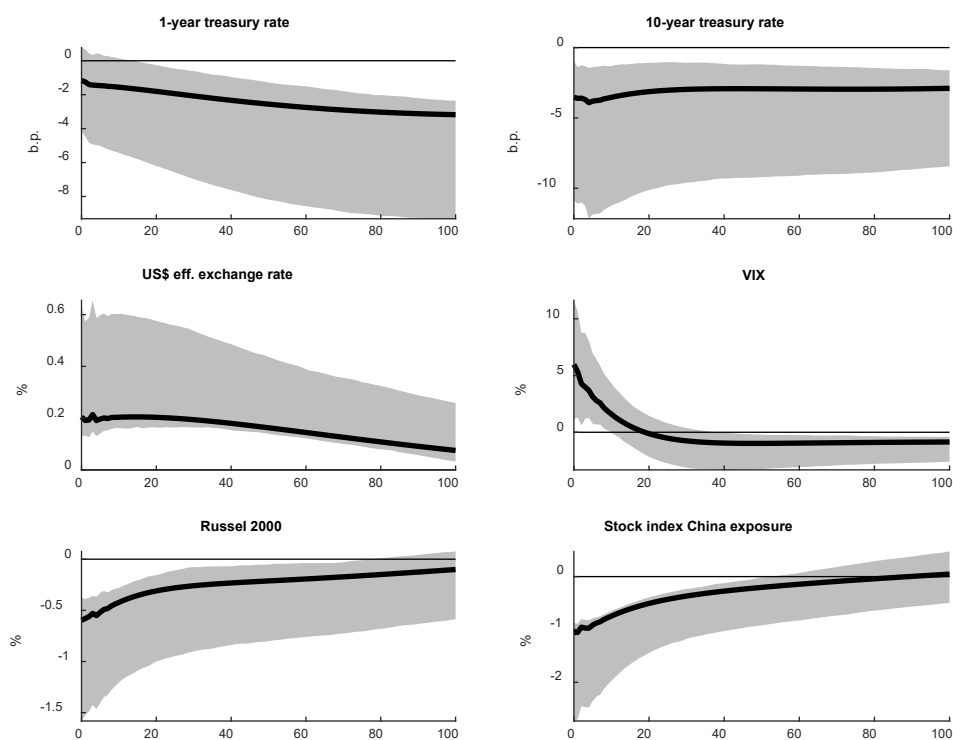
Notes: Each specification uses 5 lags. The grey areas show 90% confidence intervals for the 29-dates baseline specification.

Figure B5: Impulse responses to US trade policy shock using 32 event dates



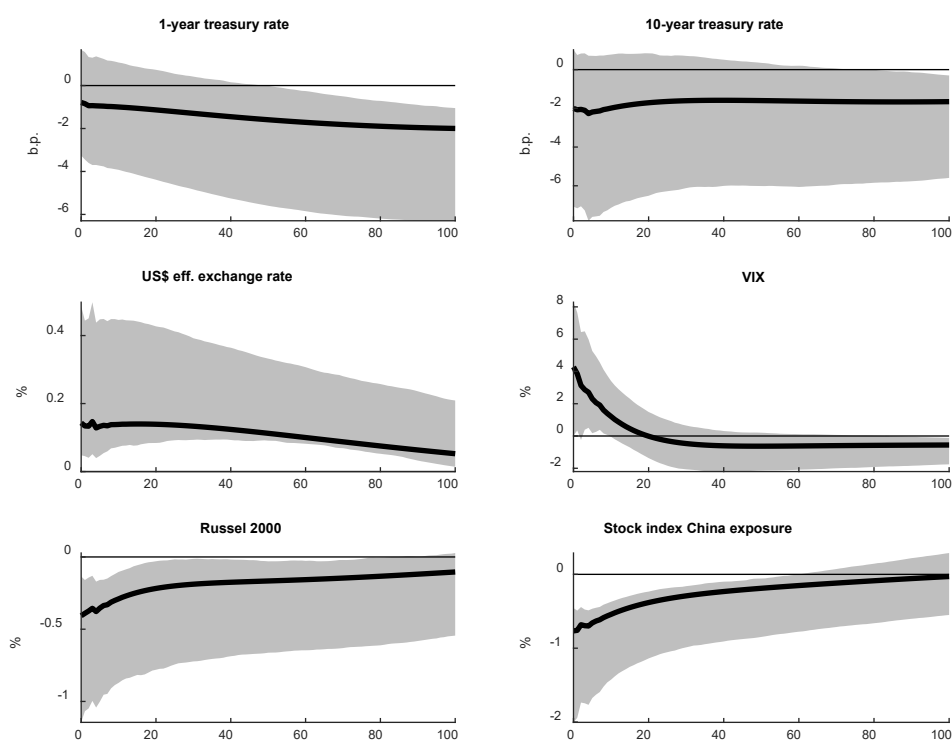
Notes: The specification uses all 32 event dates from Table 1. 5 lags. The grey areas show 90% confidence intervals.

Figure B6: Impulse responses to US trade policy shock excluding ISM release dates



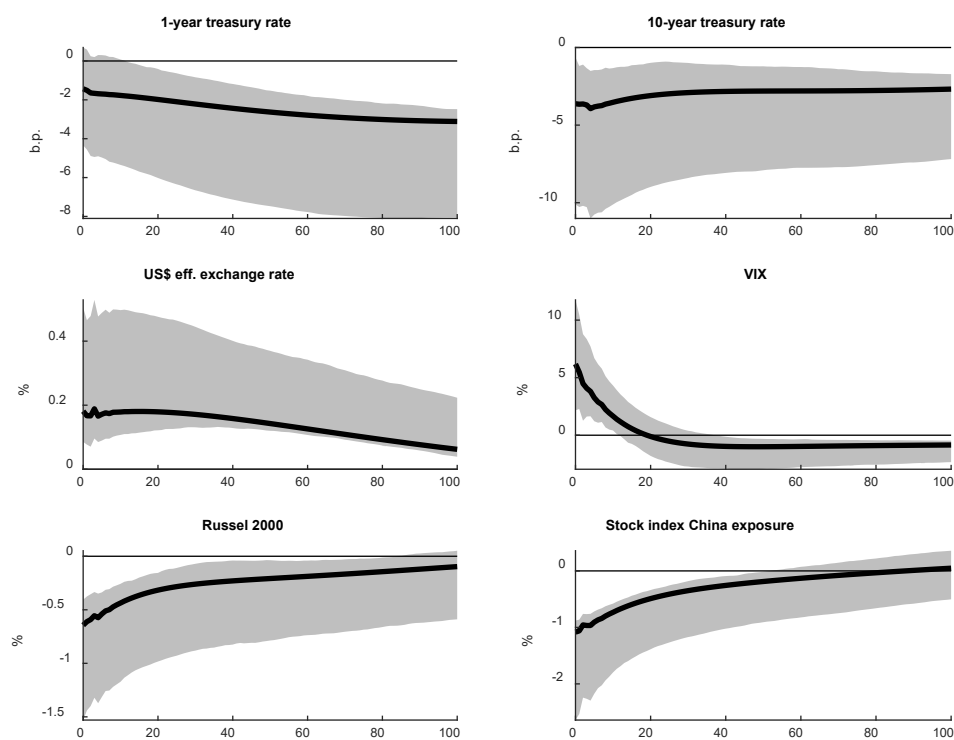
Notes: 27 event dates discarding December 1, 2018 and August 1, 2019 from the 29-events baseline case. 5 lags. The grey areas show 90% confidence intervals.

Figure B7: Impulse responses to US trade policy shock using 35 event dates including imposition dates



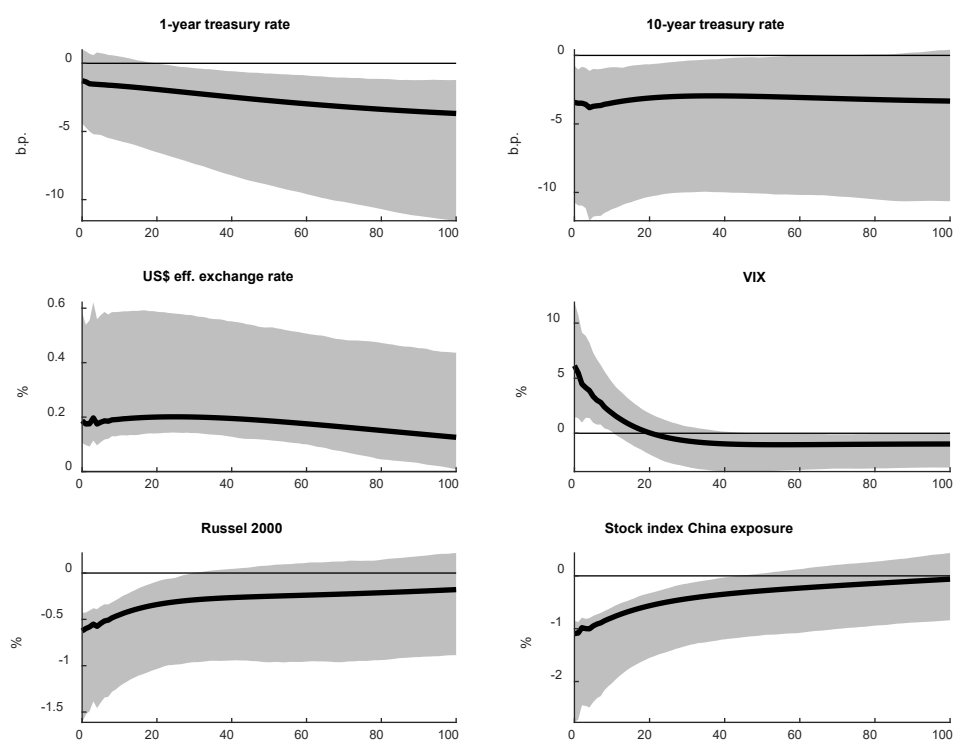
Notes: The following six events with US tariff impositions from Table A4 are added to the 29 baseline events: March 23, 2018 (steel and aluminum tariffs), July 6, 2018 (25% tariffs on US\$ 34 bn of Chinese imports), August 23, 2018 (25% tariffs on US\$ 16 bn of Chinese imports), September 24, 2018 (10% tariffs on US\$ 200 bn of Chinese imports), May 10, 2019 (rise from 10 to 15% for US\$ 200 bn list) and September 3, 2019 (10% tariffs on US\$ 112 bn of Chinese imports). 5 lags. The grey areas show 90% confidence intervals.

Figure B8: Impulse responses to US trade policy shock using residual-wild bootstrap



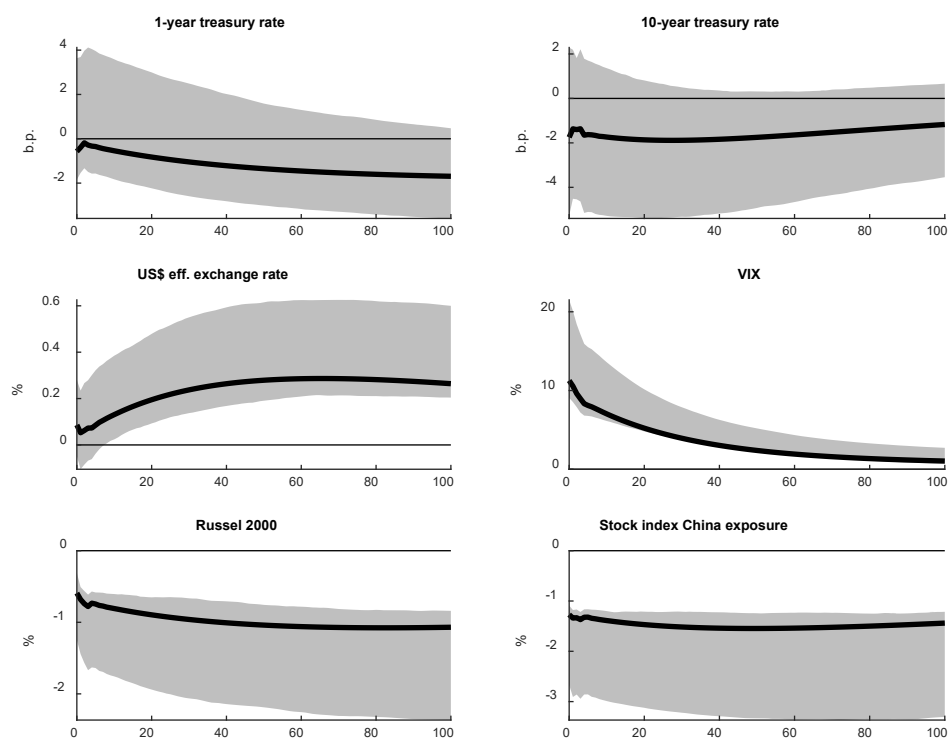
Notes: Baseline 29 event dates and 5 lags. Grey areas show 90% confidence intervals.

Figure B9: Impulse responses to US trade policy shock with bias-adjustment



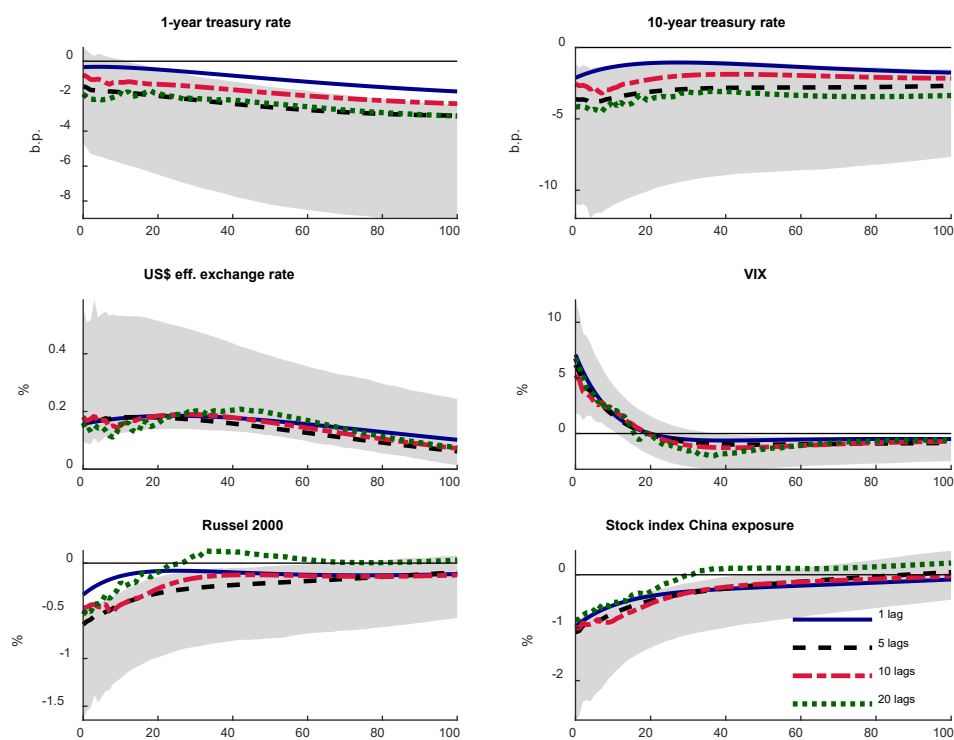
Notes: Bias-adjustment of the reduced form VAR parameters as in Kilian (1998). The structural impact matrix is constructed using the bias-adjusted reduced form residuals. The moving-block bootstrap is based on the bias-adjusted parameters and residuals. The grey areas show 90% confidence intervals.

Figure B10: Impulse responses to US trade policy shock for longer sample



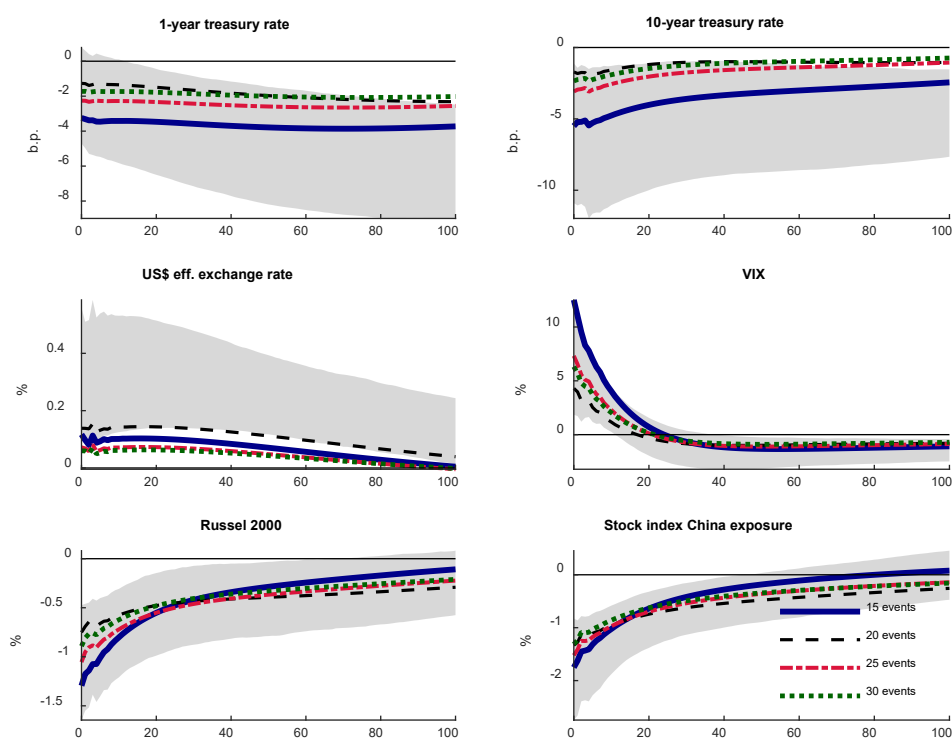
Notes: The sample horizon is June 4, 2008, to January 17, 2020. 29 baseline events and 5 lags. Stock index China exposure contains 33 of the 47 original index's firms for which the stock price is publicly available since the beginning of the sample. Excluded firms are AMD, APTV, CPRI, FBHS, LW, QRVO and WDC. The grey areas show 90% confidence intervals.

Figure B11: Overview of impulse responses with different lag lengths



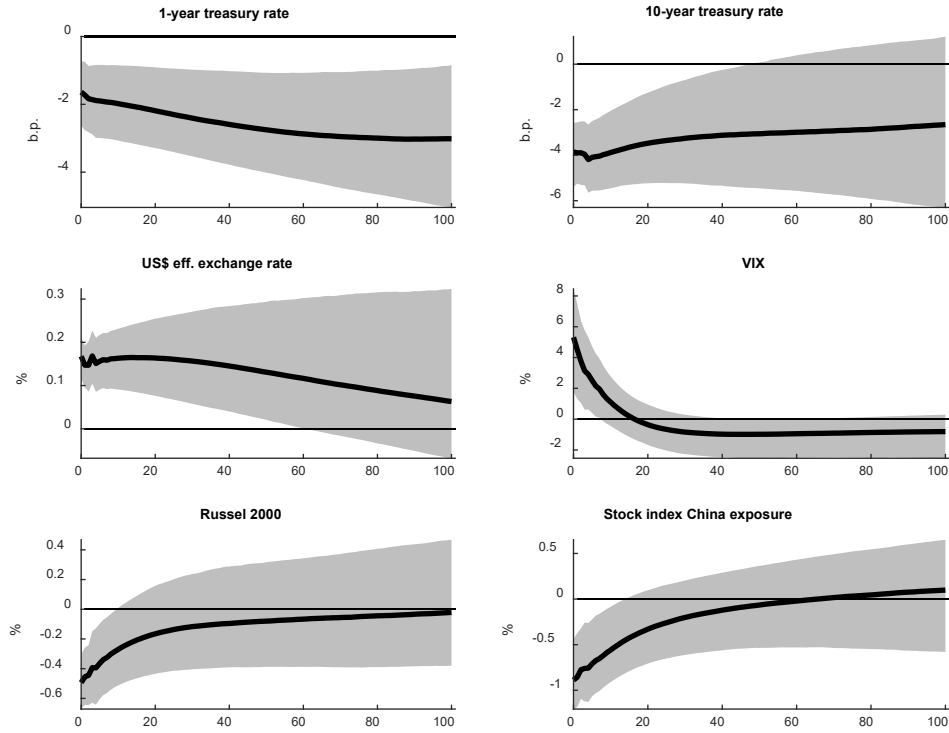
Notes: Impulse responses for 29 baseline announcement dates using VARs with 1, 5, 10 and 20 lags. 90% confidence intervals for 5-lags baseline model.

Figure B12: Impulse responses to US trade policy shock using major event dates



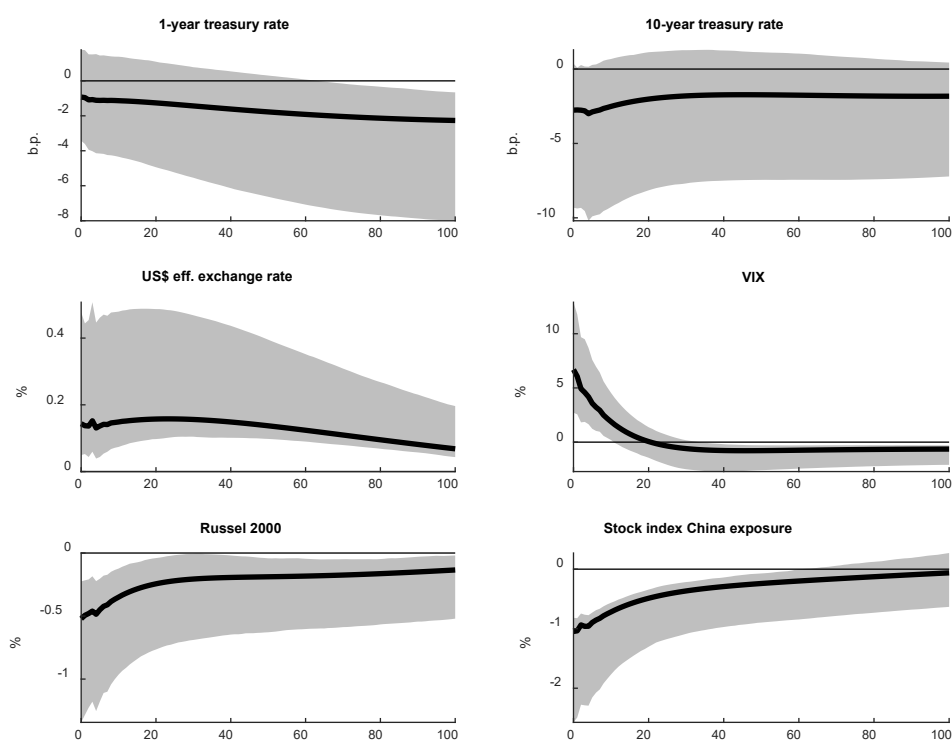
Notes: Impulse responses for 15, 20, 25, and 30 announcement dates with the absolute largest changes in the China exposure index. The events are selected from a base sample of 59 event dates (50 dates from PIIE category 1 – 6 including Fed-information dates and 7 imposition dates (see Table A3 and A4). The grey areas show 90% confidence intervals for the 29-events baseline specification.

Figure B13: Impulse responses to US trade policy shock using Minnesota prior



Notes: Minnesota type prior as in Doan et al. (1984) and Littermann (1986) where the two shrinkage parameters are set to 1. 29 baseline event dates and 5 lags. Pointwise median and 10% and 90% quantiles of the posterior distribution from 10,000 draws (as in Kilian and Lütkepohl, 2017, Section 5.2.3).

Figure B14: Impulse responses to US trade policy shock using day-of-week dummies in the VAR estimation



Notes: The reduced form VAR is estimated including day-of-week dummies as exogenous regressors. The moving-block bootstrap uses the data-generating process including the dummies. The grey areas show 90% confidence intervals for the 29-events specification with 5 lags.