

The Global Transmission of U.S. Trade Policy Uncertainty Shocks*

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Abstract

This paper examines the spillovers of U.S. trade policy uncertainty (TPU) shocks on economic activity and inflation in 36 advanced and emerging economies. Using a novel identification scheme in a Structural Vector Autoregression (SVAR) model, I complement a small number of uncontroversial sign and zero restrictions with narrative sign restrictions based on stock market jumps triggered by news about TPU during the Trump presidency. Evidence from local projections shows that, on average, U.S. TPU shocks reduce industrial production, trade, and stock prices in both the U.S. and abroad, while also leading to a depreciation of currencies against the U.S. dollar. In advanced economies, demand channels dominate the transmission, resulting in lower inflation. In contrast, in emerging economies, currency depreciation linked to a flight-to-safety channel puts upward pressure on inflation, offsetting the deflationary effects of reduced aggregate demand, creating monetary policy trade-offs for these countries.

Keywords: Trade policy uncertainty; Trade; Uncertainty shocks; International transmission

JEL codes: C11, C33, D80, F13, F42

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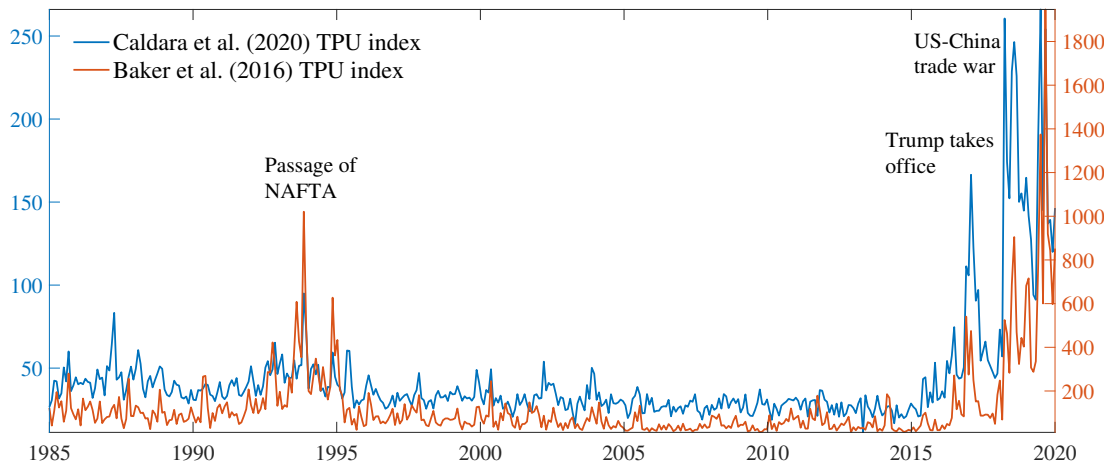
1 Introduction

“We have much experience in addressing typical macroeconomic developments [...] But [...] trade policy uncertainty [...] is a new challenge.”

Jerome Powell, Jackson Hole Symposium, August 2019

The shift toward greater protectionism in the U.S. during the Trump administration resulted in an unprecedented rise in trade policy uncertainty (TPU), as reflected in the news-based TPU indices of [Baker, Bloom, and Davis \(2016\)](#) and [Caldara, Iacoviello, Molligo, Prestipino, and Raffo \(2020\)](#) displayed in Figure 1. One significant concern for policymakers was not only its influence on economic activity but also on price stability. For instance, expressing worry about its potential impact on inflation, Jeremy Powell, Chair of the Federal Reserve, commented in the same speech quoted above: *“There are, however, no recent precedents to guide any policy response to the current situation. We can, however, [...] focus on how trade developments are affecting the outlook, and adjust policy to promote our objectives.”*

Figure 1: News-based TPU indices for the U.S. economy



Note: The figure shows the monthly news-based TPU indices constructed by [Baker et al. \(2016\)](#) and [Caldara et al. \(2020\)](#). The indices differ in the newspaper search terms. In particular, [Caldara et al. \(2020\)](#) do not search for terms of legislation or institutions such as NAFTA and the WTO that are otherwise captured in the other index. Sample period from 1985M1 to 2019M12.

TPU stemming from diverse trade developments, such as tariff announcements or threats, which were commonplace during the Trump presidency, complicates the assessment of macroeconomic risks. From the viewpoint of many economic models, TPU can influence the macroe-

economy and inflation through several channels. On the one hand, TPU can represent a source of macroeconomic fluctuations when it reflects *exogenous* events, such as trade tensions (e.g., [Caldara et al., 2020](#)). On the other hand, TPU may arise as an *endogenous* response to tariff shocks, thus amplifying their effects. The impact, in turn, may vary depending on the nature of the tariff shock, whether it is an *unanticipated* shock—referring to immediately implemented tariff announcements—or an *anticipated* one involving announced but not yet imposed tariffs (see, e.g. [Staiger and Wolak, 1994](#); [Tharakan, 1995](#); [Alessandria, Khan, and Khederlarian, 2019](#)).

As detailed below, the empirical literature has primarily provided reduced-form evidence on how TPU around key events such as China’s WTO accession, Brexit, and the U.S.-China trade war shapes microeconomic outcomes (for a comprehensive review, see [Handley, Kamal, and Monarch, 2020](#)). However, there is little well-identified empirical evidence quantifying the macroeconomic effects and international spillovers of *exogenous shifts* in TPU, i.e. TPU shocks. Additionally, the study of whether TPU shocks induce monetary policy trade-offs for central banks has been largely overlooked. This paper seeks to fill this gap. In general, identifying these shocks is challenging because (i) TPU is not directly observable, (ii) TPU shocks are not frequent ([Handley and Limão, 2015](#)), and (iii) TPU is potentially endogenous to the business cycle, as governments are more prone to adopt protectionist trade policies, especially during downturns ([Bohara and Kaempfer, 1991](#); [Bown and Crowley, 2013](#)). Overcoming these challenges, this paper addresses the following questions: How do TPU shocks originating in the U.S. influence economic activity, financial markets, and inflation in advanced and emerging economies? Are the spillovers primarily driven by real or financial channels? And ultimately, do they entail monetary policy trade-offs?

Given the possibility of a second Trump presidency, having timely estimates of the macroeconomic consequences of U.S. TPU shocks is essential to inform future policymaking decisions. If Trump wins a second term in the forthcoming November election, substantial changes in U.S. policy will likely occur. The Republican party platform, “The American Presidency Project,” outlining Trump’s policies, calls for an extensive programme to deport undocumented immigrants and implement stricter immigration regulations. Trading

partners should anticipate increased tariffs, as Trump has proposed imposing duties on all imports. In this context, this work uses the U.S. as a case study to examine the international spillovers of TPU shocks.

I find that the identification strategy proposed in this work, based on narrative information derived from a few key daily stock market jumps reacting to TPU during the Trump administration, is highly effective in assessing the impact of TPU shocks. I show that incorporating this information into a Structural Vector Autoregression (SVAR) model helps address the challenges mentioned earlier. Reverse causality of economic conditions can be ruled out because these factors are already priced in by the market at the time of the trade policy announcement and are unlikely to change within the tight window. Moreover, the trade policy developments during the Trump administration allow us to isolate exogenous shifts in TPU, as his actions were arguably unrelated to economic fundamentals. Our analysis using local projections shows that U.S. TPU shocks lead to declines in industrial production, trade, and stock prices in both the U.S. and abroad, along with a depreciation of their the U.S. dollar. In the U.S. and advanced economies, this transmission primarily occurs through demand channels, resulting in lower inflation. Conversely, in emerging economies, currency depreciation, driven by a flight-to-safety phenomenon, exerts upward pressure on inflation, countering the deflationary effects of reduced aggregate demand and creating monetary policy challenges for these economies.

To formally construct the narrative information, I identify large daily jumps in the S&P 500 index caused by news about TPU induced by Trump’s tariff threats. I rely on the stock market jumps classification by [Baker, Bloom, Davis, and Sammon \(2021\)](#), encompassing trade policy for this task. Complementing their categorisation, I select jumps stemming from Trump’s tariff threats against trade partners. I document five jumps occurring in March 2018, December 2018, and August 2019. These daily movements are large enough to pinpoint periods when TPU shocks predominantly drove monthly *realised* stock market volatility. To reach these findings, I follow a two-step approach involving (i) the identification of U.S. TPU shocks and (ii) the analysis of their transmission to the Mexican economy. In the first step, I identify TPU shocks within a SVAR model for the U.S. economy imposing

a small number of uncontroversial sign and zero restrictions on impulse response functions using the methodology proposed by [Arias, Rubio-Ramírez, and Waggoner \(2018\)](#). Following the approach of [Antolín-Díaz and Rubio-Ramírez \(2018\)](#), this identification scheme is complemented with narrative sign restrictions obtained from narrative information of a small number of key historical events of exogenous variations in U.S. TPU. The VAR model is estimated using Bayesian techniques with monthly data from January 1990 to December 2019, a period during which the U.S. implemented significant trade policy changes, including the negotiation of the NAFTA trade agreement and the recent trade war during the Trump administration. Consequently, the estimated effects capture the average impact over the entire sample period, providing a broader perspective compared to a simple event study approach, which would not account for other periods.

The first contribution of this work is the development of a new identification scheme that leverages narrative information from U.S. stock market jumps triggered by news about TPU stemming from Trump’s tariff *threats* against trade partners during 2018-2019. Trump’s trade war, which was arguably exogenous to economic fundamentals and driven by political motives, unexpectedly targeted allies, making it an ideal case for studying exogenous variations in TPU. In this context, I differentiate between trade policy *actions* and *threats*. While actions, such as unexpected tariff announcements, are linked to tariff shocks, the analysis of TPU arising from unexpected tariff threats is crucial for identifying TPU shocks. For instance, [Handley and Limão \(2017\)](#) demonstrate using a structural model that economic agents’ reactions to increased TPU from tariff threats can lead to significant macroeconomic costs, *even if these threats never materialise*.

I exploit the narrative information in a monthly SVAR model for the U.S. economy. The VAR model includes the news-based TPU index of [Caldara et al. \(2020\)](#), realised stock market volatility, import tariff rates, business confidence, and typical macroeconomic data. Motivated by the narrative information, I impose two sign restrictions: heightened TPU, as captured by higher values in the TPU index, leads to a contemporaneous increase in realised stock market volatility. Additionally, I impose zero impact restrictions on tariffs and business confidence to ensure that TPU shocks are orthogonal to tariff shocks and

tariff *news* shocks (unexpectedly announced, but not yet imposed tariffs). The second zero restriction is particularly motivated by the fact that business confidence accounts for the lion’s share of trade policy *news* shocks (see [Metiu, 2021](#)). Both sign and zero restrictions are imposed following the approach by [Arias et al. \(2018\)](#). The remaining macroeconomic variables are unrestricted. Finally, identification is sharpened by imposing that the spike in realised stock market volatility in March 2018, December 2018, and August 2019, are mainly driven by TPU shocks. This information is incorporated as narrative sign restrictions in the SVAR model, employing the methodology proposed by [Antolín-Díaz and Rubio-Ramírez \(2018\)](#).

In the second step, armed with our estimated U.S. TPU shocks from the SVAR model, I proceed to estimate their transmission to the Mexican economy. To achieve this, I regress Mexican macroeconomic variables on the U.S. TPU shocks using local projections ([Jordà, 2005](#)). The analysis covers the period from January 2002 to December 2019, during which Mexico has operated under a single monetary policy regime—inflation targeting—that has achieved lower and more stable inflation as well as financial stability. Given that this study examines whether U.S. TPU shocks induce monetary policy trade-offs, this period is particularly suitable for exploring such dynamics within this regime. In addition to measures of economic activity and inflation, I consider the responses of trade and financial variables to identify the specific channels at play. I also estimate the responses of the same variables for the U.S. to compare and contrast the transmission of U.S. TPU shocks between the two countries.

Our identification strategy uncovers several new insights. First, I demonstrate that incorporating a few narrative sign restrictions significantly enhances the identification initially achieved through sign and zero restrictions, to the extent that it alters the economic implications. Since TPU shocks are infrequent, this method is particularly effective for this application as it relies on a small number of key episodes rather than an entire time series. Our findings show that U.S. TPU shocks reduce domestic output, employment, and stock prices, consistent with theoretical predictions. Notably, the significant negative response of stock prices on impact aligns with the theoretical predictions of [Pástor and Veronesi \(2013\)](#),

indicating a risk premium channel rather than an expectations channel. A recursive identification scheme, commonly used to analyze economic policy uncertainty (EPU) shocks by placing news-based EPU indices first in VAR models, does not replicate this stock price response.

I also demonstrate that TPU shocks significantly contributed to historical fluctuations in U.S. stock market volatility following Trump’s election, particularly during the U.S.-China trade tensions. Furthermore, a forecast error variance decomposition reveals that TPU shocks account for a larger share of short-term variations in financial markets compared to macroeconomic variables. These findings contribute to the ongoing debate on the differing effects of tariffs on the aggregate economy versus stock markets, as discussed in [Fajgelbaum and Khandelwal \(2021\)](#). This evidence suggests that TPU may be a key factor in reconciling these differences.

This paper is organised as follows. Section 2 reviews the related literature and explains my contributions. Section 3 describes the SVAR model and the identification scheme to recover US TPU shocks. Section 4 presents the data, the empirical methodology, and the results. Section 5 concludes.

2 Related literature

This paper contributes to the literature that analyses the role of economic policy uncertainty in the context of trade policy. A growing literature, both theoretical and empirical, has studied the direct trade effects of TPU around key episodes: China’s WTO accession, Brexit, and the U.S.-China trade war ([Handley, 2014](#); [Handley and Limão, 2015](#); [Feng, Li, and Swenson, 2017](#); [Crowley, Meng, and Song, 2018](#); [Crowley, Exton, and Han, 2020](#); [Graziano, Handley, and Limão, 2021](#)). Other studies have explored broader impacts on asset prices ([Bianconi, Esposito, and Sammon, 2021](#)), employment ([Pierce and Schott, 2016](#)), and investment and innovation ([Pierce and Schott, 2018](#); [Bloom, Bunn, Chen, Mizen, Smietanka, and Thwaites, 2019](#); [Caldara et al., 2020](#); [Liu and Ma, 2020](#); [Benguria, Choi, Swenson, and Xu, 2022](#)). These papers provide evidence of detrimental (beneficial) effects of higher (lower) TPU at

the firm, industry, and product levels. Some of them also examine the role of trade agreements in affecting TPU. Further, they focus on either single-country or bilateral analysis. Regarding international effects, [Hassan, Hollander, van Lent, and Tahoun \(2020\)](#) demonstrate that firms more exposed to Brexit uncertainty experience a loss in market value, alongside reductions in hiring and investment, across 81 countries.

The literature has also complemented the partial equilibrium estimates with general equilibrium analysis. On the theoretical side, [Handley and Limão \(2017\)](#) employ a general equilibrium framework and provide evidence that China’s WTO accession lowered the TPU it faced in the US. They find that this reduction in TPU explains over one-third of China’s export boom to the US. [Steinberg \(2019\)](#) examine the economic effects of Brexit using a dynamic model and find a minimal impact of uncertainty on aggregate trade and welfare. ? use an inventory model and find that trade increases strongly in anticipation of uncertain future increases in tariffs taking China’s pre-WTO accession as a study case.

The empirical analysis at the aggregate level is limited likely due to the difficulties in measuring aggregate TPU and cleanly identifying its causal impact. Aggregating over firm-level responses in the Survey of Business Uncertainty (SBU), [Altig, Barrero, Bloom, Davis, Meyer, and Parker \(2020\)](#) show the trade policy concerns during the Trump administration had negative effects on US employment, sales, and investment, albeit modest in size. Other studies have employed news-based indices to identify SVAR models applying a recursive approach. Using the EPU index of [Baker et al. \(2016\)](#) for the UK, [Born, Müller, Schularick, and Sedláček \(2019\)](#) identify both Brexit uncertainty and expectations shocks and show that uncertainty shocks played a limited role in explaining the Brexit outcomes. [Caldara et al. \(2020\)](#) build two aggregate TPU indicators for the US using newspaper coverage and data on import tariffs and find that shocks to both measures reduce business investment.

There are two important differences between this work and the two aforementioned papers. First, while I resort to news-based indices of TPU, our identification scheme exploits large daily jumps in financial markets caused by news about future TPU and incorporates this information into the SVAR in the form of narrative sign restrictions. In this regard, this identification scheme addresses the simultaneity problem between uncertainty and economic

conditions inherent in a recursive ordering (see [Baker, Bloom, and Terry, 2020](#)). In addition, our approach reflects the perceptions of both journalists and market participants about future TPU, thus covering a wider sector of the population. Second, the focus of this paper is on the international transmission of U.S. TPU shocks. Therefore, our work complements the existing evidence based on microdata, proposes an alternative identification strategy at the aggregate level, and examines spillover effects.

Finally, this paper is also related to a recent wave of contributions drawing insights from stock market reactions to trade policy developments ([Breinlich, 2014](#); [Moser and Rose, 2014](#); [Breinlich, Leromain, Novy, Sampson, and Usman, 2018](#); [Huang, Lin, Liu, and Tang, 2019](#); [Greenland, Ion, Lopresti, and Schott, 2020](#); [Amiti, Kong, and Weinstein, 2021](#); [Boer, Menkhoff, and Rieth, 2021](#); [Carlomagno and Albagli, 2022](#)). This literature has concentrated on episodes related to trade liberalizations, trade agreements, and more recently Brexit and the US-China trade tensions and examines their effects on macroeconomic and/or financial variables at the firm level. In contrast, this paper focuses on stock market reactions to future TPU at the aggregate level.

3 Identification of TPU shocks

In this section, I estimate aggregate TPU shocks originating in the U.S. in a SVAR model identified with sign and zero restrictions ([Arias et al., 2018](#)) and complemented with narrative sign restrictions ([Antolín-Díaz and Rubio-Ramírez, 2018](#)). The narrative information is based on large daily jumps in financial markets caused by news about future TPU. I show that including a few narrative sign restrictions significantly sharpens the inference of the SVAR originally identified with sign and zero restrictions.

3.1 The narrative information

3.1.1 Stock Market Reactions to Trade Policy Developments

To identify historical episodes of exogenous variations in U.S. TPU, I exploit the information contained in high-frequency data, examining the stock price responses of the S&P 500 index

to trade policy developments. Many companies listed in the index, especially larger ones, are oriented towards the global economy. Given the interconnected nature of the modern economy, U.S. trade policy concerns pose a risk to their international operations, thereby diminishing their market valuation. This decrease in equity value on the U.S. stock market may occur even if the impact on the company’s domestic operations is minimal.

To this end, I resort to the stock market jumps classification by [Baker et al. \(2021\)](#). The authors identify U.S. stock market jumps, defined as large daily movements of 2.5% or more (up or down) in the S&P 500 index, and document a total of 1,116 jumps from 1900 to 2019, covering about 1% of trading days during this period. They then examine next-day news articles in the Wall Street Journal (WSJ) and other major newspapers and systematically classify the jumps into 16 categories, one of which pertains to trade policy. Additionally, they investigate the geographic source and clarity of these events. The jump threshold of 2.5% was chosen to be large enough to ensure that the next day’s newspaper always contained articles discussing the prior day’s jump.

Next-day accounts attribute 7 of 1,103 (0.63%) jumps from 1900 to 2017 to news about trade policy, with all seven jumps occurring during the 1930s. In contrast, 5 of 13 (38.5%) jumps from 2018 to 2019 are explained by trade policy news. Given our study period, [Table 1](#) lists only the dates of trade-policy jumps in 2018-2019 and includes other jumps triggered by different types of news within the same month. It also reports the geographic source of the market movement and a key description of the event. [Appendix A.1](#) provides a summary of these events based on WSJ articles.

Several insights emerge from this narrative analysis. First, journalists consistently attribute stock market jumps to trade policy news with a high degree of confidence. Second, these jumps occurred during the U.S.-China trade war, which, according to many observers, began in March 2018 (see, e.g. [Bown, 2021](#)). Third, four out of the five trade-policy jumps originated in the U.S. Notably, U.S. trade-policy jumps were the primary driver of stock market volatility in March 2018. Moreover, while other factors also influenced market fluctuations, U.S. trade-policy jumps played a significant role in the volatility observed in December 2018 and August 2019. The trade-policy jump in August 2019, which originated

Table 1: Narrative Information from Stock Market Jumps

Date	Return	Category	Origin	Event	Government policy uncertainty type
Mar 22, 2018*	-2.52%	Trade Policy	U.S.	Trump threatens China with future tariffs	Political uncertainty
Mar 26, 2018*	2.72%	Trade Policy	U.S.	Trump would be willing to negotiate	Political uncertainty
Dec 4, 2018*	-3.24%	Trade Policy	U.S.	Unclear outlook for US trade policy	Political uncertainty
Dec 24, 2018*	-2.71%	Central Banking	U.S.	Uncertainty about Fed's monetary stance	-
Aug 5, 2019*	-2.98%	Trade Policy	U.S.	US might extend tariffs to Chinese imports	Political uncertainty
Aug 14, 2019*	-2.92%	Macro News	Germany/ China	Weak economic data	-
Aug 23, 2019*	-2.59%	Trade Policy	China	China warns of retaliation against US	Political uncertainty

Note: Information based on the narrative account provided by [Baker et al. \(2021\)](#). *All stock market jumps are classified with a high level of confidence by the journalist. Journalist confidence refers to how confident (high, medium, low) the journalist seemed in attributing the reason for the market movement. Date: Market movement exceeding 2.5%, up or down. Return: Value-weighted return on the S&P 500. Category: The primary reason the WSJ article attributed the market movement to. Origin: Source of the market movement. Event: Key description. Government policy uncertainty type is based on [Pástor and Veronesi \(2012, 2013\)](#). Impact uncertainty corresponds to uncertainty about the impact of a new government policy, e.g. the imposition of tariffs. Political uncertainty refers to uncertainty about the government's future actions, e.g. whether a tariff threat will be imposed.

in China, may raise concerns that the narrative information incorporated into a monthly SVAR model could capture TPU that did not originate exclusively in the U.S. However, I will discuss below how the identification strategy based on narrative sign restrictions ([Antolín-Díaz and Rubio-Ramírez, 2018](#)) allows us to isolate only those TPU shocks originating in the U.S.

3.1.2 Trade Policy Actions vs Trade Policy Threats

It should be noted that trade policy news can generate uncertainty because (i) investors may be uncertain about the outcomes of the U.S. government's actions, such as the potential

impact of an actual imposition of tariffs; and (ii) they might face uncertainty regarding the future actions of the U.S. government, for example, whether a threatened tariff will eventually be implemented. [Pástor and Veronesi \(2012, 2013\)](#) refer to the first type of uncertainty as *impact uncertainty*, and the second as *political uncertainty*. In this context, I complement [Baker et al. \(2021\)](#)’s categorisation by selecting jumps that align with the definitions of impact uncertainty and political uncertainty. This classification is reported in the last column of Table 1.

Specifically, I distinguish between trade policy *actions* and *threats*, which were a regular feature of the Trump presidency. While actions, such as unexpected tariff announcements, are associated with tariff shocks, analyzing TPU arising from unexpected tariff threats is instrumental in identifying TPU shocks.¹ Using a structural model, [Handley and Limão \(2017\)](#) show that economic agents’ reactions to heightened TPU due to threats of future tariffs can result in significant macroeconomic costs, *even if these threats never materialise*. Furthermore, through a general equilibrium model, [Pástor and Veronesi \(2013\)](#) illustrate how shocks to political uncertainty can depress asset prices by raising discount rates through a risk premium. In their model, stock prices respond to *political signals* (e.g., a tariff threat in the trade context), not to the eventual action.

A careful reading of WSJ articles suggests that the trade-policy jumps documented in Table 1 stem from political uncertainty. For example, on March 22, 2018, the S&P 500 index dropped by 2.5% following President Trump’s tariff threat on Chinese products, spurred by a report highlighting China’s unfair trade practices. Note that the decline in stock prices was in response to the political signal—the threat of tariffs—rather than the actual implementation of tariffs. Accordingly, I broadly interpret trade policy uncertainty as uncertainty regarding the U.S. government’s future actions on trade policy. A similar reasoning applies to each trade-policy jump reported in Table 1.

I argue that the trade-policy jumps caused by political uncertainty during the Trump presidency represent historical events of U.S. TPU shocks. First, Trump’s trade war was

¹The distinction between actions and threats has also received attention in other political contexts. For instance, in their analysis of geopolitical risks, [Caldara and Iacoviello \(2022\)](#) distinguish between threat, realisation, and escalation of adverse geopolitical events to construct news-based geopolitical risk indices.

largely exogenous to the state of the economy, driven by political motives and unexpectedly targeting allies, providing a scenario for observing exogenous variations in TPU. Second, by measuring stock market jumps in a tight window around trade policy announcements, it is possible to isolate the impact of TPU. The reverse causality of economic conditions can be ruled out since they are already priced in at the time of the announcement and is unlikely to change within the tight window.

Note that [Baker et al. \(2021\)](#) classify *daily* jumps in their analysis. Unlike the monetary policy literature, which often examines interest rate movements within narrower windows around monetary policy announcements to identify monetary policy shocks (see, e.g. [Kuttner, 2001](#); [Cochrane and Piazzesi, 2002](#)), a daily window is not problematic for this study. Policy news is not as straightforward as central bank announcements, and markets require more time to interpret its implications. For example, despite high uncertainty regarding the future policies of the Trump administration, market volatility remained low in 2017. The theoretical framework of [Pástor and Veronesi \(2013\)](#) suggests that the lack of clarity in government communication made it challenging for investors to process policy news during that period.²

Overall, the narrative information derived from stock market jumps allows us to pinpoint periods when U.S. TPU shocks predominantly drove monthly *realised* stock market volatility, specifically in March 2018, December 2018, and August 2019. In the following sections, I analyse whether incorporating this information into our SVAR model is effective in identifying TPU shocks.

3.2 Bayesian Structural Vector Autoregression (SVAR) Model

3.2.1 Reduced-form VAR

Consider the following Structural Vector Autoregression (SVAR) model of the form

$$\mathbf{A}_0 \mathbf{y}_t = \mathbf{a} + \mathbf{A}_1 \mathbf{y}_{t-1} + \dots + \mathbf{A}_p \mathbf{y}_{t-p} + \boldsymbol{\varepsilon}_t, \quad (1)$$

²For details, see [this](#) column from the CEPR's policy portal.

where p is the lag order, $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables, $\mathbf{a}$ is an $n \times 1$ vector of constants, and $\mathbf{A}_1, \dots, \mathbf{A}_p$ are $n \times n$ coefficient matrices. $\boldsymbol{\varepsilon}_t$ is an $n \times 1$ vector of structural shocks and $\mathbf{A}_0$ is a non-singular $n \times n$ structural impact matrix. By definition, the structural shocks are mutually uncorrelated, with $\text{var}(\boldsymbol{\varepsilon}_t) = \boldsymbol{\Omega}$ diagonal. Denoting $\mathbf{S} = \mathbf{A}_0^{-1}$, the reduced-form version of the SVAR model is given by

$$\mathbf{y}_t = \mathbf{b} + \mathbf{B}_1 \mathbf{y}_{t-1} + \dots + \mathbf{B}_p \mathbf{y}_{t-p} + \mathbf{u}_t, \quad (2)$$

where $\mathbf{b} = \mathbf{S}\mathbf{a}$ is an $n \times 1$ vector of constants and $\mathbf{B}_j = \mathbf{S}\mathbf{A}_j$, $1 \leq j \leq p$, are $n \times n$ coefficient matrices. The $n \times 1$ vector of reduced-form innovations $\mathbf{u}_t$ is related to the structural shocks $\boldsymbol{\varepsilon}_t$ via a linear mapping

$$\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t, \quad (3)$$

with covariance matrix $\text{var}(\mathbf{u}_t) = \boldsymbol{\Sigma} = \mathbf{S}\boldsymbol{\Omega}\mathbf{S}'$. In the literature, equation (3) is known as the invertibility assumption.

3.2.2 Data and Bayesian Estimation

The (reduced-form) VAR specification consists of seven U.S. variables: (1) the TPU index of [Caldara et al. \(2020\)](#), (2) realised stock market volatility (RVOL) calculated as the scaled sum of daily squared returns on the S&P 500 index, (3) the option-implied volatility on the S&P 500 index measured by the VIX, (4) the S&P 500 index, (5) industrial production used as a proxy for output, (6) employment which serves to capture labour market conditions, (7) import tariffs to control for implemented trade policy actions, and (8) business confidence to control for anticipation effects of trade policies. Appendix [A.2](#) provides further dataset details.

All variables are in log levels, except tariffs (expressed in percent), and the data frequency is monthly from January 1990 to December 2019. During this period, the U.S. implemented substantial trade policy changes, including the renegotiation of the NAFTA agreement and the recent trade war under the Trump administration. As a result, the estimated effects reflect the average impact across the entire sample period, offering a more comprehensive perspective than a simple event study, which would not capture the influence of other periods.

The VAR model is estimated using Bayesian techniques. In particular, I employ Minnesota-type priors (Litterman, 1986; Bańbura, Giannone, and Reichlin, 2010) for which I impose a normal-inverse-Wishart distribution over the reduced-form parameters. I estimate the model using 6 lags of the endogenous variables and also include a constant. I follow Giannone, Lenza, and Primiceri (2015) in the choice of hyperparameters. Appendix A.2 describes the dataset and provides details of the priors imposed.

3.2.3 Identification strategy

The SVAR model in equation (A.1) faces an identification challenge as the covariance matrix Σ only provides $n(n+1)/2$ restrictions to identify the n^2 free parameters in $\mathbf{S}$. Therefore, I have to impose restrictions on the structural parameters to solve the identification problem. In this study, I resort to SVAR identification based on imposing sign and zero restrictions on impulse response functions (IRFs) following the approach developed by Arias et al. (2018).

These restrictions are imposed on impact and are summarized in Table 2. I impose two sign restrictions where a shock to TPU induces an increase in both the TPU index and the RVOL. The sign restriction on the RVOL is motivated by the evidence based on the stock market jumps. I impose zero restrictions on tariffs and business confidence to ensure that TPU shocks remain orthogonal to both tariff shocks and tariff *news* shocks (unexpectedly announced but not yet implemented tariffs). The second zero restriction, in particular, is motivated by the role of business confidence in capturing an expectations channel, which is crucial in the transmission of tariff news shocks (see Metiu, 2021). Finally, I remain agnostic about the responses of the remaining variables and impose no signs on them.

Sign restrictions alone may not be enough to achieve meaningful conclusions when the structural parameters are both set and partially identified as expressed by Kilian and Murphy (2014). Therefore, I complement the identification with narrative sign restrictions (NSR) based on stock market jumps caused by news about TPU following the algorithm proposed by Antolín-Díaz and Rubio-Ramírez (2018). This approach amounts to imposing additional restrictions on the signs of structural shocks and/or their contributions to the change in

Table 2: Sign Restrictions on Impact Responses

TPU	RVOL	VIX	Stock Prices	Industrial Prod.	Employment	Tariffs	Business Confidence
+	+					0	0

Note: Blank entries denote that no restriction is imposed.

particular variables in specific historical episodes. In our application, I focus on the second type and impose restrictions on the historical decomposition of RVOL.

Note that, by construction, a jump in daily stock prices mechanically generates high monthly RVOL, which means that NSR can be imposed directly on this measure. As pointed out by [Berger, Dew-Becker, and Giglio \(2020\)](#), RVOL measures how large are the shocks that have just occurred, while expected future volatility as measured by the VIX is about how large agents expect future shocks to be. In this regard, RVOL allows imposing restrictions on the historical decomposition given that I know the magnitude of the trade-policy jumps.

[Antolín-Díaz and Rubio-Ramírez \(2018\)](#)'s algorithm allows the researcher to express different levels of confidence in the narrative information about a particular episode. The authors introduce two types of NSRs on the historical decomposition, namely Type A and Type B restrictions. We use a Type A restriction when we want to impose that a given shock is the most important contributor to the unexpected change in a given variable during a particular period, i.e. its contribution in absolute value is larger than the absolute value of the contribution of any other structural shock. On the other hand, we use a Type B restriction when we want to specify that a given shock was the overwhelming contributor to the unexpected change in a given variable during a particular period, i.e. its contribution is larger in absolute value than the sum of the absolute contributions of all other structural shocks.³

³Formally, Type A restriction can be expressed as

$$|H_{i,j,t_v,t_v+h_v}| > \max_{j' \neq j} |H_{i,j',t_v,t_v+h_v}|,$$

where $|H_{i,j,t_v,t_v+h_v}|$ denotes the historical contribution of the j th shock to the i th variable in the VAR from periods t_v to $t_v + h_v$. Similarly, Type B restriction can be formulated as

$$|H_{i,j,t_v,t_v+h_v}| > \sum_{j' \neq j} |H_{i,j',t_v,t_v+h_v}|.$$

Based on the narrative information above, I am more certain that U.S. TPU shocks were the overwhelming contributor to the RVOL in March 2018. Thus, I impose the following Type B narrative sign restriction:

Narrative Sign Restriction 1. *For the observation corresponding to March 2018, TPU shocks are the overwhelming driver of the RVOL.*

In contrast, U.S. TPU shocks were the most important contributors to the RVOL in December 2018 and in August 2019 given that other relevant shocks—related to central banking and macroeconomic news—were also at play, but with a lower contribution (see Table 1). Therefore, I use the following Type A narrative sign restrictions:

Narrative Sign Restrictions 2 and 3. *For the observations corresponding to December 2018 and August 2019, TPU shocks are the most important contributor to the RVOL.*

The NSR 3, in particular, helps to alleviate concerns about our identification being contaminated by TPU originating in China in August 2019, related to China’s retaliation threats against the U.S., as documented in Table 1. This ensures that the shocks captured are solely those originating in the U.S.

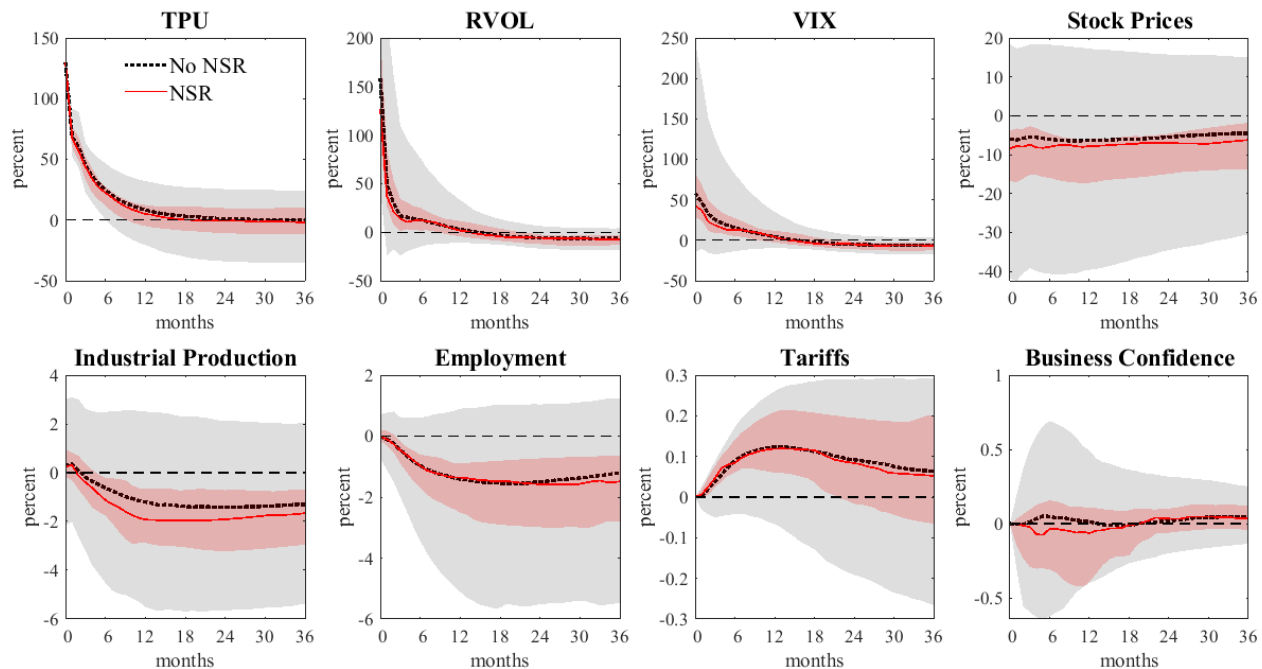
3.3 Results

Figure 2 compares the IRFs to a U.S. TPU shock, with and without the NSRs.⁴ The light-shaded areas represent the 68% pointwise credible sets for the IRFs and the dotted lines are the median IRFs using sign and zero restrictions only. The darker shaded areas and solid lines display the equivalent quantities when the NSRs are also satisfied. The TPU shock is normalised to induce a 130-point increase in the TPU index. This normalisation corresponds to the change from the average value in 2018-2019, coinciding with the recent trade disputes, to its average value in 1990-2015, when the TPU index was stable at low levels.

Note that Type B is more restrictive than Type A because if a particular shock contributes more than the sum of all other contributions, it implies that it is always larger than any single contribution.

⁴I calibrate Antolín-Díaz and Rubio-Ramírez (2018)’s algorithm to obtain around 1,000 draws that satisfy sign, zero, and narrative sign restrictions.

Figure 2: IRFs to a U.S. TPU Shock



Note: The TPU shock is normalised to induce a 130-point increase in the TPU index. The light-shaded area represents the 68% pointwise credible sets for the IRFs and the dotted lines are the median IRFs using sign restrictions only. The darker shaded area and the solid line display the equivalent quantities when the narrative sign restrictions (NSR) are also satisfied. Sample estimation from 1990M1 to 2019M12.

As we can observe, the inclusion of the NSRs significantly narrows the uncertainty around the IRFs, altering the economic implications. The TPU index rises persistently, remaining elevated for nearly a year, followed by a short-lived increase in RVOL. High TPU is associated with a substantial impact on the VIX, which increases by around 50%. The response of stock prices is both economically and statistically significant, dropping by 10% on impact and taking about three years to revert to trend. It is worth noting that no sign restriction was imposed on the response of stock prices.

Economic and labour market conditions deteriorate, with industrial production and employment both gradually declining, reaching persistent effects of 2% and 1.5%, respectively, one year after the shock. The aggregate employment response complements the microeconomic evidence from [Pierce and Schott \(2016\)](#), who, using China's 2001 WTO accession,

show that reduced uncertainty about import tariffs lowered U.S. manufacturing employment.⁵

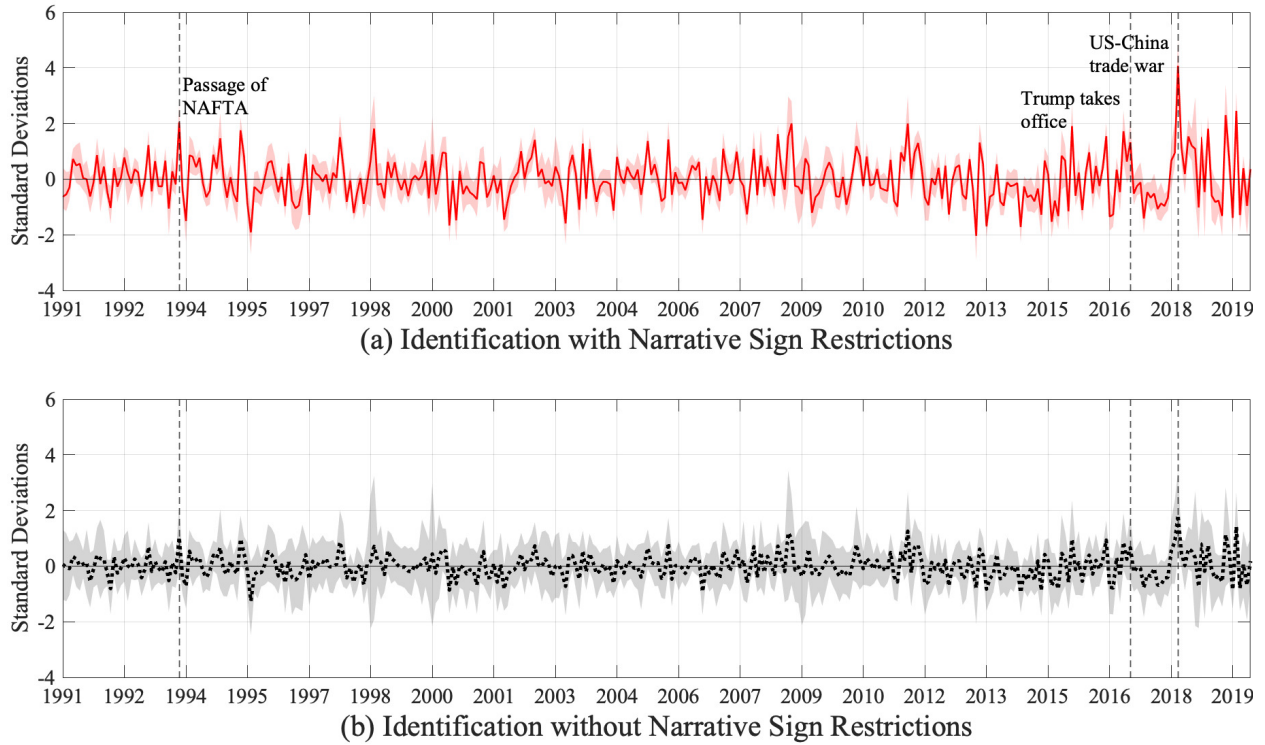
The response of import tariffs shows a slight reaction over a 3-year horizon, indicating that the previously threatened tariffs eventually materialised. Consequently, the response of the TPU index after the shock may reflect an endogenous reaction to the materialisation of these tariffs. As a robustness check, I demonstrate through a counterfactual exercise, following [Sims and Zha \(2006\)](#), that setting the endogenous response of import tariffs to zero leads to similar IRFs, suggesting that import tariffs are not a significant transmission channel for TPU shocks.⁶ Finally, the response of business confidence remains insignificant throughout the TPU shock, indicating that potential “bad news” stemming from trade policy threats does not play a role in the transmission of TPU shocks. Such bad news is associated with an *expectations channel*, which explains the lion’s share of trade policy news shocks (see [Metiu, 2021](#)).

The significant negative response of stock prices on impact aligns with [Pástor and Veronesi \(2013\)](#)’s theoretical predictions, indicating a risk premium channel rather than an expectations channel. A recursive identification scheme, typically used to analyse the transmission of EPU shocks and involving the ordering of news-based EPU indices first in VAR models (see, e.g., [Baker et al., 2016](#)), does not reproduce this finding. [Caldara, Iacoviello, Molligo, Prestipino, and Raffo \(2019b\)](#), using such a scheme and ordering their TPU index first, find similar responses in economic activity to those in our analysis; however, they find that stock prices do not react on impact but decline gradually. This suggests their results may capture trade policy news shocks through an expectations channel. Additionally, our findings align with microeconomic evidence from [Bianconi et al. \(2021\)](#), who demonstrate that industries more exposed to TPU, due to Congressional votes on revoking China’s preferential tariff treatment between 1990 and 2001, experienced larger initial

⁵Although the narrative information is derived from the recent trade war during Trump’s administration, our time series approach, unlike an event study, captures average responses across multiple events in the sample, not just the recent trade war.

⁶In the counterfactual exercise, for completeness, I also set the endogenous response of business confidence to zero at all horizons, even though the response is not significant.

Figure 3: Time Series of the Identified U.S. TPU Shocks



Note: The solid and dotted lines plot the median time series of U.S. TPU shocks (a) when narrative sign restrictions are satisfied, and (b) when they are not considered, respectively. Shaded areas are 68% pointwise credible sets. Sample from 1991M1 to 2019M12.

drops in stock prices and greater return volatility around key policy dates, driven by a risk premium channel rather than changes in expected cash flows.

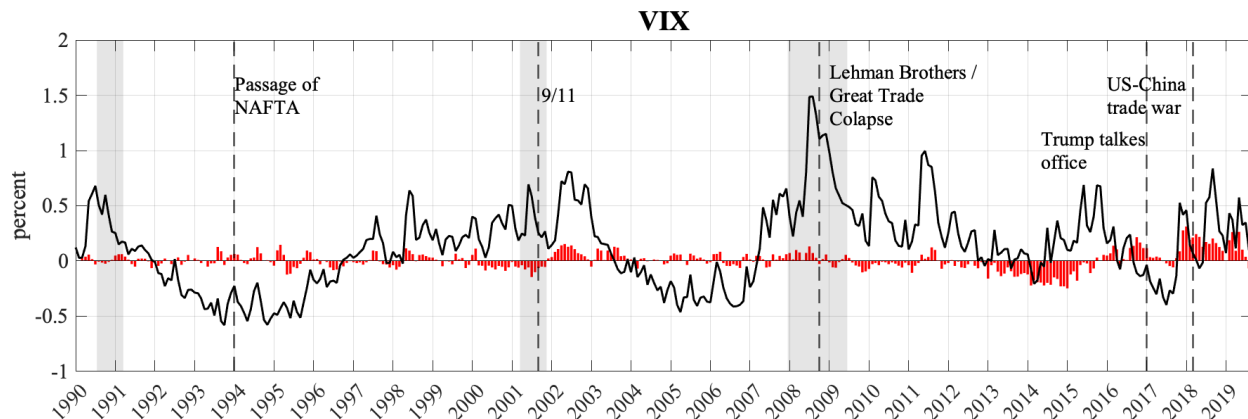
Finally, panel A of Figure 3 plots the median time series of TPU shocks recovered from the SVAR identified with NSRs. The shaded area represents the 68% pointwise credible sets. The largest shock occurs in March 2018, coinciding with the onset of the US-China trade war. For comparison, Panel B shows the median time series when NSRs are not applied. As we can observe, the inclusion of narrative information not only reduces the uncertainty around the estimated shocks but also predicts larger shocks.

3.4 TPU shocks as a driver of Stock Market Volatility

The narrative information documented above demonstrates that stock markets became highly responsive to trade policy developments during the Trump administration. Therefore,

I analyse the significance of TPU shocks in explaining historical episodes in stock markets. To do so, I conduct a historical decomposition of U.S. stock market volatility over the period 1991-2019.

Figure 4: Historical Decomposition of U.S. Stock Market Volatility



Note: The figure shows the historical contribution of U.S. TPU shocks to the VIX (in deviation from its deterministic component). The bars correspond to the median of the distribution of the posterior estimates based on the identification with narratives sign restrictions. Sample from 1991M1 to 2019M12. Grey areas indicate NBER recession dates.

Figure 4 displays the portion of the VIX (in deviation from its deterministic component) that is attributable to TPU shocks based on the identification with NSRs. There is significant evidence that TPU shocks drove the VIX during the US-China trade war in 2018-2019. Notably, the contribution is significant not only for the episode for which NSRs were imposed but also for the whole period of the trade tensions. In addition, the contribution of TPU shocks is significant in January 2017, when Trump took office and threatened Mexico with import tariffs.

This result aligns with evidence provided by [Baker, Bloom, Davis, and Kost \(2019b\)](#). Using text analysis of major U.S. newspapers, they constructed an Equity Market Volatility (EMV) tracker, which closely follows the VIX. They quantified journalists' perceptions of the forces underlying stock market volatility and categorized them into about forty groups. The authors show that trade policy concerns, which were an unimportant factor in explaining EMV in the twenty years before Donald Trump's election, became a leading source afterwards, particularly during the U.S.-China trade tensions.

However, unlike these authors, I find that TPU shocks did not play a major role in influencing the VIX during the NAFTA negotiations in 1993 involving Mexico, Canada, and the U.S. This result suggests that although NAFTA attracted significant media attention, it did not represent a major risk for market participants at the aggregate level. This finding supports the point made by [Handley and Limão \(2022\)](#): while news-based indexes of TPU may be useful for identifying certain events, they do not necessarily reflect the perceptions of relevant agents. This could be explained by the fact that, before the implementation of NAFTA, Mexico had lower trade openness with the U.S., but its trade exposure grew fourfold in the decades following the agreement.

It is worth noting that TPU shocks do not account for the variability in the VIX during economic downturns when TPU may arise endogenously ([Bown and Crowley, 2013](#)). It is instructive to focus on two episodes: the 9/11 attacks in September 2001 and the Lehman Brothers collapse in September 2008. On the one hand, [Caldara and Iacoviello \(2022\)](#) identify 9/11 as a geopolitical shock. Additionally, [Baker et al. \(2021\)](#) document that the stock market jumps and ensuing volatility in September 2001 were due to the terrorist attacks. On the other hand, TPU shocks do not explain the movements in the VIX around September 2008. This aligns with the consensus that the stock market volatility in September 2008 was driven by financial uncertainty, macro uncertainty, or both, as noted by [Ludvigson, Ma, and Ng \(2021\)](#).

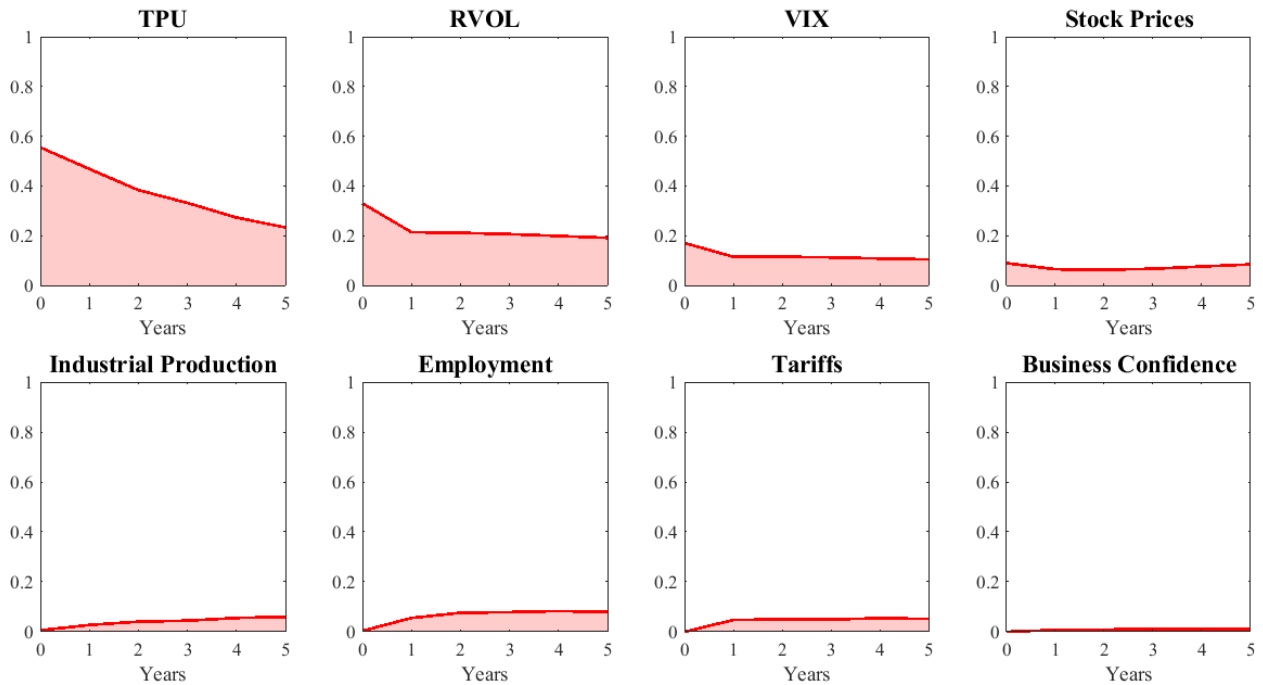
3.5 Quantitative importance

In this section, I assess how important U.S. TPU shocks are in explaining the variations of the variables in the VAR model. Figure 5 shows the forecast error variance decomposition (FEVD) of U.S. variables at various horizons. The figure reports the median posterior percentiles of the identification with NSRs.

The figure shows that TPU shocks explain approximately 55% of the FEVD of the TPU index at short horizons, with this contribution declining to around 25% over a five-year horizon. Within a one-year horizon, TPU shocks significantly influence stock market volatility and stock prices, explaining about 20% of the variation in RVOL and 10% in the VIX and

stock prices. In contrast, the impact of TPU shocks on industrial production and employment is more modest, accounting for about 5% and 10% of their variation, respectively. For comparison, the well-known [Smets and Wouters \(2007\)](#) DSGE model attributes less than 10% of GDP fluctuations to monetary policy shocks at a similar horizon. Regarding import tariffs, TPU shocks contribute only a minor fraction to their FEVD at short horizons, while the influence on business confidence is almost negligible. Overall, this evidence suggests that financial variables are more affected by TPU shocks than real variables.

Figure 5: Forecast Error Variance Decomposition



Note: The figure shows the forecast error variance decomposition of U.S. variables explained by TPU shocks at horizons from 0 to 5 years. The shaded areas correspond to the median of the distribution of the posterior estimates based on the identification with narratives sign restrictions. Sample estimation from 1990M1 to 2019M12.

These results contribute to the ongoing debate on the differing impacts of U.S.-China trade tensions on the aggregate economy and stock markets during the trade war. Static trade models generally conclude that the trade war modestly reduced aggregate real income relative to GDP in the U.S. (for a review, see [Fajgelbaum and Khandelwal, 2021](#)). The evidence presented in this paper suggests that trade policy uncertainty may be a key factor

in explaining these differences. Additionally, static models that do not account for trade policy uncertainty and dynamic effects might underestimate the impact on the real economy.

3.6 Validation check

I show that the median time series of TPU shocks, presented in Panel A of Figure 3, exhibits desirable properties that a true shock should have, as outlined by Ramey (2016): it is neither autocorrelated nor correlated with other structural shocks. On the one hand, Figure A.2 displays the autocorrelation function of TPU shocks, and I find no evidence of serial correlation in the series. On the other hand, Table A.2 reports pairwise correlations between the identified TPU shocks and external time series of structural shocks commonly studied in the macroeconomic literature (Stock and Watson, 2012; Ramey, 2016), as well as Granger causality tests. All correlations and Granger tests are not statistically different from zero. These results support the lack of systematic contemporaneous and lagged associations between the identified TPU shocks and other types of macroeconomic shocks, namely oil shocks, monetary policy shocks, news shocks, productivity shocks, and fiscal policy shocks.

3.7 Summary of Key Findings and Final Remarks

I have demonstrated that the identification strategy proposed in this work, based on narrative information derived from a few key stock market reactions to TPU during the Trump administration, is highly effective in assessing the impact of TPU shocks. Our approach addresses the challenges associated with the rare occurrence of such shocks and the endogeneity of TPU to economic conditions. By incorporating a few episodes of exogenous variations in TPU as narrative sign restrictions, our method proves particularly well-suited for this application, as it requires only a small number of key historical episodes. This approach yields theoretically consistent signs in the IRFs of variables, especially for stock prices, which cannot be achieved through a recursive identification scheme.

4 Spillovers from US TPU Shocks

In this section, I analyse the domestic and foreign impact of U.S. TPU shocks using panel local projection methods based on [Jordà \(2005\)](#). I set out the empirical approach in three different subsections. I first define the data used in the estimation. Then, I describe the empirical model. Last, I discuss the international transmission.

4.1 Data

I study the international transmission of U.S. TPU shocks in a panel of 36 economies (18 advanced and 18 emerging).⁷ For each country I collect monthly data for industrial production, imports, exports, consumer prices, stock prices, and the nominal effective exchange rate. The estimation sample spans January 1990 to December 2019 (conditional on data availability). The main data sources are international institutions, namely the OECD (MEI) and the IMF (IFS), and national statistical agencies. All variables are in log levels. The tables in [Appendix B](#) describe in detail all variables and their sources.

4.2 Estimation of domestic and global effects

To estimate impulse responses, I employ the local projection (LP) method developed by [Jordà \(2005\)](#). This methodology requires to estimate a series of regressions for each horizon h as follows

$$y_{t+h} = \alpha_h + \beta_h \varepsilon_t^{TPU} + \sum_{\ell=1}^p \theta_{h,\ell} \mathbf{z}'_{t-\ell} + \gamma_t^h + \xi_{t+h} \quad \text{for } 0 \leq h \leq H, \quad (4)$$

where y_{t+h} is the domestic variable of interest in period $t+h$, ε_t^{TPU} is the median time series of TPU shocks recovered from the SVAR identified with NSRs, $\mathbf{z}_t$ is a vector of controls, and γ_t^h is a quadratic time trend. The LP impulse response function of y_t with respect to

⁷**Advanced:** Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Japan, Korea, Netherlands, Norway, Portugal, Spain, Sweden, UK. **Emerging:** Brazil, Chile, China, Colombia, Czech Republic, Estonia, Hungary, India, Latvia, Lithuania, Malaysia, Mexico, Philippines, Poland, Russia, South Africa, Thailand, Turkey.

ε_t^{TPU} is given by the sequence $\{\beta_h\}_{h=0}^H$. In the baseline, I set $p = 2$ lags and the vector of controls includes the dependent variable y_t .⁸

The specification in equation (4) can be extended to a panel dimension to compute foreign responses as

$$y_{i,t+h} = \alpha_{i,h} + \beta_h \varepsilon_t^{TPU} + \sum_{\ell=1}^p \theta_{h,\ell} \mathbf{z}'_{i,t-\ell} + \gamma_{i,t}^h + \xi_{i,t+h} \quad \text{for } 0 \leq h \leq H, \quad (5)$$

where $y_{i,t+h}$ is the variable of interest of country i for $1 \leq i \leq N$ in period $t + h$, $\alpha_{i,h}$ is a country fixed effect, which captures time invariant country heterogeneity, and $\gamma_{i,t}^h$ is a country-specific quadratic time trend. Note that all countries in the sample are projected on the same shock ε_t^{TPU} . Accordingly, the sequence $\{\beta_h\}_{h=0}^H$ measures the *average response* of the variable of interest across countries with respect to ε_t^{TPU} . In the baseline estimation, I set $p = 2$ lags and the vector of control $\mathbf{z}_{i,t}$ includes the dependent variable $y_{i,t}$.

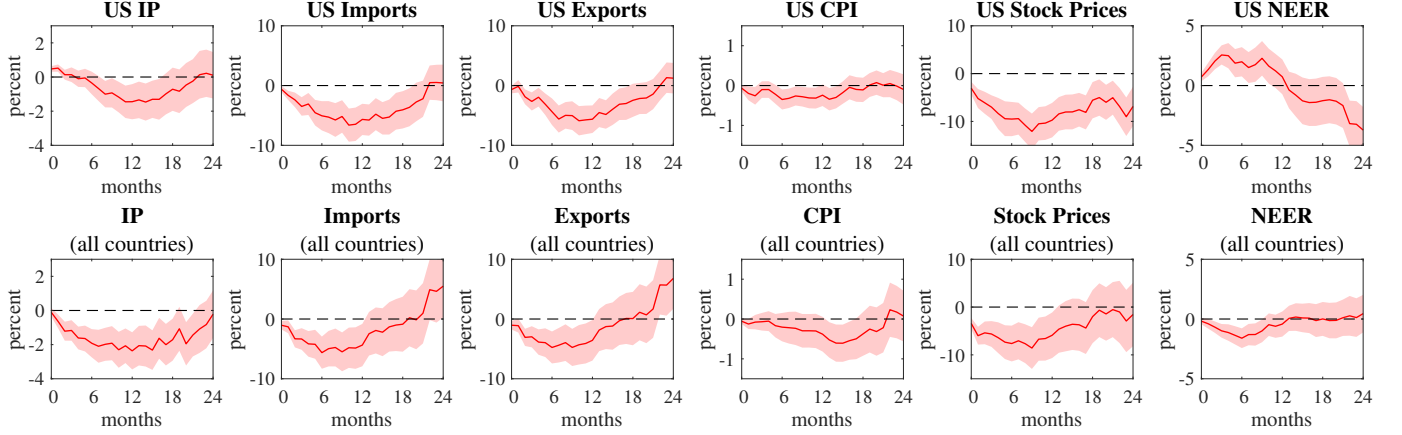
Notice that except for horizon $h = 0$, the error terms ξ_{t+h} and $\xi_{i,t+h}$ in equations (4) and (5), respectively, will be serially correlated due to the successive leading of the dependent variable. Therefore, for the time series context, I employ the Newey-West standard errors, while for the panel case I use the Driscoll-Kraay standard errors which allow double clustering by time and country.

4.3 Average effects

Figure 6 displays the average responses of key macroeconomic and financial indicators for the U.S. and all countries in the panel to a U.S. TPU shock, normalised to induce a 130-point increase in the TPU index. The shaded areas represent 68 percent confidence intervals. Because LP is less efficient than SVARs, I plot IRFs only up to horizon $h = 24$. The euro was introduced in 1999, replacing multiple national currencies within the sample. Consequently, I treat euro area countries individually for all variables except the nominal effective exchange rate, for which the euro is considered as an aggregate measure from 1999 onwards.

⁸Ramey (2016) argues that the set of controls does not need to include variables other than y_t as long as the shock of interest is exogenous to these variables.

Figure 6: Effects of TPU Shocks on the US and All Countries in the Panel



Note: The TPU shock is normalized to induce a 130-point increase in the TPU index. The shaded areas represent 68% confidence intervals. The second row shows the responses of all countries in the panel. The last column of this row presents the response of the nominal effective exchange rate (an increase reflects an appreciation). Sample estimation from 1985M1 to 2019M12.

Economic activity and trade. The first column of Figure 6 shows the responses of industrial production. U.S. industrial production shows a delayed but steady significant decline, dropping by as much as 1% one year after the shock, whereas the effect on all countries in the panel is as twice as damaging as that in the U.S. The second and third columns show the impact on international trade. In the domestic economy, the responses of both imports and exports are similar and decline by 5% one year after the shock and recover thereafter. In contrast, imports and exports abroad fall about 4% and 3% six months after the shock, respectively, and then both increase steadily thereafter.

Stock prices. The fourth column shows that stock price responses are economically and statistically significant, losing about 5% on impact both in the US and in all economies in the panel. In the U.S., the effect is more persistent, while stock prices abroad revert to trend two years after the shock. The contemporaneous impact on U.S. stock prices to a TPU shock agrees with the evidence of the SVAR estimated above (cf. Figure 2), although the LP response shows a more severe effect. These empirical results align with the theoretical predictions of [Pástor and Veronesi \(2012\)](#). In their framework, the authors analyze how changes in government policy affect stock prices. Their model predicts that stock market returns should be negative, on average, at the announcement of a policy change,

and their magnitude should be large if uncertainty about government policy is large or if the announcement is unanticipated by the market. The evidence documented here stems from uncertainty around trade policy that is both large and exogenous. In addition, [Pástor and Veronesi \(2013\)](#) also predict that stocks should be more volatile and correlated when there is more political uncertainty. The responses of stock prices documented here show strong support for their predictions.

Exchange rate and consumer prices. The last two columns display the responses of nominal effective exchange rates (NEER) and consumer prices. Following a TPU shock, the U.S. dollar appreciates on impact and reverts to trend after a year. [Georgiadis, Müller, and Schumann \(2021\)](#) also document an appreciation of the US dollar in response to global risk shocks. In contrast, a TPU shock leads to an exchange rate depreciation on average in all countries in the panel, which lasts about a year. Consistent with the contractionary effects of TPU shocks, consumer prices as measured by the CPI go down in the U.S. and all countries in the sample, albeit the effects are stronger in the latter.

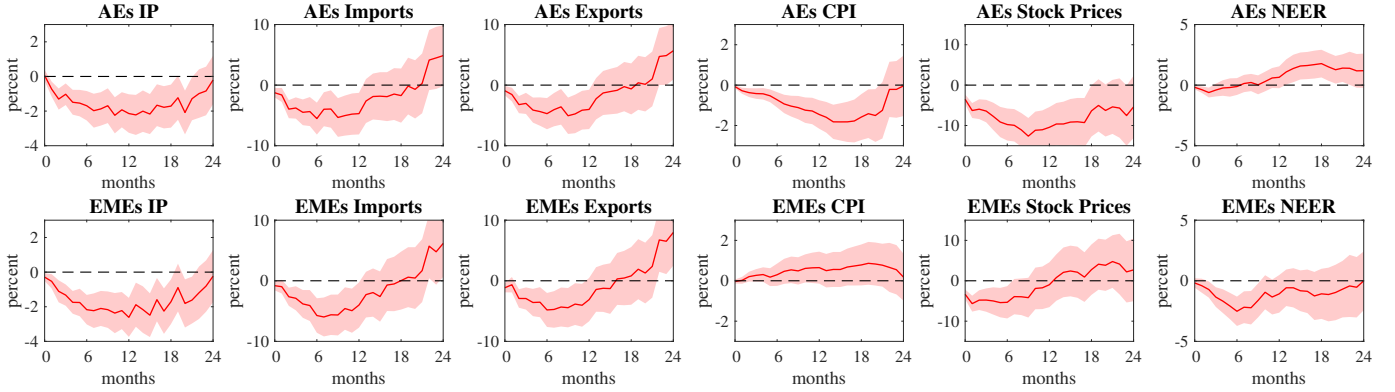
4.4 Average effects in Advanced and Emerging Economies

To shed light on the international transmission of US TPU shocks I compute the responses for advanced (AEs) and emerging (EMEs) economies and show the results in Figure 7.⁹ First, industrial production in AEs and EMEs, shown in the first column, contracts in tandem. In both cases, there is a sharp contraction with a trough of 2 percent reached after one year. Similarly, imports and exports fall by about percent in AEs and percent in EMEs. Second, stock prices go down on impact by about 5 percent both in AEs and EMEs, but the effects are more important and persistent in AEs. In particular, the response of stock prices in AEs mirrors that of their U.S. counterpart.

Third, EMEs tend to experience a more substantial and persistent depreciation of their currency compared to AEs. These results along with the impact appreciation of the U.S. dollar suggest that TPU shocks in the U.S. trigger a flight-to-quality phenomenon leading

⁹For this, I interact a dummy variable with the TPU shock (ε_t^{TPU}) in the panel regression (5). The dummy equals 1 if country i , $1 \leq i \leq N$, is an advanced economy and 0 otherwise.

Figure 7: Effects of TPU Shocks on Advanced (AEs) and Emerging (EMEs) economies



Note: The TPU shock is normalized to induce a 130-point increase in the TPU index. The shaded areas represent 68% confidence intervals. The second row shows the responses of all countries in the panel. The last column of this row presents the response of the nominal effective exchange rate (an increase reflects an appreciation). Sample estimation from 1985M1 to 2019M12.

investors to pull capital out of riskier markets, thus negatively affecting their exchange rates. Finally, consumer prices in EMEs tend to increase, whereas prices gradually decline in AEs, probably due to the sharper depreciation in EMEs, which puts upward pressure on consumer prices.

4.5 Monetary policy trade-offs

The monetary policy responses to U.S. Trade Policy Uncertainty (TPU) shocks reveal critical differences between advanced economies (AEs) and emerging market economies (EMEs). In AEs, TPU shocks primarily operate through demand channels, where declines in industrial production and inflation allow central banks to mitigate both inflationary and output effects by adopting accommodative monetary policies. This creates a more straightforward policy environment where central banks can stimulate economic activity without significant risk of inflationary pressure, making monetary easing a more viable option.

In contrast, EMEs experience a distinct transmission mechanism, driven predominantly by the exchange rate channel. TPU shocks lead to substantial currency depreciations in these economies, which, in turn, exert upward pressure on import prices, fuelling inflation. This creates a challenging policy trade-off: central banks must decide whether to raise interest rates to control inflation, even though doing so would further suppress already weak

economic activity. This trade-off highlights the structural vulnerabilities of EMEs to global shocks, as their monetary policies must balance inflation stability with growth support, a far more complex situation than in AEs.

Moreover, the widening of interest rate differentials between AEs and EMEs exacerbates capital outflows from the latter, further weakening their currencies. As the Federal Reserve lowers rates in response to TPU shocks, EMEs face added depreciation pressures, which compel their central banks to adopt tighter monetary policies to defend their currencies. However, such tightening can deepen recessions, leading to further reductions in output and compounding the economic costs of TPU shocks. This dynamic underscores the global spillovers of U.S. monetary policy decisions and the disproportionate impact on more vulnerable economies.

These asymmetric effects point to the need for differentiated policy responses. While AEs can primarily rely on conventional monetary policy tools, EMEs may need to deploy a broader set of instruments, including macroprudential measures, to stabilise their economies. By using capital controls, foreign exchange interventions, or liquidity provisions, EMEs could mitigate the adverse effects of capital flight and inflation without relying solely on interest rate hikes, which could be overly contractionary in an already challenging environment.

5 Conclusions

This paper proposes a narrative identification strategy to isolate exogenous shifts in trade policy uncertainty originating in the U.S., aiming to estimate the causal effects of TPU on economic activity and inflation both domestically and internationally. Incorporating information from stock market jumps, triggered by news about TPU during the Trump administration, as narrative sign restrictions in the historical decomposition of stock market volatility, I demonstrate that these jumps are highly informative for shaping the identification originally identified with sign restrictions.

I have shown that, on average, the effects of U.S. TPU shocks on AEs and EMEs mirror those of their U.S. counterpart, including negative consequences on industrial production,

trade, consumer prices, and stock prices. However, the transmission of these shocks to AEs and EMEs differs; EMEs experience a larger and more persistent depreciation in their nominal effective exchange rates than AEs, suggesting a flight-to-quality phenomenon. Moreover, consumer prices in EMEs tend to rise, in contrast to the slow and mild decline observed in AEs, likely due to the more pronounced exchange rate depreciation. These findings carry important policy implications. To address the EMEs' depreciation without depending solely on interest rate hikes, central banks in these countries could implement macroprudential policies focused on enhancing financial stability and curbing capital flow volatility. For instance, [Coman and Lloyd \(2022\)](#) find that emerging markets with stricter prudential policies tend to face milder spillover effects from U.S. monetary policy.

The identification strategy proposed in this paper can be relevant to quantifying the causal effect of other sources of economic policy uncertainty. This can be feasible as [Baker, Bloom, and Davis \(2019a\)](#) provide a stock market jump classification across 16 categories. A common practice in the empirical literature is to order news-based economic policy uncertainty indices first in a recursive VAR to estimate their aggregate impact. Instead, an approach based on sign restrictions complemented with a few narrative restrictions addresses the simultaneity problem between uncertainty and economic conditions inherent in a recursive ordering ([Baker et al., 2020](#)).

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A Identification of TPU shocks

In this Appendix, I present a summary of the narrative information used for identification. I also conduct validity checks on the identified TPU shocks from the SVAR that are not featured in the main body of the paper. Finally, I describe the data, sources, and prior specification of the VAR model to recover TPU shocks.

A.1 Narrative Information

This section details the narrative information extracted from stock market jumps based on the narrative account of [Baker, Bloom, Davis, and Sammon \(2019c\)](#). The following summaries come from WSJ articles, which can be found at Marco Sammon’s website.

March 22, 2018 (Trade Policy). “Trade tensions ratcheted higher as the Trump administration said it would impose tariffs on tens of billions of dollars of Chinese imports on top of duties on steel and aluminum imports, provoking the ire of officials from China to Germany to Mexico. [...] The Dow industrials gave up [...] 2.9%, posting their biggest one-day percentage decline since February 8, when they fell into correction territory for the first time in more than two years. The S&P 500 fell [...] 2.5%, sliding back into negative territory for the year, while the Nasdaq Composite lost [...] 2.4%.” (WSJ, March 22, 2018).

March 26, 2018 (Trade Policy). “U.S. stocks staged a powerful rebound on Monday [March 26], surging on signs that recent trade tensions were easing as the Dow Jones Industrial Average notched its third biggest point-gain ever. The Dow Industrials advanced [...] 2.8%, [...] its largest one-day point gain since October 2008. [...] The Nasdaq Composite added [...] 3.3%, [...] and the S&P 500 rose [...] 2.7% [...] Both these indexes and the Dow Industrials recorded their biggest percentage jumps since August 2015. [...] Investor fears that escalating trade tensions could eventually lead to a trade war eased after reports of renewed discussions between the two countries [China and the U.S.]. The Wall Street Journal reported Sunday [March 25] that China and the U.S. have started negotiating to improve U.S. access to mainland Chinese markets.” (WSJ, March 26, 2018).

December 4, 2018 (Trade Policy). “Waning enthusiasm for the 90-day tariff cease-fire struck over the weekend by China and the U.S. fueled the losses, several investors said, stirring worries the disagreement between the world’s two biggest economies could unravel U.S. growth and put more pressure on struggling Europe and Asia. [...] The Dow industrials tumbled [...] 3.1%, [...] closing near session lows. The S&P 500 fell [...] 3.2%, [...] while the Nasdaq slid [...] 3.8% [...]” (WSJ, December 4, 2018).

December 24, 2018 (Central Banking). “Coming off the stock market’s worst week since the 2008 financial crisis, the Dow Jones Industrial Average, S&P 500 and Nasdaq Composite fell for a fourth straight session as investors continued to weigh the impact of rising interest rates, slowing U.S. growth and the ramifications of a government shutdown extending into January. [...] The Dow Industrials fell [...] 2.9%,

[...] to notch its biggest four-day decline since 2015, while the S&P 500 slipped [...] 2.7%, [...] putting it less than half a percentage point away from entering a bear market. The Nasdaq Composite also fell, shedding [...] 2.2%, [...] after closing more than 20% below its recent high to enter bear-market territory on Friday [December 24].” (WSJ, December 27, 2018).

August 5, 2019 (Trade Policy). “Waves of selling battered stock indexes [...] as fresh trade threats between Beijing and Washington raised fears of an economic slowdown. The Dow Jones Industrial Average fell [...] 2.9%, [...] The S&P 500 shed 3% [...] and the Nasdaq Composite declined 3.5% [...] The stock-market declines [...] began last week after President Trump said he would extend tariffs to almost all Chinese imports. Selling accelerated Monday [August 5] after the Chinese yuan dropped beyond the level of seven to the dollar, with local officials blaming the depreciation on Mr. Trump’s decision on tariffs. Mr. Trump responded on Twitter, accusing China of engaging in currency manipulation.” (WSJ, August 5, 2019).

August 14, 2019 (Macroeconomics News). “The Dow Jones Industrial Average posted its largest decline this year and government-bond markets sent a fresh warning about the risk of a coming recession, highlighting anxiety on Wall Street about the prospects for the decade long economic expansion. [...] Weak data out of Germany and China exacerbated fears that the biggest economies around the world, which less than two years ago were growing in sync, are now struggling as the effects of the trade war become more pronounced. Traders now fear those woes could spill over to the U.S. [...] The declines in U.S. stocks and bond yields erased the optimism sparked a day earlier when the Trump administration abruptly suspended plans to impose new tariffs on goods from China and suggest the volatile swings that have defined trading in August are showing no signs of easing. The S&P 500 declined [...] 2.9%, [...] while the Nasdaq Composite lost 3% [...]” (WSJ, August 14, 2019).

August 23, 2019 (Trade Policy). “The Dow Jones Industrial Average dropped [...] 2.4%, after China said it would impose retaliatory tariffs on additional U.S. products and President Trump vowed on Twitter to respond. [...] The developments marked an escalation of trade tensions between two of the biggest global economies, stoking waves of selling in the stock market and continuing a stretch of turbulence in August. [...] The drop marked the Dow industrials’ third decline of at least 2% this month [...] The S&P 500 dropped [...] 2.6%, while the Nasdaq Composite shed [...] 3%.” (WSJ, August 23, 2019).

A.2 Data, Bayesian VAR, and prior specification

A.2.1 Reduced-form VAR

Let Y_t be an $n \times 1$ vector of endogenous variables, such that the structural aggregate dynamics is represented by the following SVAR(p),

$$A_0 Y_t = d + \sum_{\ell=1}^p A_\ell Y_{t-\ell} + \varepsilon_t, \quad (\text{A.1})$$

where d is an $n \times 1$ vector of constants, A_ℓ is an $n \times n$ matrix of coefficients for $0 \leq \ell \leq p$, where A_0 is invertible and captures contemporaneous structural relations, p is the lag length, and ε_t is a normally distributed vector of structural shocks with mean zero, not autocorrelated, and a covariance matrix equal to $E[\varepsilon_t \varepsilon_t'] = I_n$, i.e. the $n \times n$ identity matrix.

The reduced-form representation implied by Equation (A.1) is

$$Y_t = c + \sum_{\ell=1}^p B_\ell Y_{t-\ell} + u_t, \quad (\text{A.2})$$

where $c = A_0^{-1}d$, $B_\ell = A_0^{-1}A_\ell$ for $1 \leq \ell \leq p$, and $u_t = A_0^{-1}\varepsilon_t$ is a vector of reduced-form innovations with $\Sigma = E[u_t u_t'] = A_0^{-1}A_0^{-1'}$. Structural shocks are orthogonal and have an economic interpretation, while the innovations are, in general, correlated and do not have an interpretation.

A.2.2 Prior specification

I estimate the VAR(p) model of Equation (A.2) using Bayesian techniques. In particular, I assume a normal-inverse-Wishart prior distribution over the reduced-form parameters of the form:

$$\Sigma \sim \mathcal{IW}(S_0, \alpha_0) \quad \text{and} \quad B|\Sigma \sim \mathcal{N}(B_0, \Sigma \otimes \Omega_0) \quad (\text{A.3})$$

where $B = \text{vec}([c, B_1, \dots, B_p]')$. The degrees of freedom of the inverse-Wishart distribution are set to $\alpha_0 = n + 2$, a value that guarantees the existence of the scale matrix S_0 (Kadiyala and Karlsson, 1997), which is diagonal with elements σ_i^2 , the residual variance of an AR(1) for variable i for $1 \leq i \leq n$. The prior mean and variance for B are characterized by a Minnesota-type prior such that

$$E[(B_{0,\ell})_{ij}|\Sigma] = \begin{cases} \delta_i, & i = j, \ell = 1 \\ 0, & \text{otherwise} \end{cases}, \quad \text{Var}[(B_{0,\ell}|\Sigma)_{ij}] = \begin{cases} \frac{\lambda^2}{\ell^2}, & i = j \\ \frac{\lambda^2}{\ell^2} \frac{\sigma_i^2}{\sigma_j^2}, & \text{otherwise} \end{cases}, \quad (\text{A.4})$$

where $(B_{0,\ell})_{ij}$ is the element in position (i, j) in the partition matrix $B_{0,\ell}$, which corresponds to matrix B_0 at lag ℓ for $1 \leq \ell \leq p$. Setting $\delta_i = 1$ for all i reflects the belief that all variables are characterized by a random walk with drift as originally proposed by [Litterman \(1986\)](#). However, for variables believed to feature mean reversion this prior is not suitable. For those I impose a prior belief of white noise by setting $\delta_i = 0$ as in [Bańbura et al. \(2010\)](#). The hyperparameter λ governs the overall tightness of the priors. I follow [Giannone et al. \(2015\)](#) and optimally choose λ by treating it as an additional parameter in the model, in the spirit of hierarchical modelling.

A.2.3 Data

I apply logarithms to most of the series, with the exception of those already expressed in rates. For non-stationary variables, I impose a random walk prior. For stationary variables, I use a white-noise prior. Table [A.1](#) provides a description of the dataset, including the information on the transformations and the specification of the priors for each series. The data are at monthly frequency and span the period from January 1990 to December 2019.

Table A.1: Set of Endogenous Variables

Variable	Description	Source	Logs	RW
TPU	Caldara et al. (2020) 's TPU index	Matteo Iacoviello's website	✓	✓
	Baker et al. (2016) 's TPU index	EPU website	✓	✓
RVOL	Scaled sum of daily squared returns on the S&P 500 index	CRSP & Own Calculation	✓	
VIX	CBOE Volatility Index	FRED	✓	
Stock Prices	S&P500 Composite Stock Price Index	CRSP	✓	✓
Industrial Production	Manufacturing Sector (NAICS)	FRED	✓	✓
Employment	All Employees, Manufacturing Sector	FRED	✓	✓
Tariffs ^{a,b}	Ratio of custom duties to nominal imports of goods (inclusive of customs)	FRED & Own Calculation		✓
Business confidence	Composite Business Confidence Amplitude Adjusted for United States	FRED	✓	

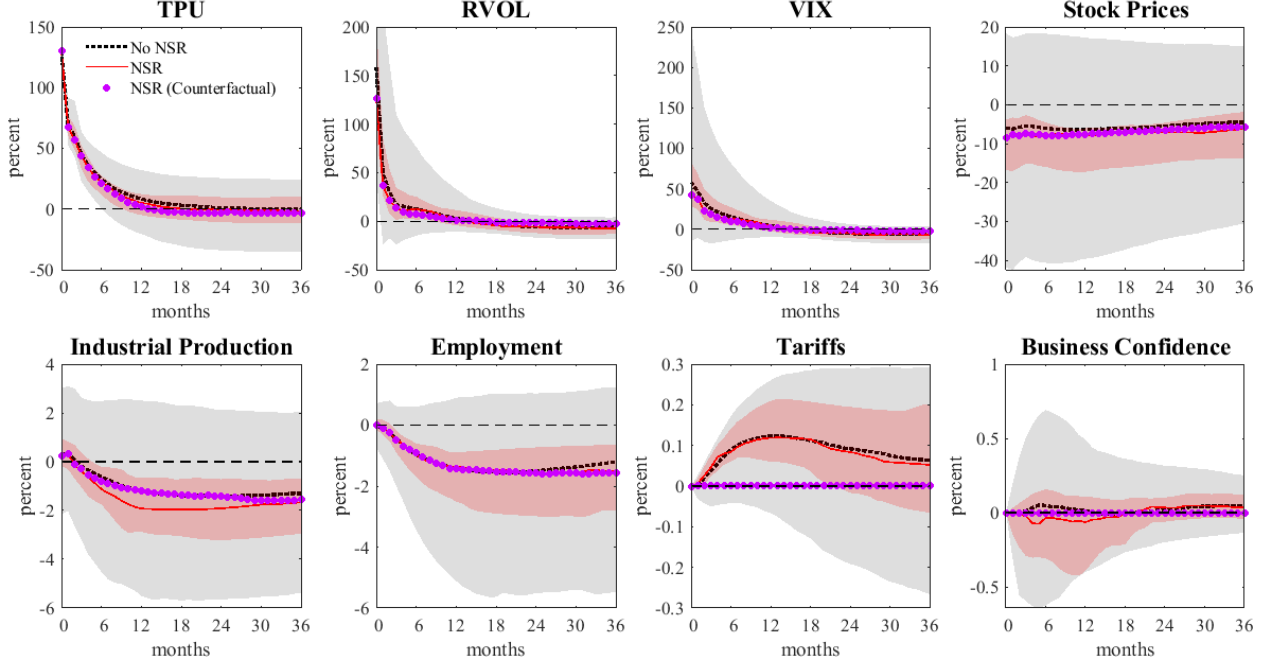
Note: The series are collected from January 1990 to December 2019. The last two columns indicate the transformation of the data to logarithms and whether a random walk (RW) prior was imposed on those variables, respectively.

^a I follow [Fernández-Villaverde, Guerrón-Quintana, Kuester, and Rubio-Ramírez \(2015\)](#) and [Caldara et al. \(2020\)](#) to construct a quarterly measure of tariff rates.

^b Series linearly interpolated from quarterly data.

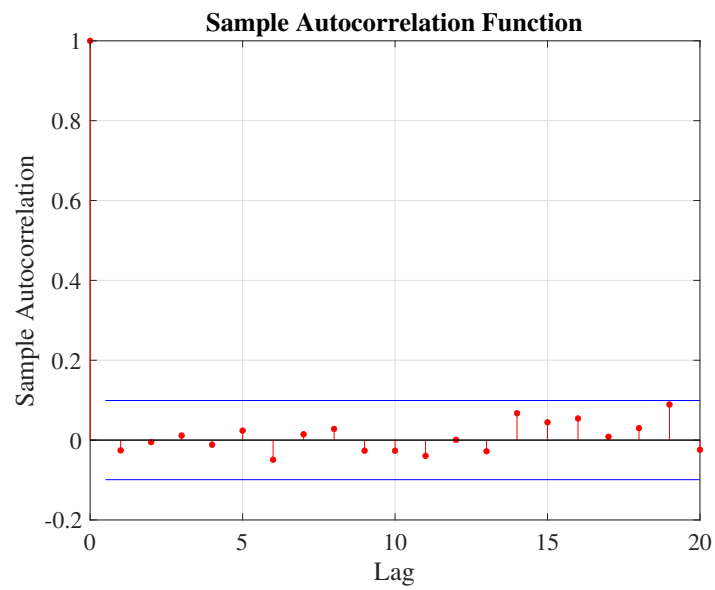
A.3 Validation Checks and Robustness

Figure A.1: Actual and Counterfactual IRFs to a U.S. TPU Shock



Note: The TPU shock is normalised to induce a 130-point increase in the TPU index. The light-shaded area represents the 68% pointwise credible sets for the IRFs and the dotted lines are the median IRFs using sign restrictions only. The darker shaded area and the solid line display the equivalent quantities when the narrative sign restrictions (NSRs) are also satisfied. Points represent the counterfactual responses under NSRs when setting the endogenous response of import tariffs and business confidence to zero at all horizons, following the approach by [Sims and Zha \(2006\)](#). Sample estimation from 1990M1 to 2019M12.

Figure A.2: Autocorrelation Function of TPU shocks



Note: The estimation is based on the median time series of TPU shocks extracted from the SVAR identified with narrative sign restrictions. Sample period 1991M1 to 2019M12.

Table A.2: Orthogonality with other Structural Shocks

Shock	Correlation (p-value)	Granger F-test (p-value)	Sample
Oil			
Hamilton (2003)	0.01 (0.45)	0.25 (0.78)	1991Q1-2019Q2
Baumeister and Hamilton (2019)	−0.01 (0.55)	0.66 (0.57)	1991M1-2019M12
Caldara, Cavallo, and Iacoviello (2019a)	0.01 (0.39)	0.42 (0.74)	1991M1-2015M12
Monetary Policy			
Romer and Romer (2004)^a	0.06 (0.18)	0.48 (0.70)	1991M1-2007M12
Sims and Zha (2006)	−0.07 (0.85)	0.86 (0.47)	1991M1-2003M3
Gertler and Karadi (2015)	0.04 (0.22)	1.06 (0.37)	1991M1-2012M6
News			
Barsky and Sims (2011)	−0.04 (0.68)	0.20 (0.82)	1991Q1-2007Q3
Beaudry and Portier (2014)^a	−0.20 (0.99)	2.31 (0.10)	1991Q1-2015Q3
Kurmman and Otrok (2013, 2017)	0.08 (0.26)	1.65 (0.20)	1991Q1-2005Q2
Productivity			
Basu, Kimball, and Fernald (2006)^b	0.04 (0.31)	0.38 (0.68)	1991Q1-2019Q2
Justiniano, Primiceri, and Tambalotti (2011)	−0.05 (0.73)	1.42 (0.25)	1991Q1-2009Q1
Francis, Owyang, Roush, and DiCecio (2014)	0.07 (0.24)	0.77 (0.46)	1991Q1-2009Q4
Fiscal Policy			
Fisher and Peters (2010)	−0.01 (0.54)	0.07 (0.93)	1991Q1-2007Q4
Romer and Romer (2010)	−0.09 (0.94)	0.40 (0.67)	1991Q1-2007Q4
Ramey (2011)	0.01 (0.46)	2.26 (0.11)	1991Q1-2013Q4

Note: The entries in the table denote the pairwise correlations and Granger causality tests between the median time series of TPU shocks extracted from the SVAR identified with narrative sign restrictions and a set of external time series of structural shocks. The p-values are reported in parenthesis. In particular, the p-values in the column of correlations correspond to a regression of the series of TPU shocks on the external shock series, computed with the Newey-West HAC estimator. When the external shock is only available at the monthly frequency, the TPU shock series is aggregated by averaging across months. The sample period for the TPU shocks is from January 1991 to December 2019.

^a Series updated by [Ramey \(2016\)](#).

^b Residuals from an AR(1) of the log-difference in the utilization-adjusted total factor productivity (see [Fernald, 2012](#)).

B Data Appendix

Table B.1: Data Coverage

Countries	Industrial Prod.	Imports	Exports	CPI	Stock Prices	Bilateral NER
Australia	2000M1-2019M12	1985M1-2019M12	1985M1-2019M12	-	1985M1-2019M12	1985M1-2019M12
Austria	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-1998M12
Belgium	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-1998M12
Brazil	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Canada	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Chile	1991M1-2019M12	1996M1-2019M12	1996M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
China	2010M1-2018M11	1992M1-2019M12	1992M1-2019M12	1993M1-2019M12	1985M1-2019M12	1985M1-2019M12
Colombia	1990M1-2019M12	1991M1-2019M12	1991M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Czech Republic	1991M1-2019M12	1991M1-2019M12	1991M1-2019M12	1991M1-2019M12	1985M1-2019M12	1985M1-2019M12
Denmark	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Estonia	1998M1-2019M12	1993M1-2019M12	1993M1-2019M12	1998M1-2019M12	1985M1-2019M12	1992M6-2019M12
Finland	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-1998M12
France	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-1998M12
Germany	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-1998M12
Greece	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-1998M12
Hungary	1992M1-2019M12	1991M1-2019M12	1991M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
India	1986M1-2019M12	1990M1-2019M12	1990M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Italy	1990M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-1998M12
Japan	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Korea	1990M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Latvia	2000M1-2019M12	1999M1-2019M12	1999M1-2019M12	1991M1-2019M12	1985M1-2019M12	1992M2-2019M12
Lithuania	1998M1-2019M12	1999M1-2019M12	1999M1-2019M12	1991M1-2019M12	1985M1-2019M12	1992M12-2019M12
Malaysia	2010M1-2019M03	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Mexico	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Netherlands	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-1998M12
Norway	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Philippines	1993M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Poland	1985M1-2019M12	1991M1-2019M12	1991M1-2019M12	1989M1-2019M12	1985M1-2019M12	1985M1-2019M12
Portugal	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1992M1-2019M12	1985M1-2019M12	1985M1-1998M12
Russia	1999M1-2019M12	1991M1-2019M12	1991M1-2019M12	1985M1-2019M12	1985M1-2019M12	1995M6-2019M12
SouthAfrica	1990M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Spain	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-1998M12
Sweden	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Thailand	1997M1-2018M01	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
Turkey	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
UK	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
USA	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12	1985M1-2019M12
EA	-	-	-	-	-	1999M1-2019M12

Table B.2: Data Sources

Countries	Industrial Prod.	Imports	Exports	CPI	Stock Prices	Bilateral NER
Australia	IMF (IFS)	IMF (IFS)	IMF (IFS)	-	OECD (MEI)	IMF (IFS)
Austria	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Belgium	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Brazil	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Canada	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Chile	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
China	IMF (IFS)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	OECD (MEI)
Colombia	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Czech Republic	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Denmark	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Estonia	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	OECD (MEI)
Finland	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
France	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Germany	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Greece	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Hungary	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
India	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Italy	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Japan	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Korea	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Latvia	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	OECD (MEI)
Lithuania	OECD (MEI)	IMF (IFS)	IMF (IFS)	IMF (IFS)	IMF (IFS)	OECD (MEI)
Malaysia	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)	IMF (IFS)	IMF (IFS)
Mexico	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Netherlands	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Norway	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Philippines	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)	OECD (MEI)	IMF (IFS)
Poland	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Portugal	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Russia	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
SouthAfrica	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Spain	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Sweden	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
Thailand	CB	OECD (MEI)	OECD (MEI)	IMF (IFS)	IMF (IFS)	IMF (IFS)
Turkey	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
UK	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
USA	OECD (MEI)	IMF (IFS)	IMF (IFS)	OECD (MEI)	OECD (MEI)	IMF (IFS)
EA	-	-	-	-	-	IMF (IFS)

Note: IMF (IFS): IMF (International Financial Statistics); OECD (MEI): OECD (Main Economic Indicators); CB: Central Bank