The Transmission of U.S. Trade Policy Uncertainty Shocks to the Mexican Economy*

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Abstract

Given Trump's second presidency, timely estimates of the macroeconomic impact of U.S. trade policy uncertainty (TPU) shocks on Mexico—an emerging economy with strong trade and financial ties to the U.S.—are crucial for informing future policy decisions. This paper examines the impact of TPU shocks on Mexico's economic activity and inflation during Trump's first term. Using a novel identification strategy in a Structural Vector Autoregression (SVAR) model, we combine a small set of uncontroversial sign and zero restrictions with narrative sign restrictions based on stock market jumps triggered by TPU-related news 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 Mexico while causing a depreciation of the Mexican peso against the U.S. dollar. In the U.S., demand effects dominate, leading to lower inflation. In contrast, in Mexico, currency depreciation—driven by a flight-to-safety channel—exerts upward pressure on inflation, counteracting the deflationary effects of weaker aggregate demand and creating monetary policy trade-offs.

Keywords: Trade policy uncertainty; Trade; Uncertainty shocks; International transmission
JEL codes: C11, C33, D80, F13, F42

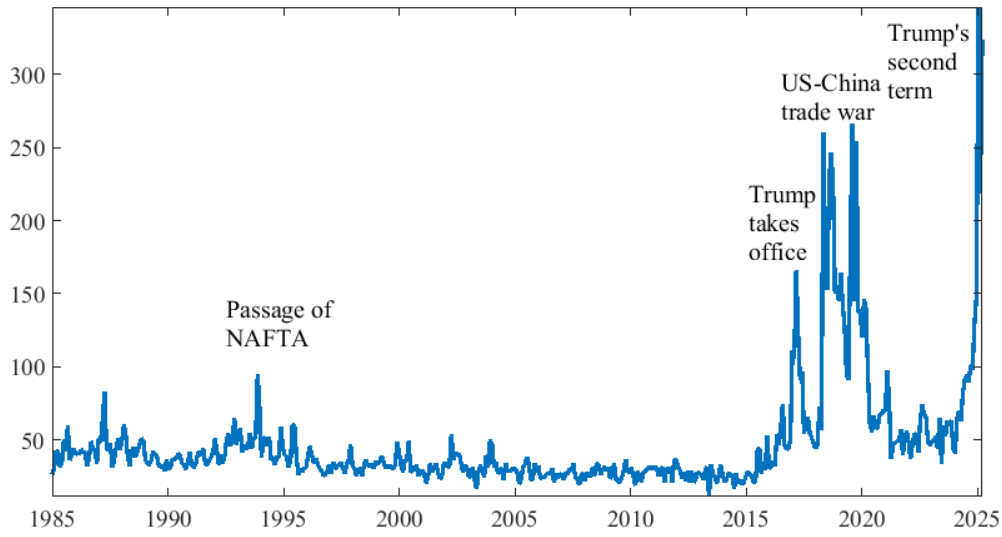
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1 Introduction

Trump's second term has begun with a trade war, marked by threats and the imposition of tariffs on key trade partners such as China, Canada, and Mexico. This escalating conflict has led to heightened trade policy uncertainty (TPU). For instance, after announcing tariffs on Canada and Mexico on February 1st, the administration reversed course two days later, postponing them by a month. Meanwhile, tariffs on China remained in place, triggering retaliatory measures. These developments have pushed TPU levels even higher than those observed during his first term, as reflected in the news-based TPU index by Caldara, Iacoviello, Molligo, Prestipino, and Raffo (2020).

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



Note: The figure shows the monthly news-based TPU index constructed by Caldara et al. (2020). Sample period from 1985M1 to 2025M1.

TPU stemming from diverse trade developments, such as tariff announcements or threats, complicates the assessment of macroeconomic risks. From the viewpoint of many economic models, TPU can influence the macroeconomy 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).[1] 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

[1]Reduced-form evidence refers to empirical findings that directly relate economic variables to TPU without explicitly modelling the underlying structural relationships that generate TPU.

inflation in Mexico? Are the spillovers primarily driven by real or financial channels? And ultimately, do they entail monetary policy trade-offs in Mexico?

Given Trump's second presidency, having timely estimates of the macroeconomic consequences of U.S. TPU shocks is essential to inform future policymaking. Some of Trump's campaign promises are already taking effect. For instance, an extensive programme to deport undocumented immigrants and enforce stricter immigration regulations has begun. Additionally, key trading allies should brace for higher tariffs, as Trump has proposed imposing duties on all imports. In this context, this study uses the U.S. as a case study to examine the international spillovers of TPU shocks. This analysis is particularly relevant from Mexico's perspective, given its deep economic ties with the U.S. and the significant impact these policies could have on its economy.

We 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's first administration, is highly effective in assessing the impact of TPU shocks. We 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 Mexico, along with a

depreciation of the Mexican peso against the U.S. dollar. In the U.S., this transmission primarily occurs through demand channels, resulting in lower inflation. Conversely, in Mexico, the 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 Banxico, Mexico's central bank.

To formally construct the narrative information, we identify large daily jumps in the S&P 500 index caused by news about TPU induced by Trump's tariff threats. For this task, we rely on the stock market jumps classification by Baker, Bloom, Davis, and Sammon (2021), encompassing trade policy. Complementing their categorisation, we select jumps stemming from Trump's tariff threats against trade partners. We 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, we 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, we 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, we 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*.

We 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, we 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, we proceed to estimate their transmission to the Mexican economy. To achieve this, we 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, we consider the responses of trade and financial variables to identify the specific channels at play. We 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, we 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.

We 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, have 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, Bloom, and Davis (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 we 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, we 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. We 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, we 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.

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.

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 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, we 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, we 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, we 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.[2] 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, we 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.

[2]The 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.

We 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 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.[3]

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,

[3]For details, see this column from the CEPR's policy portal.

we 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

$$\boldsymbol{A}_0\boldsymbol{y}_t = \boldsymbol{a} + \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \ldots + \boldsymbol{A}_p\boldsymbol{y}_{t-p} + \boldsymbol{\varepsilon}_t, \tag{1}$$

where p is the lag order, $\boldsymbol{y}_t$ is an $n \times 1$ vector of endogenous variables, $\boldsymbol{a}$ is an $n \times 1$ vector of constants, and $\boldsymbol{A}_1, \ldots, \boldsymbol{A}_p$ are $n \times n$ coefficient matrices. $\boldsymbol{\varepsilon}_t$ is an $n \times 1$ vector of structural shocks and $\boldsymbol{A}_0$ 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 $\boldsymbol{S} = \boldsymbol{A}_0^{-1}$, the reduced-form version of the SVAR model is given by

$$\boldsymbol{y}_t = \boldsymbol{b} + \boldsymbol{B}_1\boldsymbol{y}_{t-1} + \ldots + \boldsymbol{B}_p\boldsymbol{y}_{t-p} + \boldsymbol{u}_t, \tag{2}$$

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

$$\boldsymbol{u}_t = \boldsymbol{S}\boldsymbol{\varepsilon}_t, \tag{3}$$

with covariance matrix $\text{var}(\boldsymbol{u}_t) = \boldsymbol{\Sigma} = \boldsymbol{S}\boldsymbol{\Omega}\boldsymbol{S}'$. 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 (1) faces an identification challenge as the covariance matrix $\boldsymbol{\Sigma}$ only provides $n(n+1)/2$ restrictions to identify the n^2 free parameters in $\boldsymbol{S}$. Therefore, we have to impose restrictions on the structural parameters to solve the identification problem. In this study, we 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. We 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. We 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, we 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, we 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, we 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 we 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.[4]

Based on the narrative information above, we are 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 macroecnomic 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

[4]Formally, 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 $|H_{i_v,j,t_v,t_v+h_v}|$ denotes the historical contribution of the jth shock to the ith variable in the VAR from periods t_v to $t_v + h_v$. Similarly, Type B restriction can be formulated as

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

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.

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

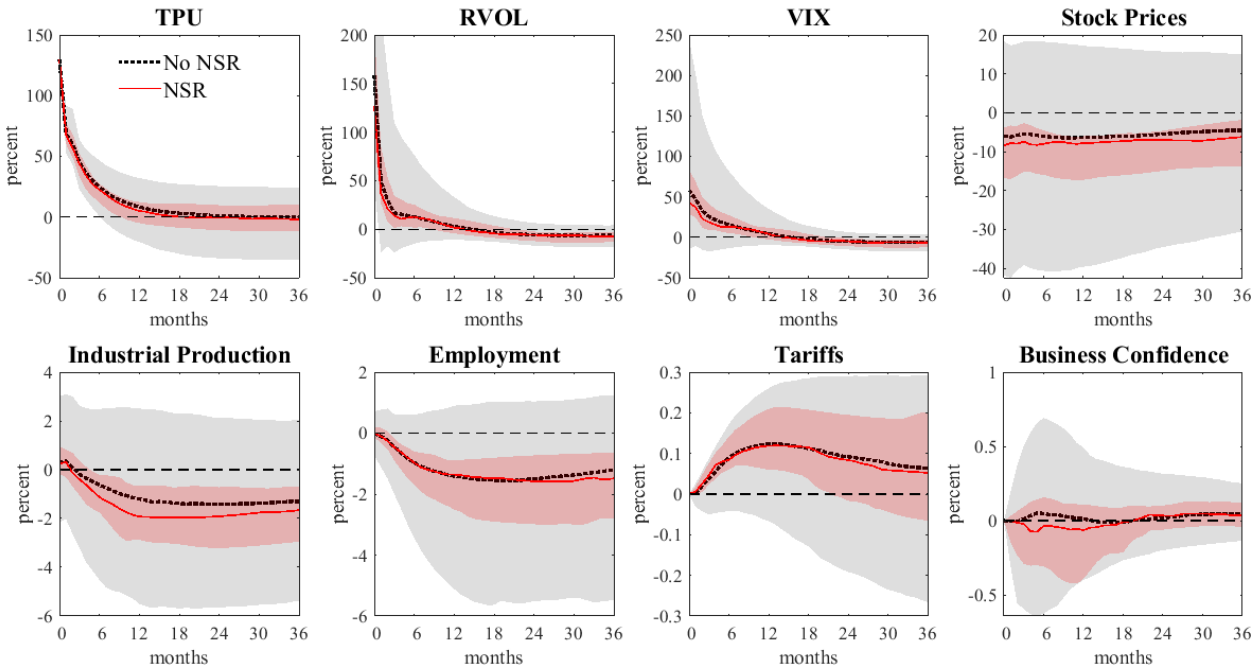
Figure 2 compares the IRFs to a U.S. TPU shock, with and without the NSRs.[5] The light-shaded areas represent the 68% pointwise credible sets for the IRFs and the dotted lines are the median IRFs using sign and zero restrictions only. The darker shaded areas and solid lines display the equivalent quantities 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.

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 microeco-

[5] I 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.

nomic 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.[6]

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, we demonstrate through a counterfactual exercise, following Sims and Zha (2006), that setting the endogenous response of import tariffs to

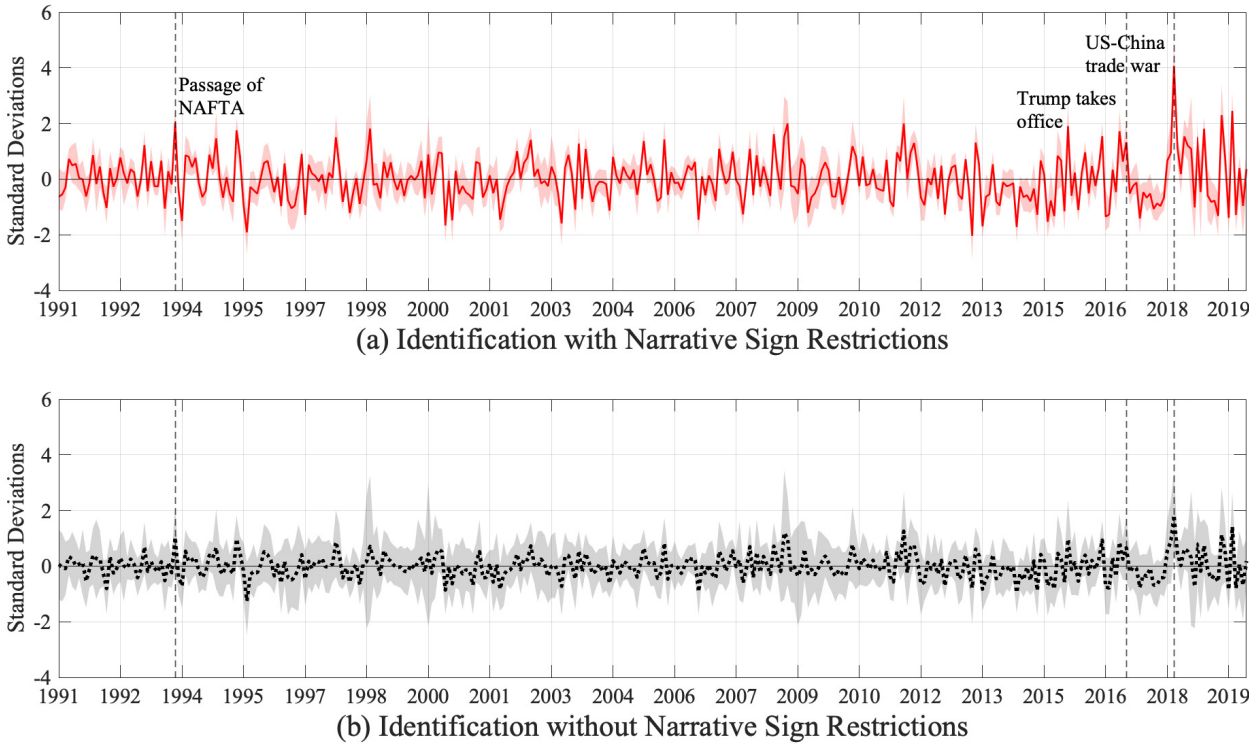
[6] Although the narrative information is derived from the recent trade war during Trump's administration, our time series approach, unlike an event study, captures average responses across multiple events in the sample, not just the recent trade war.

zero leads to similar IRFs, suggesting that import tariffs are not a significant transmission channel for TPU shocks.[7] 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 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.

[7] In the counterfactual exercise, for completeness, we 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



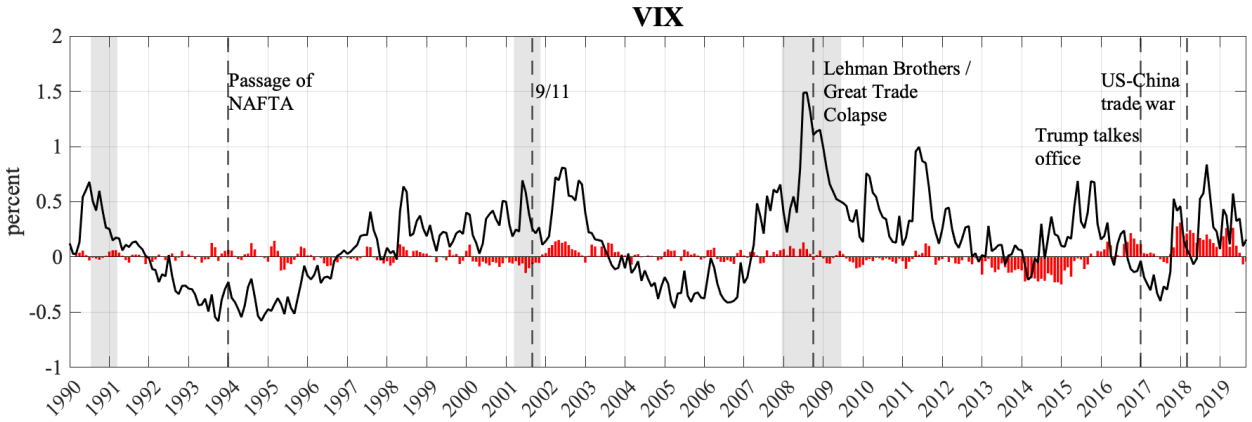
Note: The solid and dotted lines plot the median time series of U.S. TPU shocks (a) when narrative sign restrictions are satisfied, and (b) when they are not considered, respectively. Shaded areas are 68% pointwise credible sets. Sample from 1991M1 to 2019M12.

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, we 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 (2019a). 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, we 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).

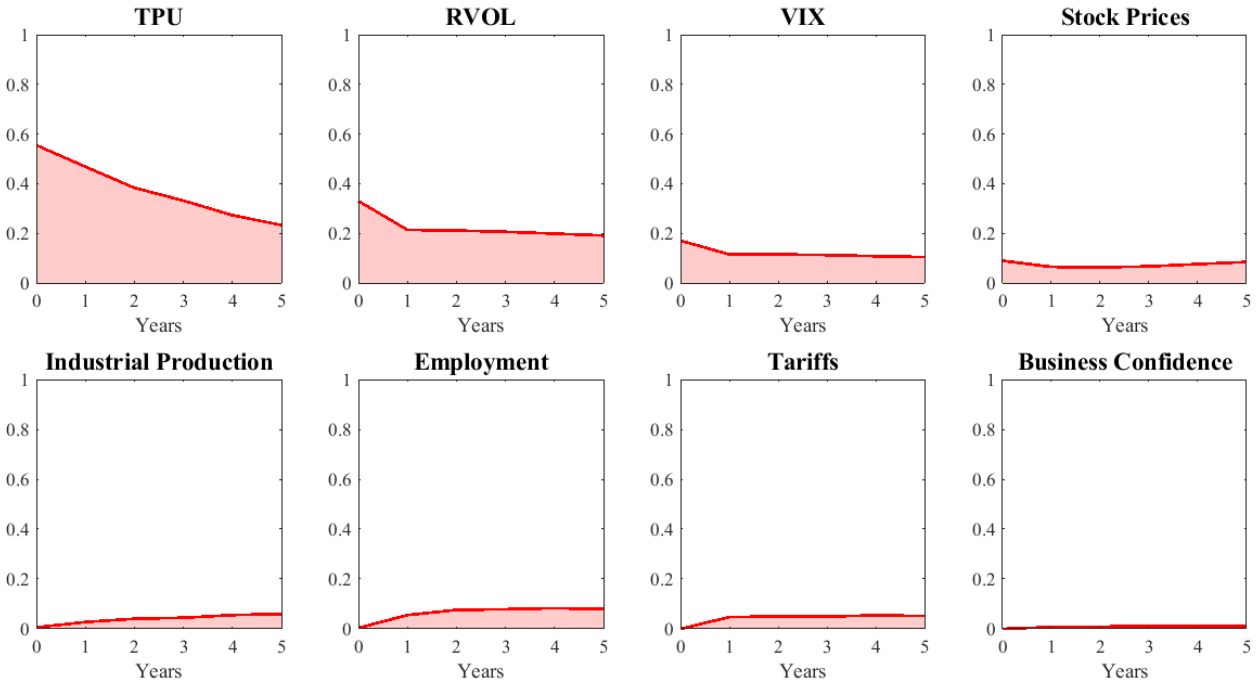
3.5 Quantitative importance

In this section, we 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

We 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 we 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

We 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 The Transmission to the Mexican Economy

In this section, we analyse the domestic impacts and those on Mexico of U.S. TPU shocks using local projection methods based on Jordà (2005). The empirical approach is outlined in three subsections. First, we define the data used in the estimation. Next, we describe the empirical model. Finally, we discuss the transmission of TPU shocks to Mexico.

4.1 Data

For both Mexico and the U.S., we collect monthly data on industrial production, imports, exports, consumer prices, stock prices, and the nominal effective exchange rate. The analysis covers the period from January 2002 to December 2019, during which Mexico operated under a single monetary policy framework—inflation targeting—that successfully achieved lower and more stable inflation as well as financial stability. Since this study examines whether U.S. TPU shocks create monetary policy trade-offs, this timeframe is particularly suitable for exploring these dynamics within the established regime. The main data sources are international institutions, namely the OECD (MEI) and the IMF (IFS), as well as national statistical agencies. All variables are in log levels.

4.2 Empirical Model

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

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

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 ε_t^{TPU} is given by the sequence $\{\beta_h\}_{h=0}^{H}$. In the baseline, I set $p = 3$ lags and the vector of controls includes the dependent variable y_t.[8] Notice that except for horizon $h = 0$, the error term ξ_{t+h} in equation (4) will be serially correlated due to the successive leading of the dependent variable. Therefore, we employ robust Newey-West standard errors.[9]

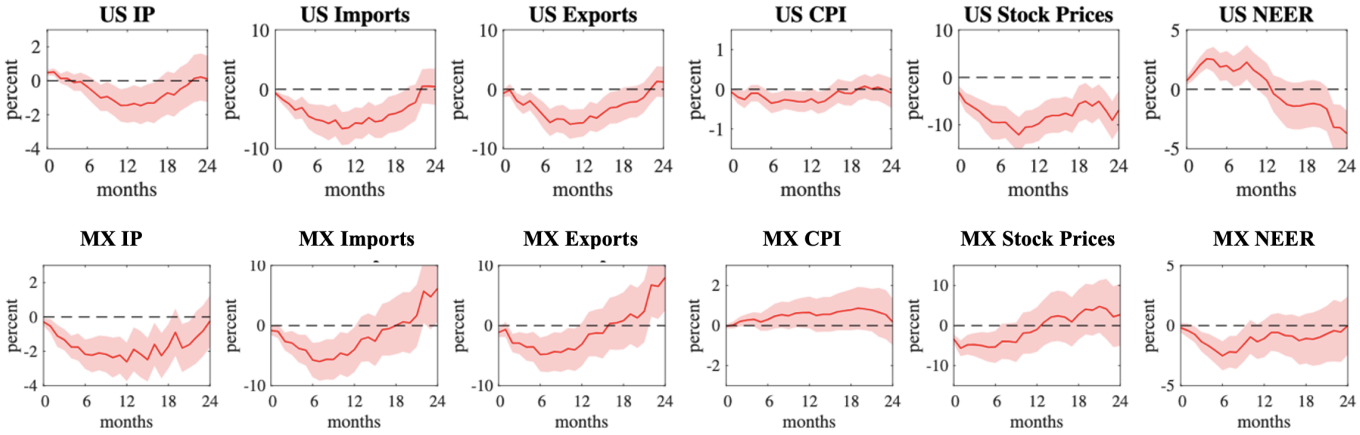
4.3 Domestic and Spillover effects

Figure 6 displays the LP responses of key macroeconomic and financial indicators for the U.S. and Mexico to a U.S. TPU shock, normalised to induce a 130-point increase in the TPU index. The shaded areas represent 68%confidence intervals. Because LP is less efficient than SVARs, we plot IRFs only up to horizon $h = 24$.

[8] Ramey (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.

[9] The TPU shocks estimated in the first step are based on a Bayesian approach. Ideally, one should account for the additional uncertainty introduced by the TPU shock series when computing standard errors. However, as shown in Figure 3, the shocks are estimated very tightly. Therefore, this additional uncertainty is unlikely to have a significant impact on subsequent regressions in practice.

Figure 6: Effects of U.S. TPU Shocks on the US and Mexico (MX)



Note: The TPU shock is normalised to induce a 130-point increase in the TPU index. The shaded areas represent 68% confidence intervals. The second row shows the responses of Mexican variables. The last column of this row presents the response of the nominal effective exchange rate (an increase reflects an appreciation). Sample estimation from 2002M1 to 2019M12.

Economic activity and trade. The first column of Figure 6 displays the responses of industrial production. U.S. industrial production shows a delayed but steady significant decline, dropping by about 2% one year after the shock, while the effect on Mexico is larger, with a drop of 2.5%. The second and third columns illustrate the impact on international trade. In the domestic economy, the responses of both imports and exports are similar, each declining by 5% one year after the shock before recovering. The responses of imports and exports in Mexico follow a similar pattern.

Stock prices. The fifth column shows that stock price responses are both economically and statistically significant, with a decline of about 5% on impact in both the U.S. and Mexico. In the U.S., the effect is more persistent, while stock prices in Mexico revert to trend two years after the shock. The contemporaneous impact of a TPU shock on U.S. stock prices aligns with the evidence from the SVAR estimated above (cf. Figure 2), although the LP response indicates a more severe effect. These empirical results are consistent with the theoretical

predictions of Pástor and Veronesi (2012). In their framework, the authors analyze how changes in government policy affect stock prices, predicting that stock market returns should be negative, on average, at the announcement of a policy change, with a larger magnitude if uncertainty about government policy is high or if the announcement is unanticipated by the market. The evidence documented here arises from uncertainty around trade policy that is both substantial and exogenous. Additionally, Pástor and Veronesi (2013) predict that stocks should be more volatile and correlated during periods of heightened political uncertainty. The responses of stock prices observed here provide strong support for their predictions.

Consumer prices and exchange rate. The fourth and final columns display the responses of consumer prices and nominal effective exchange rates (NEER). 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 U.S. dollar in response to global risk shocks. In contrast, Mexico experiences a substantial and persistent depreciation of its currency. These results, along with the appreciation of the U.S. dollar, suggest that TPU shocks in the U.S. trigger a flight-to-quality phenomenon, leading investors to withdraw capital from riskier markets, thereby negatively affecting their exchange rates. Consumer prices in Mexico tend to increase, whereas prices gradually decline in the U.S., likely due to the sharper depreciation in Mexico, which puts upward pressure on consumer prices.

4.4 Transmission Channels

The responses documented in the previous subsection shed light on the channels through which U.S. TPU shocks may affect the Mexican economy. First, a demand channel can operate via *expenditure-reducing effects* when a rise in TPU adversely affects U.S. output growth, leading to a lower demand for foreign goods. An economic contraction in Mexico and the global economy, in turn, can depress the demand for U.S. exports, amplifying the impact on the U.S. economy. A second channel is driven by the role of the exchange rate in creating *expenditure-switching effects*. With flexible exchange rates, an appreciation of the U.S. dollar induced by a TPU shock can improve the price competitiveness of goods and services abroad, thus stimulating Mexican exports and output.

The responses of industrial production, exports, and imports for the U.S. and Mexico suggest that, on average, the demand channel is more significant than the exchange rate channel in explaining these effects. However, the transmission channels affecting consumer prices operate differently in the two countries. In the U.S., a negative demand channel appears to dominate the exchange rate channel, whereas the opposite is true for Mexico. In Mexico, the exchange rate channel seems to operate through a flight-to-quality phenomenon, as discussed earlier.

4.5 Monetary policy trade-offs in the U.S. and Mexico

The monetary policy trade-offs in the U.S. and Mexico differ significantly due to the distinct channels through which U.S. TPU shocks affect their economies. In the U.S., the demand channel is more influential, allowing the Federal Reserve to potentially stabilize both eco-

nomic activity and inflation through monetary policy loosening. Conversely, in Mexico, the exchange rate channel is more significant, with TPU shocks leading to a depreciation of the peso, which raises inflationary pressures and complicates Banxico's monetary policy decisions due to the negative impact of TPU shocks on economic activity.

These differences result in asymmetric policy responses between the two central banks. While the Federal Reserve might lower interest rates to achieve its dual mandate, this could widen the interest rate differential between the U.S. and Mexico, putting further pressure on the peso and forcing Banxico to consider raising rates to curb inflation. This situation highlights the complex trade-offs Banxico faces between stabilising inflation and supporting economic growth.

5 Conclusions

In light of Trump's second term, obtaining timely estimates of the macroeconomic impact of U.S. TPU shocks on Mexico is crucial for guiding future policymaking decisions. This paper has proposed a narrative identification strategy to isolate exogenous shifts in trade policy uncertainty originating in the U.S., with the goal of estimating the causal effects of TPU on economic activity and inflation both domestically and in Mexico. By incorporating information from stock market jumps triggered by news about TPU during Trump's first administration as narrative sign restrictions in the historical decomposition of stock market volatility, we have demonstrated that these jumps are highly informative for refining the identification initially based on sign and zero restrictions.

Our analysis has demonstrated that U.S. TPU shocks typically lead to declines in industrial production, trade, and stock prices in both the U.S. and Mexico, alongside a depreciation of the Mexican peso against the U.S. dollar. In the U.S., this transmission primarily occurs through demand channels, which results in lower inflation. Conversely, in Mexico, the currency depreciation, driven by a flight-to-safety phenomenon, increases inflationary pressure, offsetting the deflationary impact of reduced aggregate demand and creating monetary policy trade-offs for Mexico's Central Bank. While this analysis does not cover the post-COVID-19 period, which saw a reconfiguration of supply chains, the identification strategy remains applicable to this timeframe. These aspects are left for future research.

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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 (2019b). 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 and Bayesian Estimation

A.2.1 Bayesian Estimation

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

$$\Sigma \sim \mathcal{IW}(S_0, \alpha_0) \qquad \text{and} \qquad B|\Sigma \sim \mathcal{N}(B_0, \Sigma \otimes \Omega_0) \tag{A.1}$$

where $B = \text{vec}([c, B_1, \ldots, B_p]')$. 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

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

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.2.2 Data and Prior Specification

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 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.

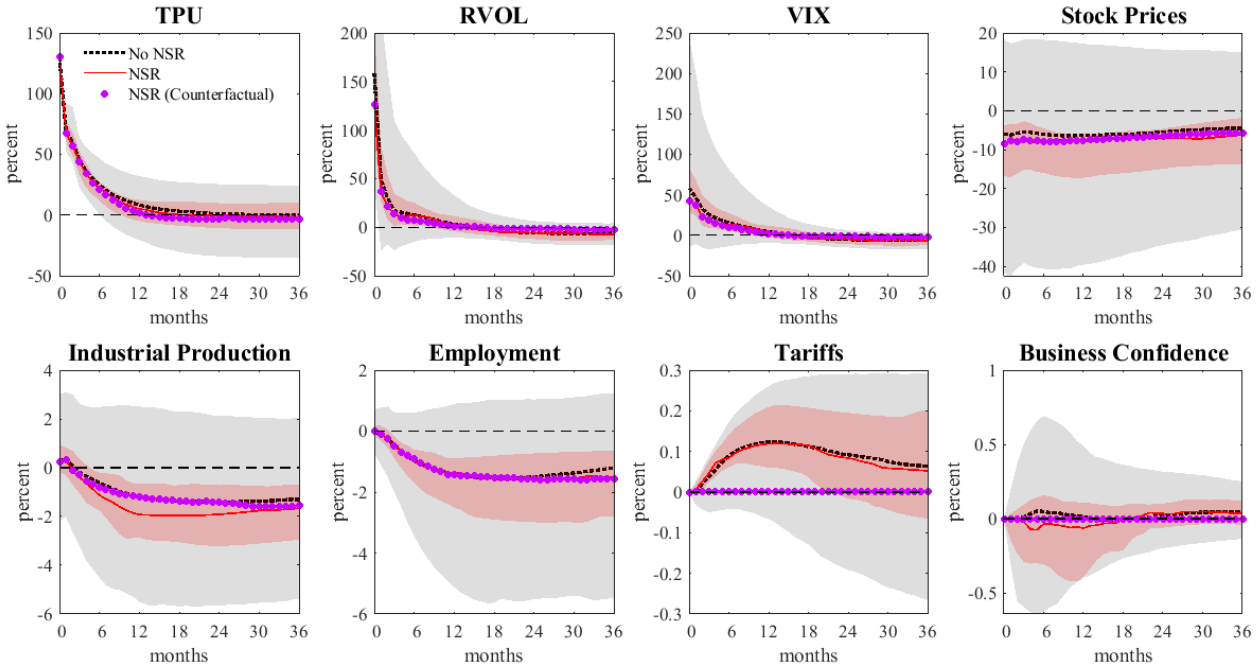
Table A.1: Set of Endogenous Variables

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.

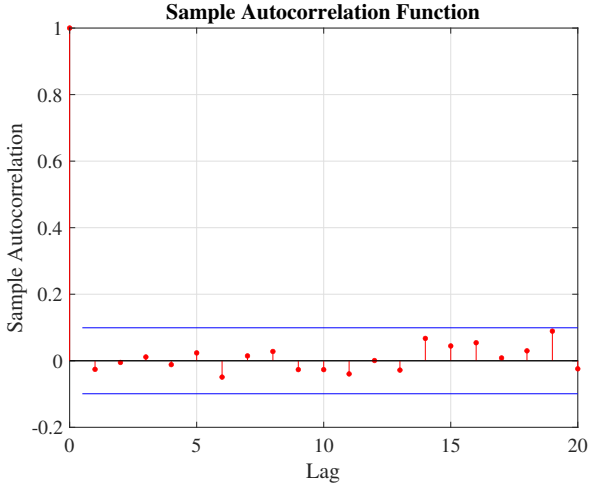
A.3 Robustness and Validation Checks

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
Kurmann 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 parentheses. 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).