Measuring Trade Policy Uncertainty and Its Impact On Financial Market Volatility

By Youssef A. Benasser *

The weakening multilateral trade policy framework and the pursuit of protectionist agendas have reduced the predictability of trade policy in recent years. This paper investigates the impact of trade policy uncertainty (TPU) on stock market volatility. In doing so, it proposes a new forward-looking index to measure public perceptions of TPU. In-sample results reveal that markets do not respond to TPU shocks with increased volatility. Out-of-sample analysis indicates that TPU does not have predictive power for market volatility and that accounting for it in asset allocation decisions does not improve investors' utility. These results align well with theoretical predictions of behavioral responses to uncertainty. They also significantly deviate from the existing empirical literature on the volatility-impact of other sources of policy uncertainty. I discuss possible reasons that explain this new result.
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* University of Oregon, 1585 E 13th Ave, Eugene, OR 97403, youssefa@uoregon.edu.
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Introduction

Does trade policy uncertainty increase volatility in financial markets? Affirmative answers to this question pervaded stock market news coverage in 2018-2019 [1]. In the context of rising trade and geostrategic tensions, the financial news sources widely accredited trade policy for increasing market volatility, pointing out both policy actions and the perceived uncertainty surrounding them as potential causality channels. In this paper, I investigate this hypothesis by quantifying the contribution of trade policy uncertainty (TPU) to excess financial volatility. I examine this relationship using a novel measure of TPU that addresses concerns with prevalent news-based measures, and employ these existing measures for robustness checks.

That trade policy could contribute to stock market volatility is a reasonable hypothesis. Rational asset-pricing theory conceives of stock prices as the discounted value of the stream of future dividends. Therefore, changes to the expectations of future returns or the discount parameters will translate into larger variations that add to excess volatility. In this context, news, including trade policy news, can drive volatility. A news-based equity volatility tracker proposed by Baker et al. (2019) shows that the share of trade-policy-related articles has increased from just over 2% in 1985 to 26% in 2015. Less clear is the impact of the uncertainty that the public perceives when internalizing trade policy trajectories. This paper bridges this gap in the literature by providing a timely analysis of the impact of TPU on stock market volatility from 2015 to 2021.

Improving our understanding of TPU and its impacts is imperative. The predictability of U.S. trade policy has weakened over the past few years. This reduced predictability came from the Trump administration's willingness to deviate from the World Trade Organization's (WTO) multilateral rules to pursue its own policy goals on trade relations with China and other partners. This widening trade policy space continues under the Biden administration, which has endorsed an active industrial policy. In this context, the weakening commitment to the multilateral trade system coupled with the WTO's inability to enforce its own rules, as its dispute resolution mechanisms grind to a halt, opens the economy to new and repeated TPU shocks. Measuring the size of these shocks, and their impact on sectors of the economy has therefore become a new focus of the trade literature (Caldara et al. (2020), Liu et al. (n.d.), Steinberg (2019), Feng, Li and Swenson (2017), Handley and Limao (2017), Handley and Limão (2015)). This paper gives the most extensive account to date on the impact of TPU on stock

[1] Example headlines include: "Lagarde Expects More Market Volatility With Trade Trouble" (Bloomberg, 10/13/2018), "Volatility Erupts Everywhere as Trade War Becomes a Currency War" (Bloomberg, 8/6/2019), "Dow Plunges 760 points in worst day of 2019 as trade war intensifies" (CNBC, 8/4/2019), "Markets close lower, hit by earnings and trade war uncertainty" (Los Angeles Times, 5/22/2019), "How the trade war became the stock market's biggest driver" (MarketWatch, 9/9/2019), "US-China trade tensions lead to volatile markets" (Marketplace, 6/19/2018)

price volatility, distinguishing short- and long-run dynamics as well as industry heterogeneity.

The market volatility / economic policy uncertainty nexus carries renewed importance in this context. To the extent that policy uncertainty is a byproduct of a unilateral trade policy agenda and that uncertainty in policymaking is undesirable for investors, a trade-off between the unilateral pursuit of trade policy goals and the stability of financial markets might arise. The bull market has dominated U.S. equities since the end of the Great Recession. It has come to be perceived as an indicator of the state of the economy, therefore, creating incentives for policymakers to protect the bull market against transitory volatility and reversals. Attention to market volatility also has economic motivations, given its role in asset-pricing and investment behaviors. Volatility shocks change the compensations that shareholders require for bearing systematic risk (Guo (2002)), which in turn impacts the cost of equity capital. Through its implications for investors and publicly traded firms, volatility can spill over to the real economy. Campbell et al. (2001) shows that stock market volatility leads volatility in other economic indicators and has significant predictive power for real GDP growth. Further, and precisely because it leads volatility in other economic series, volatility can be an early sign of financially induced recessions (Chauvet, Senyuz and Yoldas (2015)).

This paper employs time-series methods to measure the impact of TPU shocks on volatility and looks both at in-sample causality and out-sample forecasting gains. In addition to overall market volatility, I look at the volatility of specific portfolios with varying degrees of exposure to international trade. I also allow for heterogeneity in the outcome variable by distinguishing transitory and persistent components of volatility.

Two contributions stand out. First, the methodological approach delivers a new measure of TPU perceptions, which combines social network data and institutional signals. It displays desired properties of consistency with known shocks and improves upon existing news-based measures. It can be replicated and used for future research. Second, the analysis delivers a new result that negates the causal effect of TPU on market volatility. I find that TPU shocks do not create excess volatility, meaning that investors do not respond systematically to trade policy uncertainty shocks. This result contrasts with the finding in the literature that uses news-based measures to identify the volatility impact of broad economic policy uncertainty (e.g. Brogaard and Detzel (2015), Phan, Sharma and Tran (2018), Liu and Zhang (2015)). I argue that this discrepancy emphasizes the unique character of trade as a component of policy uncertainty and reflects methodological differences in proxying for uncertainty.

The rest of the paper is structured as follows—section 1 reviews both the literature on trade policy uncertainty and stock market volatility. Section 2 describes data construction methods and a new approach to measuring public perceptions of trade policy uncertainty. Section 3 elicits causal relationships between market volatility and TPU using in and out-of-sample analyses and discusses the results.

I. Background

A. Literature on Trade Policy Uncertainty

Economists distinguish notions of risk from volatility (Knight (1921)). An agent facing risks can assign probabilities to different outcomes and optimize based on the resulting expectations. Uncertainty results in a failure of the probabilistic approach: the probabilities are unknown, or the outcome space itself is not known (Bloom (2014)).

In the context of policy, uncertainty is often used to refer to a mix of risk and uncertainty proper. Economic policy uncertainty is an umbrella term covering uncertainty in all policy fields: fiscal, monetary, regulatory, and otherwise. The contribution of policy to agents' perception of economic uncertainty is a corollary of the increasing role of governments in the economy. To the extent that they engage in decision-making that relies on expectational optimization, economic agents bear the costs of economic policy uncertainty. Increased uncertainty means that assigned probabilities are more likely to be erroneous or incomplete, leading to optimization mistakes and economic and welfare losses. Using firm-level data, Baker, Bloom and Davis (2016) find that economic policy uncertainty is associated with greater stock price volatility and reduced investment and employment in policy-sensitive sectors like defense, healthcare, finance, and infrastructure construction.

Earlier research of trade policy uncertainty was theoretical. Handley and Limão (2015) theoretically model export market entry in the context of policy uncertainty. The policy variable is the tariff level imposed by the foreign market, the policy space is comprised of three different scenarios, and the switching probabilities follow an exogenous stochastic process. Firms optimize entry decisions using beliefs about switching probabilities. Unsurprisingly, the model predicts that entry is a decreasing function of switching probabilities when tariffs are below their maximum level. The model is tested empirically using Portuguese-Spanish trade in the wake of the countries' accession to the European Community. The evidence suggests that when uncertainty subsides following a trade agreement, industries with higher potential profit loss in the worst-case scenario see the most entries.

The early empirical studies of the impacts of TPU use policy events as a proxy for time-variation in uncertainty. One such event is the US-China trade relation prior to the latter's WTO accession. Starting in 1980, the United States extended MFN treatment to China. This decision was conditional on yearly Congressional renewal, which created a recurrent uncertainty shock every time the regime came up for a vote. Alessandria, Khan and Khederlarian (2019) use these moments of increased uncertainty to examine trade response to uncertainty shocks. The results suggest that trade increases in anticipation of uncertain future increases in tariffs. These recurrent positive TPU shocks resolved in 2000 when China received permanent MFN status as a WTO member. The resolution of the uncertainty was associated with simultaneous entries and exits into export markets, favoring more competitive firms (Feng, Li and Swenson (2017)), and delivered higher growth to the industries that had higher initial potential losses from uncertainty (Handley and Limao (2017)).

Brexit has also served as an experiment to study the impact of TPU. Steinberg (2019) builds a three-country heterogeneous firm model using an input-output production structure, and where uncertainty about trade costs impacts the firm's export entry decision. Uncertainty is captured through a stochastic process for trade costs. The model is calibrated to match a pre-Brexit I-O Table. The predicted post-Brexit equilibrium indeed delivers a significant welfare loss; however, uncertainty's contribution to the loss is marginal and accounts for less than a quarter of a percent of the overall welfare cost. In sum, uncertainty in trade policymaking appears to impact the real economy negatively, mainly through its impact on firms that participate in international trade.

Recently, the literature focused on developing empirical measures of TPU to study its impact. This approach promises several advantages. The use of proxies in theoretical and empirical studies focuses heavily on tariff-related uncertainty, consequently downplaying other components of trade policy such as non-trade barriers. A direct empirical measure can be more comprehensive in scope if it does not target a single aspect of TPU. Further, directly measuring TPU is the first step towards studying its short and long-term time-series dynamics and making more general statements about its impacts that are not constricted to specific case studies. Finally, tractable time-variant indices can capture the public perception of uncertainty and the ensuing implications of this perception for agents' behaviors and market outcomes, which is the intent of this paper.

Two attempts at building such empirical measures of TPU stand out. Following their previously referenced 2016 seminal paper on economic policy uncertainty (EPU) measurements, Baker, Bloom, and Davis have developed corollary breakdowns of EPU components as part of their Economic Policy Uncertainty project. Their approach to identifying the trade component of EPU relies on frequency counts of uncertainty-related news articles. They select articles from a panel of 10 leading newspapers based on the occurrence of uncertainty terms. Caldara et al. (2020) introduces a similar news-based index, with a variation in the selection of key terms, and also adds two new indices: a firm-specific index using word counts from earnings call transcripts and a tariff-volatility measure of TPU. The authors favor the news-based measure as an index of aggregate trade policy uncertainty. Accordingly, variations of the news-based measures of TPU are the most common empirical indices currently available to and employed by researchers. Olasehinde-

Williams (n.d.) uses the trade component of Baker, Bloom and Davis (2016)'s EPU to evaluate the ability of U.S. trade policy uncertainty to predict global output volatility. Ongan and Gocer (2020) also uses the news-based index to analyze the role of uncertainty in US-China trade balances.

Though they align well with general events of U.S. trade policy history, the news-based measures currently used in the literature present some shortcomings. Perhaps the most important is the conflation of realized volatility and future uncertainty. Realized volatility relates to the size of realized policy shocks, such as a change in tariff. On the other hand, future uncertainty is about the size of future shocks as expected by agents. The ability to distinguish the two forms of shocks is important to the extent that recent literature reveals that responses of macroeconomic variables - and possibly financial variables - to the two classes of shocks can be very different. Berger, Dew-Becker and Giglio (2019) shows that while financial outcomes are sensitive to volatility shocks, they do not respond to uncertainty. In their assessment of their own measures, Caldara et al. (2020) point out that their tariff volatility measure requires changes in tariff rates to signal changes in tariff uncertainty – making it unresponsive to negotiations and proposals. They also indicate that the news-based measure picks up high tariff volatility episodes as uncertainty shocks. Additionally, a high coincidence between the index and the timeline of known policy actions can be a source of concern. A news-based measure that mostly picks up policy breaks is more likely to measure policy volatility, which, while a contributing factor to uncertainty, is only a functional input and not a sufficient statistic. Finally, newspaper coverage might not exactly coincide with market participants' perceptions.

In this paper, I develop a novel trade policy uncertainty index that aims to precisely replicate public perceptions of uncertainty and anticipation surrounding trade policy rather than the actual policy breaks and ex-post responses. To do this, I employ two different types of datasets: a social-media-based dataset consisting of tweets and twitter-based interactions over policy uncertainty content and institutional data comprising the USTR's published notices and calls for comments. Section II discusses data strategy, including methodology for constructing the proposed TPU index.

B. Market Volatility: Stylized Facts

The subject of stock market volatility continues to receive ample attention in economics. Schwert (1989)'s seminal paper revealed a 'volatility puzzle.' The author observes that macroeconomic fundamentals and other economic variables cannot explain the time variation in stock volatility between 1857 and 1987. Attempts at resolving this puzzle have sought to identify causalities by introducing new variables or applying new methods (Christiansen, Schmeling and Schrimpf (2012), Choudhry, Papadimitriou and Shabi (2016), Asgharian, Hou and Javed (2013), Chiu et al. (2018)). Another equally prolific strand of the literature is methodological in nature and aims to improve volatility forecasting by introducing new models (see Poon and Granger (2003) for review). A precise forecasting model and a comprehensive list of determinants continue to be elusive.

This broad attention to market volatility from economists has several justifications. When market participants are risk-averse, volatility plays a role in asset-pricing and investment behaviors. Volatility shocks change the compensations that shareholders require for bearing systematic risk (Guo (2002)), which in turn impacts the cost of equity capital. Through its implications for investors and publicly traded firms, volatility can spill over to the real economy. Campbell et al. (2001) shows that stock market volatility leads volatility in other economic indicators and has significant predictive power for real GDP growth. Further, and precisely because it leads volatility in other economic series, volatility can be an early sign of financially induced recessions (Chauvet, Senyuz and Yoldas (2015)).

Figures 1-2 show recent trends in market volatility. Figure 1 displays the number of high session days, defined as days with returns larger than $\pm 1\%$, per month. 2020 stands out as a high volatility year, with March consisting almost exclusively of high return sessions. Before the pandemic, 2018 saw a significant increase in volatility after a two-year retreat. Compared to 2016 and 2017, the number of high return sessions was significantly up. Figure 2 also shows that 2018 was marked by rapid successions of high return days. The financial press interpreted the rise in volatility as a consequence of the anti-globalist pivot of U.S. trade policy and the implied uncertainty surrounding the U.S. and world economic trends. However, this hypothesis has not been analyzed by the academic literature, a gap that this paper tries to fill. The following section describes the construction of market volatility and trade policy uncertainty measures, later used in analyzing the causal claim.

II. Data and measurements

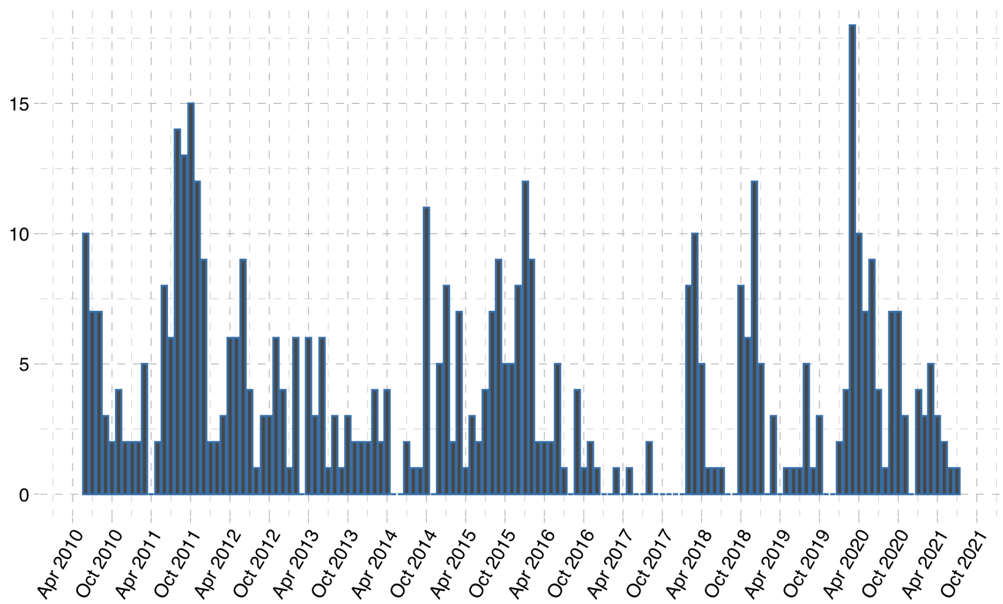
A. *Modelling financial volatility*

I am interested in evaluating the impact of TPU on the persistent and transitory components of stock market volatility. In constructing the outcome variables, I follow the cyclical volatility model proposed by Harris, Stoja and Yilmaz (2011) and outlined in Chiu et al. (2018) paper on investor sentiment and financial market volatility. In this model, the natural logarithm of the asset price at time s follows a continuous-time diffusion given by :

$$dp(s) = \sigma^2(s)dW(s) \tag{1}$$

Where $dW(s)$ is the increment of a Wiener process and $\sigma^2(s)$ is the instantaneous

FIGURE 1. NUMBER OF HIGH RETURN SESSIONS PER MONTH



Note: High return session defined as trading days with a +/- 1% S&P500 close.

variance, which is strictly stationary and independent of $dW(s)$.

Conditional on the sample path of $\sigma^2(s)$, the logarithmic return is normally distributed with variance :

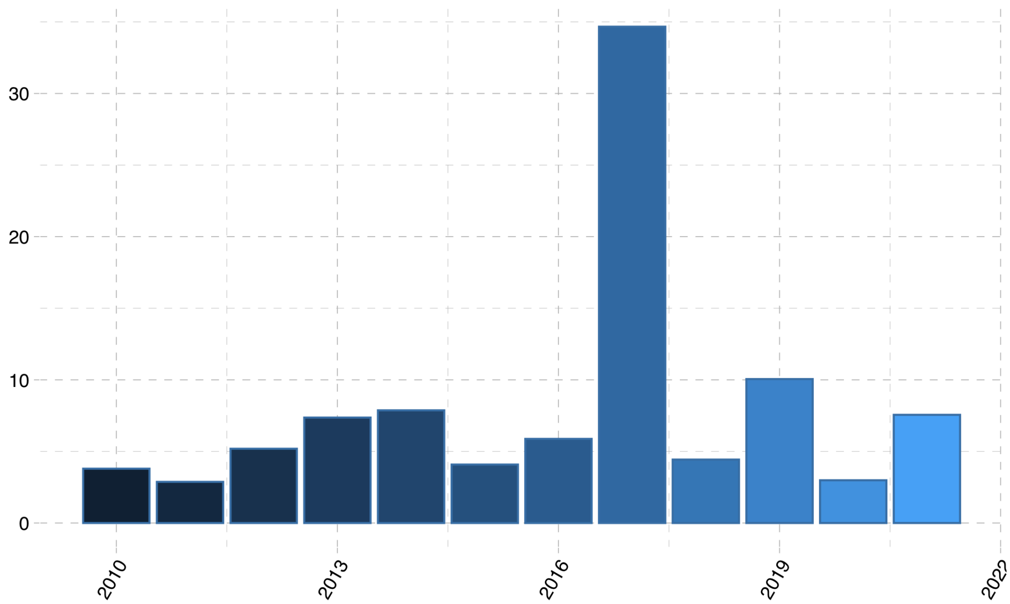
$$\sigma_t^2 = \int_{t_1}^{t} \sigma^2(s)ds \tag{2}$$

This framework assumes that the integrated standard deviation follows a two-factor dynamic structure of the form :

$$\begin{aligned}\sigma_t &= q_t + c_t,\\ c_t &= \alpha c_{t-1} + u_t\end{aligned}$$

where q_t is a long-run component, and c_t is a transitory component of volatility. Several papers in the finance literature corroborate this two factor approach to modelling volatility (Lee and Engle (1999), Alizadeh, Brandt and Diebold (2002), Brandt and Jones (2006)).

Figure 2. Average Number of Days Between Two High Return Sessions



Note: High return session defined as trading days with a +/- 1% S&P500 close.

For empirical implementation, I follow Chiu et al. (2018). I proxy daily standard deviation using daily returns defined as the logarithmic difference of close and open prices:

$$r_t = p_{close,t} - p_{open,t} \tag{3}$$

I then apply the Hodrick and Prescott one-sided low-pass filter to the daily standard deviation to estimate the daily transitory component of volatility. To avoid look-ahead bias, the filter is applied to a rolling window of 134 days. The filter's tuning parameter is set to $\lambda = 5,760,000$ which is the recommended value for data of daily frequency (Ravn and Uhlig (2002)). The resulting daily persistent component, and daily standard deviation are aggregated to a monthly measure as :

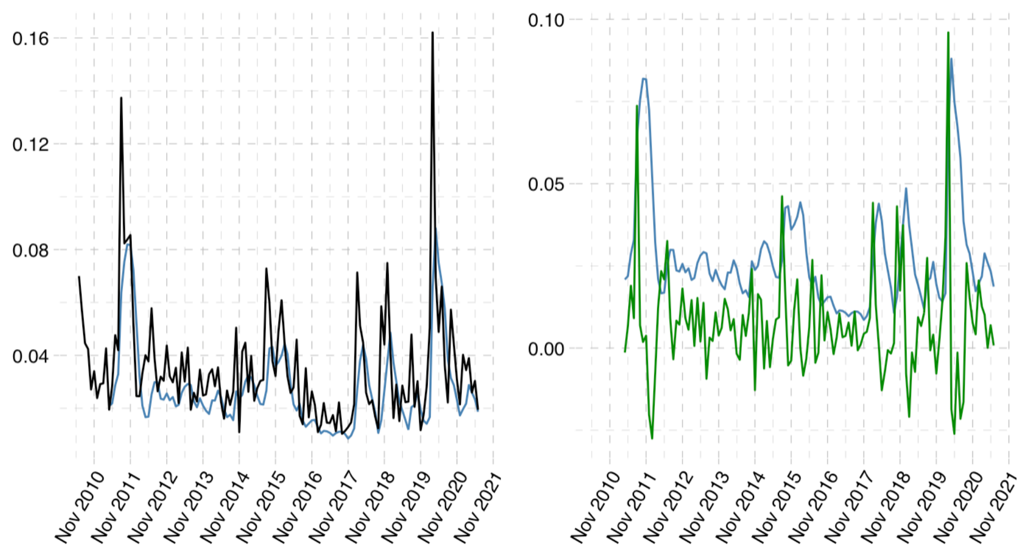
$$\begin{aligned} q_t &= \left(\sum_{i=1}^{N_t} q_{t_i}^2 \right)^{1/2} \\ \sigma_t &= \left(\sum_{i=1}^{N_t} r_{t_i}^2 \right)^{1/2} \end{aligned}$$

Finally, I calculate the transitory component of monthly volatility using the two factor definition of volatility:

$$c_t = \sigma_t - q_t \tag{4}$$

For the baseline estimation, I compute persistent and transitory volatility for the S&P500 index over the study period. The resulting volatility series for the S&P500 index are presented in figure 3.

Figure 3. Volatility Measures for the S&P500 Index



Note: Left panel : Total monthly volatility (black) and persistent volatility (blue). Right panel : persistent (blue) and transitory (green) components of monthly volatility.

B. A perception based measure of TPU: Twitter Component

I propose a composite measure of TPU that tracks perceptions and policy developments by combining two indicators. The first indicator measures the public's attention to trade policy and trade policy uncertainty, using Twitter data. A Twitter application programming interface (API) allows me to achieve better precision and explore richer data than news-based proxies. First, due to the limited character count, tweets are more concise statements than articles. Keyword searches can therefore lead to fewer misclassification of tweets as TPU-focused than of news articles. In other words, the joint appearance of uncertainty-related and trade-related keywords in a non-TPU related news article is more likely than in a non-TPU related tweet. Second, by using Twitter data, I can look beyond press coverage and further into the responsiveness of the wider public to trade policy news. Indeed, newspaper reporting on trade policy does inform public perception, but the relationship is mediated by the size, attention, and interaction of the readership. Newspaper-based indicators cannot capture these dimensions. Social media, due to their network structure, allow us to measure reactions to TPU-content, specifically the size of the audience and the share of recipients who deem the message worth spreading or responding to.

FIGURE 4. WORD CLOUD: WORD FREQUENCY IN SELECTED TPU TWEETS

Note: Based on a panel of 1543 trade policy uncertainty related tweets

How to convert tweets into data? In generating the Twitter-based TPU measure, I begin by constructing a panel of 12 news sources[2] and 15 economist commentators[3] with a significant presence on the social network platform. For the news sources, I pick the most circulated national newspapers and referential sources in the finance and economics spheres, such as Bloomberg and CNBC. I selected economists with large follower bases who are more likely to represent and influence

[2]The panel's 12 news sources are: Bloomberg, CNN, The Financial Times, The Washington Post, CNBC, Newsweek, The Boston Globe, The Wall Street Journal, The New York Times, The Los Angeles Times, USA Today, The Economist (US)

[3]The economist in the panel are: Dean Baker, Sandy Black, Leah Boustan, Beatrice Cherrier, Steeve Hanke, Seema Jayachandran, Paul Krugman, Dina Pomeranz, Dani Rodrik, Nouriel Roubini, Claudia Sahm, Betsey Stevenson, Joseph Stiglitz, Mark Thoma, Justin Wolfers

general perceptions. I also seek to build a panel that is gender and background-balanced so as not to pick up the bias of a specific subset of economists. I survey the timelines of each of the accounts in the panel for trade policy uncertainty content over the period extending from January 2015 to June 2021. For tweet selection, I use a similar approach to Caldara et al. (2020) and Baker et al. (2014). To be selected into the panel, the tweet needs to contain one word each from a set of trade policy terms and a set of uncertainty words. The keywords are listed in Table 1.

Table 1—Tweet Selection keywords

Trade Policy	Uncertainty
Trade polic*	Uncertain*
Trade agreement*	Risk*
Trade deal*	Potential
Tariff*	Unclear
Import*	Likely
Export*	
Trade deficit*	
Dumping	

Note: The asterisks indicate potential additional letters - mostly to account for plurals. Import and Export must appear in conjunction with additional policy words (polic*, tax*, quota*, fee*, limit*, restriction*, duty*, deal*, agreement*).

Using a Twitter API, I extract all trade-uncertainty-related tweets generated by the panel members throughout January 2015 to June 2021. The proposed index is a perception-based indicator that reflects the public's attention to TPU and how much they interact with trade uncertainty-related content. Let:

$i = 1...N$ indexes the tweets,
$j = 1, ..., K$ indexes users active in month t
$t = 1...T$, with $T = 65$ index the time.

I define the *amplification weighted-frequency* measure as :

$$AWF_t = \sum_{j=1}^{K} \frac{\sum_{i=1}^{N} Interactions_{ijt}}{followers_{jt}} \tag{5}$$

Interactions are defined as the sum of retweets, likes, replies, and quotes. The historical follower data is not available via Twitter API and was recovered using the Internet Archive's Wayback Machine. The followers' data is missing in 9 tweet-month observations, and the associated tweets are dropped. This generates a slight loss of information. For this, and all other indices presented here, the series are standardized to unit-standard deviation and then normalized to have a mean of 100.

Notice that this index is a weighted sum of published TPU tweets, where the associated weights are the number of received interactions (normalized by follower base). Each one of these interactions in itself amplifies the original message: retweets expand the readership base, likes indicate the number of people who align themselves with the message, and replies measure the number of readers who engage with the content favorably or unfavorably. Together, they indicate the contemporary relevance of the tweet and determine the size of the audience it will reach, thus propagating the uncertainty message. For normalization purposes and to give a notion of scale, the total number of reactions is divided by the total number of followers at the end of the given month.

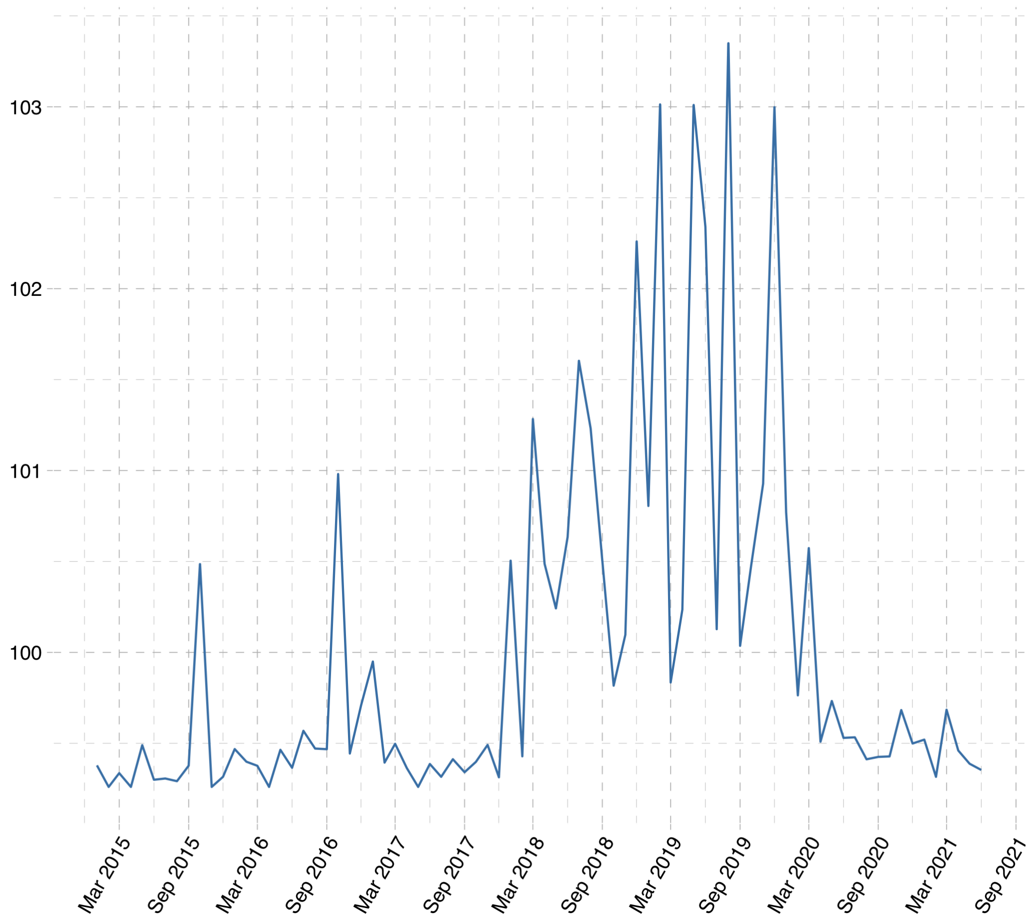
One property of this indicator is that it will not count tweets that do not draw any reactions. This is a desirable property because such tweets are likely not indicative of increased uncertainty perception by the public. Conversely, a tweet that elicits large numbers of interactions receives a higher weight. In short, the indicator answers the following question: among the persons who were exposed to the TPU-related tweet, how many deemed the topic relevant and/or worthy of amplification?

C. A perception based measure of TPU: Institutional Component

The second indicator uses institutional signals of trade policy uncertainty. Within the architecture of the U.S. government, the United States Trade Representative (USTR) enjoys a wide purview overrules and policies that regulate U.S. trade. The USTR is responsible for negotiating, implementing, and reviewing the U.S. trade agreement, resolving disputes, and shaping global trade policy in the different multilateral venues such as the WTO. Under the Administrative Procedure Act (APA), the USTR's decisions are subject to public notice and call for comment procedures. Potential policy changes and actions are signaled at a very early stage, as they become entertained by the administration. At this stage, rules and policies are yet unformed and very much in progress: their scope, implementation, and viability are uncertain. This process provides a rare opportunity for capturing uncertainty about policymaking ex-ante instead of picking up the informed response to fully formed policy changes ex-post.

I have reviewed and extracted data on all USTR public notices and calls for comments from 2013 to 2021. I classified all releases by theme and by partner. In the federal register, notices are associated with a release date and, if applicable, an expiration date. For each notice, I research a *resolution date*, that is, the date at which the issue raised by the notice is resolved. For instance, the resolution date of a notice announcing a WTO dispute is the release date of the WTO

FIGURE 5. TWITTER-BASED INDICATOR OF TRADE POLICY UNCERTAINTY



Note: Designed using Twitter application programming interface.

panel report. In contrast, the resolution date for a notice announcing an out-of-cycle country review under the Generalized System of Preferences (GSP) is the publication of the review decision. Between its publication and its resolution, each notice corresponds to a potential disruption in the way trade and trade policy are conducted - generating additional uncertainty. A notice is considered *open* at time t if and only if t is between the publication and resolution times. Under this assumption, the count of *open* notices at any given time becomes a good indicator of the trade policy uncertainty that market participants experience at any given time. This indicator is simply defined as :

$$ORC_t = \text{the number of open calls and notices at time } t \tag{6}$$

where ORC stands for *open review count*. This indicator addresses a common issue with existing indices and proxies of trade policy uncertainty. Previous studies of policy uncertainty exploited policy changes, specifically tariff policy, as proxies for uncertainty, due to the volatility they can generate in the time window following their enactment. Such a proxy can be misleading. After a policy is enacted, agents only face the risks of implementation. The state of the world, as relates to that policy component, is well known to agents who can now update their optimization frameworks with knowledge of the surrounding environment. This makes policy breaks an inadequate proxy to measure policy uncertainty. My proposed indicator measures genuine uncertainty around trade policy: at the time where a policy is added to the count in ORC_t, there is uncertainty about whether the policy will, in fact, change, and even more uncertainty about how it will change if it does. As a result, the release of a new policy-related call for comments increases the level of uncertainty that agents face by bringing into question their optimization environment without providing complete probabilities on the possibility, direction, and size of the change.

Arguably, this measure can be further refined. While every additional call for comment increases perceived uncertainty, not all calls for comments contribute in equal proportions to agents' perceptions depending on the scope of the announcement. For instance, calls for comments could be weighted by the impacted trade volumes to account for these disparities. I do without this refinement to reduce the number of inputs and facilitate the replication of the index.

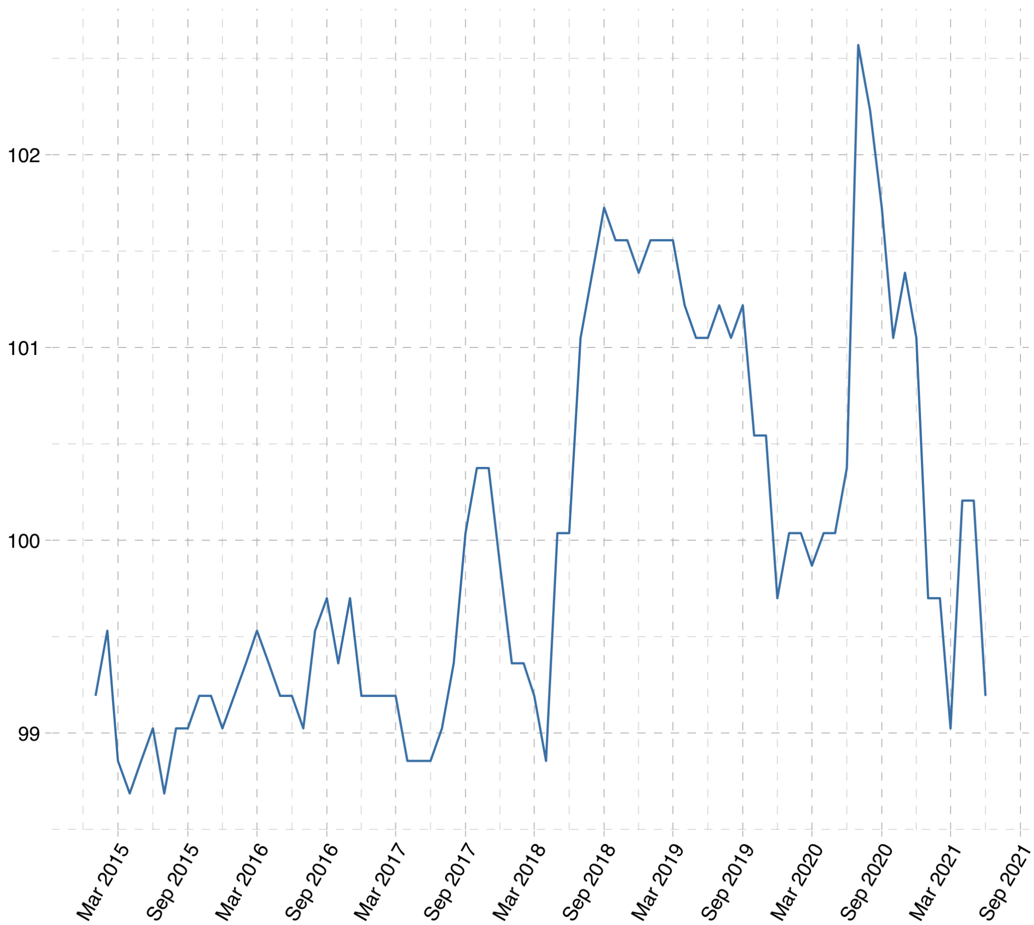
The two individual indicators capture different components of public perceptions of TPU. They also each contain noisy signals that are not related to TPU. I employ a dynamic factor model to extract TPU information from both series while reducing the amount of noise they contain. One can decompose each of the time-series into two orthogonal unobserved processes: the common component, driven by a shock that captures policy uncertainty, and the idiosyncratic component, which is driven by shocks that are series-specific or local. This approach reinforces the consistency of the final index in that it elicits the underlying process that is common to both the institutional signals of TPU and media coverage and discussions of the same while minimizing noisy signals. It also improves upon existing methods in the literature that are limited to a single source and type of uncertainty, and therefore more prone to imprecision.

Let f_t be the single hidden factor (or common component). Each one of the indicators is a function of the hidden factor such that :

$$I_{it} = \lambda_{i,0} f_t + \lambda_{i,1} f_{t-1} + ... + \lambda_{i,p} f_{t-p} + e_{i,t} \tag{7}$$

where $I_{it} = [AFW_t, ORC_t]'$ and,

Figure 6. Institutional Signals Indicator of Trade Policy Uncertainty



Note: Designed using USTR notices and calls for comments.

$$f_t = \psi_1 f_{t-1} + ... + \psi_r f_{t-r} + \eta_t \tag{8}$$

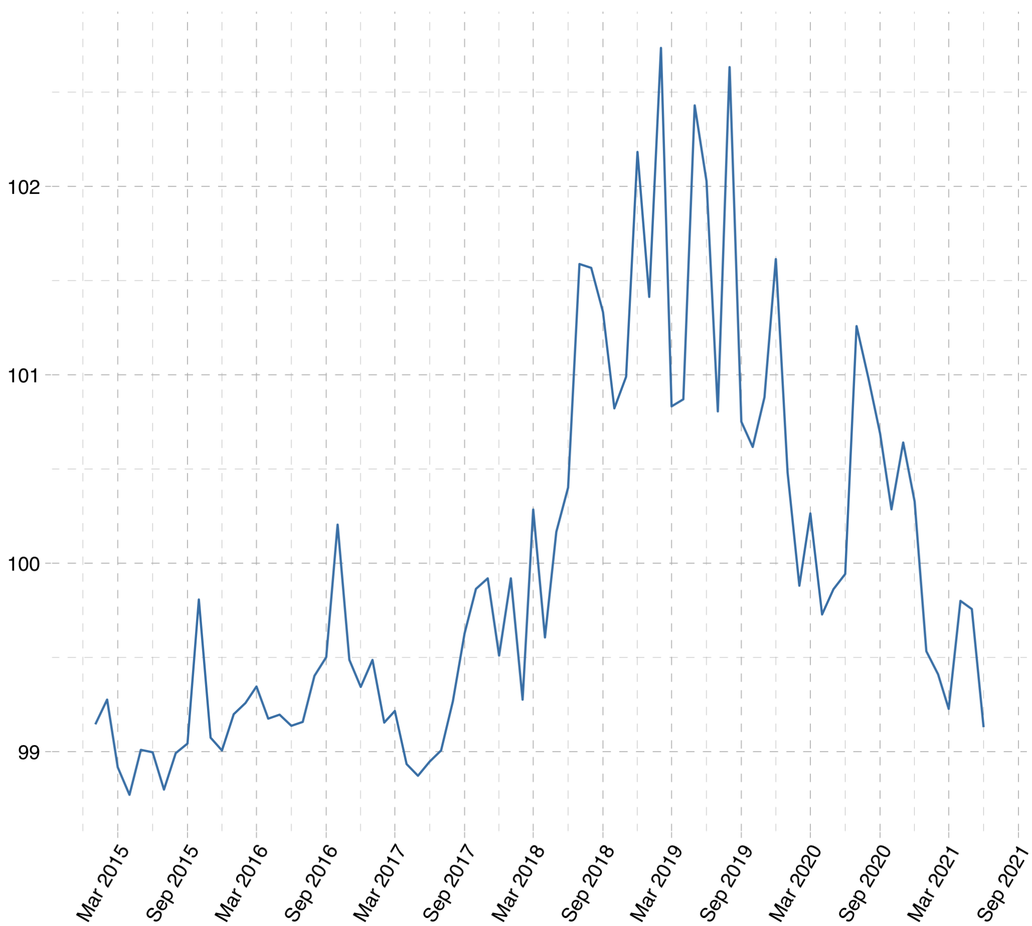
where, p is the lag order of the measurement equation, $e_{i,t}$ is an idiosyncratic component and r is the lag order of the common factor's autoregressive process. The static version of the model can be written as :

$$\begin{cases} I_t = \Lambda F_t + e_t \\ F_t = \Phi(L) F_{t-1} + G\eta_t \end{cases} \tag{9}$$

The dynamic factor model is estimated via Principal Component Analysis (PCA). Being a non-parametric technique, PCA does not require additional model specifications and thus provides potential robustness against misspecification. This property allows me to remain agnostic about underlying relationships in the model.

The final TPU perception index is presented in figure 6.

FIGURE 7. PROPOSED TPU PERCEPTION INDEX



Note: The index is constructed as the common factor of the Twitter and Policy signal indicators.

D. *Discussion of proposed index*

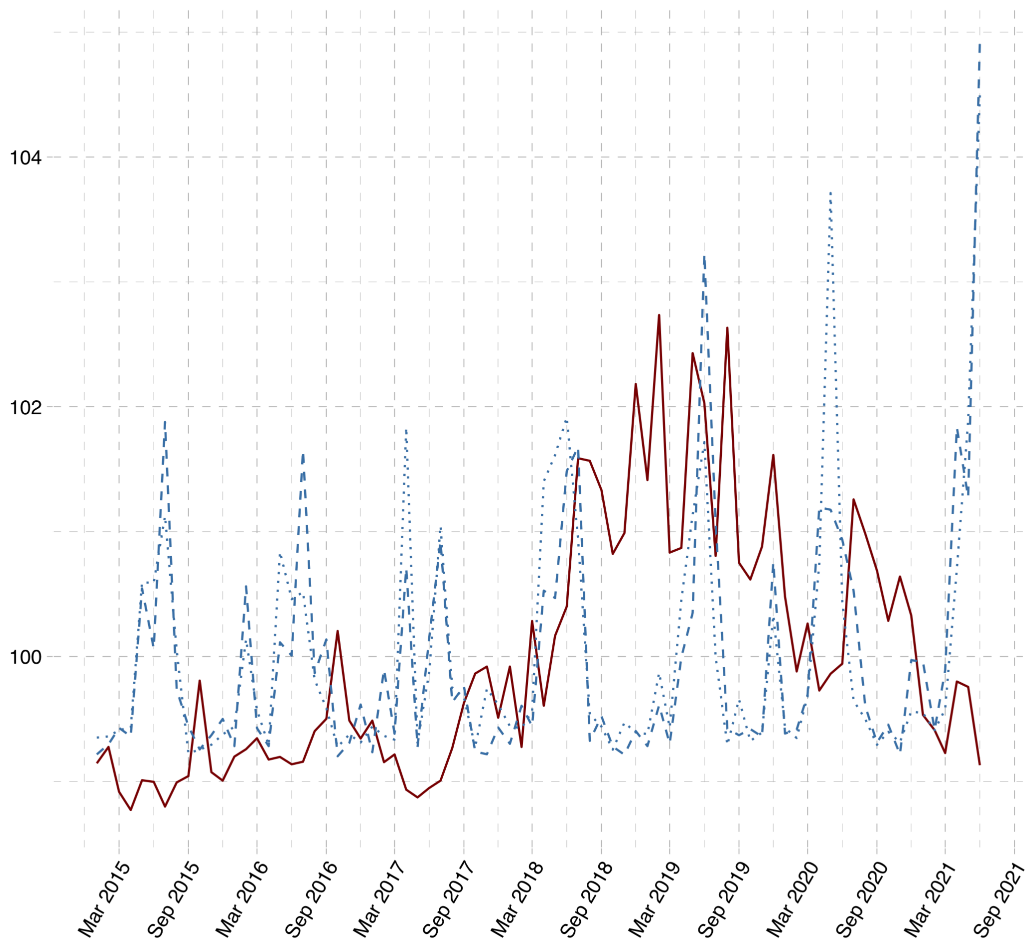
The Twitter amplification-weighted frequency measure aligns well with event-based priors on TPU. The series, presented in figure 3, is below average throughout 2015 and for most of 2016. The first peak appears in the lead-up to the 2016 election. The index remains consistently above the period's average from March 2018, which coincides with the early tariff decisions of the new U.S. administration. The February 2019 peak was caused by highly-amplified tweets about the likely impact of tariffs on future inflation and growth, a possible US-China trade deal, and renewed tensions in the US-EU trade relations, including threats of tariffs on European car-makers. The August 2019 peak picks up wide attention to Fed statements about TPU and trade policy in general, including statements by Federal Reserve Chairman Jerome Powell and branch presidents about monetary policy adjustments in the face of mounting trade tensions. The peak also incorporates tweets about a possible change in the first tranche of tariffs imposed on Chinese goods, the finalization of the second tranche, and threats of retaliation from China. This month is also marked by a general interest in economist commentaries on trade policy uncertainty as a risk factor for the economy. This is reflected in the unusually high interactions received by these tweets. A main advantage of this proposed index is precisely its ability to go beyond the news cycle, and monitor the intensity and breadth of TPU-related conversations amongst the public as they happen.

Similar to the first indicator, institutional signals of uncertainty increase after March 2018 and post-above-average measures for the remainder of the study period (figure 6). The shape of the series also presents a clear break following the political transition of 2017. Unlike its twitter-based counterpart, this indicator is more persistent, which appears consistent with its institutional nature. It is not surprising that public attention should be more volatile than the underlying policy signals of uncertainty.

Figure 8 plots the proposed index against two existing TPU indicators in the literature, both proposed by Baker and co-authors. The dashed line represents their newspaper-based TPU component of EPU index Baker, Bloom and Davis (2016), whereas the dotted line is the trade-component of their equity market volatility tracker Baker et al. (2019). The two indices are similar in construction, but the latter is normalized to match the period average of the CBOE volatility index, the VIX.

My proposed index has a comparable shape to existing measures. However, it presents desirable properties that separate it from them. First, it is noticeably smooth. Figure 9 depicts the quantile distribution of first-order differences. Large and sudden jumps and troughs are fewer in the proposed index. This property results from the index's inclusion of fundamental policymaking developments by including the USTR data and its comparatively small dependence on the fast-moving news cycle. Indeed, while we expect to see some variability in the index, vast movements are not commensurate with public perception of uncertainty, which should be highly serially correlated. We can see an expression of the index smoothness towards the end of the study period. Policy actions have significantly

Figure 8. Proposed Index and Existing TPU measures

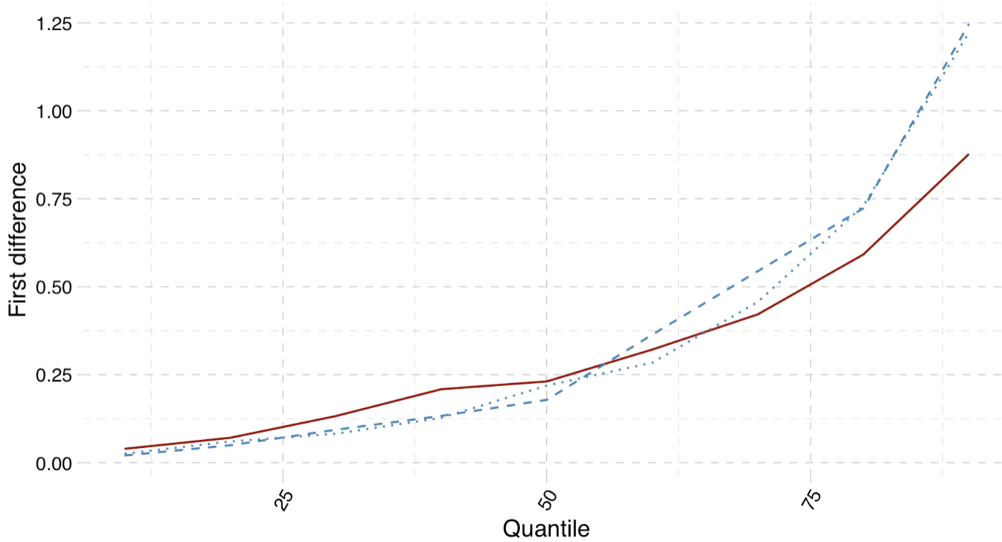


Note: proposed TPU perception index (solid line) against Baker et al. 2016 TPU component of EPU (dashed line) and Baker et al. 2019 TPU component of a news-based Equity Market Volatility Tracker (dotted line).

subsided in the second half of 2019 and going into 2020. The landing of the perception index is phased and progressive in this period but much faster in the alternative measures. News outlets might be quicker to turn the pages of the news cycle than the informed public perceptions, and institutional process develop. The higher persistence of the index is a desirable property for a measure of perceptions.

The USTR policy signals instill a forward-looking property into the index, which is a desirable property. This is visible in the behavior of the indices in March 2018, a period when the U.S. took several highly mediatized policy actions. The decision to slap tariffs on aluminum imports was announced on March 1st. The

Figure 9. Proposed Index and Existing Measures : Quantile Distributions



Note: Quantile distribution of first difference series of compared indices : proposed TPU perception index (solid line) against Baker et al. 2016 TPU component of EPU (dashed line) and Baker et al. 2019 TPU component of a news-based Equity Market Volatility Tracker (dotted line).

unfair trade practices review of China was released on March 22nd, laying the ground for the ensuing tariff increases. Both of these developments were, however, already folded into the perception index. The steel and aluminum tariffs enter the index as early as March 2016, when the USTR issued a call for comments on the global steel and aluminum markets, teasing a possible policy action. The out-of-cycle review of China's trade practices under section 301 was announced in August 2017 and enter our index then. Neither the decision to enforce tariffs nor the release of the report is clear positive shocks to uncertainty. In fact, both of these developments resolve some uncertainty about the trajectory of U.S. trade policy. They are primarily realized shocks to policy rather than a change in the size or direction of expectations about the future. The forward-looking property of the index is also demonstrated by the earlier and slower build-up towards the high uncertainty period. In contrast, the alternative indices rapidly climb on the first reports of policy actions.

Finally, the indices carry different information. The comparatively high peaks recorded by the alternative indices in December 2018 are much smaller in my proposed index. It is unclear what these peaks are associated with. In that month, the major U.S. trade policy development was a tariff truce agreed to by the United States and China following a G-20 summit, arguably a negative shock to uncertainty. The large February 2019 peak in the proposed index is conversely absent from the other series. Instead, the proposed index picks up the U.S. last-minute decision to delay to an unspecified date a 15-percentage-points tariff increase on $200 billion of imported Chinese goods. It is also heavily boosted by the public attention to a January U.S. government threat against European auto imports.

In sum, the proposed index meets the design goals. It captures variations in TPU, as shown by its similarity with alternative indices. It is forward-looking and does not track moments of policy changes. Finally, it successfully integrates institutional and social media signals on trade policy uncertainty and displays the stickiness that characterizes public perceptions.

III. TPU and Stock Market Volatility

Analyzing the impact of TPU on stock market volatility serves two purposes. First, it attempts to assess the economic and financial cost of the recent high uncertainty episode. The policy goals telescoped by the U.S. administration from 2017 to 2020 were narrowly defined in terms of trade balance improvement with specific trading partners. This has translated into deviations from past policy trends, revisions of existing agreements, and suspension of WTO resolution mechanisms, all of which have significantly increased the level of uncertainty as perceived by market participants, and as relayed by the media coverage.

Nevertheless, due to the short track record of the policy shift, the literature has focused less on counting the cost and more on simulating potential impacts[4], understanding the tariff and retaliation policy designs (Fetzer and Schwarz (n.d.)), or cataloging previous episodes of trade conflicts (Mattoo and Staiger (2020)). Using the constructed TPU perception index, we can begin to investigate one of the consequences of this policy change: increased uncertainty. In this context, financial markets offer an excellent early case study: they respond quickly to policy changes, they inform about investors' attitudes towards policymaking, and their dynamics can have relevance for the real economy. Stock market volatility, according to Schwert (1989), reflects uncertainty about future cash flows and discount rates, and thus informs on future economic activity. It also increases the cost-of-capital, which can reduce future investment (Guo (2002)). Campbell et al. (2001) shows that stock market volatility is a significant predictor of GDP growth. Therefore, through its impact on volatility, we can make informed hypotheses on TPU's impact on aggregate economic performance. Furthermore, understanding the stock market impact of uncertainty can support investors in designing adequate responses to adjust their positions when they anticipate an uncertainty shock.

This section describes the approach for in-sample and out-of-sample analyses and

[4] Bouët and Laborde (2018), Caceres, Cerdeiro and Mano (2019) and Jeanne (2019) for theoretical modeling of trade wars consequences

discusses the results of this exercise.

A. Model and Estimation

The relationship between the TPU and market volatility series is explored using a structural vector autoregression (Sims (1980)). This is a common approach in the investigation of sentiment shocks and their market outcomes. I begin with the following VAR equation:

$$Y_t = A_0 + \sum_{k=1}^{p} A_k Y_{t-k} + u_t \tag{10}$$

And,

$$Y_t = [g_t, \pi_t, r_t, tpu_t, vol_t]' \tag{11}$$

The inclusion of macroeconomic variables allows one to control for business-cycle-related shocks. The macroeconomic variables are from the St Louis Fed database, FRED. g_t is output growth, proxied by the log difference of the monthly industrial production index, π_t is monthly PCE inflation, and r_t is the effective federal funds rate to capture shocks to monetary policy. tpu_t is the TPU perception index. The model is separately estimated for different specifications of vol_t: total, persistent and transitory volatility. The main estimation centers on the volatility response of the S&P 500 index, and I look at heterogeneity responses of a selection of individual stocks in a following subsection. The chosen lag for the VAR equation is $k = 1$, as suggested by the AIC criterion.

The structural shocks are derived using the Cholesky decomposition. The ordering of the endogenous variables captures the restriction imposed on the system. The key restriction is that TPU shocks do not propagate contemporaneously to the macroeconomic variables. This restriction rests on the notion that the changes in investor and market participant behavior that lead to variation in macroeconomic variables lag changes in perception and sentiment, as measured by the index (Baker and Wurgler (2006)).

B. Baseline Results

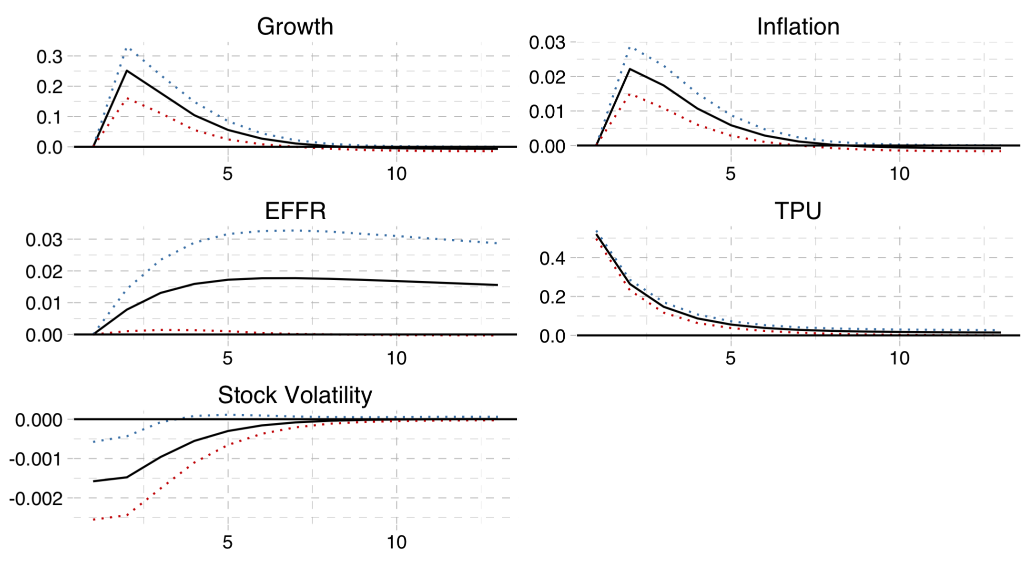
Figure 10 presents the resulting impulse response functions of macroeconomic fundamentals and S&P500 volatility following a positive shock to TPU as computed by the Cholesky decomposition. A positive shock to TPU leads to a positive response of industrial production and inflation. The response appears short-lived.

Monetary policy responds with lower rates initially, but the response is not significant at the 95% confidence level.

Figure 11 shows that the volatility components respond uniformly to TPU shocks: both persistent and transitory volatilities decline slightly at the 95% confidence level. Transitory volatility is quicker to absorb the shock, whereas persistent volatility is slower to adjust back from an initial dip. As a result, total index volatility responds with a quick dip and a somewhat slow recovery. The persistent and transitory volatility responses are larger at the peak than total volatility response. This reflects a negative correlation between the persistent and transitory component. The Spearman correlation coefficient between the two series over the study period is -0.18.

The negative and consistent response of stock market volatility suggests that TPU has a chilling effect on market transactions overall, generating perhaps a wait-and-see attitude that stabilizes stock prices. Bootstrapped confidence intervals show that we cannot, however, rule out the null hypothesis that TPU shocks do not propagate to stock market volatility. The volatility forecast-error variance decomposition in the context of the specified SVAR, as reported in table 2, further reflects the weak contribution of TPU shocks to volatility variations.

FIGURE 10. RESPONSES TO A TRADE POLICY SHOCK



Note: Impulse response function of the SVAR system variables (industrial production growth, inflation, interest rate, TPU and total monthly volatility of the S&P500 index) to a one standard deviation shock to Trade policy uncertainty.

TABLE 2—FORECAST ERROR VARIANCE DECOMPOSITION OF S&P500 MONTHLY REALIZED VOLATILITY

Horizon	Economic Growth Shock	Inflation Shock	Monetary Shock	TPU Shock	Other Shocks
1	0.0013	0.0656	0.2191	0.01024	0.70362
5	0.0020	0.0636	0.2165	0.01320	0.70455
10	0.0020	0.0636	0.2165	0.01323	0.70449
15	0.0020	0.0636	0.2165	0.01323	0.70447
19	0.0020	0.0636	0.2166	0.01323	0.70446

C. *Out-of-Sample Analysis*

Investors and market participants use historical trends and correlations to predict future market dynamics better. The in-sample performance of TPU in explaining volatility is weak. Can the inclusion of trade policy uncertainty in forecast models of volatility improve their accuracy?

In keeping with the literature, I estimate an AR(6) benchmark forecasting model of volatility. The benchmark forecasts are denoted $V_{t+m,B}$. I then use this benchmark to evaluate the performance of a TPU-augmented forecast model given by:

$$Vol_{t+m,\mathrm{A}} = \alpha_m + \sum_{p=1}^{6} \beta_{p,m} Vol_{t+m-p} + \delta_m TPU_{t+m-1} + \varepsilon_{t+m} \tag{12}$$

Forecasts are generated using a one-step-ahead recursive approach with an expanding window, starting with an in-sample of 35 observations. At each step, from $t = 35$ onwards, the model's parameters are estimated via OLS using historical data available up to time t. The forecast is generated using the observed lag values of the predictive variables. This process generates monthly volatility forecasts from July 2018 through June 2021.

Following Wang et al. (2018), Rapach, Strauss and Zhou (2009) and Campbell and Thompson (2007), I evaluate model performance using out-of-sample R^2 given by:

$$\Delta R^2_{OOS} = 1 - \frac{MSPE_B}{MSPE_A} \tag{13}$$

where ΔR^2_{OOS} measures the percent reduction in mean squared predictive error (MSPE) gained by transition from the benchmark to the augmented model. A positive value therefore means that the augmented model improves upon the accuracy of the benchmark model. Following Wang et al. (2018), I compute the

ΔR^2_{OOS} for two versions of the augmented model: with and without restrictions. The unrestricted model follows the method laid out above. The restricted model is such that:

$$\hat{Vol}_{t+m,\text{A,R}} = \begin{cases} \hat{\alpha}_m + \sum_{p=1}^{6} \hat{\beta}_{p,m} Vol_{t+m-p} + \hat{\delta}_m TPU_{t-1}, & \text{if } \delta_m > 0 \\ \hat{\alpha}_m + \sum_{p=1}^{6} \hat{\beta}_{p,m} Vol_{t+m-p}, & \text{if } \delta_m < 0 \end{cases} \tag{14}$$

The investor using the restricted model minimizes overfitting by excluding TPU from the forecast when the associated coefficient is not consistent with their prior that TPU must correlate positively with volatility.

Figure 12 reports the forecast performance results. The out-of-sample R-squared on the unrestricted and restricted models are -49.19 and -16.20, respectively. The inclusion of TPU into volatility forecast models does not improve upon the benchmark auto-regressive model, further reinforcing the results from the in-sample analysis.

D. Portfolio Evaluation

Lastly, I identify the utility gain from the internalization of TPU dynamics in portfolio allocation decisions. This exercise follows Wang et al. (2018) which builds on prior literature (Neely et al. (2014), Rapach, Strauss and Zhou (2009)).

Assume that a risk-averse investor has access to two assets: risk-free bonds and stock equity. The utility function of the investor displays mean-variance preferences. It has two components: the expected portfolio return, which enters positively, and a portfolio volatility component that enters negatively with a weight that increases with the degree of risk-aversion. The utility function can be written as:

$$U(r_t) = E_t(w_t r_t + r_{f,t}) - \frac{1}{2}\gamma var_t(w_t r_t + r_{f,t}) \tag{15}$$

Where $r_{f,t}$ is the risk-free rate on bonds, r_t is the excess return on stocks, and w_t is the weight of stock equity in the portfolio. γ measures risk aversion. The optimal level for the choice variable w_t is a function of expected stock returns, volatility, and risk aversion.

$$w_t^* = \frac{1}{\gamma}\left(\frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}}\right) \tag{16}$$

Where $\hat{r}_{t+1}$ is a simple historical-average forecast of stock returns. The volatility forecast is formed in three alternative ways using the benchmark forecast, the TPU-augmented model, and the TPU-augmented restricted model $\hat{\sigma}^2 = \{\hat{Vol}_{\mathrm{B}}, \hat{Vol}_{\mathrm{A}}, \hat{Vol}_{\mathrm{A,R}}\}$. This yields three possible portfolios indexed by p.

Once the weight is chosen, the portfolio return is given by:

$$R_{t+1} = w_t \times r_{t+1} + r_{f,t+1} \tag{17}$$

The performances of the three different portfolios can be compared by using the certainty equivalence return (CER):

$$CER_p = \hat{\mu}_p + \frac{\gamma}{2}\hat{\sigma}_p^2 \tag{18}$$

Where $\hat{\mu}_p$ is the mean and $\hat{\sigma}$ is the variance of the chosen portfolio over the entire period. The CERs of the three alternative portfolios are shown in figure 13. Models that internalize TPU fail to improve the asset allocation and the associated returns.

E. Heterogeneity Analysis

The limited relevance of trade policy uncertainty shocks to market volatility broadly measured through the S&P 500 might hide differences across sectors. To investigate this possibility, I conduct a heterogeneity analysis using six sectoral exchange-traded funds (ETFs) of the S&P-500. The chosen sectors have varying degrees of exposure to trade policy and to international market conditions. On the one hand, the technology (XLK) and industrials (XLE) sub-indices cover companies with high trade exposure due to both a large share of revenues from non-US sales and global value chain linkages. On the other hand, the utilities (XLU) and healthcare (XLV) ETFs represent more insulated industries whose revenues are overwhelmingly domestically derived and are thus less exposed to direct trade policy shocks. I also include two additional indices: energy (XLE) and consumer staples (XLP), intermediate sectors with majority domestic revenues and moderate sensitivity to supply chain perturbations.

Figure 14 shows impulse-response functions for the total realized volatility to a shock of TPU, across sectors. Consumer goods and manufacturing sectors appear to respond with a slight uptick in volatility, but the increase is short-lived and quickly reversed. The response of the different sectors displays similar magnitudes and trends and aligns with the response of the aggregate S&P500 index. There is no evidence of sectoral heterogeneity. This result emphasizes that rather than propagating the uncertainty shocks in specific sectors, the stock market tends to respond with decreased volatility across the board. It emphasizes that investors do not collectively and systematically change their positions or substitute across sectors following a TPU shock.

Another level of possible heterogeneity is across individual stocks. Of particular interest are stocks of firms with significant trade exposure. These firms might indeed respond more strongly and differently than general market trends. To test this hypothesis, I choose 7 US companies with some of the highest earning-exposures to China. Figure 13 shows the total volatility response of these high China-exposure stocks to a TPU shock. Here we observe both size and directional heterogeneity. Tesla's strong volatility response could be driven by the company's reliance on China both for production capacity and sales revenue. Still, revenue exposure does not appear to be a crucial discriminating factor in determining the size of the response. QCOM and MU, generate more than half their earnings through sales to China but their stocks appear less volatile in response to TPU shocks than IPGP and TSLA both of which are less reliant on exports to China. Rather than eliciting a systemic volatility response of the whole market or along specific segments, trade policy uncertainty appears to affect individual stocks idiosyncratically without significantly destabilizing financial markets.

Table 3—List of High Exposure Stocks

Ticker Symbol	China as Share of Revenues
QCOM	66%
MU	57%
TXN	44%
IPGP	43%
AMD	39%
VECO	35.8%
TSLA	21%

Note: Financial data from Yahoo! Finance and CNBC

F. *Robustness*

To insure that the results of the analysis are not driven by properties of the constructed index, I run the same SVAR using Baker, Bloom and Davis (2016) trade policy component of economic policy uncertainty as a measure of TPU. The impulse response functions are presented in figure 16. These results corroborate my own analysis. The impact of TPU on market volatility continues to be insignificant initially, and then slightly negative.

G. Discussion

The above analysis demonstrates that trade policy uncertainty does not systematically increase volatility on stock markets and that where a causal relation is significant, it is usually negative. Trade policy uncertainty also has no predictive power for volatility, and internalizing it in investment decisions does not improve portfolio performance. Trade policy uncertainty does not contribute to market instability. Furthermore, the heterogeneity analysis emphasizes that the absence of a financial volatility response to TPU cannot be explained away by the moderate degree of exposure to international trade of U.S. markets.

The findings of this paper stand in contrast with the existing literature on the volatility-effect of economic policy uncertainty (EPU). Using Baker, Bloom and Davis (2016) EPU index, Liu and Zhang (2015) show that a one standard deviation increase in EPU leads to a 0.03% increase in volatility and that EPU has a strong out-of-sample predictive power. Running a structural VAR using my main specification in (10) but replacing TPU by Baker, Bloom and Davis (2016) EPU index yields similar results (figure 17). Asgharian, Hou and Javed (2013) find that a macroeconomic uncertainty index based on forecast dispersion significantly increases long-run stock market volatility. This increased volatility causes a flight-to-quality behavior as evidenced by a reduced cross-correlation of stock and bond markets at times of high macroeconomic uncertainty. Amengual and Xiu (2018) find that downward volatility jumps are associated with a resolution of monetary policy uncertainty, mostly through statements from the FOMC and Fed chairman speeches.

What drives the difference in volatility response to EPU and TPU? Trade policy uncertainty is a new form of uncertainty. For most of recent economic history, trade policy has been stabilized by the commitment of the U.S. government to the WTO's multilateral framework that dictates the rules of global engagement. The transparency and anti-discriminatory intent of the rules-based trading system and the alignment of consecutive administrations with global trade liberalization enhanced the predictability and stability of the policy framework. The precipitated rise in trade policy uncertainty in recent years is unusual. It combines institutional changes, global tensions, a volatile domestic policy agenda, rendering it harder to navigate for the public. Faced with an unfamiliar shock, investors might fail to develop a hedging strategy or reallocate assets - and choose to hold positions in a wait-and-see attitude. In other words, investors choose to ignore uncertainty when they do not know how to interpret it correctly.

This interpretation finds support in the theoretical literature on uncertainty and volatility. According to Ederington and Lee (1993), unanticipated news are resolved by the market through increased volatility. Indeed, Berger, Dew-Becker and Giglio (2019) show that economic variables respond to current economic volatility, defined as the size of shocks that have just occurred. However, uncertainty shocks, defined as changes to agents' expectations of large future shocks, do not affect economic variables. The authors show that investors paid premia that average to zero to hedge shocks to uncertainty. Dew-Becker, Giglio and Kelly (2021) supports this distinction between realized shocks and perceived uncertainty. The former carries negative risk premia, whereas the latter does not. According to the authors, forward-looking uncertainty shocks do not drive investor's marginal utility - an argument that the asset allocation exercise in this paper supports. The previously cited studies that relate uncertainty shocks to increased volatility rely on uncertainty proxies that might not narrowly capture pure uncertainty. News indices are indeed much more likely to capture realized shocks to policy rather than forward-looking uncertainty perceptions. It follows that attempts at studying TPU using news-based indices are likely to lead to mistaken conclusions precisely because they are backward-looking and reflective of the size of realized shocks rather than expectations of future shocks. Hedging behavior appears very limited when trade policy uncertainty shocks are measured using forward-looking perception indices. The stock market response is limited in scope and small in size across sectors.

Conclusion

The secular stability of trade policy brought about by the post-war multilateral trade system has been disrupted by new geopolitical rivalries, populist discourses, and the supply-chain challenges posed by a global pandemic. Protectionist policies are challenging the sense of inevitability that cloaked multilateral liberalism. As a result, market participants have to contend with a new and increasingly relevant source of uncertainty: trade policy uncertainty (TPU).

I propose a new measure of trade policy uncertainty to support empirical research into its drivers and economic consequences. The index aims at capturing market participants' perceptions of TPU. It combines information from two distinct indicators measuring public attitudes towards TPU on Twitter and institutional signals of trade policy changes. The index reveals a large and sustained increase in TPU between March 2018 and early 2020.

Using the constructed index, I study the effects of TPU on macroeconomic variables and stock market volatility. Whereas the literature shows a positive relationship between economic policy uncertainty and returns volatility, I find that trade policy uncertainty, in particular, does not increase overall market volatility. Heterogeneity analysis reveals that increased uncertainty does not impact sectors differently. Investors do not appear to flee to under-exposed sectors. The negative relation between TPU and excess returns stresses the particularity of the uncertainty episode under study.

This paper advances the research on trade policy uncertainty in two significant regards. On the one hand, it puts forth a new tractable, reproducible measure of

TPU perception that can support further empirical research of this increasingly relevant source of uncertainty. On the other hand, it shows that the market's response to TPU is markedly different from its response to uncertainty stemming from other economic policy components. The results of this paper invite questions about the significance of impacts of short-term trade uncertainty episodes on the real economy. Its methodological contribution provides a tool that can help address such questions.

REFERENCES

Alessandria, George A., Shafaat Y. Khan, and Armen Khederlarian. 2019. "Taking Stock of Trade Policy Uncertainty: Evidence From China's Pre-WTO Accession."

Alizadeh, Sassan, Michael W Brandt, and Francis X Diebold. 2002. "Range-Based Estimation of Stochastic Volatility Models." *The Journal of finance (New York)*, 57(3): 1047–1091.

Amengual, Dante, and Dacheng Xiu. 2018. "Resolution of policy uncertainty and sudden declines in volatility." *Journal of Econometrics*, 203(2): 297–315.

Asgharian, Hossein, Ai Jun Hou, and Farrukh Javed. 2013. "The Importance of the Macroeconomic Variables in Forecasting Stock Return Variance: A GARCH-MIDAS Approach." *Journal of Forecasting*, 32(7): 600–612.

Baker, Malcolm, and Jeffrey Wurgler. 2006. "Investor Sentiment and the Cross-Section of Stock Returns." *The Journal of Finance*, 61(4): 1645–1680.

Baker, Scott R, Nicholas Bloom, and Steven J Davis. 2016. "Measuring economic policy uncertainty.(Report)." *Quarterly Journal of Economics*, 131(4): 1593.

Baker, Scott R, Nicholas Bloom, Brandice Canes-Wrone, Steven J Davis, and Jonathan Rodden. 2014. "Why has US policy uncertainty risen since 1960?(Author abstract)." *American Economic Review*, 104(5): 56–60.

Baker, Scott R, Nicholas Bloom, Steven J Davis, and Kyle Kost. 2019. "Policy News and Stock Market Volatility." *SSRN Electronic Journal*.

Berger, David, Ian Dew-Becker, and Stefano Giglio. 2019. "Uncertainty Shocks as Second-Moment News Shocks." *The Review of Economic Studies*, 87(1): 40–76.

Bloom, Nicholas. 2014. "Fluctuations in Uncertainty." *The Journal of Economic Perspectives*, 28(2): 153–175.

Bouët, Antoine, and David Laborde. 2018. "US trade wars in the twenty-first century with emerging countries: Make America and its partners lose again." *World economy*, 41(9): 2276–2319.

Brandt, Michael W, and Christopher S Jones. 2006. "Volatility Forecasting With Range-Based EGARCH Models." *Journal of business & economic statistics*, 24(4): 470–486.

Brogaard, Jonathan, and Andrew Detzel. 2015. "The asset-pricing implications of government economic policy uncertainty." *Management Science*, 61(1): 3.

Caceres, Carlos, Diego A Cerdeiro, and Rui C Mano. 2019. "Trade Wars and Trade Deals: Estimated Effects using a Multi-Sector Model." *IMF working paper*.

Caldara, Dario, Matteo Iacoviello, Patrick Molligo, Andrea Prestipino, and Andrea Raffo. 2020. "The economic effects of trade policy uncertainty." *Journal of Monetary Economics*, 109: 38–59.

Campbell, John Y., and Samuel B. Thompson. 2007. "Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average?" *The Review of Financial Studies*, 21(4): 1509–1531.

Campbell, John Y, Martin Lettau, Burton G Malkiel, and Yexiao Xu. 2001. "Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk." *The Journal of finance (New York)*, 56(1): 1–43.

Chauvet, Marcelle, Zeynep Senyuz, and Emre Yoldas. 2015. "What does financial volatility tell us about macroeconomic fluctuations?" *Journal of Economic Dynamics and Control*, 52: 340–360.

Chiu, Ching-Wai, Richard D F Harris, Evarist Stoja, and Michael Chin. 2018. "Financial market Volatility, macroeconomic fundamentals and investor Sentiment." *Journal of Banking & Finance*, 92: 130–145.

Choudhry, Taufiq, Fotios I. Papadimitriou, and Sarosh Shabi. 2016. "Stock market volatility and business cycle: Evidence from linear and nonlinear causality tests." *Journal of Banking & Finance*, 66: 89–101.

Christiansen, Charlotte, Maik Schmeling, and Andreas Schrimpf. 2012. "A comprehensive look at financial volatility prediction by economic variables." *Journal of Applied Econometrics*, 27(6).

Dew-Becker, Ian, Stefano Giglio, and Bryan Kelly. 2021. "Hedging macroeconomic and financial uncertainty and volatility." *Journal of Financial Economics*.

Ederington, Louis H., and Jae HA Lee. 1993. "How Markets Process Information: News Releases and Volatility." *The Journal of Finance*, 48(4): 1161–1191.

Feng, Ling, Zhiyuan Li, and Deborah L Swenson. 2017. "Trade policy uncertainty and exports: Evidence from China's WTO accession." *Journal of International Economics*, 106: 20.

Fetzer, Thiemo, and Carlo Schwarz. n.d.. "Tariffs and Politics: Evidence from Trump's Trade Wars." *SSRN Electronic Journal*.

Guo, Hui. 2002. "Stock Market Returns, Volatility, and Future Output." *Review*, 84(5).

Handley, Kyle, and Nu Limao. 2017. "Policy Uncertainty, Trade, and Welfare: Theory and Evidence for China and the United States.(Author abstract)." *American Economic Review*, 107(9): 2731–2783.

Handley, Kyle, and Nuno Limão. 2015. "Trade and Investment under Policy Uncertainty: Theory and Firm Evidence." *American Economic Journal: Economic Policy*, 7(4): 189–222.

Harris, Richard D F, Evarist Stoja, and Fatih Yilmaz. 2011. "A cyclical model of exchange rate volatility." *Journal of banking & finance*, 35(11): 3055–3064.

Jeanne, O. 2019. "Currency Wars, Trade Wars and Global Demand."

Knight, Frank. 1921. *Risk, Uncertainty and Profit.* Houghton Mifflin.

Lee, Gary GJ, and Robert Engle. 1999. "A permanent and transitory component model of stock return volatility." In *Cointegration, Causality, and Forecasting: A Festschrift in Honor of Clive W.J. Granger.* , ed. R. Engle and H. White, 475–497. New York:Oxford University Press.

Liu, Li, and Tao Zhang. 2015. "Economic policy uncertainty and stock market volatility." *Finance Research Letters*, 15: 99–105.

Liu, Qing, Fei Pei, Huaqing Wu, and Xianfeng Zhang. n.d.. "Trade Policy Uncertainty, Firm Heterogeneity and Export Mode." *Emerging Markets Finance and Trade*.

Mattoo, Aaditya, and Robert W Staiger. 2020. "Trade Wars: What do they mean? Why are they happening now? What are the costs?" *Economic policy*.

Neely, Christopher J., David E. Rapach, Jun Tu, and Guofu Zhou. 2014. "Forecasting the Equity Risk Premium: The Role of Technical Indicators." *Management Science*, 60(7): 1772–1791.

Olasehinde-Williams, Godwin. n.d.. "Is US trade policy uncertainty powerful enough to predict global output volatility?" *Journal of International Trade & Economic Development*.

Ongan, Serdar, and Ismet Gocer. 2020. "Does trade policy related uncertainty affect international trade? Evidence from the US-China commodity trade." *China Economic Journal*.

Phan, Dinh Hoang Bach, Susan Sunila Sharma, and Vuong Thao Tran. 2018. "Can economic policy uncertainty predict stock returns? Global evidence.(Report)." *Journal of International Financial Markets, Institutions & Money*, 55: 134.

Poon, Ser-Huang, and Clive W.J. Granger. 2003. "Forecasting Volatility in Financial Markets: A Review." *Journal of Economic Literature*, 41(2): 478–539.

Rapach, David E., Jack K. Strauss, and Guofu Zhou. 2009. "Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy." *The Review of Financial Studies*, 23(2): 821–862.

Ravn, Morten O, and Harald Uhlig. 2002. "On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations." *The review of economics and statistics*, 84(2): 371–376.

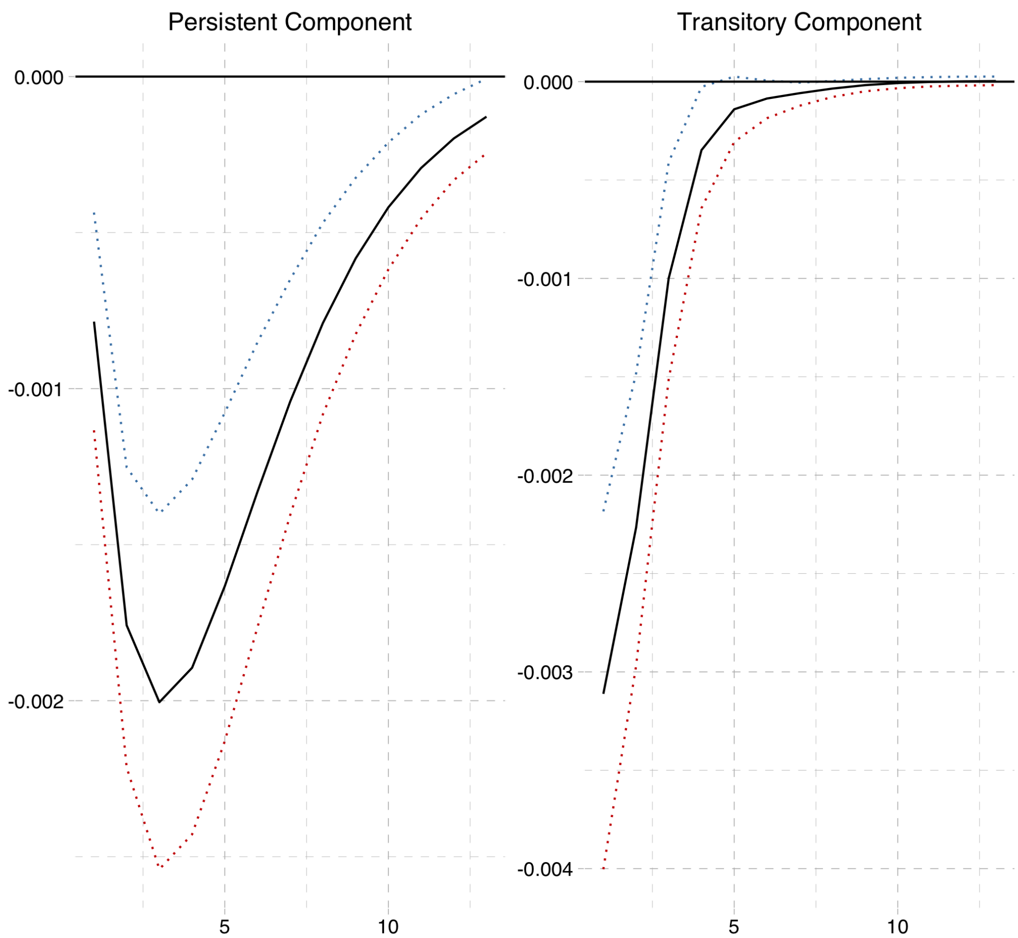
Schwert, G William. 1989. "Why Does Stock Market Volatility Change Over Time?" *The Journal of finance (New York)*, 44(5): 1115–1153.

Sims, Christopher A. 1980. "Macroeconomics and Reality." *Econometrica*, 48(1): 1–48.

Steinberg, Jb. 2019. "Brexit and the macroeconomic impact of trade policy uncertainty." *Journal Of International Economics*, 117: 175–195.

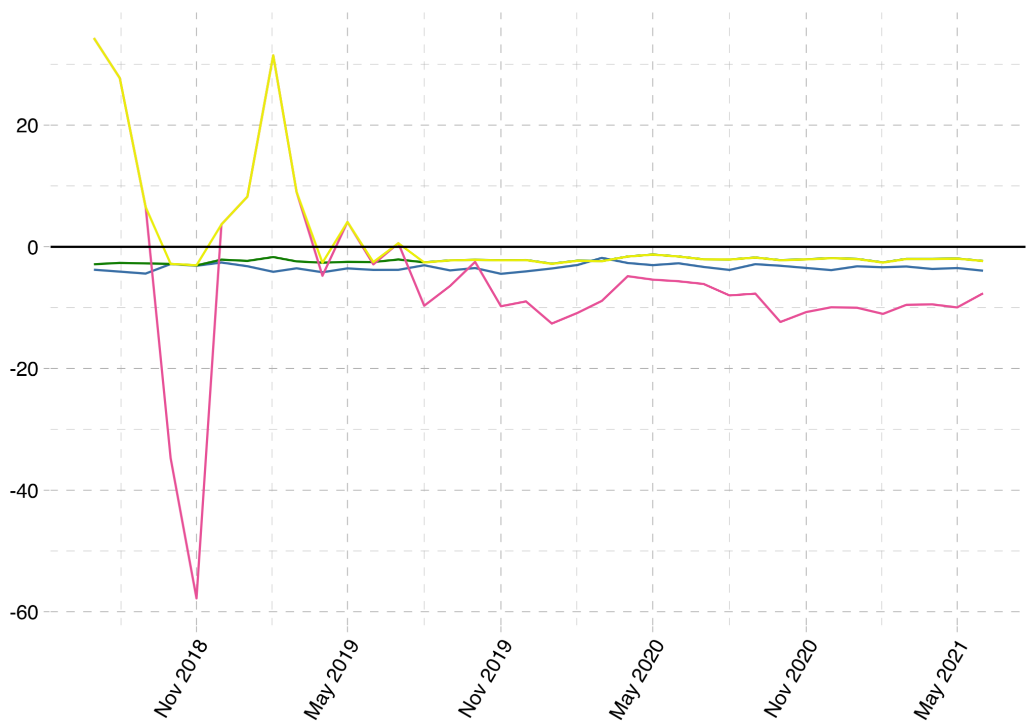
Wang, Yudong, Yu Wei, Chongfeng Wu, and Libo Yin. 2018. "Oil and the short-term predictability of stock return volatility." *Journal of Empirical Finance*, 47: 90–104.

Figure 11. Responses of Volatility Components to a Trade Policy Shock



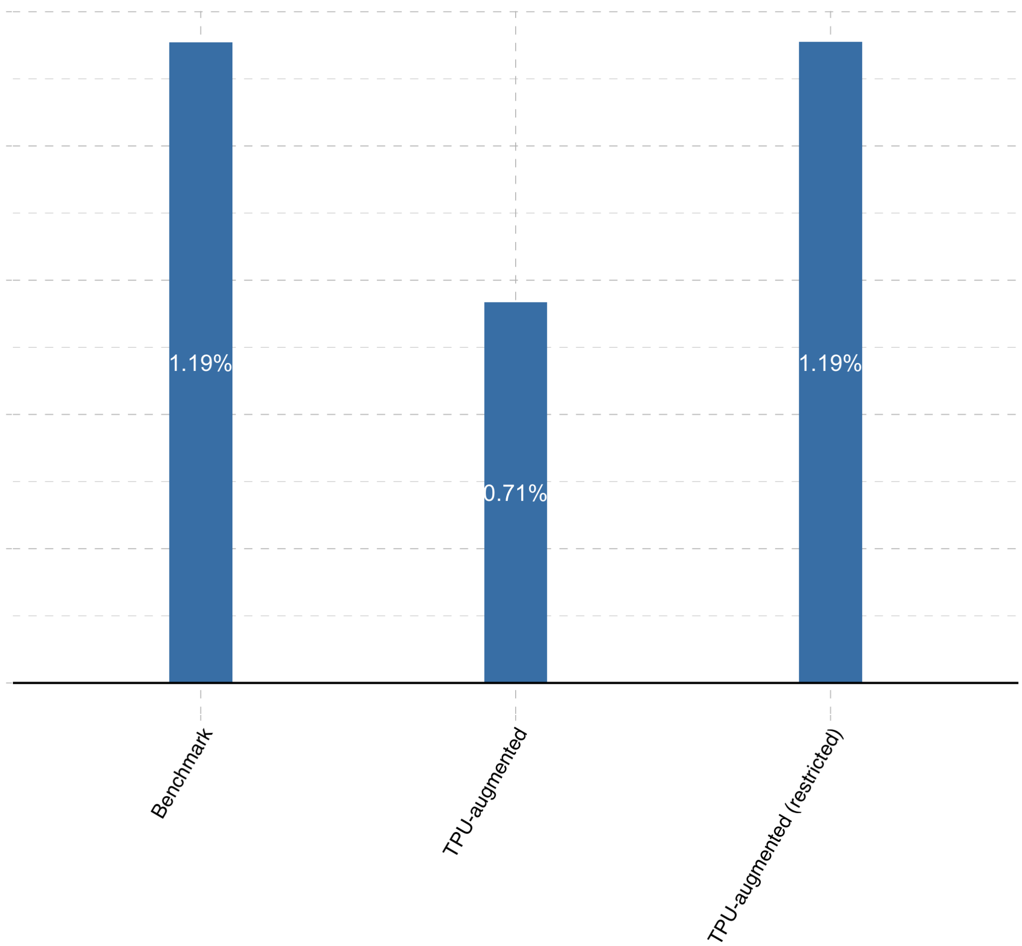
Note: Impulse response function estimated using the structural VAR model separately using transitory and persistent volatility components as fifth endogenous variables.

FIGURE 12. LOG VOLATILITY: TRUE VALUE AND ALTERNATIVE FORECASTS



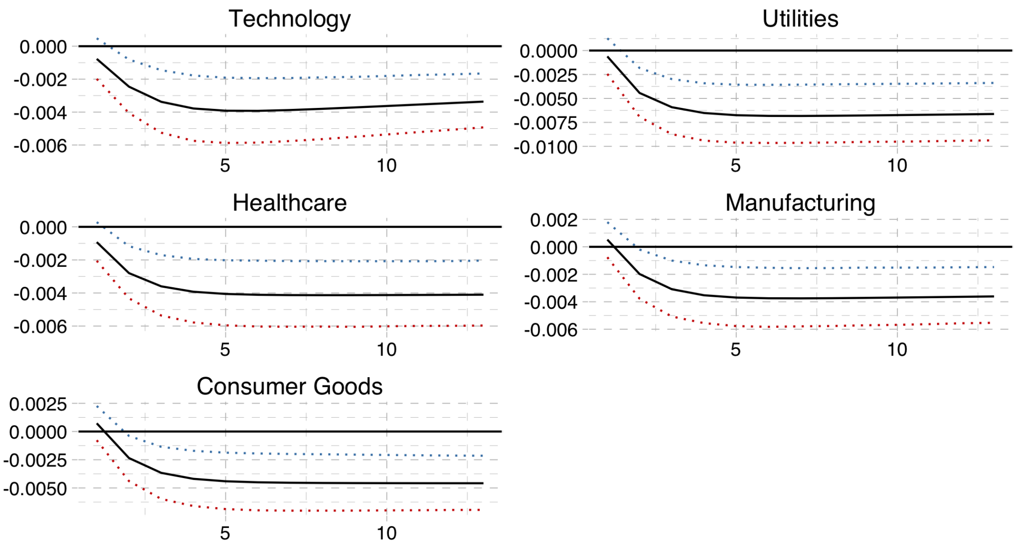
Note: TPU-augmented forecast (pink) $\Delta R^2_{OOS} = -49.19$ and restricted TPU-augmented forecast (yellow) $\Delta R^2_{OOS} = -16.20$ against the benchmark volatility forecast (green) and the true volatility value (blue).

Figure 13. Certainty Equivalence Return of Alternative Portfolios



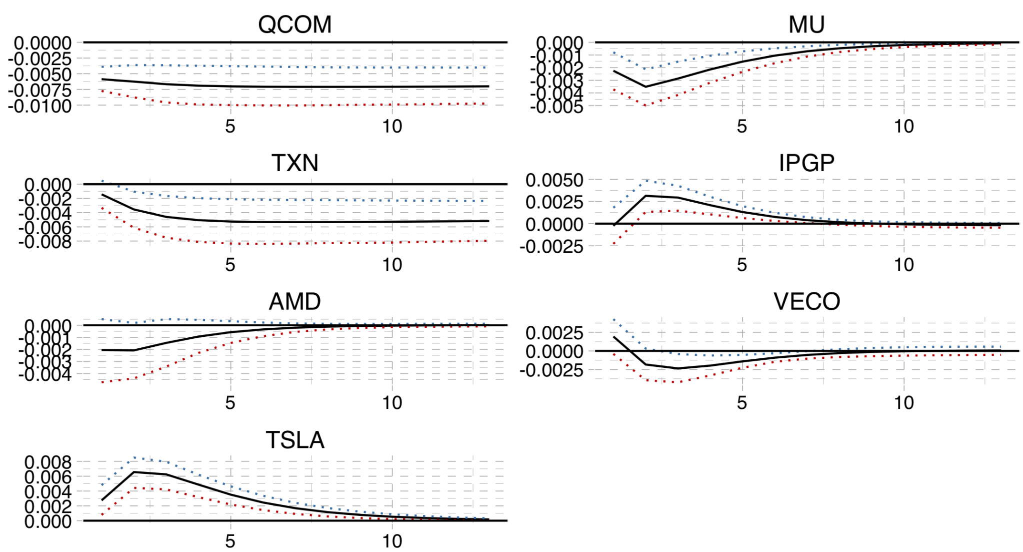
Note: Portfolios constructed using three different forecasting methods for the derivation of the optimal equity weight: a benchmark forecast, a TPU augmented model and a restricted TPU augmented model.

Figure 14. Impulse Response Function of Volatility to TPU Shocks: By Sector



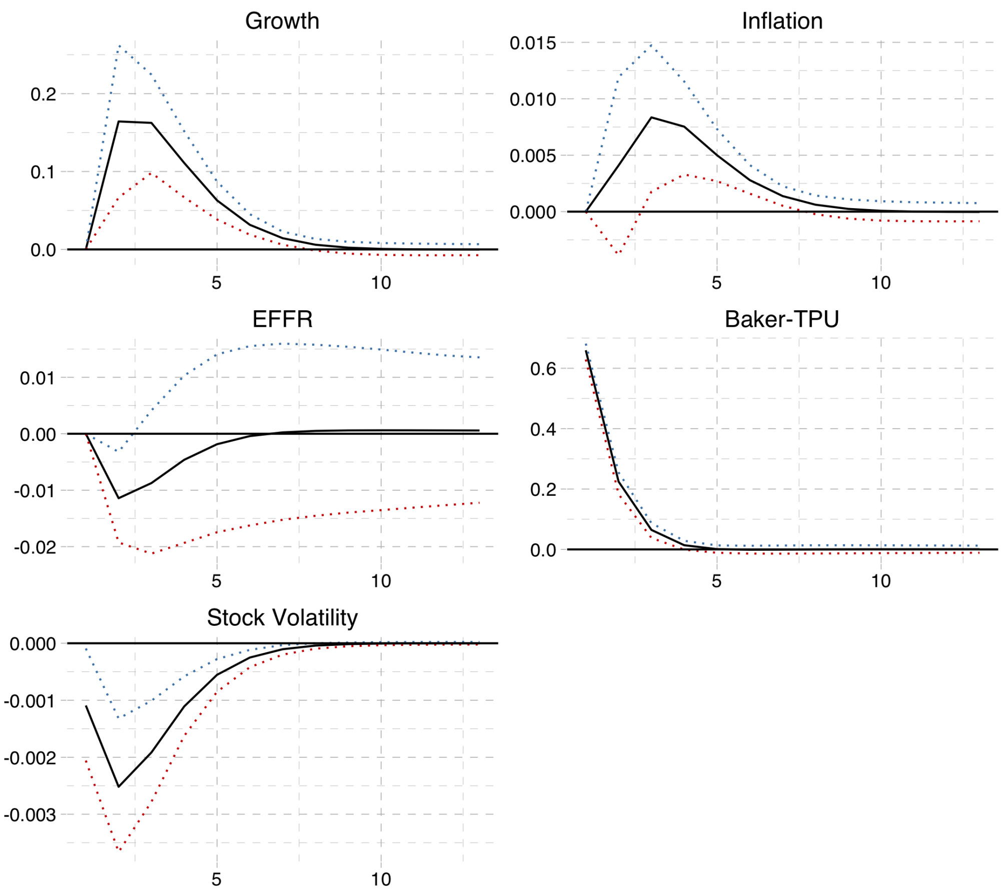
Note: IRFs estimated using the specified SVAR in (10) using different measures of volatility for specific sector-ETFs.

Figure 15. Impulse Response Function of Volatility to TPU Shocks: Individual Stocks



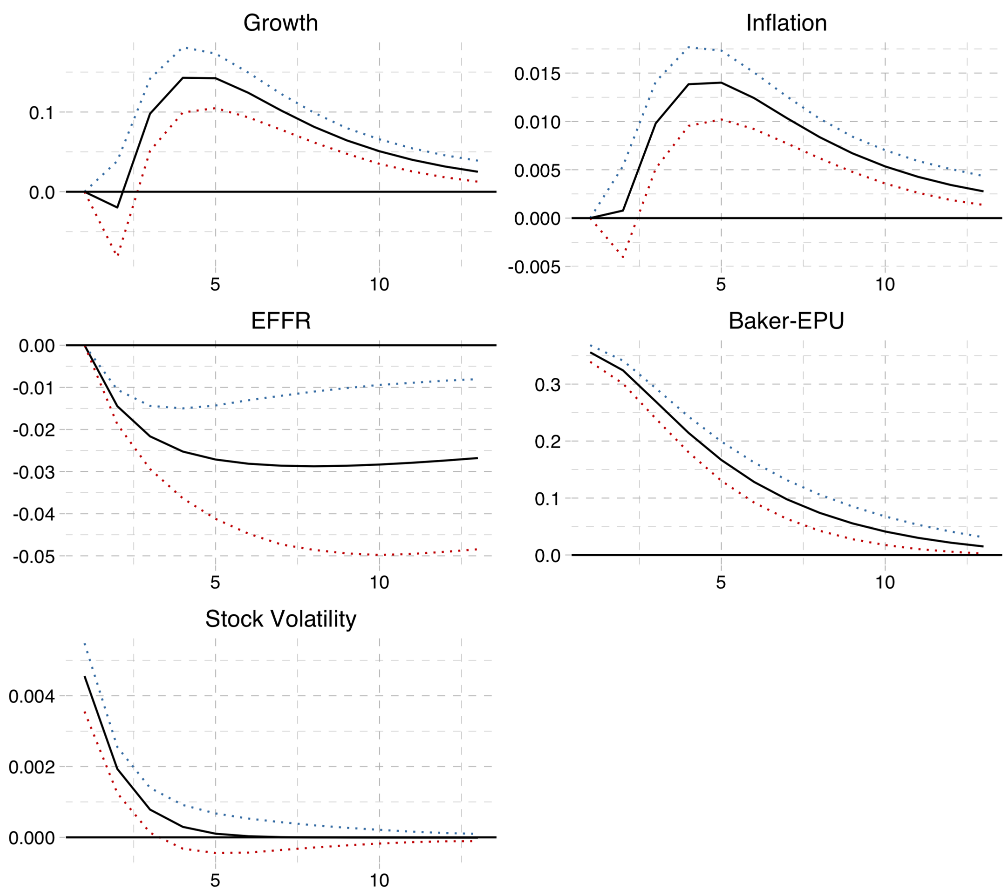
Note: IRFs estimated using the specified SVAR in (10) using different measures of volatility for specific companies.

Figure 16. Impulse Response Function to a TPU Shock, using Baker et al's Trade Component of EPU



Note: IRFs estimated using the specified SVAR in (10), and using total S&P500 volatility as stock volatility measure.

Figure 17. Impulse Response Function to an EPU Shock



Note: IRFs estimated using the specified SVAR in (10), and using total S&P500 volatility as stock volatility measure.