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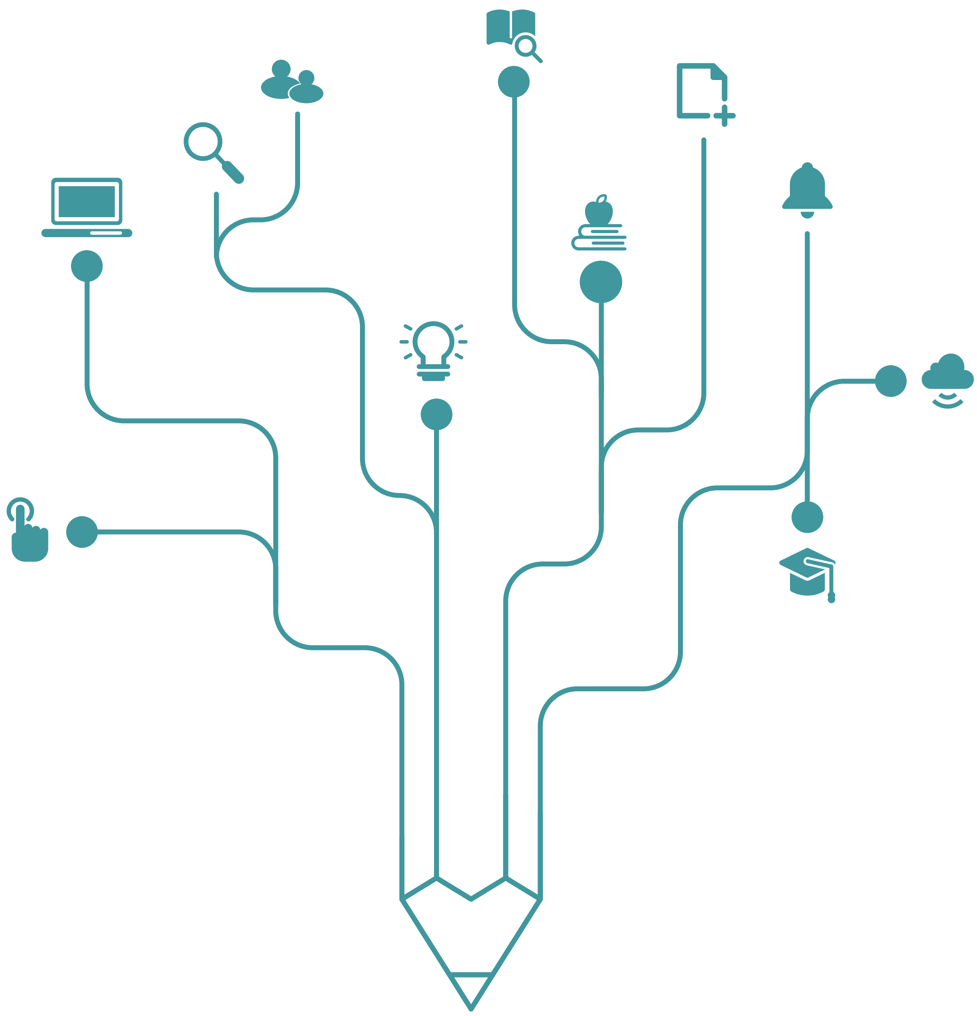

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Tracking Economic Policy Uncertainty through the Relative Sentiment Shift[1]

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We examine the causal dynamic relationship between economic policy uncertainty and economic activities, using a Local Projection model with an external instrument. Based on the psychological theory of conviction narratives, we construct a Relative Sentiment Shift (RSS) index and use it as an instrumental variable that captures exogenous variations in economic policy uncertainty. Our empirical results using the US data from January 1996 to December 2019 suggest that an increase in economic policy uncertainty induces recessionary pressures in the economy: reductions in production and employment, a sharp stock market downturn, and a constrained financial market.

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1 Introduction

Uncertainty is being increasingly recognized as one of the significant causes of the prolonged recession since the Great Financial Crisis of 2008. A heightened level of perceived uncertainty originating from various sources can discourage individuals from making economic decisions. The real options theory explains the countercyclicality of uncertainty as the *wait-and-see* effect it has on firms' investment decisions (e.g. Bernanke, 1983; Dixit and Pindyck, 1994), while others advance theories that stress the roles of uncertainty in terms of consumption (or savings), labour, productivity and the financial markets.[5]

Besides theoretical developments, empirical strategies for measuring uncertainty and tracing the causal links between uncertainty and macroeconomic activities have been widely examined. Related studies include, inter alia, Bloom (2009), Bachmann, Elstner and Sims (2013), Baker, Bloom and Davis (2016), and Jurado, Ludvigson and Ng (2015). Among others, the Economic Policy Uncertainty (EPU) index of Baker, Bloom and Davis (2016) is one of the most highlighted and widely-used indicators of uncertainty. The growing popularity of the EPU index is due in part to the fact that people have become more aware of the uncertainties surrounding economic policy as policymakers have had to implement unconventional economic policies to cope with the economic and financial crisis. Its wide recognition among both academics and policymakers is also attributable to the intuitive design of the measure. It measures the number of articles from major newspapers that contain words related to "economic", "policy", and "uncertainty". Due to its straightforward structure, an increase (decrease) in the EPU index tends to be interpreted as a factor that has a negative (positive) impact on economic activities based on the wait-and-see effect.

However, choosing a well-defined empirical model to estimate the impact of economic policy uncertainty is intricate. Previous studies, including Baker, Bloom and Davis (2016), rely mostly on recursive schemes using Cholesky decomposition to identify structural uncertainty shocks. The prevalent ordering in the literature has uncertainty ordered first, or at least before other macro variables, implying that uncertainty can affect real activities contemporaneously but that the reverse causality does not hold. Such recursive VAR models are valid only if the

[5] There are ample studies on theoretical models of uncertainty through (1) The consumption and savings channel: Romer, 1990; Carroll, 1996; Benito, 2006; (2) the productivity channel: Disney, Haskell and Heden, 2003; Bloom et al., 2018; Bachmann, Elstner and Sims, 2013; (3) the labour channel: Bentolila and Bertola, 1990; Lazear and Spletzer, 2012; Arellano, Bai and Kehoe, *2019*; and (4) the financial channel: Arellano, Bai and Kehoe, *2019*; Gilchrist, Sim and Zakrajsek, 2014.

variations in uncertainty are assumed to be exogenous to other macro variables, but it is difficult to justify a recursive scheme when there are potential endogeneity issues.

Endogeneity problems can arise for various reasons. We cannot completely rule out the possibility of reverse causality in cases where a high level of policy uncertainty can be seen as a consequence of sluggish economic conditions. For example, Fajgelbaum, Schaal and Taschereau-Dumouchel (2017) model an uncertainty trap in which high uncertainty is not only a cause of downturns in the business cycle, but also a consequence of recessions due to inefficient delivery of information among agents. In terms of measurement, the EPU index is likely to capture uncertainty shocks that are endogenous to economic outcomes. Because the term "economic" is included in the text search query, the variations in the EPU index could, by construction, be influenced by economic conditions in general. Moreover, policy can be endogenous because unconventional monetary and/or fiscal policies that are implemented in adverse economic conditions might cause increases in political uncertainty in return.[6]

To tackle potential endogeneity issues, empirical strategies have been extended to various types of estimation methods in order to identify exogenous variations in uncertainty.[7] One strand of the literature uses external instruments (or proxies) to identify exogenous uncertainty shocks.[8] Baker and Bloom (2013) use unprecedented events – natural disasters, terrorist attacks, political coups, and revolutions – as instrument variables for changes in the first and second moments of stock market returns, and estimate the effects of those shocks on GDP growth in a single equation setting. Carriero et al. (2015) use a dummy variable, assigning it the value of 1 for VXO peaks, as an instrumental variable and estimate VAR models. Piffer and Podstawski (2017) also employ an IV VAR model, where the proxy is changes in the price of gold when uncertainty-inducing events occur. Ha, Lee and So (2022) identify geopolitical uncertainty on the Korean Peninsula using the high-frequency price changes at around the times of events provoked by rising and easing geopolitical tensions in the region.

In this paper we propose a new estimation strategy, using an external instrument that captures plausibly exogenous variations in economic policy uncertainty. We exploit the rich real-time resources of news archives to extract narrative sentiments that are closely related to

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6 See Pástor and Veronesi (2013) for a theoretical model.

7 See Baker and Bloom, 2013; Alessandri and Mumtaz, 2017; Ludvigson, Ma and Ng, 2021; Segal, Shaliastovich and Yaron, 2015; Carriero et al., 2015; Berger, Dew-Becker and Giglio, 2016; Caldara et al., 2016; Piffer and Podstawski, 2017; Cesa-Bianchi, Pesaran and Rebucci, 2020; and Lee, So and Ha, 202022.

8 As Stock and Watson (2018) discussed, proxies used in macroeconometrics (e.g., Gertler and Karadi, 2015) can be simply interpreted as instrumental variables for identifying causal effects through quasi-experiments in microeconometrics.

uncertainty but exogenous to economic activities, at the very least from the point of view of *measurement*. The importance of narratives as a source of exogenous shocks to aggregate economic fluctuations has been increasingly discussed in the literature.[9] The Relative Sentiment Shift (RSS) index of Nyman et al. (2021) is constructed using the Thomson-Reuters news archive, motivated by a social-psychological theory of decision-making, Conviction Narrative Theory. The theory specifies how agents are able to make decisions under Knightian uncertainty, by drawing on narratives that intensify emotions related to *approach* rather than to *avoidance*. Using news articles, the RSS computes the relative occurrences of emotion-related words belonging to two groups – involving either *approach* or *avoidance* – in order to track the narratives that initiate economic decisions.

Two aspects of the RSS index distinguish it from news-based measures of uncertainty. First, the idea of constructing the RSS index is closely related to the concept of Knightian uncertainty. Knight (1921) emphasizes that the degree of confidence in the evaluation of probability can be determined not only by whether the estimate is the best guess from the model, but by how much the forecaster (or decision-maker) is *confident* of it.[10] The RSS offers a complete account for this degree of confidence, as it is based on a behavioural aspect of the individual whereby excitement explains an attraction process in the gain domain and anxiety signals an inhibition process in the loss domain. Moreover, the RSS could be interpreted as operationalising Keynes' concept of *animal spirits*. As Keynes (1936) noted, changes in the level of animal spirits are the tipping points for making economic decisions toward either more expansionary or more contractionary actions, which the RSS, by definition, attempts to measure.

The construction of the RSS index is intentionally simple; it is transparent and can be easily applied to different databases with a straightforward interpretation. Two emotion dictionaries were compiled (see e.g., Tuckett et al. 2014), and experimentally validated, representing *approach* and *avoidance* (for simplicity these can be thought of as *excitement* and *anxiety*, respectively) consisting of approximately 150 words each. The RSS algorithm simply searches for the relative number of approach words to avoidance words mentioned in any given period, e.g., a month. The difference is normed by the total number of articles published over the period. More sophisticated supervised machine-learning algorithms would likely improve

[9] See Shiller (2017) for recent advances in the subject.
[10] Knightian uncertainty can be linked to the subjective probability theory in microeconomics. In the subjective probability theory (Savage, 1972), if the probability density is unknown individuals make decisions *as if* they held probabilistic beliefs.

on the accuracy of the measure, but with the cost of being somewhat less straight forward to interpret (especially in terms of potential endogeneity issues).

In general, the identifying assumption for the RSS being a valid instrumental variable for economic policy uncertainty boils down to the evaluation of two conditions: the relevance and the exclusion restrictions. The relevance condition can be easily examined by computing the correlation between the instrument and the instrumented variable. We find that the relevance condition is likely to hold. However, similar to the cases of other studies that use instrumental variables, it is difficult to empirically demonstrate whether the exclusion restriction is valid. Instead, we contend that the variations in the RSS may capture exogenous changes in uncertainty and at least suffer less from endogeneity than does the EPU index. Unlike with the EPU index, the emotional words that are used to construct the RSS index are not directly linked to the economic conditions and/or policy. Furthermore, sentiments or confidence triggered by emotions are often considered in the literature to be exogenous to economic activities.[11]

With the RSS being an external instrument, our baseline estimation model for estimating the effect of economic policy uncertainty on economic activities is a Local Projection model (Jordá, 2005). To identify uncertainty shocks we assume that, among the variations in the EPU, the ones that provoke economic decisions are those that are driven by the agents' conviction narratives. We estimate structural impulse responses directly using external instruments, without estimating a VAR step, a method that is called local projection with instruments (LP-IV) in Stock and Watson (2018).

We select the LP-IV model instead of the IV VAR that is prevalent in the literature mainly because it provides the best linear unbiased direct forecasts when the underlying data generating process is unknown. The conventional approach to constructing the standard errors for the Impulse Response Function (IRF) could be problematic if the model is misspecified. Traditional VAR estimation represents a linear global approximation of the true Data Generating Process (DGP). Therefore, if the VAR fails to portray the actual dynamics of the

[11] There is a voluminous literature discussing sentiment and confidence and their effects on economic activities. Recently, several studies have reassessed the existing literature related to uncertainty. For example, Nowzohour and Stracca (2020) review the literature and compare six measures of sentiment or uncertainty. Pappa, Lagerborg and Ravn (2018) disentangle the variations in sentiment due to news about fundamentals from those due to non-fundamental shocks. The latter are referred to as "autonomous changes in sentiment," which they identify using mass shooting events in the US. Di Bella and Grigoli (2019) lay out the three categories of literature on confidence and its economic impacts: (i) the animal spirits (or sunspot) view, (ii) the view emphasizing the self-fulfilling property of sentiment, and (iii) the view pointing to the news-driven business cycle.

variables in the system, estimation of the IRFs based on the misspecified VAR could be biased. As the IRFs are functions of the forecast horizons, errors in the coefficients naturally accumulate in IRF estimation, and the inference of the impulse responses could suffer from low precision. Instead of extrapolating the distant horizon estimates from a globally estimated model, local projection estimates the impulse responses through sequential regressions with overlapping points in each adjacent regression. Local projection estimates are consistent and efficient even under conditions of misspecification (Jordá, 2005).[12]

Using US monthly data from January 1996 to December 2019, we find that a high level of economic policy uncertainty driven by conviction narratives is associated with subdued macroeconomic activities. An uncertainty shock of a size similar to the average increase in the EPU index during the Global Financial Crisis generates substantial decreases in production (8.8 percent) and employment (5.2 percent). The stock market index plunges by as much as 23 percent and the federal funds rate falls by 2 percent point in response to the shock. We also highlight that the effects remain substantial and significant after controlling for other macroeconomic conditions.

The organization of this paper is as follows. In Section 2 we explain the theoretical foundations and the methodologies used to construct the RSS index. In Section 3 we set out the details of the empirical model and describe the data and specifications for estimating the dynamic causal effects of economic policy uncertainty using our external instrument. Section 4 summarizes the empirical results and robustness, and Section 5 concludes.

2 Relative Sentiment Shift index

2.1 Theoretical foundations

The Relative Sentiment Shift (RSS) index is constructed using a theoretically-directed algorithm that measures emotion from text data.[13] In this paper, we use an RSS index derived from financial, economic and political news published by Reuters in the Washington and New York offices, as a proxy for macro-sentiment in the US. In other words, essentially no further

[12] Stock and Watson (2018) comprehensively discuss the relationship between the LP-IV and IV VAR (or SVAR-IV) models.

[13] For a more detailed explanation of the underlying theory, we refer the reader to either Tuckett (2011) and Tuckett and Nikolic (2017).

filtering of the Reuters news database is carried out other than to exclude articles about weather, sport and 'human interests' (i.e., entertainment). The algorithm counts the occurrences of predefined emotion-stimulating words within the articles from two groups – "approach" and "avoidance" – and maps the relative occurrences of the two emotions into an index. An increase (decrease) in the index indicates a relative increase (decrease) in approach-related words compared to avoidance-related words in the news source.[14]

The construction of the RSS index, i.e., the specific words searched for, is based on the socio-psychological theory of conviction narratives (Conviction Narrative Theory, or CNT) proposed in interview studies of asset managers (Tuckett, 2011, Chong and Tuckett, 2015). CNT describes how agents are able to make decisions under uncertainty by drawing on those narratives that generate a dominance of approach relative to avoidance emotions. In an increasingly global and connected world, social interactions enhance and spread some conviction narratives over social networks; providing a link between microeconomic decision making and macroeconomic consequences (Tuckett and Nikolic, 2017). "Conviction narratives are particularly important when agents make non-routine decisions, such as on whether or how to innovate, or on how to respond to new technological innovations in complex strategic environments" (Tuckett and Nyman, 2017). Agents rely more on conviction narratives for decisions that are made rarely and under different, often unseen, complex and unrepeatable, conditions.

2.2 Dictionary word lists and their validation

The dictionary is made up of ordinary English words expressing these two emotions. Twenty randomly drawn examples from each list can be found in Table 1. The words were first selected from the much longer list of categories of emotional words in the Harvard IV-4 list.[15] A professional social-psychologist went through the words and excluded some on the basis of not representing the given emotions with enough clarity or having specific economic or financial meaning (such as the words 'recession' and 'crash'). Some additional words were also added to the lists at this stage.

A crucial point to emphasise is that the dictionaries used to construct the RSS index

[14] In order to match the EPU index, we multiply the RSS index by -1 for our empirical analyses in Section 3-4.

[15] The Harvard IV-4 dictionary can be retrieved from www.wjh.hamecat.htmrvard.edu/ inquirer/ho.

contain only ordinary English emotion words. They do **not** include words that have become associated with specific economic meanings such as ‘crisis’, ‘boom’, ‘bubble’, ‘bankrupt’, ‘downturn’, ‘disaster’, ‘interest’, ‘inflation’, etc.[16] Rather, they are words in everyday use in a wide variety of contexts, which stimulate emotions encouraging either ‘approach’ or ‘avoidance’ (Nyman et al., 2021).

The dictionaries were then validated through an online experiment (Strauss, 2013) following the methodology of Burke and James (2006). A subset of the words from each emotion category were presented to subjects. The lemmas of the words, instead of the complete forms, were presented to participants and the emotional intensities were rated. It has been shown that the emotional values of lemmas generalise to their inflected forms (Warriner et al., 2013). In summary, it was shown that financial and non-financial professionals alike were clearly able to distinguish between excitement and anxiety evoking words and the ratings correlated across participants. For more detail see, e.g., Tuckett and Nyman (2017).

2.3 Computation of Relative Sentiment Shift index

News data are now available in machine-readable form in increasing quantities at increasing frequencies. An RSS index can in theory be computed at any frequency in real time, given enough time-stamped text data that contain the emotion words with high enough frequency.

The summary statistic of a collection of texts T is the number of approach words and avoidance words for any specific period, scaled by the total number of articles over the given period. Therefore, it can be interpreted as the relative frequency of the use of these words per ‘story’. For any period, *T*, in this case a month:

$$RSS[T] = \frac{|Approach| - |Avoidance|}{|Articles|}$$

We keep the method simple and transparent on purpose. Notably, the method leads to clarity about what is measured (for example, ordinary English emotion words rather than any ‘economic’ indicator words). We can therefore be more confident that changes in the RSS index are more likely to be exogenous to the economy than changes in the Economic Policy

[16] Note that the words ‘uncertain’ and ‘uncertainty’ are in the avoidance list, and the words ‘boost’, ‘boosted’ and ‘boosts’ in the approach wordlist. These are words that have come to have economic meanings, but they are also general emotion-stimulating words. As a robustness check, we have established that if these words are excluded from analysis the results are no different.

Uncertainty index.

We have not profited from sophisticated natural language processing techniques or deep learning, and have not drawn from supervised machine learning to identify the words and phrases (together with weights and potential non-linear combinations) that cognate with approach and avoidance. It is very likely that the RSS measure could be further refined by applying such techniques. However, to re-iterate, this relatively simple methodology is arguably more transparent (although, at the time of writing, model interpretability is a very active research topic in machine learning, see e.g., Riberio et al., 2016) and variations in the index are therefore somewhat easier to interpret. This is critical to the argument made in this paper, in particular the requirement that the index is an external instrument.

We find that changes in the balance of approach and avoidance word occurrences are in line with expected patterns, although we cannot entirely rule out potential measurement insensitivity. There are no good grounds to believe that the bluntness of the approach would yield any transitory biases (for example, the use of negation occurring more frequently in, say, April, than in July), and therefore the changes of the index over time should not be affected by any such biases. But simple checks have nonetheless been carried out. For example, a test for 'negation' was carried out (e.g., Nyman et al., 2021) by excluding all target words appearing close to negation words such as 'no' and 'not'. We find that the shape and trend of the RSS index is robust to such test.[17]

3 Estimation model and data

3.1 Econometrics model

To estimate the effects of uncertainty on real economic activities, we propose Local Projection with an external instrument (LP-IV) as in Stock and Watson (2018). As long as it uses a valid external instrument, LP-IV is a direct and model-free estimation of the structural Impulse Response Functions (IRFs).

Let $\varepsilon_{1,t}$ denote a random uncertainty shock at time t. Then the causal effect on a macro variable, Y_i, after h period due to a unit change in $\varepsilon_{1,t}$ is

$$E(Y_{i,t+h}|\varepsilon_{1,t} = 1) - E(Y_{i,t+h}|\varepsilon_{1,t} = 0) \tag{1}$$

[17] As a test of negation, we consider excluding all words that are adjacent to, within three words, one of the words in the following negation word list: "no", "not", "none", "neither", "never" or "nobody". We find that the new and the original series are highly correlated (above 0.99).

Assuming linearity, the h period ahead treatment effect of uncertainty on the variable Y_i is denoted by $\Theta_{h,i1}$. The impulse responses from the shock $\varepsilon_{1,t}$ are

$$Y_{i,t+h} = \Theta_{h,i1}\varepsilon_{1,t} + u_{i,t+h} \tag{2}$$

where $u_{i,t+h}$ is the error term. If $\varepsilon_{1,t}$ is observable and randomly assigned, i.e. a structural shock, then the causal effects can be estimated by OLS of Equation (2).

Extending the representation of the model with vector notations, and assuming linearity and stationarity, a dynamic moving average representation of a vector (Y_t), including macro variables and uncertainty, can be written as follows:

$$Y_t = \Theta(L)\varepsilon_t \tag{3}$$

where L is the lag operator, $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \cdots$, Θ_h is a matrix of coefficients, and ε_t are the structural shocks. The shock variance is defined as $\Sigma_\varepsilon = E\varepsilon_t\varepsilon_t$ and assumed to be positive definite.

The conventional Structural VAR (SVAR) estimation estimates first a reduced form vector autoregression of Y_t:

$$A(L)Y_t = v_t \tag{4}$$

where $v_t = Y_t - Proj(Y_t|Y_{t-1}, Y_{t-2}, \ldots)$ by the Wold theorem. The SVAR model then assumes that the innovations, v_t, are a linear combination of structural shocks: $v_t = \Theta_0\varepsilon_t$. Assuming the invertability of $A(L)$, Equation (4) coincides with Equation (3).[18] Therefore, the identification problem of the SVAR is not different from estimating Θ_0 and the variance-covariance matrix of structural shocks.

But the estimation of impulse responses based on the estimated SVAR is meaningful if and only if the original Data Generating Process is well-represented by the identification assumptions. Otherwise the estimation of the SVAR and the IRFs based on the misspecified SVAR could be biased. Moreover, as the impulse responses are functions of the forecast horizons, there tends to be an accumulation of errors in the coefficients during IRF estimation.

In the literature on uncertainty and its impact on macroeconomics, there are considerable differences in the specifications used to identify structural uncertainty shocks, and it is often found to be very difficult to defend those identifying assumptions. Bloom (2009) and Baker, Bloom and Davis (2016) applied similar recursive identification schemes: 5-variable (uncertainty, stock market index, federal funds rate, employment, industrial production) Cholesky ordering VARs. Jurado, Ludvigson and Ng (2015) experimented with two main

[18] The invertibility of a structural VAR is simply $Y_t = A(L)^{-1}\Theta_0\varepsilon_t$.

specifications along with several specifications for their robustness check: an 8-variable VAR by adapting Bloom (2009), and an 11-variable VAR by modifying Christiano, Eichenbaum and Evans (2005). Bachmann, Elstner and Sims (2013) employed a bivariate VAR, consisting of the uncertainty measure and a real activity variable – either manufacturing production or manufacturing employment – in order to avoid misspecification.

Instead of extrapolating the distant horizon estimates from a globally estimated and highly restrictive SVAR model, we use for this paper an LP-IV model to estimate the impulse responses to EPU shocks by sequential regressions with overlapping points in each adjacent regression. Provided a valid instrument is used, an LP-IV provides consistent and efficient estimates in a less restrictive manner when the underlying data generating process is unknown.[19]

We first apply unit effect normalization to the uncertainty shocks, $\varepsilon_{1,t}$, as the shocks are unobservable and their scales are indeterminate. For the normalization of $\varepsilon_{1,t}$, we assume that a one-unit increase in $\varepsilon_{1,t}$ at $h = 0$ causes an increase in $Y_{1,t}$ by one unit:

$$\Theta_{0,11} = 1 \tag{5}$$

Applying the unit effect normalization for $Y_{1,t}$,

$$Y_{1,t} = \varepsilon_{1,t} + \{\varepsilon_{\cdot,t}, \varepsilon_{t-1}, \varepsilon_{t-2}, \cdots\}, \tag{6}$$

where $\varepsilon_{\cdot,t} = (\varepsilon_{2,t}, \cdots, \varepsilon_{n,t})$ and $\{\dots\}$ denote linear combinations of the terms in braces. By the normalization, a 1 percentage point shock causes $\mathrm{Y}_{1,\mathrm{t}}$ to increase by 1 percentage point. As Stock and Watson (2018) note, the unit normalization is more useful than the unit standard deviation normalization widely used in the empirical literature. It allows us to directly estimate the dynamic causal effects in the native unit.

Substituting Equation (6) for $\varepsilon_{1,t}$ in Equation (2) yields

$$Y_{i,t+h} = \Theta_{h,i1} Y_{1,t} + u_{i,t+h}^{h} \ , \tag{7}$$

where $u_{i,t+h} = \{\varepsilon_{t+h}, \cdots, \varepsilon_{t+1}, \varepsilon_{\cdot,t}, \varepsilon_{t-1}, \varepsilon_{t-2}, \cdots\}$. Since the error term, $u_{i,t+h}$, is a linear combination of the past, current (except $\varepsilon_{1,t}$), and future structural shocks up to h period ahead, $Y_{1,t}$ is endogenous and the OLS estimation of the equation is not valid.

[19] Jordá (2005) shows that the estimates from local projections are consistent and efficient even under conditions of misspecification. For further discussion of the relationship between the LP-IV and SVAR-IV models and the related assumptions, see Stock and Watson (2018). Specifically, they prove that the conditions for validity of the SVAR-IV are equivalent to those for the LP-IV when the LP-IV requires lagged endogenous variables as controls. We provide the results from estimating the SVAR-IV in order to check the robustness of our estimation in Section 4.3.

The dynamic causal effect can be estimated by the LP-IV if an instrument, Z_t, can be found that satisfies the following conditions:

1. $E(\varepsilon_{1,t}Z_t) = \alpha \neq 0$ (Relevance)
2. $E(\varepsilon_{\cdot,t}Z_t) = 0$ (Contemporaneous exogeneity)
3. $E(\varepsilon_{t+j}Z_t) = 0$ for $j \neq 0$ (Lead/lag exogeneity)

The moving average representation of Y_t along with the relevance and exogeneity conditions of IV implies

$$E(Y_{i,t+h}Z_t) = \Theta_{h,i1}\alpha \quad . \tag{8}$$

Combining the contemporaneous exogeneity condition and the relevance condition yields

$$E(y_{1t}Z_t) = E(\varepsilon_{1t}z_t) = \alpha \quad . \tag{9}$$

Therefore, the moment condition of the IV estimation of $\Theta_{h,i1}$ is as follows:[20]

$$\frac{E(Y_{i,t+h}Z_t)}{E(Y_{1,t}Z_t)} = \Theta_{h,i1} \tag{10}$$

We next consider extension of the LP-IV by including controls, as usually done in microeconometrics. This reduces the standard errors of the estimates and, most importantly, increases the likelihood of satisfying the relevance condition. Controlling for W_t, the causal effect on a macro variable Y_i after h period due to a unit change in $\varepsilon_{1,t}$ is

$$E\left(Y_{i,t+h} \middle| \varepsilon_{1,t} = 1; W_t\right) - E\left(Y_{i,t+h} \middle| \varepsilon_{1,t} = 0; W_t\right). \tag{11}$$

We define the residuals of a variable, x_t, from its projection on to the controls, w_t, as $x_t^{\perp} = x_t - Proj(x_t|w_t)$. The LP regression with W_t controlled for is

$$Y_{i,t+h} = \Theta_{h,i1}Y_{1t} + \gamma_h W_t + u_{i,t+h}^{h\perp}. \tag{12}$$

The corresponding IV conditions are:

1. $E(\varepsilon_{1t}^{\perp}Z_t^{\perp}) = \alpha \neq 0$ (Relevance)
2. $E(\varepsilon_{\cdot t}^{\perp}Z_t^{\perp}) = 0$ (Contemporaneous exogeneity)
3. $E(\varepsilon_{t+j}^{\perp}Z_t^{\perp}) = 0$ for $j \neq 0$ (Lead/lag exogeneity)

[20] Equation (10) is the representation when Z_t is a scalar. If Z_t is a vector,

$$\frac{E(Y_{i,t+h}Z_t)\Lambda E(Z_tY_{1,t})}{E(Y_{1,t}Z_t)\Lambda E(Z_tY_{1,t})} = \Theta_{h,i1}$$

for any positive definite matrix Λ.

Under these conditions, the moment conditions for IV estimation with controls is as follows:[21]

$$\frac{E(Y_{i,t+h}^{\perp} Z_t^{\perp})}{E(Y_{1,t}^{\perp} Z_t^{\perp})} = \Theta_{h,i1}. \tag{13}$$

The validity of the instrument depends largely on the choice of controls, since it is difficult to prove whether the lead/lag exogeneity condition is satisfied. Suppose Z_t is correlated with the past values of the uncertainty shock (ε_{1t}) but not with the lags of other shocks ($\varepsilon_{\cdot,t}$). The lagged values of Z_t can be included as controls in order to capture the dynamics of the past values of ε_{1t}. If Z_t is correlated with all past shocks, then generic controls can be added. Examples of such controls include a vector of macroeconomic variables, and factors that can be estimated using dynamic factor models. In the literature, the lagged values of Y_t, the lagged values of other macro variables, and lagged factors from a dynamic factor model are typically used as controls.[22]

3.2 Data and estimation

For our benchmark analysis, we employ the LP-IV model with controls, Equation (12), to estimate the effects of economic policy uncertainty shocks on economic activities. We use the US monthly data from January 1996 to December 2019. We consider the EPU index as an uncertainty measure ($Y_{1,t} = EPU$) and the RSS index as an instrumental variable for uncertainty shocks ($Z_t = RSS_t$). The other five endogenous variables are the S&P stock market index ($Stock_t$), the federal funds rate (FFR_t), the excess bond premium (EBP_t),[23] industrial production (IP_t), and employment (EMP_t). As controls, we use lagged endogenous variables ($Y's$) separately as controls, to ensure satisfaction of the exogeneity conditions. We also consider principal component factors computed from the large dataset of macro and financial variables used in McCracken and Ng (2016).[24]

For estimating the impacts of a shock as the deviations from the steady states, most estimation models require that the data be covariance stationary. We note that the existing

[21] Similarly, if Z_t is a vector,

$$\frac{E(Y_{i,t+h}^{\perp} Z_t^{\perp})\Lambda E(Z_t^{\perp} Y_{1,t}^{\perp})}{E(Y_{1,t}^{\perp} Z_t^{\perp})\Lambda E(Z_t^{\perp} Y_{1,t}^{\perp})} = \Theta_{h,i1}$$

for any positive definite matrix Λ.

[22] See Stock and Watson (2018) for an example of controls when implementing an LP-IV in the case of the monetary policy shocks in Gertler and Karadi (2015).

[23] We use the data from Gilchrist and Zakrajsěk (2012) as an indicator of financial stress.

[24] For robustness, we also estimate Equation (12) with controls of lagged $Z's$.

literature that estimates the uncertainty effects seems to be less attentive to potential issues in the data preparation to obtain stationarity. While Jurado, Ludvigson and Ng (2015) touched on this issue by explicitly mentioning that they depart from Bloom (2009) and do not detrend any variables using the Hodrick and Prescott (HP) filter, in-depth investigation is still lacking.[25] We carefully weigh the pros and cons of the alternative methods of preparing the data to remove trends and isolate cycles, and use the method suggested by Hamilton (2017):[26]

1. Run an OLS regression of y_{t+h} on a constant and the $p = 4$ most recent values of y as of date t for the appropriate choice of h:[27]

$$y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \beta_4 y_{t-3} + v_{t+h}$$

2. Obtain the filtered series, which is the residuals from the regression:

$$\widehat{v_{t+h}} = y_{t+h} - \hat{\beta}_0 - \hat{\beta}_1 y_t - \hat{\beta}_2 y_{t-1} - \hat{\beta}_3 y_{t-2} - \hat{\beta}_4 y_{t-3}$$

The filter has several advantages: (1) the residuals from the estimates of the projections represent a pure transient component of the underlying DGP; (2) any findings that the residuals predict some other variable represent the true ability of y to predict x; (3) by construction, the residuals are components that are difficult to predict from the variables dated t and earlier, and any associations between the filtered series can therefore be easily interpreted as Granger-causality; (4) the residuals are a model-free and assumption-free summary of the data.

All macroeconomic variables are collected from the FRED economic database. Industrial production, employment and the stock market index are logged and filtered using Hamilton's (2017) methodology. The federal funds rate and the excess bond premium (in percent) are also detrended using the same technique. For the uncertainty variable and its instrument, we use the raw data of the EPU and RSS indices. Table 2 shows the descriptive statistics and Figure 1 the time series plots for all variables included in the model.[28]

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[25] In the literature, in order to ensure stationarity variables in time series models are either specified in levels, differenced or filtered. The first approach emphasizes the possibility of a cointegrating relationship among variables as in Sims, Stock and Watson (1990) and Hamilton (1994), while the second takes the logs of and differences the variables based on unit root test results. HP filtering is also popular for detrending, but there are drawbacks to applying HP filters. It could generate a spurious business cycle even if the underlying raw data of a model do not exhibit cyclicality. In particular, in the presence of a persistent and deep recession, the potential drawbacks of HP filtering could be aggravated. See King and Rebelo (1993) and Cogley and Nason (1995) for a discussion of the drawbacks of the HP filter.

[26] See Appendix for a discussion of the data preparation in the time series models.

[27] $h = 24$ is chosen following Hamilton (2017), which should be referred to for the details.

[28] We present the time series plots of the filtered (panel (a)) and the raw data (panel (b)).

We estimate the LP-IV regression equations of each horizon in Equation (12) using two-stage least squares estimation. The standard errors of the IRFs are computed by Newey-West Heteroskedasticity and autocorrelation consistent (HAC) estimation with $h + 1$ lags. In addition to the endogenous variables in the baseline regressions, we include inflation and estimate the responses of inflation to shed light on the contentious issues on whether the effect of uncertainty is inflationary or disinflationary.[29]

For robustness we estimate the baseline model with different uncertainty measures. First, we consider the implied volatility of the stock market, VIX, which is widely used as a proxy for uncertainty. Second, we estimate the macroeconomic impact of the Geopolitical Risk (GPR) index or Caldara and Iacoviello (2022). We in addition estimate our baseline model with log-differenced macroeconomic variables, to examine how sensitive the estimation model is to the detrending methods. Next, we set up a simple SVAR-IV model and estimate it using the RSS as an instrumental variable for uncertainty shocks.

4 Results

4.1 Instrumental variable

To examine the validity of the instrumental variable, we first compute the coefficients of correlation between the instrument (RSS) and the instrumented variable (EPU). Next, we use the Granger causality results to indirectly examine whether the exogeneity conditions are likely to hold.

As can be seen in Figure 2, the two measures exhibit strong co-movements. The correlation coefficient between the EPU and the RSS is 0.56 and significant at the 1% level.[30] Although the RSS and the EPU show similar trend over time, there are some episodes of divergence. In order to examine the underlying narratives, three cases of divergence are examined: (i) an increase in the RSS without any significant changes in the EPU, (ii) increases

[29] See p. 133 in Choi (2017) for a detailed discussion about the inflationary vs. disinflationary effect of uncertainty shocks in the empirical and theoretical literature.

[30] The RSS index that is used for our estimation is a standardised measure (z-score), i.e. the raw series is subtracted by its mean and divided by its standard deviation over the sample period. Therefore, we compare the same standardized series of the EPU index in Figure 2. But it is also worthwhile to investigate whether the unscaled data of the RSS exhibits the similar trend as the EPU index. We present the unscaled (raw) series of the RSS and the EPU index in Figure 3. As expected, we observe clear upward trend in both series (unscaled), suggesting that the uncertainty has indeed increased over time since the late 1990s. In Figure 4, we also present the trend of the number of emotion words (avoidance and approach) per article. The number of avoidance words is larger in levels and much volatile than that of approach words.

in both measures but with the RSS increasing more, and (iii) increases in both but with the EPU increasing more.

First, there are four episodes in which the RSS increased sharply without any significant sign of an EPU increase.[31] These events of dramatic increases in the RSS relative to the EPU occurred in relation to global financial events. In particular, the RSS acted as an early warning of subsequent financial crises in some cases. During the stock market downturn in September 2002, the RSS increased sharply due to the bursting of the dotcom bubble, while the level of the EPU did not rise to the same degree. Similarly, only the RSS rose dramatically in August 2007 when BNP Paribas froze redemptions for three investment funds and announced that it could not value the underlying assets of their funds fairly due to their exposures to subprime mortgage loans. This event is considered as the first acknowledgment of the risks of major banks' high exposures to subprime mortgages.[32] The next example is the failure of IndyMac Bank in the US in July 2008. IndyMac, one of the largest US mortgage lenders at that time, was closed by the Office of Thrift Supervision, and the Federal Deposit Insurance Corporation (FDIC) established IndyMac Federal Bank, FSB, as its successor.[33] In May 2010 the RSS rose sharply due to global financial market turbulence after the Greek government's announcement of austerity measures, while the EPU remained at a relatively stable level.

Second, we investigate the other two cases where both measures increase but one of them increases more. In hindsight, it seems that the EPU tends to react relatively sensitively to political events, such as elections and war, whereas the variations in the RSS coincide with financial events. For example, there were steeper increases in the EPU than the RSS during the US interest rate cuts and stimulus measures in January 2008, the banking crisis in February 2009, and the US midterm elections in September 2010. In contrast, the episodes when the RSS increased more than the EPU can be found mostly during times of financial turbulence: the Russian financial crisis/LTCM collapse in September 1998, 9/11 in 2001, the bankruptcy of Lehman Brothers in September 2008, the European debt crisis in November 2011, and the US debt ceiling debate in October 2013.[34]

[31] These episodes occurred in September 2002, August 2007, July 2008 and May 2010 respectively.
[32] Brunnermeier (2008) dubbed this episode an "illiquidity wave," arguing that the interbank market froze up as the perceived default and liquidity risks of banks rose significantly and LIBOR increased sharply.
[33] For more detail see the FDIC press release, July 11 2008, https://www.fdic.gov/news/news/press/2008/pr08056.html.
[34] (I). Major events associated with substantial increases in the EPU and RSS: Russian Crisis/LTCM collapse (August 1998), Bush election controversy (November 2000), 9/11 (September 2001), Second Gulf War (March 2003), large interest rate cuts and stimulus measures (January 2008), Lehman Brothers and TARP (September 2008), Obama election (November 2008), banking crisis (February 2009), midterm elections (September 2010),

This narrative evidence suggests that the RSS index tends to be more sensitive to external shocks, such as the Russian financial, Greece debt and European debt crises and the 9/11 terrorist attack, which are exogenous to US domestic economic conditions.[35] However, the EPU index rises substantially during events that could also affect the domestic macroeconomic outlook in general: policy rate cuts and monetary stimulus by the Fed, and the midterm and presidential elections. Our identification strategy exploits the relationship between these two uncertainty measures. After controlling for covariates, including overall economic and financial market conditions, we find that changes in the RSS index are correlated with changes in economic policy uncertainty but uncorrelated with the error term.

Additionally, we indirectly examine the exogeneity of the RSS index to economic variables by estimating bivariate VAR regressions of every pair of the RSS index and economic variables.[36] We then perform Wald tests of Granger causality. We also estimate bivariate VARs with the EPU index, the variable that is instrumented for, and see whether that index is indeed endogenous to economic conditions. The lag lengths of the VARs are chosen using Akaike Information Criteria (AIC).

The results of Granger causality presented in Table 3 show that none of the economic variables, either real or financial, are useful in predicting the RSS. Even short-term financial market data does not have significant forecasting power over the RSS. As expected, however, the EPU does have some degree of endogeneity due to the method by which the index is constructed. First, at monthly frequency, the preceding stock market performances can explain

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debt ceiling dispute (July 2011), government shutdown and debt ceiling debate (September 2013).
(II). Major events associated with substantial increases in the RSS but not the EPU: dotcom bubble stock market burst (September 2002), interbank illiquidity wave (August 2007).

[35] One may wonder whether the RSS index actually captures information about financial market uncertainty, often proxied by the VIX. In order to distinguish different nature of two indices and show that the RSS captures the information beyond financial markets, we compare the RSS to the VIX by computing correlation coefficients and identifying specific episodes when these indices diverge from one another (see Figure 5-6 for time series plots).

First, the correlation between the two indices is 0.43 ($p<0.01$). The linear relationship between the RSS and the VIX is somewhat weaker than the correlation between the RSS and the EPU. Second, we examine the major episodes when there was significant divergence between the two indices. The VIX increased more than the RSS during the times of significant financial turmoil: Asian Financial Crisis (October 1997), Russian Crisis/LTCM collapse (August 1998), Emergency Economic Stabilization Act and the Term Asset-Backed Securities Loan Facility (October-November 2008), and banking crisis (February 2009). However, the RSS responded more sensitively to the economic policy disturbances than the VIX did: Debt ceiling disputes (June-July 2011), European debt crisis (July 2012), and the US government shutdown (October 2013).

The statistical and narrative evidence suggests that the RSS index covers much general sentiment perceived by economic agents than the financial market uncertainty does. We are thankful to anonymous referee for pointing this out.

[36] A Sargan-Hansen test of overidentifying restrictions cannot be performed, because we estimate an exactly identified model with one instrumental variable.

the variations in the EPU index. Second, the past paths of the federal funds rate, a proxy for the monetary policy stance, can explain economic policy uncertainty. This is because the federal funds rate may be one of the most important and rich sources of information about monetary policy and its uncertainty. Third, we find that the lagged excess bond premium is associated with the current level of the EPU index. This suggests the possibility that monetary, fiscal and macroprudential policies may react to increases in the excess bond premium, a proxy for financial distress.

Overall, the statistical and narrative evidence provided above supports the validity of our choice of the instrumental variable, the RSS index.

4.2 Baseline estimation results

Figures 7 and 8 are the results of our baseline estimation. Figure 7 shows the IRFs from the LP-IV (I) model that includes 12 lags of Y_t's as controls. Figure 8 are the IRFs from the LP-IV (II) model that includes 12 lags of factors computed from the FRED-MD dataset (McCracken and Ng, 2016).

The first stage F-statistics of both models are well above the rule-of-thumb value of 10: $F^{LP-IV(I)} = 20.84$, and $F^{LP-IV(II)} = 20.19$.[37] This confirms the findings in Section 4.1 that the relevance condition is likely to hold.

LP-IV (I) shows that, on average, economic policy uncertainty has negative effects on industrial production and employment while the first few months of the impulse responses are positive but insignificant. A one-unit increase in the EPU index causes decreases in production of nearly 0.22 percent and in employment of 0.13 percent from the steady state levels at the maximum at around 21- and 24-months ahead horizon. If there were a 40-unit increase in the EPU index, the average during the Global Financial Crisis, the magnitudes of these negative impacts would be substantial: 8.8 and 5.2 percent.[38] The financial market is immediately distressed in response to a one-unit increase in policy uncertainty, leading to a 1 basis point rise in the excess bond premium. The federal funds rate falls by up to 5 basis points as the central bank reduces interest rates to stimulate the economy. The stock returns plunge by 0.17 percent immediately after the shock, and this falls steadily to 0.58 percent. An increase in the

[37] The rule-of-thumb value for the F-statistics is suggested by Staiger and Stock (1997).
[38] The pre-crisis (2000-2006) average level of the EPU is 87.6, and the average during the Global Financial Crisis (GFC) period (2008-2013) is 125.4.

EPU index of 40 units would lead to a rise in the excess bond premium of 40 basis points, and to decreases in the federal funds rate of 200 basis points and in the stock market index of as much as 23 percent.

LP-IV (II) yields similar results, except that the economic effects of increased uncertainty are less pronounced than with LP-IV (I). A one-unit increase in economic policy uncertainty is associated with declines in production of 0.06 percent, statistically insignificant, and in employment of 0.05 percent at 15-months ahead horizon. The response of the excess bond premium to a one-unit uncertainty shock is above 1 basis point. The federal funds rate declines by 0.02 percentage point, and the stock market collapses as the index falls by 0.39 percent at its maximum. These are translated into a 0.8 percentage point drop in the federal funds rates and a 15 percent decline in the stock market index for an uncertainty shock like that which hit the economy during the GFC.

We also estimate a model with a lagged instrumental variable, LP-IV (III). The F-statistic decreases ($F^{LP-IV(III)} = 11.78$) but is still above 10, consistent with the baseline model results. The overall responses are congruous with our earlier findings: drops in production, employment, stock returns and the policy rate, and considerable financial market distress. As seen in Figure 9, the real-options effects of uncertainty on macroeconomic variables become insignificant, while the responses of the financial market variables remain significant. A one-unit increase in the EPU index is related to a 0.11 percent drop in production and a 0.08 percent decline in employment. The excess bond premium soars by nearly 2 basis points, and the stock market falls by 0.38 percent. The federal funds rate drops by 3 basis points.

The responses of employment and the stock market returns show signs of overshooting, as seen in the literature.[39] Employment starts to pick up from 28 to 36 months after the initial uncertainty shock, while the stock market index rebounds to positive territory at around 25 months after the shock. At the maximum three-year horizon, the overshooting is not clear except in LP-IV (III) where the 12 lags of the instrumental variable are included as controls.

Lastly, we add inflation into our baseline model to shed light on the issue of uncertainty effects on inflation (Figures 10-12). We find that uncertainty shocks resemble negative aggregate demand shock as the uncertainty shocks decrease inflation as well as production and employment. This is consistent with the findings in Choi (2017) that shows the disinflationary

[39] See, for example, Bloom (2009) and Bachmann, Elstner and Sims (2013). The existing literature documents the overshooting behaviour of IRFs of endogenous variables in their VAR models. It should be noted that such overshooting behaviour after uncertainty shocks in VARs cannot be directly compared to that in LP-IV since they use different techniques in estimating IRFs.

effect of uncertainty shocks in the post-Great moderation period (1984m1-2014m12). The impulse responses generally show declines in inflation in all three specifications. An uncertainty shock of a size similar to the average increase in the EPU index during the GFC generates a maximum of 1.1 percentage point decline in inflation.

4.3 Robustness

We provide evidence that our results are robust to different uncertainty indices, types of data, and model specifications.

First, we examine our results' robustness to models that replace the EPU index with other uncertainty measures that are widely used in the literature: the implied volatility of the US stock market index (VIX) and the geopolitical uncertainty index (GPR).

Figure 13 shows the estimated impulse responses in the LP-IV (III) model with the VIX as the proxy for uncertainty where the F-statistic is the highest (9.12) among the other specifications. A one-unit increase in the VIX index is associated with a 0.6 percent decrease in production, a 0.47 percent decline in employment, a 11 basis point rise in the excess bond premium, a 18 basis point increase in the federal funds rate, and a 2.1 percent stock market decline.[40] Based on the average increase in the VIX during the GFC period,[41] the estimated responses of the economic variables can be translated into the responses to a four-unit VIX index rise. The economic and financial effects of uncertainty measured by the VIX are consistent with the findings in our baseline results.

We also estimate the impact of geopolitical risk on economic activities using the GPR index as the proxy for uncertainty and the RSS index as the instrument (see Figure 14).[42] The F-statistic of the first stage regression is 17.9, above the threshold level for validating the relevance condition of an instrument. A one-unit rise in the GPR index leads to a decrease in industrial production of 0.05 percent at most. It is estimated that a one-unit increase in the GPR index causes a reduction in employment of 0.04 percent. The effects are statistically

[40] To compare the magnitudes of the estimated responses to shocks based on different measures of uncertainty, we examine the relative levels of the EPU and the VIX. The EPU index is normalized to an average value of 100 for the period from January 1985 to December 2009. The average of the VIX from January 1990 through December 2009 is 20.22. Therefore, we assume that the ratio of the size of the VIX relative to that of the EPU is approximately 1:5.

[41] The average level of the VIX index increases by nearly 4 units during the GFC period: the 2000-2006 average is 19.7 and the 2008-2013 average 23.9.

[42] The GPR index is normalized to have an average value of 100 during the period from January 2000 to December 2009.

insignificant throughout horizons from one to 36 months. The financial market reactions to geopolitical uncertainty are more pronounced and significant: a one-unit increase in the GPR index leads to a 0.8 basis point rise in the excess bond premium, a decline in the federal funds rate of 1.5 basis points, and a 0.32 percent drop in the stock market index.[43]

To verify whether the results are robust to detrending, we estimate the baseline models with differenced data. The variables that are I(1) in logged levels, IP_t, EMP_t and $Stock_t$, are differenced. The results shown in Figure 15 are the estimated responses in an LP-IV model with 12 lags of endogenous variables. The estimated F-statistic of the first stage equation is 25.52. The responses to a one-unit shock in economic policy uncertainty are a 0.18 percent decrease in production, a 0.05 percent decline in employment, a 1.5 basis point increase in the excess bond premium, a 7 basis point reduction in the federal funds rate and a 0.42 drop in the stock market. The effects on the macro variables are statistically insignificant except for the financial variables with very short periods of forecasting horizons.

Figure 16 shows the results of LP-IV estimation with 12 lags of factors as controls. The estimated F-statistic is 20.19. The responses of production are longer lasting and larger than the baseline results: up to a 0.09 percent reduction three years after the initial shock. The responses of employment are statistically insignificant, while those of the stock market are significant for only up to six months. The impulse responses also do not exhibit any overshooting in the long run.

Figure 17 shows the IRFs from the specification with 12 lags of the instrument as controls. The F-statistics is estimated to be 11.78, just above the conventional threshold. The magnitudes of the uncertainty effects are similar to those for the baseline model with filtered data: -0.10 percent for production, -0.06 percent for employment, +2 basis points for the excess bond premium, -3 basis points for the federal funds rate, and -0.38 percent for the stock market index. However, only the responses of the financial variables, such as EBP and stock price, are statistically significant.

Next we check the robustness of our baseline specifications using an SVAR-IV model. The endogenous variables are IP_t, EMP_t, EBP_t, FFR_t, EPU_t and $Stock_t$, as in the baseline model. The lag length is determined based on the Akaike Information Criterion.[44] The

[43] Comparison of the effects of a GPR shock and an EPU shock is not simple because the historical trend of GPR index is substantially different from that of EPU index: geopolitical risk remained at low level during the GFC period.

[44] The lag length chosen based on AIC is 2. We also consider other information criteria: Schwarz and Hannan-Quinn information criteria suggest lag length of 1.

standard errors for the confidence intervals of the impulse responses are computed by a recursive wild bootstrap using 1,000 random draws. Figure 18 shows the results of the IRF estimations. The first stage F-statistic is 32.98, indicating that the relevance condition is likely to hold. The magnitudes of the estimated responses are similar to those in the baseline estimations. The maximum effects of the variables in the IRFs are shown at the horizon of less than a year, which is earlier than the baseline results. An increase in economic policy uncertainty has particularly pronounced adverse effects on the real and financial variables – industrial production, the federal funds rate, the excess bond premium and the stock market index.

5 Conclusions

Uncertainty is being increasingly recognised as one of the significant causes of the prolonged recession since the Global Financial Crisis of 2008. Against this backdrop, empirical strategies for tracing the causal links between uncertainty and macroeconomic activities have been widely examined. Most existing studies focus on Vector Autoregressive (VAR) models and identify uncertainty shocks to estimate the macroeconomic effects of uncertainty. The recursive VAR models are reasonable if the variations in uncertainty are assumed to be exogenous to other macro variables. However, endogeneity of uncertainty can arise due to various sources, e.g. reverse causality and measurement errors.

In this paper we exploit the rich real-time resources of one online news archive to extract narrative sentiment, the Relative Sentiment Shift (RSS) series of Nyman et al. (2021). As the RSS is an external instrument, we propose a Local Projection model (Jordá, 2005) to estimate the effects of economic policy uncertainty on macroeconomic activities. For identification of the uncertainty shocks, we assume that, among the variations in the EPU, the ones that provoke economic decisions are those that are driven by the agents' conviction narratives.

In our macroeconometrics model, we estimate the structural impulse responses directly using external instruments without estimating a VAR step, a method which is called Local Projection with instruments (LP-IV) in Stock and Watson (2018). We choose this estimation method because Local Projection estimates are consistent and efficient even under misspecification (Jordá, 2005). Provided that the RSS is a valid instrument, the use of LP could restore the data dynamics in a less restrictive manner.

We examine the macroeconomic effects of economic policy uncertainties driven by conviction narratives using US monthly data from January 1996 to December 2019. Our key findings are as follows: First, the RSS index is likely to be a valid instrument; the F-statistics in various specifications are well above the rule-of-thumb level. Although it is difficult to prove the validity of the exogeneity condition, we provide both empirical and narrative evidence to support the identifying assumption. Second, in the baseline LP-IV estimation model, the uncertainty effects on the real economy are substantial and significant. A one-unit increase in the EPU index leads to a 0.22 percent decrease in production, a 0.13 percent decline in employment, and a 0.58 percent drop in the stock market index. The federal funds rate falls (by 5 basis points) and the excess bond premium rises due to the recessionary pressures on the economy. Finally, we find that the results are robust to different specifications.

To the best of our knowledge, our paper is the first to employ an LP-IV model to examine the uncertainty effects on economic activities, and the results provide a model-free estimate of the impulse response functions of economic activities to exogenous variations in uncertainty.

Developing various measures and proxies for uncertainty and understanding their differences in capturing diverse aspects of uncertainty is important for policymakers. Furthermore, the empirical study to unravel transmission channels of uncertainty shocks would help design policy that can effectively respond to adverse economic and financial consequences caused by uncertainty shocks.

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Figures and Tables

Table 1: Randomly Drawn Selection of Words of Emotion

Avoidance	Avoidance	Approach	Approach
Jitter	Erodes	Excited	Perfect
Threatening	Uneasy	Incredible	Win
Distrusted	Distressed	Ideal	Amazes
Jeopardized	Unease	Attract	Energizing
Jitters	Disquieted	Tremendous	Gush
Hurdles	Perils	Satisfactorily	Wonderful
Fears	Traumas	Brilliant	Attracts
Feared	Alarm	Meritorious	Enthusiastically
Traumatic	Distrusting	Superbly	Exceptionally
Fail	Doubtable	Satisfied	Encouraged

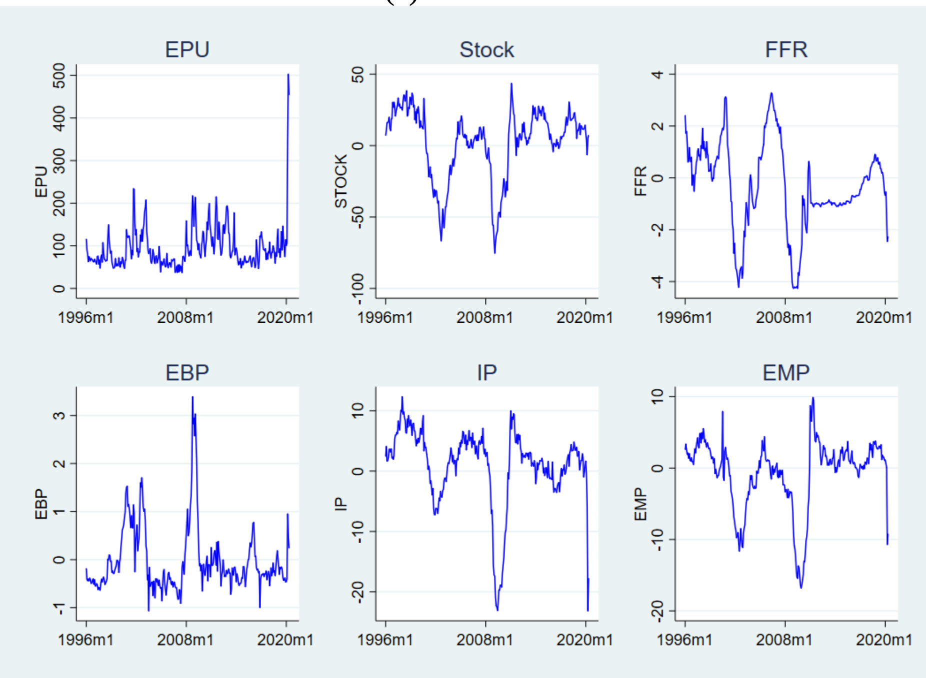
Table 2: Descriptive Statistics

	Obs.	Mean	SD	Min	Max
Filtered series					
Industrial production	288	1.060	6.317	-23.106	12.339
Employment	288	-0.697	4.993	-16.801	9.897
Federal funds rate	288	-0.323	1.699	-4.265	3.280
Stocks	288	2.286	24.539	-75.337	43.630
Excess Bond Premium	288	-0.017	0.696	-1.067	3.391
Raw series					
Industrial production	288	4.568	0.088	4.274	4.688
Employment	288	2.631	0.144	2.438	2.870
Federal funds rate	288	2.365	2.183	0.070	6.540
Stocks	288	7.229	0.371	6.455	8.080
Excess Bond Premium	288	0.034	0.701	-1.108	3.474
EPU	288	91.830	39.602	37.270	234.090
RSS	288	-0.015	0.992	-1.859	3.186

Notes: All variables are monthly data from January 1996 to December 2019. Economic variables in the upper panel are detrended using the Hamilton filter.

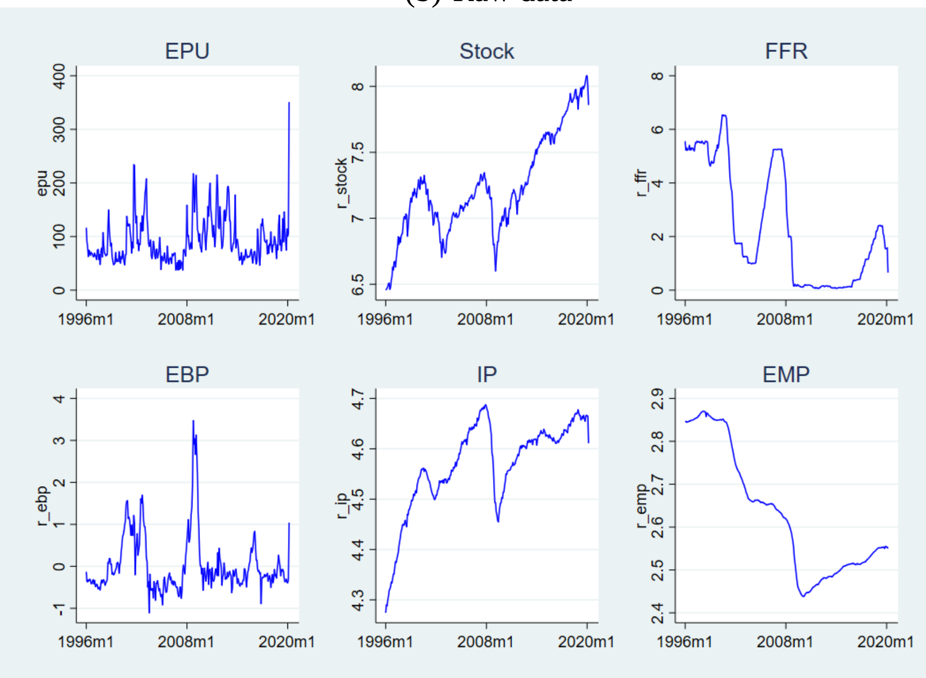
Figure 1: Time series plots of data in LP-IV model

(a) Filtered data



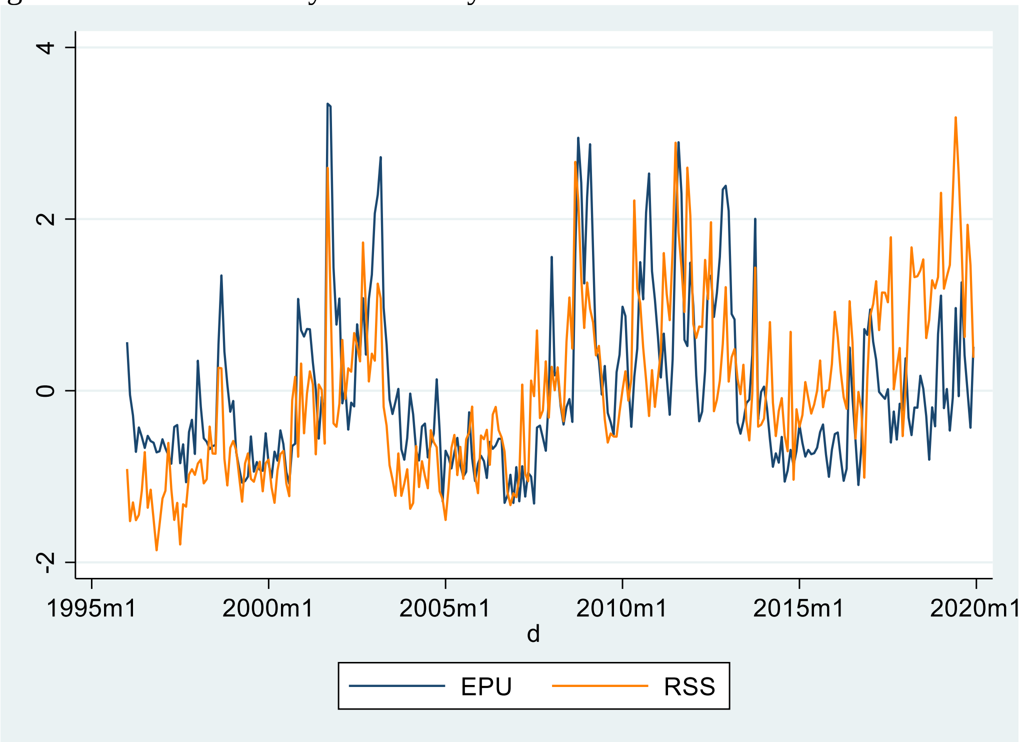
Notes: Hamilton (2017) filter is applied to all variables except uncertainty index.

(b) Raw data



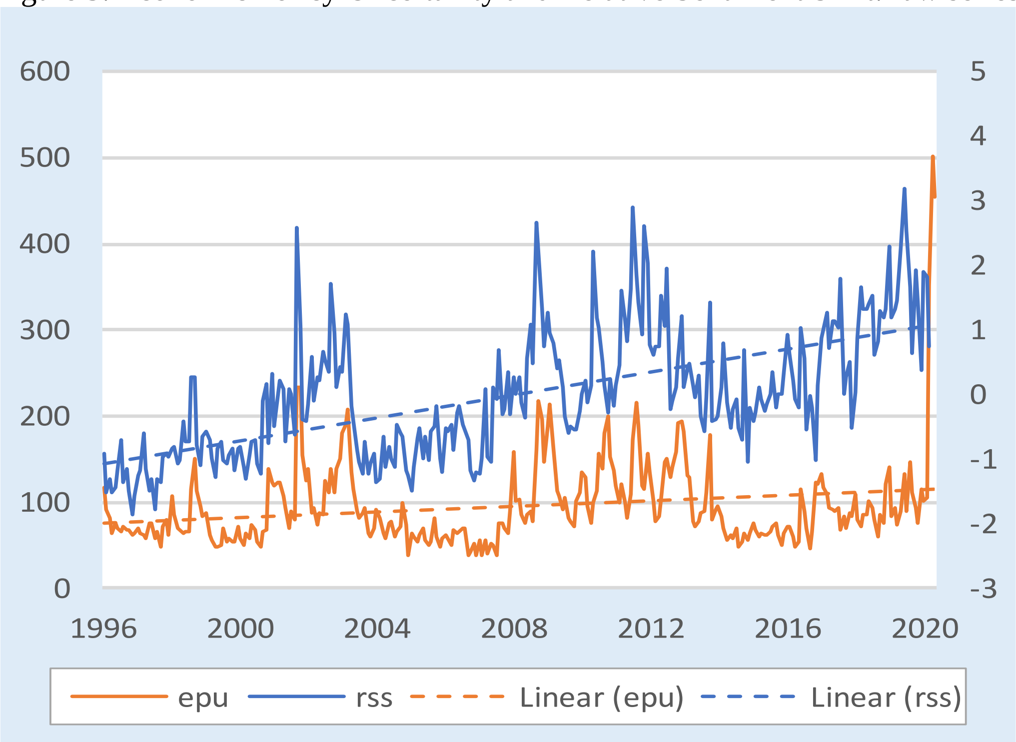
Notes: Stock index, industrial production and employment are in logs. Federal funds rate is in percent.

Figure 2: Economic Policy Uncertainty and Relative Sentiment Shift: standardized



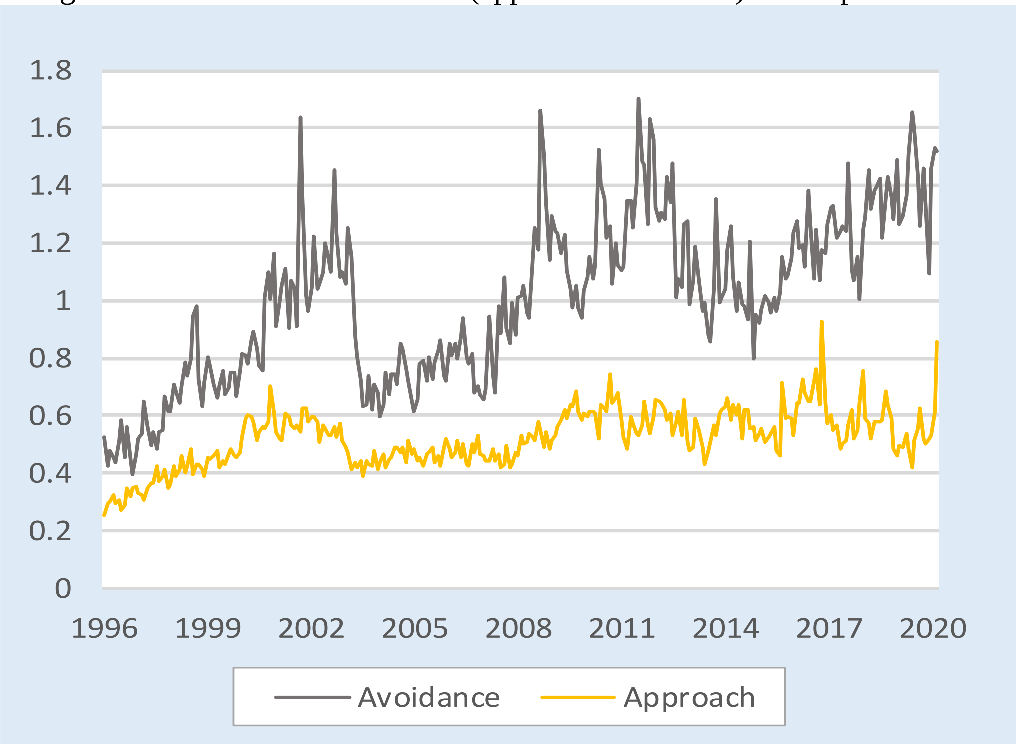
Notes: The EPU index is standardized using its mean and standard deviation during the sample period (1996m1-2019m12). Correlation coefficient, $\rho(EPU, RSS) = 0.5595$, significant at 1%.

Figure 3: Economic Policy Uncertainty and Relative Sentiment Shift: raw series



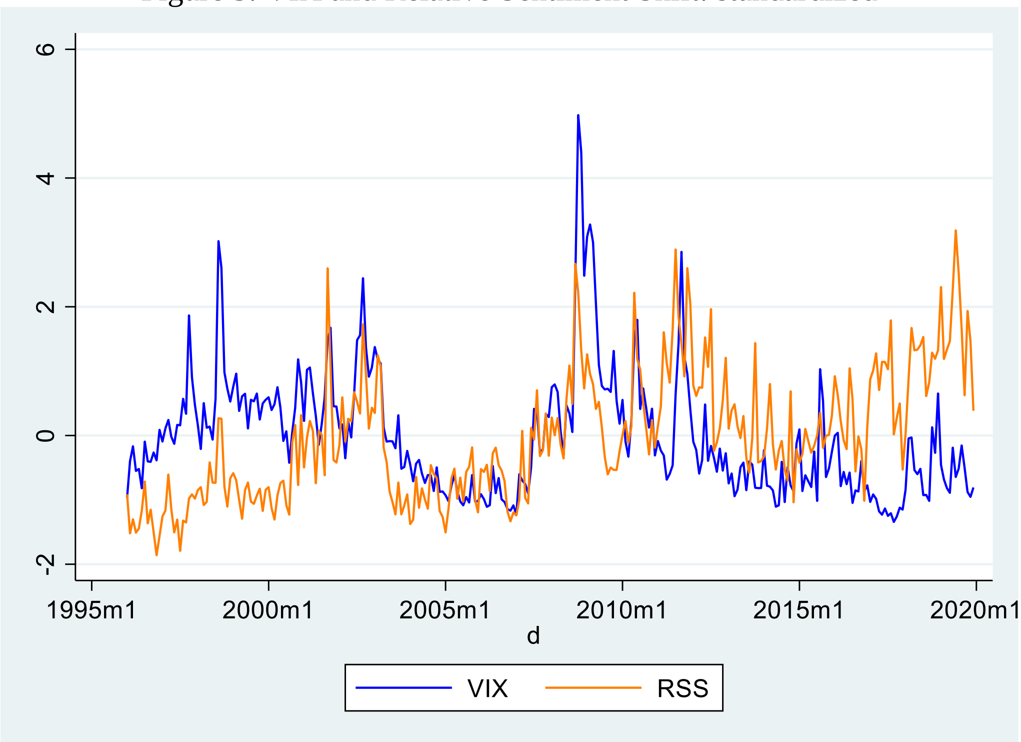
Notes: The EPU index (left axis) and the RSS index (right axis) are the raw series before standardization. RSS = (number of avoidance words – number of approach words)/size of text. Linear line of each index indicates the best linear fit of the series.

Figure 4: The number of emotion (approach/avoidance) words per article



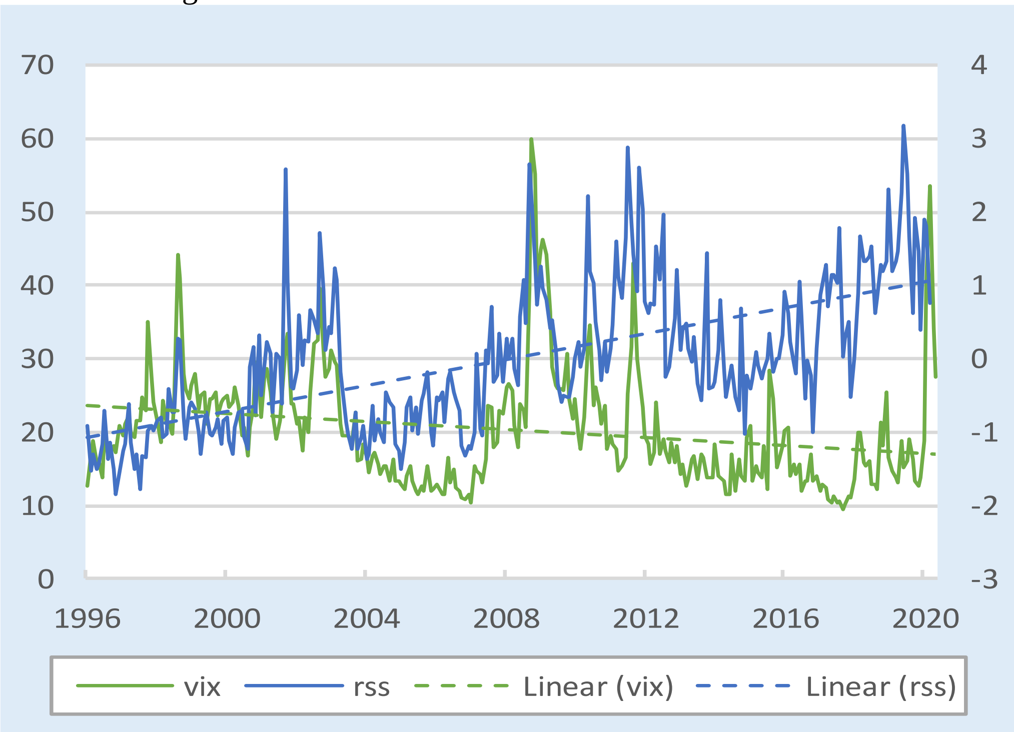
Notes: The monthly series of the ratio of the number of words in each emotional category – avoidance and approach – to the total number of articles.

Figure 5: VIX and Relative Sentiment Shift: standardized



Notes: The VIX is standardized using its mean and standard deviation during the sample period (1995m1-2019m12). Correlation coefficient, $\rho(VIX, RSS) = 0.2315$, significant at 1%.

Figure 6: VIX and Relative Sentiment Shift: raw series



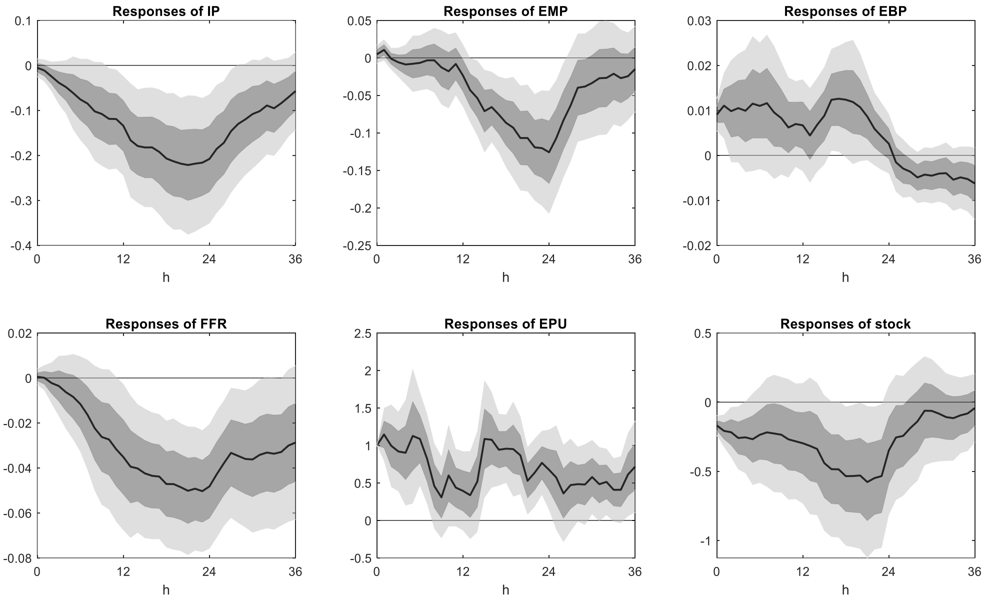
Notes: The dashed lines are linear trend of each uncertainty index. VIX (left axis) is in its raw level.

Table 3: Granger Causality

	RSS			EPU		
	(1) Predicting RSS	(2) Predicting Economic variables	(3) Lag length	(1) Predicting EPU	(2) Predicting Economic Variables	(3) Lag length
Stock	0.325	0.604	4	0.012**	0.814	1
FFR	0.618	0.089*	3	0.009***	0.097*	3
EBP	0.194	0.025**	3	0.001***	0.007***	3
IP	0.877	0.082*	4	0.275	0.581	4
EMP	0.781	0.515	4	0.158	0.914	1

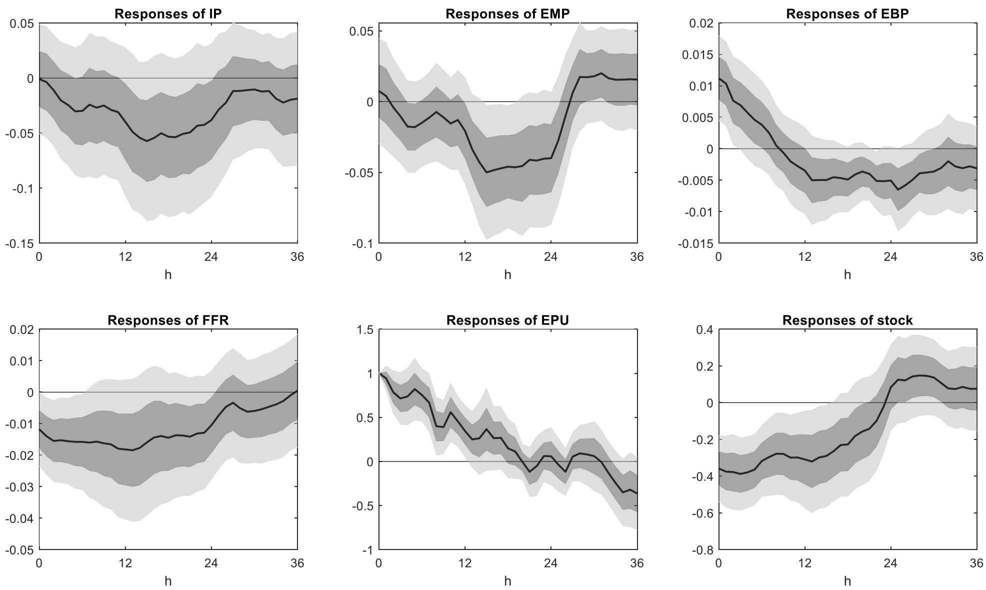
Notes: *, ** and *** indicate levels of significance of 10%, 5% and 1%, respectively. Column (1) reports the p-values of the Wald tests from the bivariate regressions of the uncertainty indices (either RSS or EPU) on the different economic variables. Column (2) reports the p-values of the Wald tests from the bivariate regressions of the economic variables on the uncertainty indices (either RSS or EPU). Column (3) indicates the lag lengths selected by the AIC criteria. All economic variable data is logged and filtered as in Hamilton (2017). The data is monthly from January 1996 until December 2020.

Figure 7: Impulse responses to uncertainty shocks: LP-IV (I)



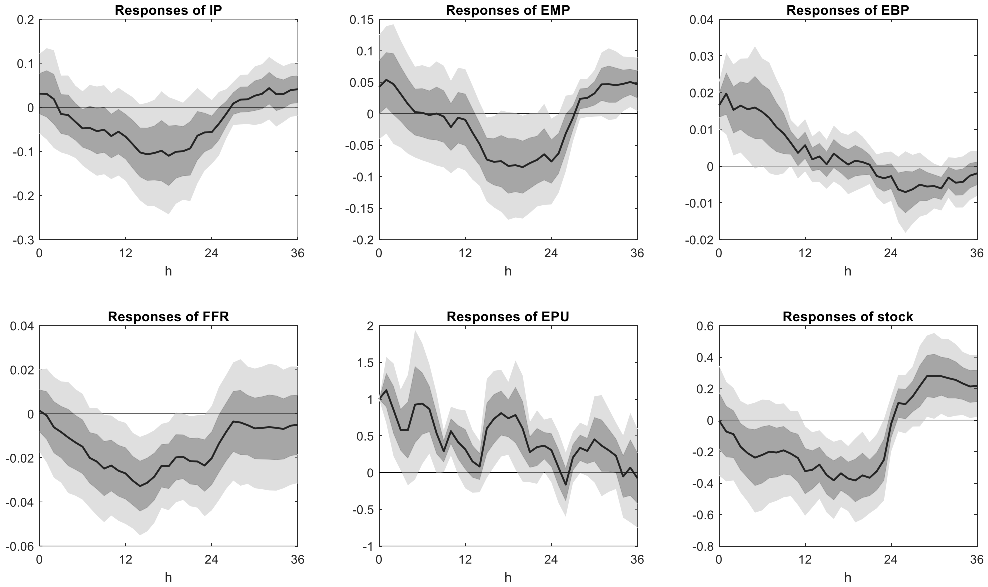
Notes: The IRFs are computed based on the LP-IV model with controls of 12 lags of the y's. The standard errors of the IRFs are computed by Newey-West HAC with $h+1$ lags for the local projections. The shaded areas indicate the 68% (dark) and the 95% (light) error bands. $F^{HOM} = 30.32$; $F^{HAC} = 20.84$.

Figure 8: Impulse responses to uncertainty shocks: LP-IV (II)



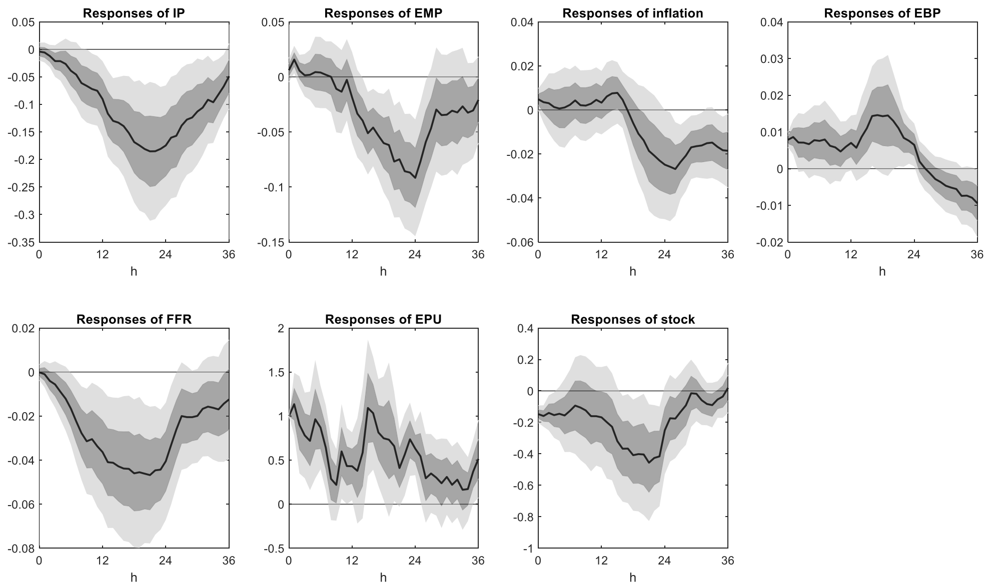
Notes: The IRFs are computed based on the LP-IV model with controls of 12 lags of the macroeconomic principal component factor. The standard errors of the IRFs are computed by Newey-West HAC with $h+1$ lags for the local projections. The shaded areas indicate the 68% (dark) and the 95% (light) error bands. $F^{HOM} = 49.50$; $F^{HAC} = 20.19$.

Figure 9: Impulse responses to uncertainty shocks: LP-IV (III)



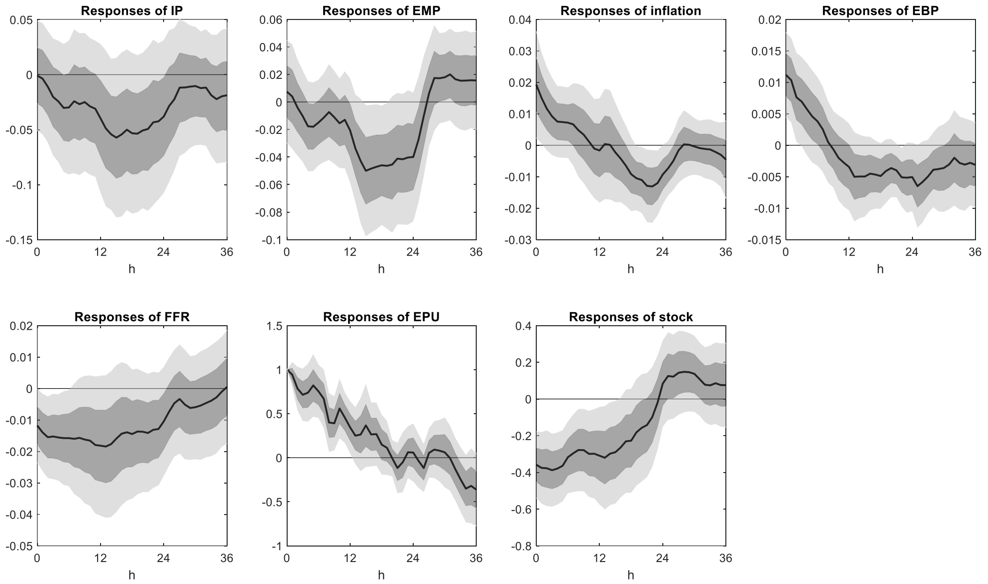
Notes: The IRFs are computed based on the LP-IV model with controls of 12 lags of the z's. The standard errors of the IRFs are computed by Newey-West HAC with $h+1$ lags for the local projections. The shaded areas indicate the 68% (dark) and the 95% (light) error bands. $F^{HOM}=14.96$; $F^{HAC}=11.78$.

Figure 10: Impulse responses to uncertainty shocks: LP-IV (I), inflation



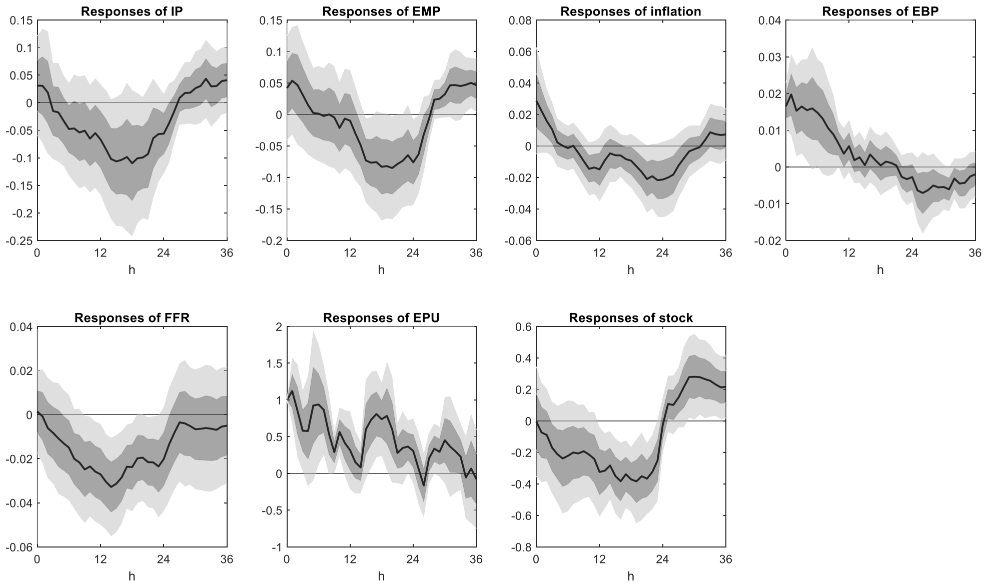
Notes: The IRFs are computed based on the LP-IV model with controls of 12 lags of the y's. The standard errors of the IRFs are computed by Newey-West HAC with $h+1$ lags for the local projections. The shaded areas indicate the 68% (dark) and the 95% (light) error bands. $F^{HOM}=29.24$; $F^{HAC}=19.59$.

Figure 11: Impulse responses to uncertainty shocks: LP-IV (II), inflation



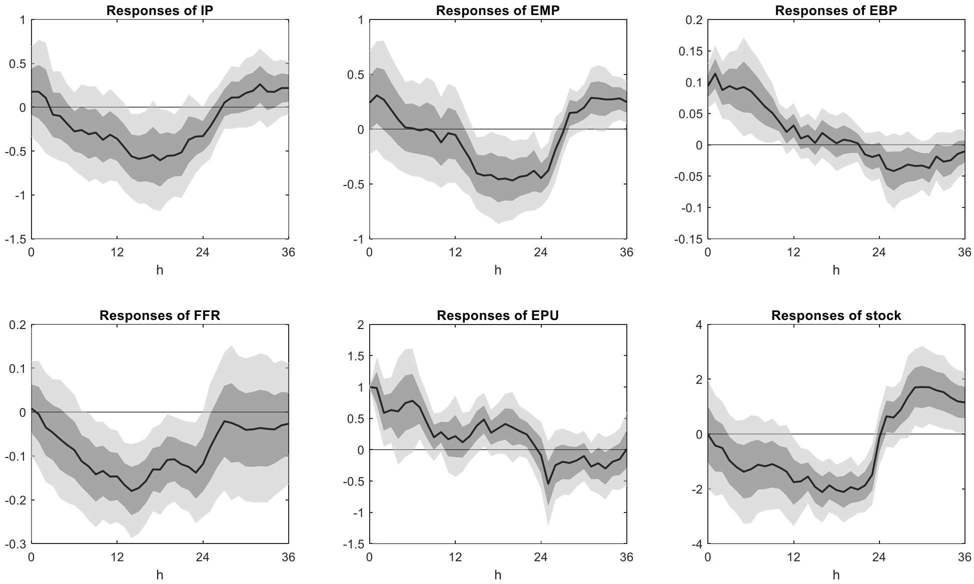
Notes: The IRFs are computed based on the LP-IV model with controls of 12 lags of the macroeconomic principal component factor. The standard errors of the IRFs are computed by Newey-West HAC with $h+1$ lags for the local projections. The shaded areas indicate the 68% (dark) and the 95% (light) error bands. $F^{HOM} = 49.50$; $F^{HAC} = 20.19$.

Figure 12: Impulse responses to uncertainty shocks: LP-IV (III), inflation



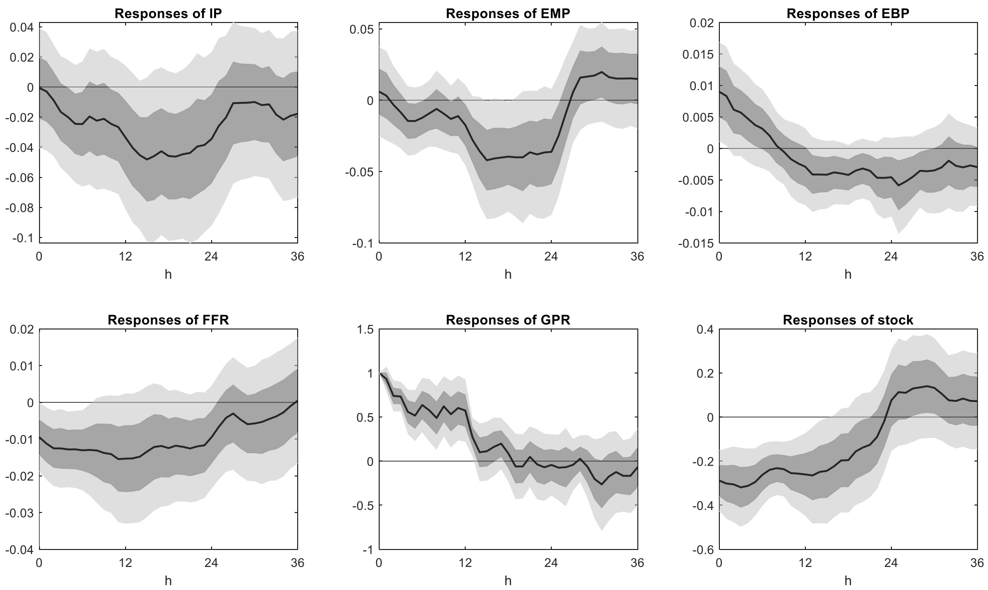
Notes: The IRFs are computed based on the LP-IV model with controls of 12 lags of the z's. The standard errors of the IRFs are computed by Newey-West HAC with $h+1$ lags for the local projections. The shaded areas indicate the 68% (dark) and the 95% (light) error bands. $F^{HOM} = 14.96$; $F^{HAC} = 11.78$.

Figure 13: Impulse responses to uncertainty shocks: LP-IV, VIX



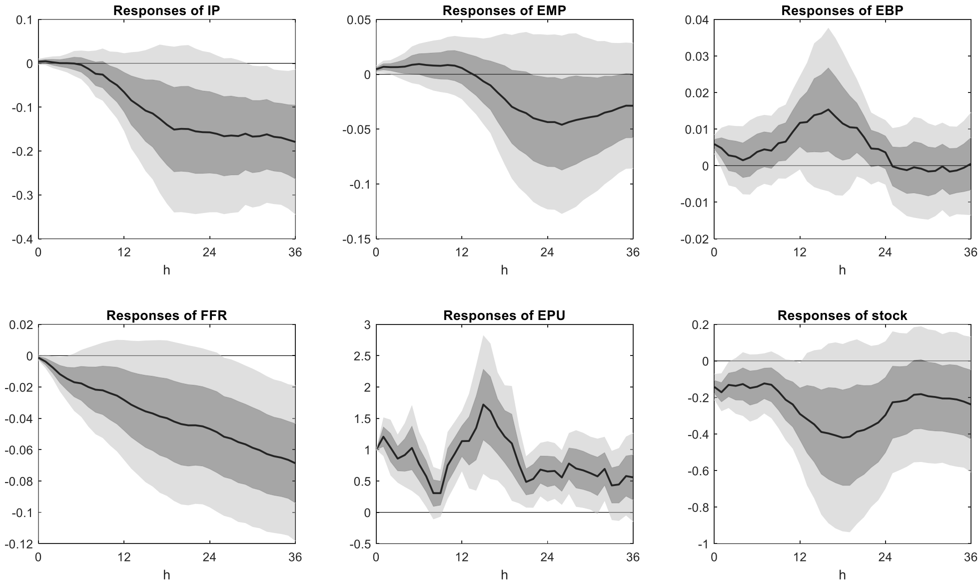
Notes: The uncertainty measure is the VIX. The IRFs are computed based on the LP-IV model with controls of 12 lags of the z's.. The standard errors of the IRFs are computed by Newey-West HAC with $h+1$ lags for the local projections. The shaded areas indicate the 68% (dark) and the 95% (light) error bands. $F^{HOM} = 8.95$; $F^{HAC} = 9.12$.

Figure 14: Impulse responses to uncertainty shocks: LP-IV, GPR



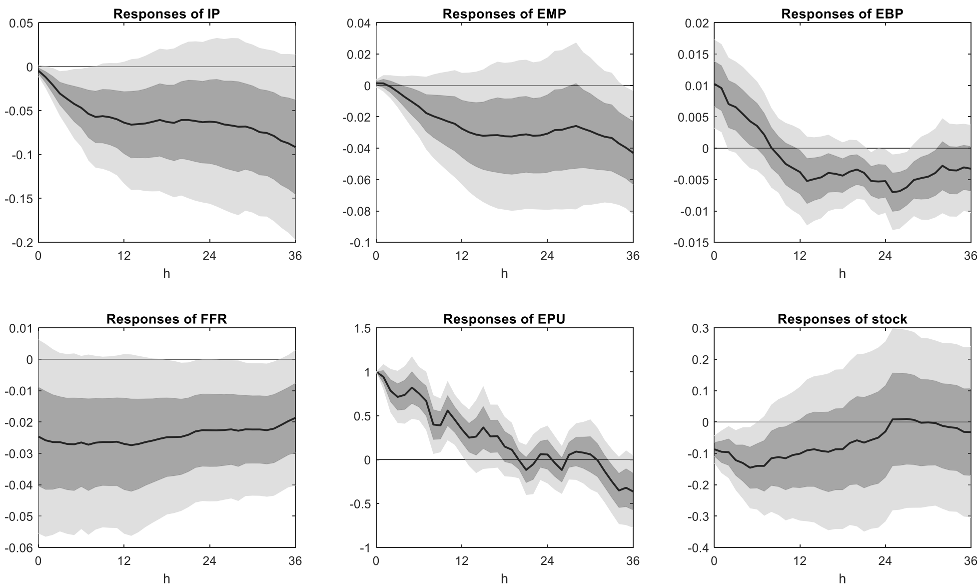
Notes: The uncertainty measure is the GPR. The IRFs are computed based on the LP-IV model with controls of 12 lags of the macroeconomic principal component factor. The standard errors of the IRFs are computed by Newey-West HAC with $h+1$ lags for the local projections. The shaded areas indicate the 68% (dark) and the 95% (light) error bands. $F^{HOM} = 38.98$; $F^{HAC} = 17.91$.

Figure 15: Impulse responses to uncertainty shocks: LP-IV (I), Differenced



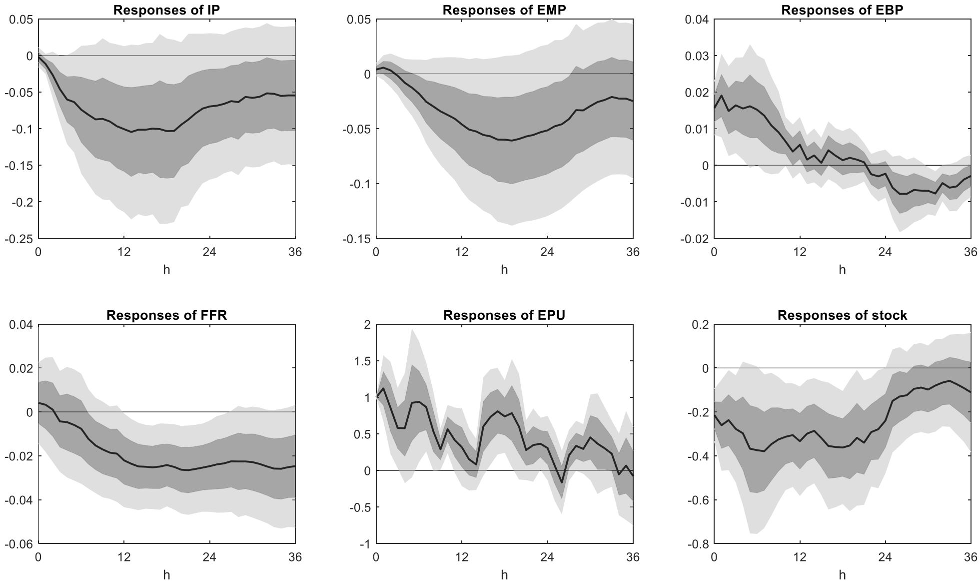
Notes: The variables (IP, EMP, Stock) are log differenced. The standard errors are computed by Newey-West HAC with $h+1$ lags for the local projections. Twelve lags of the y's are included. $F^{HOM} = 34.74$; $F^{HAC} = 25.52$.

Figure 16: Impulse responses to uncertainty shocks: LP-IV (II), Differenced



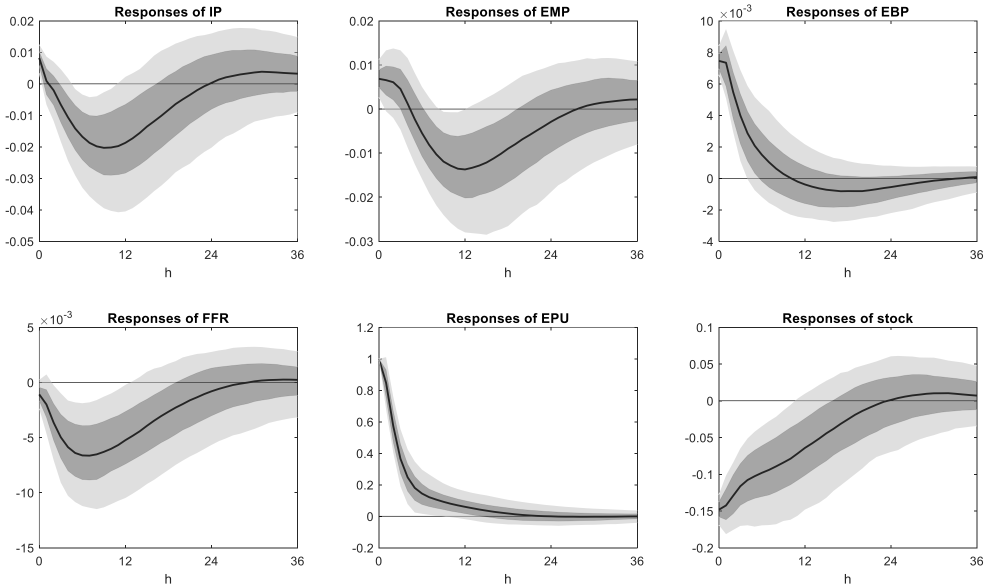
Notes: The variables (IP, EMP, Stock) are log differenced. The standard errors are computed by Newey-West HAC with $h+1$ lags for the local projections. Twelve lags of the factor are included. $F^{HOM} = 49.50$; $F^{HAC} = 20.19$.

Figure 17: Impulse responses to uncertainty shocks: LP-IV (III), Differenced



Notes: The variables (IP, EMP, Stock) are log differenced. The standard errors are computed by Newey-West HAC with $h+1$ lags for the local projections. Twelve lags of the z's are included. $F^{HOM} = 14.96$; $F^{HAC} = 11.78$.

Figure 18: Impulse responses to uncertainty shocks: SVAR-IV



Notes: The standard errors are computed by wild bootstrap of 10,000 replications. $F = 32.98$

Appendix: Data Transformation

The common principle of the data preparation for time series estimation is symmetric treatment of the actual data and the theoretical model (DeJong and Dave, 2011). In the conventional theoretical models, covariance-stationarity of the data is often required because most macroeconometric models, such as VAR, aim to estimate the impacts of a shock as deviations from the steady states. To obtain the covariance-stationary series, trend removal and isolation of cycles in log level original variables are involved.

There are three types of transformation techniques used, depending upon the assumptions of trend and cyclical behaviour: (i) linear detrending, (ii) differencing, and (iii) filtering.

If a series is characterised by a deterministic time trend, detrending by fitting the linear trend to the logged variable with OLS regression suffices to yield stationarity. In this case the series is said to be trend stationary. For unit root processes, differencing the series will induce stationarity. The choice between these two treatments hinges on the assumptions regarding which process, deterministic trend or unit root, provides a more reasonable representation of the logged variable. As Hamilton (1994) notes, if a series y_t follows a unit root process, subtracting the linear time trend from y_t will fail to remove the time trend in variance even though the time dependence in the mean can be removed by this treatment. In addition, if a trend stationary series is to be differenced, the differenced series becomes stationary but there will be a unit root process in the moving average representation, resulting in non-invertibility.

When there are structural breaks in the trend, the detrended series will show spurious persistence, causing the inferences based on the transformed data to become invalid (see Perron, 1989). To account for this problem, filtering techniques can be used for the removal of such trend behaviour. The most widely used technique has been HP filtering, which is designed to remove the trend from the cycle, provided that the trend is slowly evolving.

$\log y_t$ can be decomposed as $\log y_t = g_t + c_t$, where g_t is the growth component and c_t is the cyclical component, and the HP filter estimates g_t and c_t by minimising the following objective function:

$$\sum_{t=1}^{T} {c_t}^2 + \lambda \sum_{t=3}^{T} [(1-L)^2 g_t]^2$$

The parameter λ determines the smoothness of the evolving trend. If $\lambda = 0$, all fluctuations in $\log y_t$ will be assigned to the growth component. If $\lambda = \infty$, the weight on the trend component in the objective function becomes maximal, so that all variations in $\log y_t$ will be assigned to the cyclical component. In general, λ is set to 1,600 for quarterly data and to 129,600 for monthly data.

However, HP filtering faces substantial criticisms. For example, Cogley and Nason (1995) argue that use of an HP filter can generate a spurious business cycle even if the underlying raw data of the model does not exhibit cyclicality. In addition, Hamilton (2017) notes that the filtered values at the end of a sample are very different from those in the middle.