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On the Time-Varying Effects of Economic Policy Uncertainty on the US Economy*

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Abstract

We study the impact of Economic Policy Uncertainty (EPU) on the US Economy by using a VAR with time-varying coefficients. The coefficients are allowed to evolve gradually over time which allows us to discover structural changes without imposing them *a priori*. We find three different regimes, which match the three major periods of the US economy, namely the Great Inflation, the Great Moderation and the Great Recession. The initial impact on real GDP ranges between −0.2% for the Great Inflation and Great Recession and −0.15% for the Great Moderation. In addition, the adverse effects of EPU are more persistent during the Great Recession providing an explanation for the slow recovery. This regime dependence is unique for EPU as the macroeconomic consequences of Financial Uncertainty turn out to be rather time invariant.

I. Introduction

In the context of the Great Recession uncertainty has regained attention as a major driver of the business cycle. A high degree of uncertainty has the potential to dampen economic activity. However, measuring uncertainty is a challenging task. Therefore, it is not surprising that the literature provides several ways to quantify the level of uncertainty. One way to proxy a certain type of uncertainty is pioneered by Baker, Bloom and Davis (2016). They propose a newspaper-based index called Economic Policy Uncertainty (EPU) and provide empirical evidence that EPU shocks cause a decline in both, employment and industrial production. Based on this and other indices, a growing literature established further empirical evidence that uncertainty has a negative impact on economic activity, for example, Bloom (2009), Baker, Bloom and Davis (2012), Mumtaz and Zanetti (2013), Caldara *et al.* (2016) or Mumtaz and Surico (2018). We contribute to this literature by investigating whether the effect of EPU on the US economy is time varying. Therefore,

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this study puts emphasis on the adverse macroeconomic effects of EPU in dependence to the three major periods of the US economy, namely the Great Inflation (1965–82), the Great Moderation (1982–2007) and the Great Recession and its aftermath (2007-).[1]

To model the possibly time-varying impact of EPU shocks on the economy we use the time-varying parameter VAR (TVP-VAR) of Primiceri (2005). In the TVP-VAR the coefficients are allowed to evolve gradually over time. Thereby, it is possible to detect structural changes without imposing them *a priori*. However, this flexible structure does not come without costs. First, it bears a high risk of overfitting and, second, estimation is only feasible with a small number of variables. The first problem is typically tackled by imposing tight priors, which regularize the amount of time variation. The strength of these priors depends on a small set of hyperparameters, which have to be set by the researcher. The ideal choice is, however, subject to a trade-off. While an overly loose prior may result in overfitting, an overly tight prior may suppress possible time variation, which we want to discover. Most applications of the TVP-VAR use fixed values for the hyperparameters on an ad hoc basis or the values used by Primiceri (2005). It is, however, unclear whether these values should be employed in investigating uncertainty shocks. Moreover, previous applications do not take into account that estimation uncertainty about these hyperparameters may influence inference. We therefore estimate these hyperparameters using a fully Bayesian approach proposed by Amir-Ahmadi, Matthes and Wang (2020). We find that estimating the hyperparameters is important since using the benchmark values of Primiceri (2005) would suppress some amount of time variation. In order to address the second problem, we follow Korobilis (2013) and augment our TVP-VAR with a few factors, which capture information from a large panel of macroeconomic and financial variables without introducing a degrees of freedom problem, instead of selecting a few variables from over 100 potential variables. This enables us to investigate simultaneously the impact of EPU on variables, which represent real economic activity. This step turns out to be empirically relevant since EPU has an impact on a wide range of different variables.

Our main contribution is that we provide empirical evidence of a time-varying impact of EPU on real activity in the US economy by calculating time-varying impulse response functions, which are allowed to change at each point in time. It turns out that the time-varying impulse responses vary considerably for real GDP. During the 1970s, the time of the Great Inflation, the initial impact was relatively high (-0.2%) but was followed by overshooting. During the Great Moderation, EPU shocks had a smaller impact on the economy (-0.15%). Finally, during the Great Recession, the initial impact of EPU shocks again increased in size (-0.2%) and had a persistent effect on the economy, preventing a quick recovery. We therefore find three different regimes which match the three major periods of the US economy, namely the Great Inflation, the Great Moderation and the Great Recession. While there is a large literature which finds that uncertainty shocks are more powerful if the economy is in extreme conditions (see citation below), such as an economic recession and high financial stress, previous literature has ignored whether this effect is credible in a statistical sense. In order to fill this gap in the literature, we provide credible bands for the difference across the three regime-dependent impulse response functions.

[1]A comprehensive overview about the major economic and political circumstances during those periods can be found at Federal Reserve History.

The credible bands allow us to assess whether the difference between the impulse response functions (IRFs) is statistically credible. We find that the three regimes differ credibly from each other. In order to show that this result is not only driven by a time-varying initial impact of EPU shocks, we calculate the IRFs when fixing the covariance matrix of the error term at its posterior mean. This reveals that, in addition to the initial impact, the dynamic response of economic agents has changed over time. Interestingly, the regime dependence discovered in this study is unique in comparison to a financial uncertainty shock which turns out to be rather time invariant.

By modelling the time-varying effects of EPU on the US economy, we contribute to the growing literature focusing on the regime dependence of uncertainty shocks. Popp and Zhang (2016) and Caggiano, Castelnuovo and Nodari (2017b) employ a smooth transition model to show that the adverse effect of uncertainty depends on whether the economy is in recession or non-recession.[2] Castelnuovo, Caggiano and Pellegrino (2017) use an interacted VAR model and examine whether the effects of uncertainty are larger when the economy is at the zero lower bound. Alessandri and Mumtaz (2019) use a threshold model and condition on the state of financial markets. One study closely related to ours is Angelini *et al.* (2018). They use a small-scale vector autoregression and an identification through heteroskedasticity approach to unravel the macroeconomic effects of financial and macroeconomic uncertainty. They find that macroeconomic uncertainty shocks possibly have time-varying effects which are related to different macroeconomic volatility regimes, similar to the pattern of the three regimes uncovered by our empirical framework. But there are several remarkable differences compared to our study. Most importantly, we use EPU as the benchmark measure for uncertainty while they are using macroeconomic uncertainty based on Jurado, Ludvigson and Ng (2015).[3] Furthermore, they impose three volatility regimes *a priori*. However, there might be circumstances when defining the number of regimes is difficult. Additionally, we impose sign restrictions in line with the corresponding economic theory. Furthermore, the model type to account for time-varying parameters differs. Our study relies on a state-space model while they are using recursive and rolling window techniques. Finally, small-scale vector autoregressions may be subject to non-fundamentalness.[4] Of course, while the approaches above have their individual appeal, we stress that we neither have to define a certain number of regimes ex ante, nor do we have to condition on a threshold variable, such as recession/non-recession, a certain stance of monetary policy or on certain volatility regimes. Instead, we let the data guide us by allowing for time-varying model parameters. In doing so, we find three different regimes in line with the major period of the US economy. Two further studies, Benati (2014) and Mumtaz and Theodoridis (2018), head in a similar direction by using a TVP-VAR. We differ from Benati (2014) by also allowing for time variation in the autoregressive

[2]The conclusions drawn from these models might be too general. For example, the recessions in 1990 and 2001 were relatively mild compared to the recessions in 1981 and 2007 so that the simple classification recession vs. non-recession might miss the relevance of the respective depth of the recession.

[3]We also consider a model where EPU is replaced by the macroeconomic uncertainty measure based on Jurado *et al.* (2015).

[4]For details about the problem of non-fundamentalness see Lippi and Reichlin (1994).

coefficients which turns out to be crucial for our empirical results.[5] Furthermore, Benati (2014) focuses on the Great Recession while we are considering the historical evolution of the macroeconomic effects of EPU. Lastly, our study differs from Mumtaz and Theodoridis (2018) by using EPU to measure economic uncertainty compared to an model endogenously derived measure of uncertainty. In consequence, they imply that uncertainty is exogenous while we allow it to be endogenous.[6] In contrast to Mumtaz and Theodoridis (2018) we do not find evidence for a systematically decreasing macroeconomic effect of uncertainty. Summing up, we extend the literature about the nonlinear effects of EPU shocks on the US economy in a time-varying parameter environment over the last five decades.

The remainder of the paper is structured as follows. Section II discusses the underlying econometric model, section III provides an overview of the data, section IV contains the empirical results and section V concludes.

II. Methodology

TVP-FAVAR

In this section we discuss our econometric framework. We start with the TVP-VAR model based on Primiceri (2005). The model can be written in state-space form as

$$\boldsymbol{y}_t = \boldsymbol{z}_t' \boldsymbol{\beta}_t + \boldsymbol{\Omega}_t^{1/2} \boldsymbol{\epsilon}_t, \tag{1}$$

$$\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \boldsymbol{\eta}_t, \tag{2}$$

$$\boldsymbol{\alpha}_t = \boldsymbol{\alpha}_{t-1} + \boldsymbol{v}_t, \tag{3}$$

$$\log \boldsymbol{\sigma}_t = \log \boldsymbol{\sigma}_{t-1} + \boldsymbol{w}_t, \tag{4}$$

where $\boldsymbol{z}_t' = \boldsymbol{I}_n \otimes [\boldsymbol{y}_{t-1}', \ldots, \boldsymbol{y}_{t-p}']$, $\boldsymbol{\epsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{I}_n)$, $\boldsymbol{\eta}_t \sim N(\boldsymbol{0}, \boldsymbol{Q})$, $\boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{S})$ and $\boldsymbol{w}_t \sim N(\boldsymbol{0}, \boldsymbol{W})$.[7] The covariance matrix $\boldsymbol{\Omega}_t$ is decomposed as

$$\boldsymbol{\Omega}_t = \boldsymbol{A}_t^{-1} \boldsymbol{\Sigma}_t \boldsymbol{\Sigma}_t' (\boldsymbol{A}_t^{-1})', \tag{5}$$

where $\boldsymbol{\Sigma}_t$ is a diagonal matrix and $\boldsymbol{A}_t$ is a lower triangular matrix with ones on the main diagonal. Let $\boldsymbol{\alpha}_t$ denote the $n(n-1)/2$ vector of below-diagonal elements of $\boldsymbol{A}_t$ and let $\boldsymbol{\sigma}_t$ denote the vector consisting of all n diagonal elements in $\boldsymbol{\Sigma}_t$. Both, the Bayesian Information Criterion and the Hannan–Quinn Criterion suggest to use a model with two lags.[8]

In this setup the autoregressive coefficients ($\boldsymbol{\beta}_t$), the contemporaneous covariances ($\boldsymbol{\alpha}_t$) and the log standard deviation ($\log \boldsymbol{\sigma}_t$) are allowed to evolve over time according to a random walk process and thereby allow us to detect structural breaks or regime changes. However, in contrast to regime switching models, this model does not need to impose a fixed number

[5] Note that Benati (2013) allows for time-varying autoregressive coefficients. However, in the later article he argues that evidence on this part of time variation is relatively weak.

[6] Several theoretical studies argue that uncertainty is endogenous, see for example, Bachmann and Moscarini (2011), Plante, Richter and Throckmorton (2016) or Fajgelbaum, Schaal and Taschereau-Dumouchel (2017).

[7] Note that $\boldsymbol{Q}$, $\boldsymbol{S}$ and $\boldsymbol{W}$ are assumed to be independent.

[8] In order to determine the lag length, a time-invariant vector autoregression with three factors, Financial Uncertainty and EPU has been used.

of regime changes prior to estimation as the parameters are allowed to take on a different value in each period. This flexible model structure, however, bears the risk of overfitting. The covariance matrix $\boldsymbol{Q}$ controls how much $\boldsymbol{\beta}_t$ is likely to change from t to $t+1$. Typically, researchers put a tight prior on $\boldsymbol{Q}$ in order to impose gradual changes in the parameters over time. The exact choice, however, is not straightforward. While an overly tight prior on $\boldsymbol{Q}$ may suppress possible time variation, an overly loose prior may result in overfitting the data. We employ similar priors to those used in Primiceri (2005),

$$\boldsymbol{\beta}_0 \sim N(\hat{\boldsymbol{\beta}}_{OLS}, V(\hat{\boldsymbol{\beta}}_{OLS})), \tag{6}$$

$$\boldsymbol{\alpha}_0 \sim N(\hat{\boldsymbol{\alpha}}_{OLS}, V(\hat{\boldsymbol{\alpha}}_{OLS})), \tag{7}$$

$$log\boldsymbol{\sigma}_0 \sim N(log\hat{\boldsymbol{\sigma}}_{OLS}, \boldsymbol{I}_n), \tag{8}$$

$$\boldsymbol{Q} \sim IW(k_{\boldsymbol{Q}} \cdot V(\hat{\boldsymbol{\beta}}_{OLS}), v_1), \tag{9}$$

$$\boldsymbol{S} \sim IW(k_{\boldsymbol{S}} \cdot V(\hat{\boldsymbol{\alpha}}_{OLS}), v_2), \tag{10}$$

$$\boldsymbol{W} \sim IW(k_{\boldsymbol{W}} \cdot \boldsymbol{I}_n, v_3), \tag{11}$$

where OLS denotes the OLS estimator using a training sample of 10 years, $k_{\boldsymbol{Q}}, k_{\boldsymbol{S}}$ and $k_{\boldsymbol{W}}$ are hyperparameters set by the researcher and v denotes the degrees of freedom and is set such that the Inverse Wishart prior has a finite mean and variance.

The importance of the hyperparameters $k_{\boldsymbol{S}}, k_{\boldsymbol{W}}$ and in particular of $k_{\boldsymbol{Q}}$ in this setup has been highlighted by Primiceri (2005) and Cogley and Sargent (2005). However, most applications with this setup use fixed values on an ad hoc basis or the estimated values of Primiceri (2005).[9] It is, however, unclear whether the estimated values of Primiceri (2005) should be employed in other applications. Furthermore, previous applications using this model class do not take into account that uncertainty about the hyperparameters may influence inference. Therefore, we estimate the hyperparameters $k_{\boldsymbol{Q}}, k_{\boldsymbol{S}}$ and $k_{\boldsymbol{W}}$ jointly with all other model parameters using a fully Bayesian approach as proposed by Amir-Ahmadi *et al.* (2020). This approach estimates the hyperparameters in a data-based fashion and takes the surrounding uncertainty into account.

The approach of Amir-Ahmadi *et al.* (2020) exploits the finding that only the prior of $\boldsymbol{X}$, $\boldsymbol{X} \in \{\boldsymbol{Q}, \boldsymbol{S}, \boldsymbol{W}\}$, depends on $k_{\boldsymbol{X}}$, and that, conditional on $\boldsymbol{X}$, all other model densities are independent from $k_{\boldsymbol{X}}$. Thus, the conditional posterior is

$$p(k_{\boldsymbol{X}}|\boldsymbol{X}) \propto p(\boldsymbol{X}|k_{\boldsymbol{X}})p(k_{\boldsymbol{X}}), \tag{12}$$

where $p(\boldsymbol{X}|k_{\boldsymbol{X}})$ denotes the prior of $\boldsymbol{X}$ and $p(k_{\boldsymbol{X}})$ the prior of $k_{\boldsymbol{X}}$, and can be obtained by a Metropolis-within-Gibbs step, as all other model densities cancel out in the acceptance probability.[10] We formulate relatively non-informative hierarchical inverse gamma priors for $p(k_{\boldsymbol{X}})$.

[9] Primiceri (2005) estimates the hyperparameters over a small grid by maximizing the marginal likelihood.
[10] For more details see Amir-Ahmadi *et al.* (2020).

The curse of dimensionality typically forces researchers to include only a small number of variables in their VAR models. Primiceri (2005) for example uses the 3-Month Treasury Bill Yield as a measure for monetary policy, the unemployment rate as a measure of economic activity and inflation measured by the growth rate of a chain weighted GDP Price Index. However, a variety of other measures for economic activity or inflation exist and results may be sensitive to such choices. Furthermore, these variables may not fully represent the economy so that it may be necessary to include further variables, for example, variables which capture information about the nature of consumers, organizations, businesses, financial or housing markets in order to be able to model the complex structure of the economy and to overcome the problem of non-fundamentalness.[11] Thus, instead of selecting a few variables from a set of over 100 potential variables, we follow Bernanke, Boivin and Eliasz (2005) and increase the information set used in a VAR by augmenting it with a few factors which capture the information of a large data set without introducing a degrees of freedom problem. Therefore, our results are less sensitive to the concrete choice of variables. That is, $\boldsymbol{y}_t$ consists of k factors and further variables of interest. The latter are typically policy or observable variables. In our benchmark model, these consist of Financial Uncertainty and EPU.

We estimate the factors and model parameters following Stock and Watson (2005) and Korobilis (2013) and use a simple two-step approach.[12] In the first step the factors $\boldsymbol{f}_t (k \times 1)$ are estimated using the first k principal components (PC) obtained from the singular value decomposition of the data matrix $\boldsymbol{x}_t$ $(m \times 1)$ with $k \ll m$. The data matrix $\boldsymbol{x}_t$ contains our panel of macroeconomic and financial variables. We use the same factor rotation as Bernanke *et al.* (2005) to ensure that factors are orthogonal to the observable variables. The PC estimates are then treated as observations. In the second step, the parameters of the vector autoregression can be estimated conditional on these observed factors. In order to model the dependence between the PC and the observable variables, the vector of endogenous variables in the VAR model (1) is given by $\boldsymbol{y}_t = [\boldsymbol{f}_t', fu_t, epu_t]'$. Each macroeconomic or financial variable x_{it}, for $i = 1, \ldots, m$, is linked to the k factors ($\boldsymbol{f}_t$), to Financial Uncertainty (fu_t) and Economic Policy Uncertainty (epu_t) via the factor regression

$$x_{it} = \boldsymbol{\lambda}_i^f \boldsymbol{f}_t + \lambda_i^{fu} fu_t + \lambda_i^{epu} epu_t + \epsilon_{it} \tag{13}$$

where $\boldsymbol{\lambda}^f$ is $(1 \times k)$, λ^{fu}, λ^{epu} are scalars and $\epsilon_{it} \sim N(0, \sigma_i^2)$.[13] Following Bernanke et al. (2005) and Korobilis (2013) we estimate the model using three factors.[14]

[11] This concern typically arises if the econometrician does not use an information set which is identical or at a minimum closely overlapping to that used by policy makers, see Lippi and Reichlin (1994).

[12] Estimating the latent factors and model parameters jointly in one step, by making use of MCMC methods, allows for full treatment of uncertainty surrounding the latent factors and model parameters. Nevertheless, identification restrictions are needed in this approach, which lead to flat (unidentified) impulse response functions, useless for economic interpretation. For a discussion of these aspects see Korobilis (2013).

[13] Note that the set of observable variables depends on the specification of the model. The specification presented above corresponds to the baseline model.

[14] We consider also estimation with four factors. As highlighted by Stock and Watson (1998), while the space spanned by the factors is still estimated consistently when the number of factors is overestimated though efficiency is reduced, an underestimation of the number of factors results in an inconsistent model as potentially important dynamics will not be captured by the factors. Bernanke *et al.* (2005) p. 406) argue that 'if the additional information was irrelevant then adding one factor to the VAR would render the estimation less precise, but the estimate should remain unbiased. We would thus not expect the estimated response to change considerably'. This is exactly what we

Identification

In order to identify an EPU shock in an economically plausible fashion, we follow the approach suggested in Canova and Nicolo (2002) and Uhlig (2005) and use a combination of sign and magnitude restrictions on the contemporaneous responses of some variables in $\boldsymbol{x}_t$. Technically, these sign and magnitude restrictions are implemented using the algorithm of Ramirez, Waggnoner and Zha (2010). First, we draw an $n \times n$ matrix, $\boldsymbol{J}$, from independent N(0,1) random variables. Second, calculating $\bar{\boldsymbol{Q}}$ from the QR decomposition of $\boldsymbol{J}$ provides a candidate structural impact matrix such as $\boldsymbol{A}_{0,t} = \boldsymbol{A}_t^{-1} \boldsymbol{\Sigma}_t \bar{\boldsymbol{Q}}$. The candidate contemporaneous impulse response functions of $x_{1,t}, \ldots, x_{m,t}$ are then given by

$$\boldsymbol{IRF}_{0,t} = \boldsymbol{\Lambda} \times \boldsymbol{A}_{0,t}, \tag{14}$$

where $\boldsymbol{\Lambda}$ denotes the $m \times n$ matrix of factor loadings. The candidate matrix $\boldsymbol{A}_{0,t}$ is accepted if it satisfies the sign and magnitude restrictions. Up to this point, the shock is only set identified. Therefore, we follow the suggestion in Fry and Pagan (2011) and collect for each draw from the posterior 100 candidates $\boldsymbol{A}_{0,t}$ which satisfy the restrictions. Out of this set of 'admissible models' we select the one with elements closest to the median across these 100 candidates.[15] Following this approach we avoid, compared to a Cholesky-based identification scheme, imposing zero restrictions and hence eschew an ordering of the variables which may be difficult to establish in an economically reasonable fashion.[16] This is especially important for uncertainty shocks since, for instance, Caggiano, Castelnuovo and Groshenny (2014) assume uncertainty to be slow-moving while Gilchrist, Sim and Zakrajšek (2014) assume it to be fast-moving. Instead, we impose restrictions in accordance with economic theory. We assume that the EPU shock has a positive influence on itself, a negative contemporaneous effect on consumption and investment as well as a positive contemporaneous effect on unemployment as suggested by the *precautionary savings* and *real options* channel developed by Romer (1990) and Bernanke (1983). However, a financial uncertainty shock may be associated with the same sign pattern. While it is easy to describe the difference between these shocks verbally, separating them econometrically is a challenging task. But doing so can be fundamental with respect to the macroeconomic characteristics of these shocks. To distinguish the EPU shock from a financial uncertainty shock, we assume that an EPU shock has the largest contemporaneous impact on EPU itself among all shocks. The same restriction is imposed on the financial uncertainty shock. These magnitude restrictions are similar to maximizing the fraction of the forecast error variance at horizon zero which has been pioneered by Uhlig (2004a) and Uhlig (2004b).[17] Table 1 provides an overview of the imposed restrictions.

The uncertainty literature is coming up with several, partly similar, identification strategies. An analogous identification approach has been used by Caldara *et al.* (2016). They impose the same magnitude restrictions as we do, but for the first six periods of their IRF.

find in our estimation. Adding an additional factor gives qualitatively similar results, but the IRFs are becoming more volatile and less smooth.

[15] For more details see Fry and Pagan (2011).

[16] Furthermore, simulation experiments suggest that identification based on sign restrictions performs well relative to identification methods based on contemporaneous zero restrictions, see Canova and Pina (1998), and that a standard Cholesky assumption can severely distort the impulse response functions, see Carlstrom, Fuerst and Paustian (2009).

[17] This approach has also been used by Benati (2013) to identify an EPU shock.

TABLE 1

Imposed sign restrictions

Variable	*FU shock*	*EPU shock*
Financial uncertainty	+	
EPU		+
Consumption	−	−
Investment	−	−
Unemployment	+	+
Magnitude restriction	On itself	On itself

Furthermore, they use a penalty function approach to select a single candidate from the set of admissible models. Another connatural identification strategy is used in Ludvigson, Ma and Ng (2019). They combine narrative sign restrictions with external variable constraints to identify an uncertainty shock.[18] Therefore, the major difference, in terms of identification between our study and the two just mentioned contributions, condenses on how to narrow the set of admissible models. While we are using a mixture of sign and magnitude restrictions in line with economic theory, Caldara *et al.* (2016) use (only) magnitude restrictions and Ludvigson *et al.* (2019) use narrative sing restrictions combined with external variable constraints. Another identification approach, which differs majorly in a econometric sense from the studies mentioned above, is employed in Mumtaz and Theodoridis (2018). Their measure of uncertainty is derived model endogenously. But in contrast to many other studies, Mumtaz and Theodoridis (2018) assume that uncertainty enters the model as an exogenous variable. Interestingly, their measure of uncertainty and the measure of Jurado *et al.* (2015) are highly correlated. Summing up, all of these identification strategies result in plausible impulse response functions in a historical and economical sense.

III. Data

We estimate the model based on a large data set covering 124 time series for the US economy. All variables are seasonally adjusted if necessary and standardized for the estimation. To account for the influence of Financial Uncertainty we rely on the corresponding state of the art measure developed in Ludvigson *et al.* (2019). EPU is approximated by the newspaper-based index suggested in Baker *et al.* (2016).[19] Our quarterly data set starts in 1960:Q3 and ends in 2018:Q4. The names and the transformation codes of all series can be found in Table B.1 of the appendix.

IV. Empirical results

In what follows, we present our empirical results. We are considering four different models which differ with respect to the measure of economic uncertainty and additional control

[18] Details about narrative sign restrictions can be found in Antolín-Díaz and Rubio-Ramírez (2018).

[19] Since the new EPU index is only available from 1985 to 2018 and the historical uncertainty index is available from 1900 to 2014, we combine them by normalizing the historical index to have the same mean and standard deviation as the new Economic Policy Uncertainty index during the overlapping period. Estimating our TVP-VAR models based on the historical EPU index yields very similar results.

variables. In the first model, referred to as the baseline model, the set of observable variables consists of Financial Uncertainty and EPU. The remaining three models are considered to strengthen the overall empirical evidence. In the second model, we exchange EPU by the uncertainty measure derived by Jurado *et al.* (2015). Thereby, we are able to evaluate whether the pattern in the IRFs is exclusive to a certain measure of economic uncertainty. Furthermore, differences in the IRFs of these two models may be due to differences in the definition of these two uncertainty measure. While the proxy of Jurado *et al.* (2015) captures mainly macroeconomic uncertainty, that of Baker *et al.* (2016) additionally considers political uncertainty. The third model considers a single observable variable, namely EPU. Therefore, we do not control for Financial Uncertainty. This is a reasonable extension to evaluate the influence of ignoring Financial Uncertainty in the identification scheme. Finally, in the fourth model, we explicitly account for the stance of monetary policy. That is, model three is extended by the Federal Funds Rate. Note that no matter which model is estimated, the identification strategy rests on the restrictions shown in Table 1.

In the following, we first focus on the results of our baseline model, followed by a second step, where we compare our baseline model with the three remaining models. In a third step, we compare the EPU shock with a Financial Uncertainty shock, and in a fourth step, we calculate the IRFs by fixing the covariance matrix of the error term of each model at its posterior mean. The fifth step compares the results of our baseline model, based on estimated hyperparameters, with the results from the same model based on hyperparameters used in Primiceri (2005). Finally, we analyse the responses of a wider range of variables to an EPU shock. Figures A.1–A.5 in the appendix display the IRFs for each of the six steps. Each plot consists of seven subplots. The three dimensional graph on the left displays the change in the response pattern over time. The upper three sub figures on the right display the effect of EPU on the respective variable for three different time periods: the Great Inflation, the Great Moderation and the Great Recession.[20] The lower three sub Figures display the difference between the three time periods along with 68% (dark blue) and 90% (light blue) credible regions. Since the model has been estimated with standardized data, the IRFs are standardized back such that the magnitude can be interpreted in the unit of measurement with respect to Table B.1.

Results from baseline model

Figure A.1a displays the response of real GDP to an EPU shock based on our baseline model and reveals substantial time variation. In principle, time-varying IRFs can vary along three dimensions: the initial impact, the overshooting behaviour[21] and the persistence of the shock. The IRF profile of real GDP varies across all three dimensions. That is, the first dimension, the initial impact, is relatively high (−0.2%) during the 1970s and the early 1980s (the Great Inflation), starts to decline in the early 1980s and stays stable (−0.15%)

[20] We have chosen the following dates to be representative for the Great Inflation (1965–82), Great Moderation (1982–2007) and Great Recession (2007-), respectively: 1975:Q1, 1996:Q1 and 2008:Q4. As the 3-D graphs suggest, using different dates would not influence our core results.

[21] Note that we define overshooting as the change in the sign of the first derivative of the IRF appearing during the Great Inflation. Furthermore, several models assign some probability to overshooting in the sense of Bloom (2009) during the Great Inflation, who defines it as a change in the sign of the IRF. This type of overshooting is the strongest in the model including the Federal Funds Rate.

until the early 2000s (the Great Moderation) before it finally becomes larger (−0.2%) with the onset of the financial crisis (the Great Recession). The overshooting behaviour, the second dimension, is pronounced during the 1970s and disappears from the 1980s onwards. Lastly, also the third dimension, the persistence of the shock, changes over time. From the 1970s onwards, the dynamic effects of the shocks are short-lived but became more persistent with the onset of the financial crisis. Summing up, the macroeconomic effects of a shock in EPU seem to depend on the major periods of the US economy rather than on business cycles at lower frequencies. This is plausible since both, the Great Inflation and the Great Recession, were periods with fundamental economic turmoil while the Great Moderation has only been interrupted by two mild recessions in 1990 and 2001. Next, we focus on whether the responses differ statistically credible across these three major periods. The three graphs on the lower right part of Figure A.1a show the credible bands corresponding to the difference between these three major periods. It turns out that the IRFs between the Great Inflation and the Great Moderation differ credibly from each other at the 68% level, the IRFs of the Great Inflation and Great Recession differ at the 90% level as well as the IRFs between the Great Moderation and the Great Recession. The difference between these three regimes becomes even more evident when calculating the IRFs with the variance–covariance matrix of the error term fixed at its posterior mean (see Figure A.3a). Within this setup, the three regimes differ credibly from each other at the 90% level. Thus, in our baseline model we find a statistically credible difference between all three periods.

Comparison with different models

Comparing the results from the models where economic uncertainty is approximated by the measure developed in Baker *et al.* (2016) to the model where economic uncertainty is approximated by the measure developed in Jurado *et al.* (2015), shown in Figure A.1b, reveals that the responses of real GDP exhibit some similarities. However, the major distinction is that not all pairwise regime comparisons in the model with macroeconomic uncertainty exhibit a credible difference at the 68% level. Thus, while both shocks have a similar effect, we find less time variation, in a statistical sense, for a macroeconomic uncertainty shock. Figure A.1c shows the EPU shock in the model where we drop Financial Uncertainty. The IRFs again reveal a similar regime dependence. However, the three regimes differ less in a statistical sense from each other compared to the model where we explicitly distinguish between EPU and Financial Uncertainty. Therefore it seems to be important to distinguish between EPU and Financial Uncertainty as we did in our baseline model. Finally, Figure A.1d shows that adding the Federal Funds Rate to the model does not change the results.

Comparison with financial uncertainty

Figure A.2 shows the response of real GDP to a financial uncertainty shock. By comparing Figures A.1a and A.2 we find that the effect size of a financial uncertainty shock is smaller compared to the effect size of an EPU shock. This result holds for all time periods. In addition, we find the effect of a financial uncertainty shock to be rather constant over time since we do not observe statistically credible differences between any IRF pair. Thus, the result that the IRFs match the three major periods of the US economy is unique for EPU.

Comparison with constant covariance matrix

During the previous analysis we allowed for time variation in the autoregressive coefficients $\boldsymbol{\beta}_t$ and in the error covariance matrix $\boldsymbol{\Omega}_t$. The time variation of the IRFs in Figure A.1a–d might be due to either changes in $\boldsymbol{\beta}_t$, or due to changes in $\boldsymbol{\Omega}_t$. In this section, the covariance matrix $\boldsymbol{\Omega}_t$ is fixed at its posterior mean.[22] This allows us to decompose the nature of the time-varying IRFs into changes in the dynamic response of economic agents and changes of the initial impact of uncertainty shocks. Figure A.3a–d show the IRFs for real GDP based on all four models with a time-invariant covariance matrix. The initial impact is the same over time by construction. Figure A.3a reveals that in our baseline model, the IRF still varies along the other two dimensions, the overshooting behaviour and the persistence of the shock. Overshooting is pronounced during the Great Inflation, but does not appear from the Great Moderation onwards. Furthermore, the persistence of the shock increases with the onset of the Great Recession. Interestingly, testing whether the three periods differ from each other suggests credible differences between all three subperiods at the 90% credible region. This finding suggests that substantial structural changes occurred moving from one regime to another and highlights our key finding that we identified three different regimes, namely the Great Inflation, the Great Moderation and the Great Recession. The Great Inflation and the Great Recession differ in how the economy responds to an EPU shock. In the Great Inflation period the responses are characterized by an overshooting behaviour and the responses in the Great Recession are characterized by a persistent effect of an EPU shock.[23] Thus, the overshooting and the persistence of the responses separate these episodes in a statistically credible sense from each other. These results hold for the other three models, see Figure A.3b–d.

Comparison with fixed hyperparameters

As a further robustness check and in order to highlight the relevance of estimating the hyperparameters by using the approach of Amir-Ahmadi *et al.* (2020), we compare the IRFs from our baseline model with the ones obtained by using the fixed values in Primiceri (2005). Figure A.4 displays the impulse responses based on the benchmark values. The IRFs still reveal a correlation with the three major business cycles of the US economy. Thus our main result is robust to using the baseline hyperparameters. However, comparing Figure A.1a with Figure A.4 reveals that the baseline values suppress some amount of time variation in the IRFs, as can be seen by a lower credible level in the pairwise comparison.

A broader macroeconomic perspective

Finally, we adopt a broader macroeconomic perspective to evaluate the adverse effects of EPU. Figure A.5a–d display the response of real gross investment, real consumption, the civilian unemployment rate and the ISM Manufacturing PMI, respectively, to an EPU

[22] To be more precise, the covariance matrix $\boldsymbol{\Omega}_t$ is only kept constant for the calculation of the IRFs. During the estimation of the models it is allowed to vary over time.

[23] Further research is needed to come up with structural explanations for this pattern. This is, however, beyond the scope of this paper.

shock. Their profiles differ, beside minor movements, mostly in terms of the effect size. Comparing the size of the initial impact on investment (GI: −1%; GM: −0.4%; GR: −0.9%) with the size of the initial impact on consumption (GI: −0.15%; GM: −0.1%; GR: −0.05%), shows that consumption is less sensitive to an EPU shock than investment. This finding is in line with Prüser and Schlösser (2019) who found a similar result for European economies and indicates that the real options is, in an absolute sense, more important than the precautionary savings channel. In the case of unemployment, shown in Figure A.5c, the initial impact varies slightly around an increase of 0.05% points. Therefore, the empirical effect of a shock in EPU on unemployment is economically small.[24] In contrast, the initial impact on real GDP, shown in Figure A.1a, ranges between almost −0.2% for the Great Inflation/Great Recession and −0.15% for the Great Moderation. The dynamic effect (persistence) increases with the onset of the Great Recession, supporting the slow recovery hypothesis. Lastly, we focus on the IRF of the PMI manufacturing index to an EPU shock. Interestingly, this IRF has the same time-profile compared to that of real GDP. Therefore, the expectations summarized in the PMI can be considered as a good guide for future economic conditions and strengthen the finding on the three different regimes, namely the Great Inflation, the Great Moderation and the Great Recession, even further.

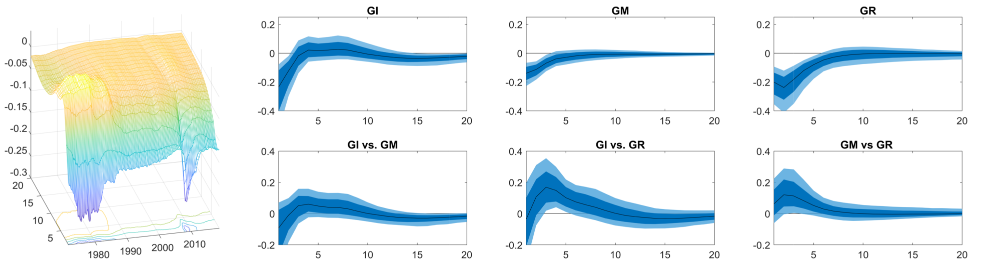
V. Conclusions

We estimate a time-varying parameter VAR in the spirit of Primiceri (2005) with data-based hyperparameters estimated in a fully Bayesian approach to investigate the time-varying impact of EPU shocks on the US economy. The TVP-VAR coefficients are allowed to evolve gradually over time. Thereby, it is possible to detect structural changes without imposing them *a priori*. To increase the information set in our model and, at the same time, keep the estimation of the model feasible, we follow Korobilis (2013) and augment our TVP-VAR with a few factors.

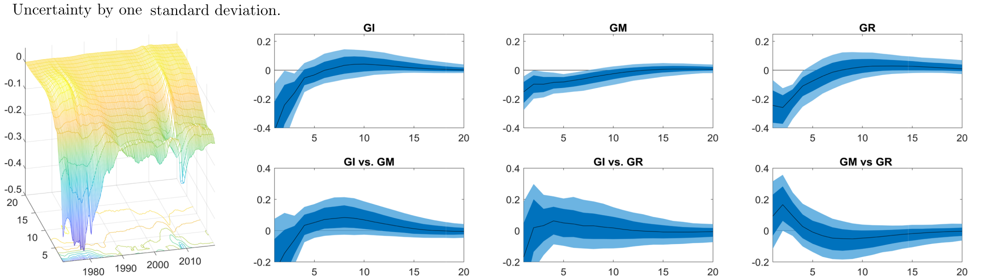
Our main result is that we find empirical evidence of a time-varying impact of EPU on the US economy. Interestingly, the shape of the IRFs strongly correlates with the three major periods of the US economy, namely the Great Inflation, the Great Moderation and the Great Recession and therefore, our econometric approach has discovered three different regimes. This finding holds for several alternative model specifications. The time-varying impulse responses vary across three dimensions: the initial impact, the overshooting behaviour and the persistence. During the 1970s, the Great Inflation, the initial impact was relatively high but was followed by overshooting. During the Great Moderation, EPU shocks had a smaller impact on the economy. Finally, during the Great Recession, the initial impact of EPU shocks again increased and had a more persistent effect on the economy, preventing a quick recovery.

[24] This result is in line with Schaal (2017) who uses a directed search model to show that uncertainty alone is not sufficient to explain the magnitude and persistence of unemployment. In addition, Caggiano, Castelnuovo and Figueres (2017a) find a similar response of unemployment to an uncertainty shock, using a smooth transition VAR. A potential reason might be a change in the intensive margin of labour supply. We investigated the response of a corresponding variable (No. 68 in Table B.1) in our data set. The IRF has, as expected, a negative sign. However, whether the response of the intensive margin of labour supply is the reason for the low response of the overall unemployment rate requires a more detailed investigation.

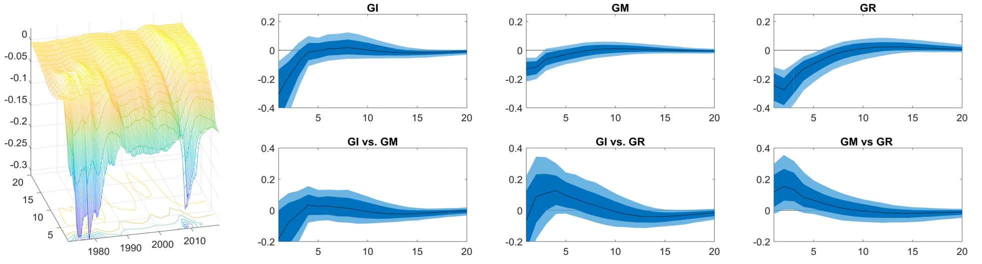
Appendix A. Figures



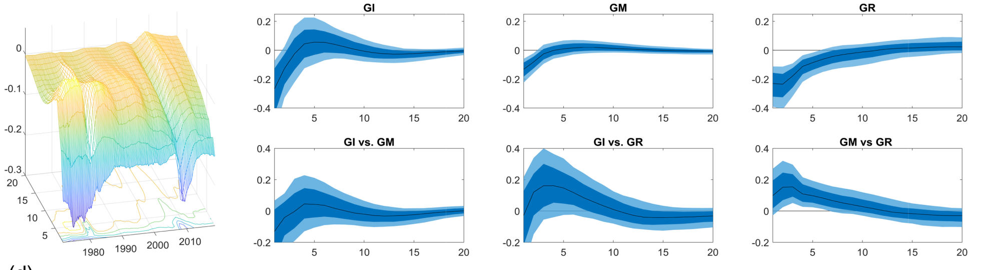
(a) *Model: Financial Uncertainty and EPU based on* Baker *et al.* (2016). Impulse response of Real GDP to an increase in Economic Policy Uncertainty by one standard deviation.



(b) *Model: Financial Uncertainty and Macroeconomic Uncertainty based on* Jurado *et al.* (2015). Impulse response of Real GDP to an increase in Macroeconomic Uncertainty by one standard deviation.



(c) *Model: Only EPU.* Impulse response of Real GDP to an increase in Economic Policy Uncertainty by one standard deviation.



(d) *Model: Federal Funds Rate and EPU.* Impulse response of Real GDP to an increase in Economic Policy Uncertainty by one standard deviation.

Figure A.1 The three dimensional graph displays the change in the pattern of the response over time. The upper three subfigures display the effect of Economic Policy Uncertainty on the respective variable for three different time periods while the lower three subfigures display the difference between the three time periods along with 68% and 90% credible regions. 'GI' denotes Great Inflation, 'GM' Great Moderation and 'GR' Great Recession. Note that the three dimensional impulse response functions have been generated by allowing for time variation in $\boldsymbol{\beta}_t$ and $\boldsymbol{\Omega}_t$

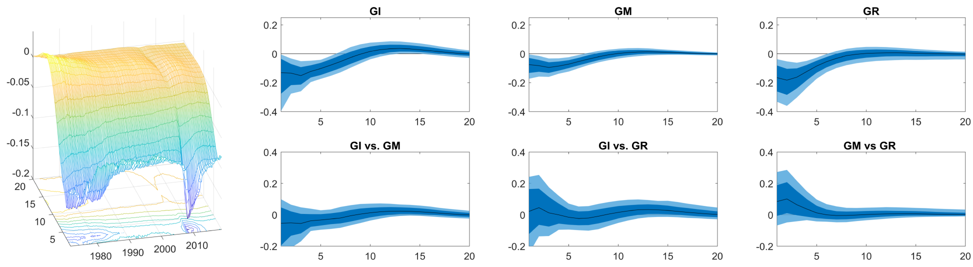
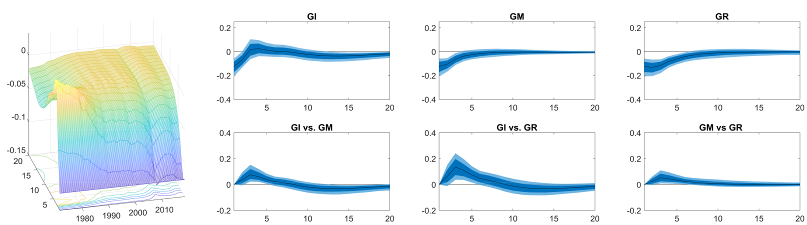
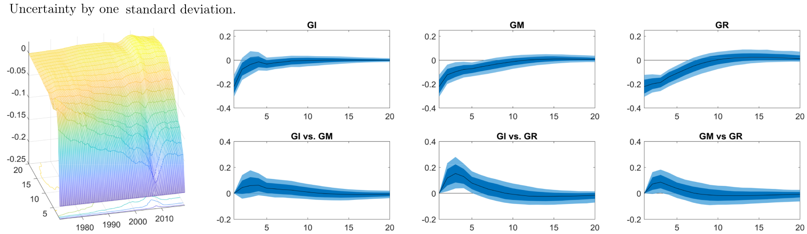


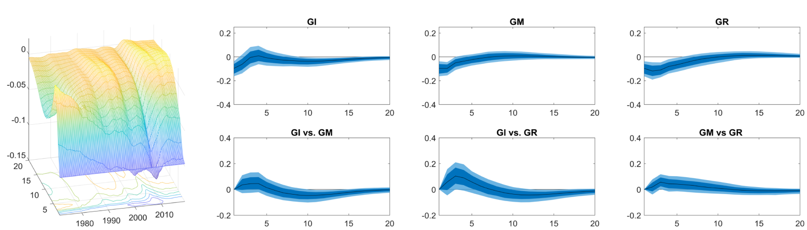
Figure A.2 *Model: Financial Uncertainty and Economic Policy Uncertainty.* Impulse response of Real GDP to a shock in Financial Uncertainty



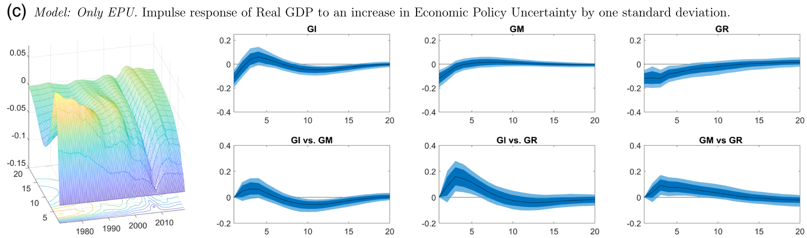
(a) *Model: Financial Uncertainty and EPU based on* Baker *et al.*(2016). Impulse response of Real GDP to an increase in Economic Policy Uncertainty by one standard deviation.



(b) *Model: Financial Uncertainty and Macroeconomic Uncertainty based on* Jurado *et al.* (2015). Impulse response of Real GDP to an increase in Macroeconomic Uncertainty by one standard deviation.



(c) *Model: Only EPU.* Impulse response of Real GDP to an increase in Economic Policy Uncertainty by one standard deviation.



(d) *Model: Federal Funds Rate and EPU.* Impulse response of Real GDP to an increase in Economic Policy Uncertainty by one standard deviation.

Figure A.3 Impulse response functions when fixing the covariance matrix $\mathbf{\Omega}_t$ at its posterior mean

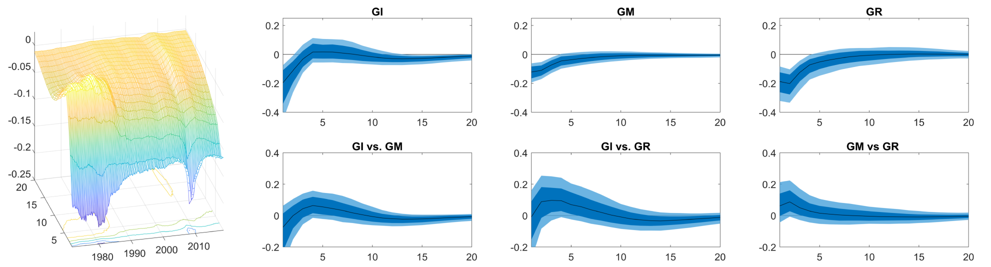
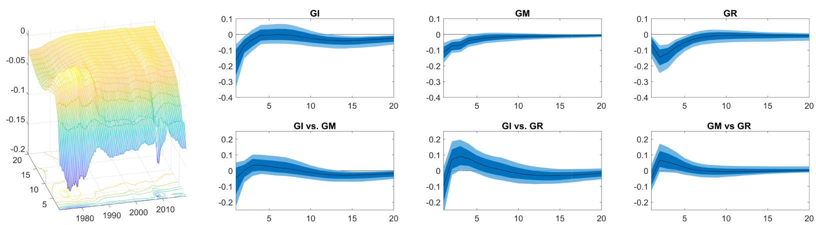
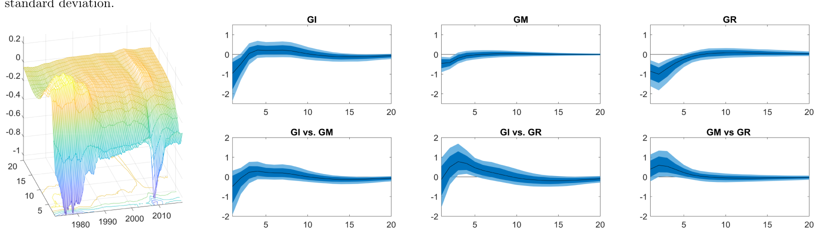


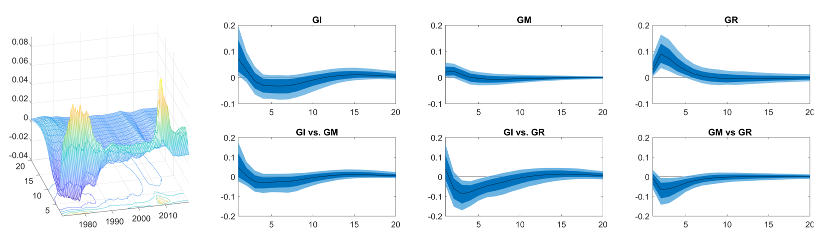
Figure A.4 *Model: Financial Uncertainty and Economic Policy Uncertainty (EPU)*. Impulse response of real GDP to a shock in EPU with the prior of Primiceri (2005)



(a) *Model: Financial Uncertainty and EPU.* Impulse response of Real Consumption to an increase in Economic Policy Uncertainty by one standard deviation.



(b) *Model: Financial Uncertainty and EPU.* Impulse response of Real Gross Investment to an increase in Economic Policy Uncertainty by one standard deviation.



(c) *Model: Financial Uncertainty and EPU.* Impulse response of the Unemployment Rate to an increase in Economic Policy Uncertainty by one standard deviation.

(d) *Model: Financial Uncertainty and EPU.* Impulse response of PMI Manufacturing Index to an increase in Economic Policy Uncertainty by one standard deviation.

Figure A.5 Economic Policy Uncertainty shock to a wider range of variables

Appendix B. Data

TABLE B.1

Data

1	Real gross domestic product, 3 decimal	GDPC96	5
2	Gross domestic product: implicit price deflator	GDPDEF	5
3	Real personal consumption expenditures	PCECC96	5
4	Personal consumption expenditures: chain-type price index	PCECTPI	5
5	Real gross private domestic investment, 3 decimal	GPDIC96	5
6	Real imports of goods & services, 3 decimal	IMPGSC96	5
7	Real exports of goods & services, 3 decimal	EXPGSC96	5
8	Real change in private inventories	CBIC96	1
9	Real final sales of domestic product	FINSLC96	5
10	Gross saving	GSAVE	5
11	Real government consumption expenditures & gross investment	GCEC96	5
12	State & local government current expenditures	SLEXPND	6
13	State & local government gross investment	SLINV	6
14	Real disposable personal income	DPIC96	6
15	Personal income	PINCOME	6
16	Personal saving	PSAVE	5
17	Private residential fixed investment	PRFI	6
18	Private nonresidential fixed investment	PNFI	6
19	Personal consumption expenditures: durable goods	PCDG	5
20	Personal consumption expenditures: nondurable goods	PCND	5
21	Personal consumption expenditures: services	PCESV	5
22	Gross private domestic investment: chain-type price index	GPDICTPI	6
23	Compensation of employees: wages & salary accruals	WASCUR	6
24	Net corporate dividends	DIVIDEND	6
25	Corporate profits after tax	CP	6
26	Corporate: consumption of fixed capital	CCFC	6
27	Housing starts: total: new privately owned housing units started	HOUST	4
28	Privately owned housing starts: 1-unit structures	HOUST1F	4
29	Privately owned housing starts: 5-unit structures or more	HOUST5F	4
30	Housing starts in midwest census region	HOUSTMW	4
31	Housing starts in northeast census region	HOUSTNE	4
32	Housing starts in south census region	HOUSTS	4
33	Housing starts in west census region	HOUSTW	4
34	Industrial production index	INDPRO	5
35	Industrial production: consumer goods	IPCONGD	5
36	Industrial production: durable consumer goods	IPDCONGD	5
37	Industrial production: nondurable consumer goods	IPNCONGD	5
38	Industrial production: materials	IPMAT	5
39	Industrial production: durable materials	IPDMAT	5
40	Industrial production: nondurable materials	IPNMAT	5
41	Industrial production: business equipment	IPBUSEQ	5
42	Industrial production: final products (market group)	IPFINAL	5
43	Capacity utilization: manufacturing	CUMFNS	1
44	Civilians unemployed - less than 5 weeks	UEMPLT5	5
45	Civilians unemployed for 5-14 weeks	UEMP5TO14	5

(*continued*)

TABLE B.1

(Continued)

46	Civilians unemployed for 15-26 weeks	UEMP15T26	5
47	Civilians unemployed for 27 weeks and over	UEMP27OV	5
48	Civilian Unemployment Rate	UNRATE	2
49	Total Nonfarm Payrolls: All Employees	PAYEMS	5
50	All employees: nondurable goods manufacturing	NDMANEMP	5
51	All employees: durable goods manufacturing	DMANEMP	5
52	All employees: construction	USCONS	5
53	All employees: goods-producing industries	USGOOD	5
54	All employees: financial activities	USFIRE	5
55	All employees: wholesale trade	USWTRADE	5
56	All employees: trade, transportation & Utilities	USTPU	5
57	All employees: retail trade	USTRADE	5
58	All employees: natural resources & mining	USMINE	5
59	All employees: professional & business services	USPBS	5
60	All employees: leisure & hospitality	USLAH	5
61	All employees: information services	USINFO	5
62	All employees: education & health services	USEHS	5
63	All employees: service-providing industries	SRVPRD	5
64	All employees: total private industries	USPRIV	5
65	All employees: government	USGOVT	5
66	Average hourly earnings: manufacturing	AHEMAN	6
67	Average hourly earnings: construction	AHECONS	6
68	Average weekly hours of production and nonsupervisory employees: manufacturing	AWHMAN	5
69	Average weekly hours: overtime: manufacturing	AWOTMAN	5
70	Civilian employment-population ratio	EMRATIO	5
71	Civilian participation rate	CIVPART	5
72	Business sector: output per hour of all persons	OPHPBS	5
73	Nonfarm business sector: unit labor cost	ULCNFB	5
74	Commercial and industrial loans at all commercial banks	BUSLOANS	6
75	Real estate loans at all commercial banks	REALLN	6
76	Total consumer credit owned and securitized, outstanding	TOTALSL	5
77	Total loans and leases at commercial banks	LOANS	6
78	Bank prime loan rate	MPRIME	2
79	1-year treasury constant maturity rate	GS1	2
80	3-year treasury constant maturity rate	GS3	2
81	5-year treasury constant maturity rate	GS5	2
82	10-year treasury constant maturity rate	GS10	2
83	Moody's seasoned aaa corporate bond yield	AAA	2
84	Moody's seasoned baa corporate bond yield	BAA	2
85	M1 money stock	M1SL	6
y86	M2 money stock	M2SL	6
87	Currency component of M1	CURRSL	6
88	Demand deposits at commercial banks	DEMDEPSL	6
89	Savings deposits - total	SAVINGSL	6
90	Total checkable deposits	TCDSL	6
91	Travelers checks outstanding	TVCKSSL	6
92	Currency in circulation	CURRCIR	6

(*continued*)

TABLE B.1

(Continued)

93	MZM Money Stock	MZMSL	6
94	Velocity of M1 money stock	M1V	5
95	Velocity of M2 money stock	M2V	5
96	Total nonrevolving credit outstanding	NONREVSL	6
97	Total consumer credit outstanding	TOTALSL	6
98	Consumer price index for all urban consumers: all items	CPIAUCSL	6
99	Consumer price index for all urban consumers: commodities	CUSR0000SAC	6
100	Consumer price index for all urban consumers: all items Less energy	CPILEGSL	6
101	Consumer price index for all urban consumers: all items less food	CPIULFSL	6
102	Consumer price index for all urban consumers: energy	CPIENGSL	6
103	Consumer price index for all urban consumers: food	CPIUFDSL	6
104	Consumer price index for all urban consumers: apparel	CPIAPPSL	6
105	Consumer price index for all urban consumers: medical care	CPIMEDSL	6
106	Consumer price index for all urban consumers: transportation	CPITRNSL	6
107	Producer price index: all commodities	PPIACO	6
108	S&P 500 index	SP500	5
109	Spot oil price: west texas intermediate	WTISPLC	5
110	U.S. / U.K foreign exchange rate	EXUSUK	5
111	Switzerland / U.S. foreign exchange rate	EXSZUS	5
112	Japan / U.S. foreign exchange rate	EXJPUS	5
113	Canada / U.S. foreign exchange rate	EXCAUS	5
114	ISM manufacturing: PMI composite index	PMI	1
115	ISM manufacturing: new orders index	NAPMNOI	1
116	ISM manufacturing: inventories index	NAPMII	1
117	ISM manufacturing: employment index	NAPMEI	1
118	ISM manufacturing: prices index	NAPMPRI	1
119	ISM manufacturing: production index	NAPMPI	1
120	ISM manufacturing: supplier deliveries Index	NAPMSDI	1
121	Total borrowings of depository institutions from the federal reserve	BORROW	6
122	Effective federal funds rate	FEDFUNDS	1

Notes: This table summarizes information regarding the time series. Transformation code (TC): 1-level; 2-first difference; 3-second difference; 4-log-level; 5-first difference of logarithm; 6-second difference of logarithm. All times series have been downloaded from FRED.

Appendix C: The Gibbs sampler for the TVP-VAR

Here we briefly describe the Markov Chain Monte Carlo (MCMC) algorithm which allows to sample from the joint posterior distributions of all coefficients. The algorithm is the same as in Del Negro and Primiceri (2015), but adds the Metropolis-within-Gibbs step to sample the hyperparameter (k_Q, k_S and k_W) as in Amir-Ahmadi *et al.* (2020). To draw from the joint posterior distributions, we draw from the following conditional posterior distributions:

(i) Draw $\mathbf{\Sigma}_t$ from its conditional distribution $p(\mathbf{\Sigma_t}|\boldsymbol{y^T}, \boldsymbol{\beta}^T, \boldsymbol{\alpha^T}, \boldsymbol{I_n}, \boldsymbol{Q}, \boldsymbol{S}, \boldsymbol{W}, \boldsymbol{s^T}, k_{\boldsymbol{Q}}, k_{\boldsymbol{S}}, k_{\boldsymbol{W}})$, where $\boldsymbol{s^T}$ denotes the indicator vector needed to use the mixtures of normals approach suggested by Kim, Shepard and Chib (1998) to sample $\mathbf{\Sigma}_t$.[25]

[25] T is a superscript and denotes a sample from the corresponding variable for $t = 1, \ldots, T$.

(ii) Draw $\boldsymbol{\beta}^T$ from its conditional distribution $p(\boldsymbol{\beta}^{\boldsymbol{T}}|-)$ by making use of the simulation smoother developed by Carter and Kohn (1994).[26]

(iii) Draw $\boldsymbol{\beta}^T$ from its conditional distribution $p(\boldsymbol{\alpha}^{\boldsymbol{T}}|-)$ by making use of the simulation smoother developed by Carter and Kohn (1994).

(iv) Draw $\boldsymbol{Q}|-, \boldsymbol{S}|-$ and $|\boldsymbol{W}|-$ using standard expression from Inverse Wishart, see Primiceri (2005).

(v) Draw $k_{\boldsymbol{X}}$, $\boldsymbol{X} \in \{\boldsymbol{Q}, \boldsymbol{W}, \boldsymbol{S}\}$ using the same Gaussian random walk Metropolis–Hastings algorithm with an automatic tuning step as in Amir-Ahmadi *et al.* (2020):
   (a) At each Gibbs iteration i, draw a candidate $k_{\boldsymbol{X}}^*$ from $N(k_{\boldsymbol{X}}^{i-1}, \sigma_{kX}^2)$.
   (b) Calculate the acceptance probability $\alpha_{k_{\boldsymbol{X}}}^i = \min\left(1, \dfrac{p(\boldsymbol{X}|k_{\boldsymbol{X}}^*)p(k_{\boldsymbol{X}}^*)}{p(\boldsymbol{X}|k_{\boldsymbol{X}}^{i-1})p(k_{\boldsymbol{X}}^{i-1})}\right)$.
   (c) Accept the candidate draw by setting $k_{\boldsymbol{X}}^i = k_{\boldsymbol{X}}^*$ with probability $\alpha_{k_{\boldsymbol{X}}}^i$. Otherwise set $k_{\boldsymbol{X}}^i = k_{\boldsymbol{X}}^{i-1}$.
   (d) Calculate the average acceptance ratio $\overline{\alpha}_{k_{\boldsymbol{X}}}$. Adjust $\sigma_{k_{\boldsymbol{X}}}$ at every qth iteration according to $\sigma_{k_{\boldsymbol{X}}}^{New} = \sigma_{k_{\boldsymbol{X}}} \frac{\overline{\alpha}_{k_{\boldsymbol{X}}}}{\alpha^*}$, with α^* being the target average acceptance ratio. This step is not used after a pre-burn-in phase.

(vi) Draw $\boldsymbol{s}^{\boldsymbol{T}}$, needed to use the mixtures of normals approach, see Kim *et al.* (1998).

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References

Alessandri, P. and Mumtaz, H. (2019). 'Financial regimes and uncertainty shocks', *Journal of Monetary Economics*, Vol. 101, pp. 31–46.

Amir-Ahmadi, P., Matthes, C., and Wang, M.-C. (2020). 'Choosing prior hyperparameters: with applications to time-varying parameter models', *Journal of Business & Economic Statistics*, Vol. 38, pp. 124–136.

Angelini, G., Bacchiocchi, E., Caggiano, G., and Fanelli, L. (2018). 'Uncertainty across volatility regimes', *Applied Econometrics*, Vol. 34, pp. 437–455.

Antolín-Díaz, J. and Rubio-Ramírez, J. (2018). 'Narrative sign restrictions for SVARs', *American Economic Review*, Vol. 108, pp. 2802–29.

Bachmann, R. and Moscarini, G. (2011). *Business Cycles and Endogenous Uncertainty*. 2011 Meetins Papers, Society for Economic Dynamics.

Baker, S. R., Bloom, N., and Davis, S. J. (2012). *Has Economic Policy Uncertainty Hampered the Recovery*? Chicago Booth Research Paper, No. 12-06.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). 'Measuring economic policy uncertainty', *Quarterly Journal of Economics*, Vol. 131, pp. 1593–1636.

Benati, L. (2013). *Economic Policy Uncertainty and the Great Recession*. University of Bern. Mimeo.

Benati, L. (2014). *Economic Policy Uncertainty, the Great Recession and the Great Depression*. University of Bern. Mimeo.

Bernanke, B. S. (1983). 'Irreversibility, uncertainty and cyclical investment', *Quarterly Journal of Economics*, Vol. 98, pp. 85–106.

Bernanke, B. S., Boivin, J., and Eliasz, P. (2005). 'Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach', *Quarterly Journal of Economics*, Vol. 120, pp. 387–422.

Bloom, N. (2009). 'The impact of uncertainty shocks', *Econometrica*, Vol. 77, pp. 623–685.

[26]The notation $\theta|-$ represents the conditional posterior of θ conditional on the data and draws of all other model parameters.

Caggiano, G., Castelnuovo, E., and Figueres, M. (2017a). 'Economic policy uncertainty and unemployment in the United States: a nonlinear approach', *Economic letters*, Vol. 151, pp. 31–34.

Caggiano, G., Castelnuovo, E., and Groshenny, N. (2014). 'Uncertainty shocks and unemployment dynamics in U.S. recessions', *Journal of Monetary Economics*, Vol. 67, pp. 78–92.

Caggiano, G., Castelnuovo, E., and Nodari, G. (2017b). *Uncertainty and Monetary Policy in Good and Bad Times*. Bank of Finland Research and Discussion Paper.

Caldara, D., Fuentes-Albero, C., Gilchrist, S., and Zakrajsek, E. (2016). 'The macroeconomic impact of financial and uncertainty shocks', *European Economic Review*, Vol. 88, pp. 185–207.

Canova, F. and Nicolo, G. (2002). 'Monetary disturbances matter for business fluctuations in the G-7', *Journal of Monetary Economics*, Vol. 49, pp. 1131–59.

Canova, F. and Pina, J. (1998). *Monetary Policy Misspecification in VAR Models*. CEPR Working Paper, (2333).

Carlstrom, C., Fuerst, T., and Paustian, M. (2009). 'Monetary policy shocks, choleski identification and DNK models', *Journal of Monetary Economics*, Vol. 56, pp. 1014–1021.

Carter, C. K. and Kohn, R. (1994). 'On Gibbs sampling for state space models', *Biometrika*, Vol. 81, pp. 541–553.

Castelnuovo, E., Caggiano, G., and Pellegrino, G. (2017). 'Estimating the real effects of uncertainty shocks at the zero lower bound', *European Economic Review*, Vol. 100, pp. 257–272.

Cogley, T. and Sargent, T. J. (2005). 'Drifts and volatilities: monetary policies and outcomes in the post WWII US', *Review of Economic Dynamics*, Vol. 8, pp. 262–302.

Del Negro, M. and Primiceri, G. (2015). 'Time-varying structural vector autoregressions and monetary policy: a corrigendum', *Review of Economic Studies*, Vol. 82, pp. 1342–1345.

Fajgelbaum, P., Schaal, E., and Taschereau-Dumouchel, M. (2017). 'Uncertainty traps', *The Quarterly Journal of Economics*, Vol. 132, pp. 1641–1692.

Fry, R. and Pagan, A. (2011). 'Sign restrictions in structural vector autoregressions: a critical review', *Journal of Economic Literature*, Vol. 49, pp. 938–60.

Gilchrist, S., Sim, J., and Zakrajšek, E. (2014). *Uncertainty, Financial Frictions, and Investment Dynamics*. NBER Working Papers, 20038.

Jurado, K., Ludvigson, S., and Ng, S. (2015). 'Measuring uncertainty', *American Economic Review*, Vol. 105, pp. 1177–1216.

Kim, S., Shepard, N., and Chib, S. (1998). 'Stochastic volatility: likelihood inference and comparison with arch models', *Review of Economic Studies*, Vol. 65, pp. 361–393.

Korobilis, D. (2013). 'Assessing the transmission of monetary policy using time-varying parameter dynamic factor models', *Oxford Bulletin of Economics and Statistics*, Vol. 75, pp. 157–179.

Lippi, M. and Reichlin, L. (1994). 'VAR analysis, nonfundamental representations, blaschke matrices', *Journal of Econometrics*, Vol. 63, pp. 307–325.

Ludvigson, S., Ma, S. and Ng, S. (2019). Uncertainty and business cycles: exogenous impulse or endogenous response. *American Economic Journal: Macroeconomics*. forthcoming.

Mumtaz, H. and Surico, P. (2018). 'Policy uncertainty and aggregate fluctuations', *Journal of Applied Econometrics*, Vol. 33, pp. 319–331.

Mumtaz, H. and Theodoridis, K. (2018). 'The changing transmission of uncertainty shocks in the US: an empirical analysis', *Journal of Business & Economic Statistics*, Vol. 36, pp. 239–252.

Mumtaz, H. and Zanetti, F. (2013). 'The impact of the volatility of monetary policy shocks', *Journal of Money, Credit, and Banking*, Vol. 45, pp. 535–558.

Plante, M., Richter, A., and Throckmorton, N. (2016). 'The zero lower bound and endogenous uncertainty', *The Economic Journal*, Vol. 128, pp. 1730–1757.

Popp, A. and Zhang, F. (2016). 'The macroeconomic effects of uncertainty shocks: the role of the financial channel', *Journal of Economic Dynamics and Control*, Vol. 69, pp. 319–349.

Primiceri, G. E. (2005). 'Time varying structural vector autoregressions and monetary policy', *Review of Economic Studies*, Vol. 72, pp. 821–852.

Prüser, J. and Schlösser, A. (2019). 'The effects of economic policy uncertainty on european economies: evidence from a TVP-FAVAR', *Empirical Economics*, Vol. 58, pp. 2889–2910.

Ramirez, J., Waggnoner, D., and Zha, T. (2010). 'Structural vector autoregressions: theory of identification and algorithms for inference', *The Review of Economic Studies*, Vol. 77, pp. 665–696.

Romer, C. D. (1990). 'The great crash and the onset of the great depression', *The Quarterly Journal of Economics*, Vol. 105, pp. 597–624.

Schaal, E. (2017). 'Uncertainty and unemployment', *Econometrica*, Vol. 85, pp. 1675–1721.

Stock, J. H. and Watson, M. (1998). *Diffusion Indexes*. NBER Working Papers, 6702.

Stock, J. H. and Watson, M. W. (2005). *Implications of Dynamic Factor Models for VAR Analysis*. NBER Working Papers, 11467.

Uhlig, H. (2004a). 'Do technology shocks lead to a fall in total hours worked? *Journal of the European Economic Association,* 2, 361–371.

Uhlig, H. (2004b). *What Moves GNP*. Econometric Society 2004 North American Winter Meetings.

Uhlig, H. (2005). 'What are the effects of monetary policy on output? results from an agnostic identification procedure', *Journal of Monetary Economics*, Vol. 52, pp. 381–419.