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Jan Prüser and Alexander Schlösser[1]

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

Abstract

We study the time-varying 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 business cycles of the US economy, namely the Great Inflation, the Great Moderation and the Great Recession. This finding is in contrast to previous literature which typically imposes two regimes a priori. Furthermore, we distinguish the effect of EPU on real economic activity and on financial markets.

JEL Classification: C11, C32, E20, E60

Keywords: TVP-FAVAR; economic policy uncertainty; fat data

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1 Jan Prüser, RGS Econ, RWI, and UDE; Alexander Schlösser, UDE. - *We thank Volker Clausen and Christoph Hanck for valuable comments. –* *All correspondence to: Jan Prüser, RWI, Hohenzollernstr. 1-3, 45128 Essen, Germany, e-mail: jan.prueser@rgs-econ.de*

1. Introduction

In the context of the Great Recession Economic Policy Uncertainty (EPU) has been recognized as a major driver of the business cycle. A high degree of EPU has the potential to dampen economic activity. Baker et al. (2016) pioneered a newspaper based index to measure EPU. They used their EPU index to provide empirical evidence that EPU shocks cause a decline in both, employment and industrial production. Based on this index a large literature established further empirical evidence that EPU has a negative impact on economic activity, e.g. Bloom (2009), Baker et al. (2012), Colombo (2013) or Caldara et al. (2016). We contribute to this literature by investigating whether the effect of EPU on the US economy is time-varying.

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 on an ad hoc basis or the values used by Primiceri (2005). It is, however, unclear whether these values should be employed in other applications. Moreover, previous applications do not take into account that uncertainty about these hyperparameters may influence inference. We therefore estimate these hyperparameters using a fully Bayesian approach proposed by Amir-Ahmadi et al. (2018). We find that estimating the hyperparameters is important since using the benchmark values of Primiceri (2005) would underestimate 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 data set 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 and on variables which mirror the activity on financial markets. This step turns out to be empirically important since EPU has an impact on a wide range of different variables. The impulse responses of macroeconomic variables share strong similarities over time while those of financial variables differ from the former.

Our main contribution is that we provide empirical evidence of a time-varying impact of EPU on the US economy by calculating time-varying impulse response functions. In principle, time-varying impulse response functions can vary along three dimensions, the initial impact, the overshooting behavior and the persistence of the shock. It turns out that the time-varying impulse responses vary across all three dimensions. During the 1970s, the Great Inflation, the initial impact was relatively high but was followed by overshooting which dampened the net impact of the shock. 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 persistent effect on the economy, preventing a quick recovery. We therefore find three different regimes which match the three major business cycles of the US economy, namely the Great Inflation, the Great Moderation and the Great Recession.

By modeling the time-varying effects of EPU on the US economy, we contribute to the growing literature focusing on the regime dependence of uncertainty shocks. Alessandri and Mumtaz (2014) use a threshold model and condition on the state of financial markets. Caggiano et al. (2017) and Popp and Zhang (2016) employ a smooth transition model and show that the effect depends on whether the economy is in recession or non-recession.[1]

[1] The conclusions drawn from these models might be too general. E.g., 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.

Castelnuovo et al. (2017) use an interacted VAR model and examine whether the effects of uncertainty are greater when the economy is at the zero lower bound. Of course, while these approaches have their individual appeal, we stress that we neither have to define ex ante a certain number of regimes, nor do we have to condition on a threshold variable, such as recession/ non-recession or a certain stance of monetary policy. Instead, we let the data guide us by allowing for time-varying model parameters. By doing so, we find three different regimes in contrast to previous research which typically imposes two regimes a priori. This is exactly the gap we are filling. Benati (2013) heads in a similar direction by using a TVP-VAR. We differ from Benati (2013) by also allowing for time variation in the autoregressive coefficients which turns out to be crucial for our empirical results. Furthermore, we additionally consider the period of the Great Inflation. Summing up, we extend the literature about the non-linear 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 2 provides a brief overview of the underlying econometric model, Section 3 contains the empirical results and Section 4 concludes.

2. Methodology

2.1. 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 $\boldsymbol{z}_t' = \boldsymbol{I}_n \otimes [\boldsymbol{y}_{t-1}', \ldots, \boldsymbol{y}_{t-p}']$, $\boldsymbol{\epsilon}_t \sim N(\mathbf{0}, \boldsymbol{I}_n)$, $\boldsymbol{\eta}_t \sim N(\mathbf{0}, \boldsymbol{Q})$, $\boldsymbol{v}_t \sim N(\mathbf{0}, \boldsymbol{S})$ and $\boldsymbol{w}_t \sim N(\mathbf{0}, \boldsymbol{W})$ and 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 $\boldsymbol{a}_t$ 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 $\boldsymbol{\Sigma}_t$. Following Primiceri (2005), Cogley and Sargent (2005), Bernanke et al. (2005) and others we use two lags for the estimation.

In this setup the autoregressive coefficients, the covariances and the log standard deviation are allowed to evolve over time according to a random walk process and thereby allows us to detect structural breaks or regime changes. However, in contrast to regime switching models it does not need to impose a fixed number 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 ten 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).[2] 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. (2018). This approach estimates the hyperparameters in a data-based fashion and takes the surrounding uncertainty into account.

The approach of Amir-Ahmadi et al. (2018) 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.[3] We formulate relatively non-informative hierarchical inverse gamma priors for $p(k_{\boldsymbol{X}})$.

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 Trea-

[2] Primiceri (2005) estimates the hyperparameters over a small grid by maximizing the marginal likelihood.

[3] For more details see Amir-Ahmadi et al. (2018).

sury 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 exists 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, e.g., variables which capture information about the nature of consumers, organizations, business, 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.[4] Thus, instead of selecting a few variables from a set of over 100 potential variables, we follow Bernanke et al. (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. That is, $\boldsymbol{y}_t$ consists of k factors and further variables of interest, in our case the monetary policy rate and EPU. Thereby our results are less sensitive to the concrete choice of variables.

We estimate the factors and model parameters following Stock and Watson (2005) and Korobilis (2013) and use a simple two step approach. 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 variables. The PC estimates are then treated as observations. In the second step the parameters can be estimated conditional on these observed factors. Each observed variable x_{it}, for $i = 1, \ldots, m$, is linked to the k factors, to the monetary policy rate (R_t) and Economic Policy Uncertainty (epu_t) via the factor regression

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

where $\boldsymbol{\lambda}^f$ is $(1 \times k)$, λ^R, λ^{epu} are scalars and $\epsilon_{it} \sim N(0, \sigma_i^2)$. In order to model the dependence between factors and policy variables, the VAR model (1) is augmented with the obtained factors $\boldsymbol{y}_t = [\boldsymbol{f}'_t, R_t, epu_t]'$. Following Bernanke et al. (2005) and Korobilis

[4]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).

(2013) we estimate the model using three factors.

2.2. Identification

We follow Canova and Nicolo (2002) and Uhlig (2005) and identify an EPU shock by placing sign restrictions on the contemporaneous responses of some of the variables in $\boldsymbol{x}_t$. In contrast to a Cholesky based identification scheme we avoid imposing zero restrictions and hence avoid an ordering of the variables which may be difficult to establish in an economically reasonable fashion, for instance, Caggiano et al. (2014) assume uncertainty to be slow-moving while Gilchrist et al. (2014) assume it to be fast-moving.[5] Instead, we impose restrictions in accordance with economic theory. We assume that the uncertainty shock has a negative contemporaneous effect on consumption and investment as well as unemployment as suggested by the *precautionary savings* and *real options* channel developed by Romer (1990) and Bernanke (1983). We leave the other shocks unidentified. Scholl and Uhlig (2008) or Rafiq and Mallick (2008) also identify a single shock. However, a monetary policy or demand shock may be associated with the same sign pattern. To distinguish the EPU shock from these shocks (i.e., shocks with the same sign pattern), we further assume that an EPU shock has the largest contemporaneous impact on EPU itself among all shocks. This approach is similar to maximizing the fraction of the forecast error variance at horizon zero which has been pioneered by Uhlig (2004b) and Uhlig (2004a) and used by Benati (2013) to identify an EPU-shock.

These sign and magnitude restrictions are implemented using the algorithm of Ramirez et al. (2010). First, we draw an $n \times n$ matrix, $\boldsymbol{J}$, from the N($\boldsymbol{0}$,$\boldsymbol{I}$) distribution. Second, calculating $\bar{\boldsymbol{Q}}$ from the QR decomposition of $\boldsymbol{J}$ provides a candidate structural impact matrix 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

[5] 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 et al. (2009).

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

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 specified restrictions. In this setup, 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 in order to deal with the multiple models problem.

3. Empirical Results

3.1. Data

We estimate the model based on a large data set covering 125 time series for the US economy. All variables are seasonally adjusted if necessary and standardized for the estimation. To incorporate the stance of monetary policy and the level of uncertainty we make use of the effective Federal Funds Rate and the historical version of the EPU index. Our quarterly data set starts in 1959:Q1 and ends in 2014:Q3. The names and the transformation codes of all series can be found in Table A.1.

3.2. Impulse Responses

Figures 1a to 1j display the impulse response functions (IRF) for 12 selected time series of the US economy. Each plot consists of seven subplots. The three dimensional graph on the left displays the change of the response pattern over time and has been generated by allowing for time-variation in $\boldsymbol{\beta}_t$, $\boldsymbol{A}_t$ and $\boldsymbol{\Sigma}_t$. The upper three subfigures on the right display the effect of EPU 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 95% credible regions. A glance at the upper three subfigures of all variables shows that the initial impact credibly differ from zero at the 95% credible region. 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 A.1. In a first step, we focus on the sign of the impulse response for the selected variables followed by a second step, in which we look in more detail at the time-varying effect. In a third step we briefly comment on the magnitude and the economic significance of an EPU shock.

3.2.1. On the Sign of the Effect

The responses of the variables are in line with the theoretical sign pattern. The impulse responses of real GDP, consumption, investment and unemployment are depicted in Figure 1a to 1d. The former three respond negatively and the latter positively to an EPU shock. Therefore the signs are in accordance with the *precautionary savings* and *real options* channel developed by Romer (1990) and Bernanke (1983), respectively.

The IRF of the velocity of M1, housing starts, the S&P500 and the 10-Year Treasury Rate are depicted in Figure 1e to 1h. The negative response of the velocity of M1 reveals that a shock in EPU slows down economic activity. This does not come as a surprise since a shock depresses consumption, investment and increases unemployment which causes a reduction in short-term transactions. The IRF of housing starts is negative as expected. Both, the responses of the S&P500 as well as of the 10-Year Treasury Rate, are negative. The effect on the latter is in line with Scheffel (2015) who also found a 'flight to safety effect'.

Finally, we turn to Figures 1i and 1j which depict the IRFs of the ISM Manufacturing Composite Index and the capacity utilization in manufacturing. Both respond negatively, showing the adverse effects of EPU on business conditions in the US. Overall up, the signs are in accordance with economic theory.

3.2.2. On the Magnitude of the Effect

Beside the sign pattern and the shape of the IRFs, the magnitude of an EPU shock on the respective variable is of economic interest. In the following, we will briefly focus on the economic relevance of an EPU shock for most important macroeconomic variables. For the remaining variables the magnitude is economically reasonable as well since it is neither to high nor to low.

The initial impact on real GDP ranges between almost -0.3% for the Great Inflation and -0.2% for the Great Moderation. The dynamic effect (presistence) increases with the onset of the Great Recession supporting the slow recovery hypothesis. The initial impact on investment ranges between -1.2% during the Great Inflation and approximately -1.0% during the Great Recession. If we compare the size of the initial impact on investment with the size of the initial impact on consumption, which ranges approximately between -0.25% during the Great Inflation and approximately -0.15% for the Great Recession, it becomes obvious that consumers are less sensitive to an EPU shock than investors. This finding is in line with Prüser and Schlösser (2017) who found a similar result for European economies. In the case of unemployment, the initial impact varies slightly around an increase of 0.05 percentage points. Therefore, the empirical effect of a shock in EPU on unemployment is economically negligible.

3.2.3. On the Time Variation of the Effect

We now turn our attention to the degree of time variation in the IRFs. In principle time-varying IRFs can vary along three dimensions, the initial impact, the overshooting behavior[6] and the persistence of the shock. Investigating Figure 1a to 1j reveals substantial time variation in the IRFs of all variables. The profiles of the IRFs vary across all three dimensions, i.e., the initial impact of the shock, the overshooting behavior and the persistence of the shock. First, we focus on the time profile of the response of real GDP, depicted in the left subfigure of Figure 1a, followed by a wider macroeconomic perspective.

[6]Within this framework, overshooting refers to a non monotonic IRF.

Focussing on Figure 1a, the response of real GDP, reveals that the first dimension, the initial impact, is relatively high during the 1970s, starts to decline in the early 1980s and stays stable until the early 2000s before it finally becomes larger with the onset of the financial crisis. The overshooting behavior, the second dimension, is pronounced during the 1970s, almost disappears from the 1980s onwards until the early 2000s and finally shows up again. 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, became more persistent in the early 2000s and were most persistent with the onset of the financial crisis.

We will now look on the wider macroeconomic impact. Most variables under consideration reflect the macroeconomic conditions of the US economy and, compared to the two financial variables, namely the S&P500 as well as the 10-Year Treasury Rate, share strong similarities across these three dimensions. Those variables are real gross investment, real consumption, the civilian unemployment rate or the ISM Manufacturing PMI Composite Index (see Figure 1b, 1d, 1c, 1i). Their profiles differ, beside minor movements, mostly in terms of the effect size. Interestingly, their IRF profiles (across the three dimensions) mimic a close relationship with the three major business cycles which have been identified previously, namely the Great Inflation, the Great Moderation and the Great Recession. During the Great Inflation, the initial impact of an uncertainty shock was relatively high followed by overshooting which dampens the net effect. With the onset of the Great Moderation, the initial impact became smaller and the overshooting behavior almost disappeared. Finally, since the onset of the Great Recession, the initial impact again increased, the shocks became more persistent and overshooting returned. Summing up, the macroeconomic effects of a shock in EPU seem to depend on the major business cycles of the US economy rather than on business cycles at lower frequencies. This seems 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.

After having identified that the impact of EPU on a wide range of different variables changes between the Great Inflation, the Great Moderation and the Great Recession we now ask whether the responses differ credibly across these business cycles. Therefore, we choose a reference date for each business cycle and calculate credible regions for the difference between these dates. The reference date for the Great Inflation is 1970 Q2, for the Great Moderation, 1996 Q1 and for the Great Recession, 2009 Q1.[7] The results are depicted in the lower right part of Figure 1a to 1j. We focus on the responses of Real GDP, depicted in Figure 1a. However, the responses of the remaining macroeconomic variables give very similar results. The comparison of the response of the US economy to a shock in EPU during the Great Inflation and the Great Moderation reveals that they do not differ credibly from each other. The pattern changes if we compare the Great Inflation with the Great Recession and the Great Moderation with the Great Recession. For the former, we clearly obtain a difference at the 68% credible region and almost a difference at the 95% credible region. The responses of the latter differ credibly at the 95% credible region. Note that the Great Inflation and the Great Moderation differ credibly from each other if we fix the error covariance matrix at its posterior mean as done in Section 3.2.4. There we will argue that the overshooting and the persistence of the responses credibly separate these episode from each other.

3.2.4. Impulse Responses with Fixed Error Covariance Matrix

During the previous analysis we allowed $\boldsymbol{\beta}_t, \boldsymbol{A}_t$ and $\boldsymbol{\Sigma}_t$ to vary over time. However, this approach does not allow to disentagle which component of the model causes the changing pattern in the IRFs. The time-variation might be due to either changes in the autoregressive coefficients $\boldsymbol{\beta}_t$, or due to changes in the error covariance matrix $\boldsymbol{\Omega}_t$. Differentiating between the two sources is important since it allows us to figure out whether the economy responds differently to an EPU shock (captured by changes in $\boldsymbol{\beta}_t$) or if the shock size and the shock structure have changed (captured by changes in $\boldsymbol{\Omega}_t$). In order

[7]The dates are chosen arbitrarily and choosing different dates would give similar results.

to differentiate between these two sources, we recalculated the IRFs for real GDP thereby keeping the error covariance matrix $\boldsymbol{\Omega}_t$ fixed at its posterior mean.[8] Figure 2 depicts the IRF for this setup. The initial impact is the same over time by construction. But the IRF still varies along the other two dimensions, the overshooting behavior and the persistence of the shock. Overshooting is pronounced during the Great Inflation, does not appear during the Great Moderation and finally returns during the Great Recession. Furthermore, the persistence of the shock increases strongly 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 95% 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 behavior and the responses in the Great recession are characterized by a persistent effect of an EPU shock.

3.3. On the Relevance of Estimating the Hyperparameters

We now turn to the importance of estimating the hyperparameters by using the approach of Amir-Ahmadi et al. (2018). Therefore, we compare our estimated hyperparameters with those usually used in the literature. Furthermore, we compare our IRFs with the ones obtained by using the benchmark values. The posterior distributions of $k_{\boldsymbol{Q}}$, $k_{\boldsymbol{W}}$ and $k_{\boldsymbol{S}}$ are depicted in Figure 3. The red line in each histogram corresponds to the typically used benchmark values. The benchmark values for $k_{\boldsymbol{Q}}$ and $k_{\boldsymbol{S}}$ are not even in the domain of the corresponding posterior distribution while the benchmark value of $k_{\boldsymbol{W}}$ is quite close to the mode of the relevant posterior distribution. Thus, if we had used the benchmark values commonly used in the literature, we would have underestimated the amount of time variation in the autoregressive coefficients, $\boldsymbol{\beta}_t$, as well as in the contemporaneous correlation of the error term $\boldsymbol{\alpha}_t$. To highlight the importance of estimating the hyper-

[8]The IRFs for all other variables are available upon request.

parameters for our results, Figure 4 displays the impulse responses derived by using the commonly used benchmark values. Comparing Figure 1a with Figure 4 clearly demonstrates the difference. Using the benchmark values suppresses a substantial amount of time variation in the IRF. The resulting IRF differs across the three dimensions described above, namely the initial impact, the overshooting behavior and the persistence profile of the shock. But without estimating the hyperparameters, the correlation with the three major business cycles of the US economy would be less clear.

4. 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. This enables us to investigate simultaneously the impact of EPU on variables which represent real economic activity and on variables which mimic the activity on financial markets.

Our main results are threefold: First, 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 business cycles 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 is in contrast to previous research which typically imposes two regimes a priori. The time-varying impulse responses vary across three dimensions, the initial impact, the overshooting behavior and the persistence. During the 1970s, the Great Inflation, the initial impact was relatively high but was followed by overshooting which dampened the net impact of the shock. 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. Second, we find that estimating the hyperparameters is important since using the benchmark values of Primiceri (2005) would underestimate the amount of time-variation. Third, we find that the responses of macroeconomic variables share strong similarities over time and that the response of financial variables differs from these.

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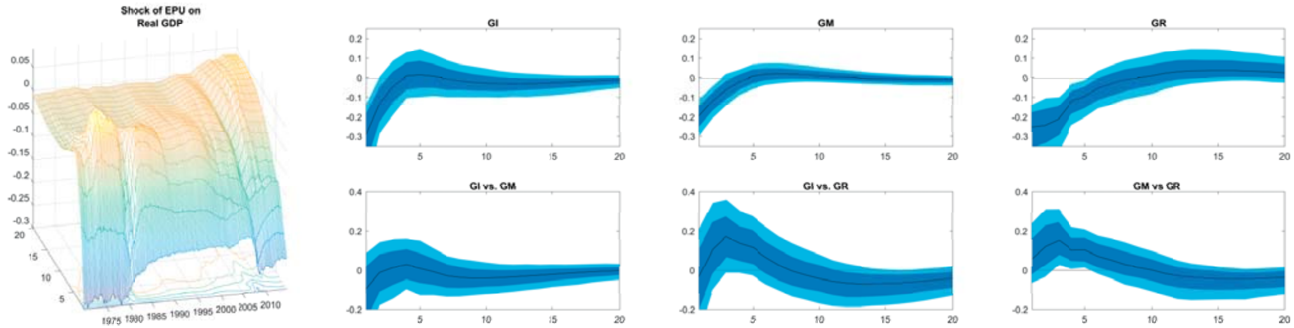
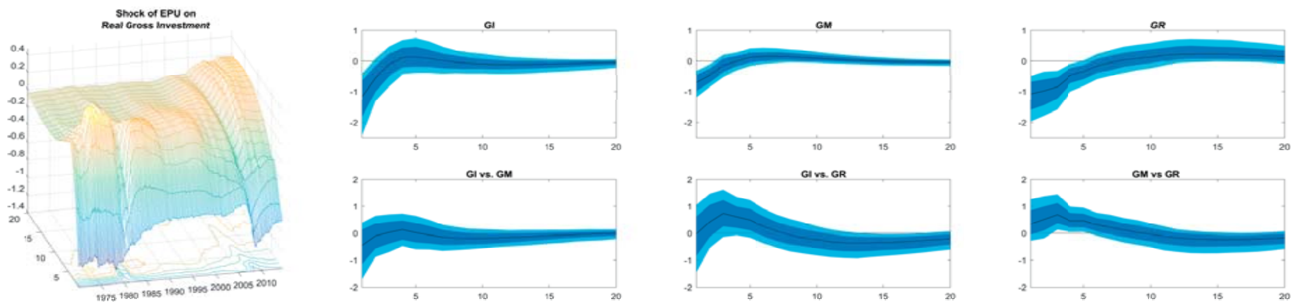
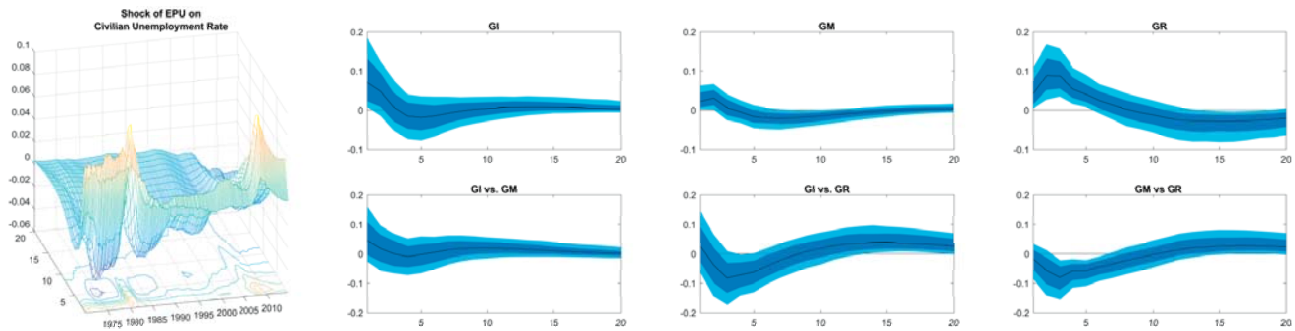
5. Figures



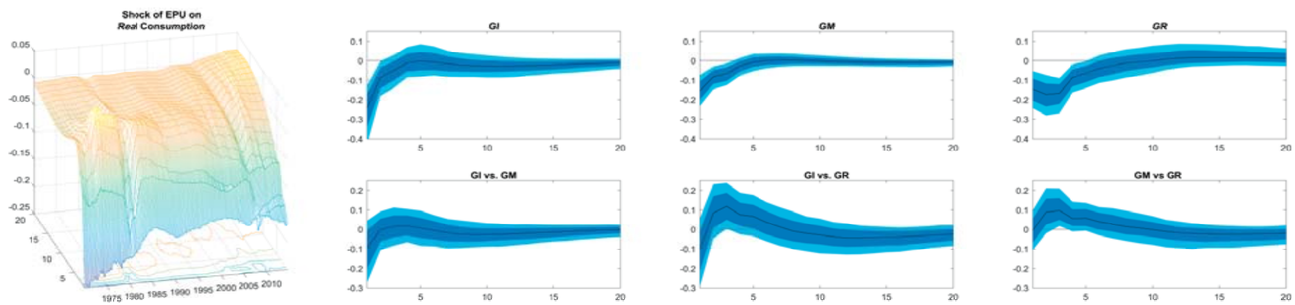
(a) *IRF of GDP to an increase in Economic Policy Uncertainty by one standard deviation.* The three dimensional graph displays the change in the pattern of the response over time. The upper three subfigures display the effect of economic policy uncertainty on the respective variable for three different time periods while the lower three subfigures display the difference between the three time periods along with 68% and 95% credible regions. 'GI' denotes Great Inflation, 'GM' Great Moderation and 'GR' Great Recession. Note that the three dimensional IRFs have been generated by allowing for time-variation in $\boldsymbol{\beta}_t, \boldsymbol{A}_t$ and $\boldsymbol{\Sigma}_t$.



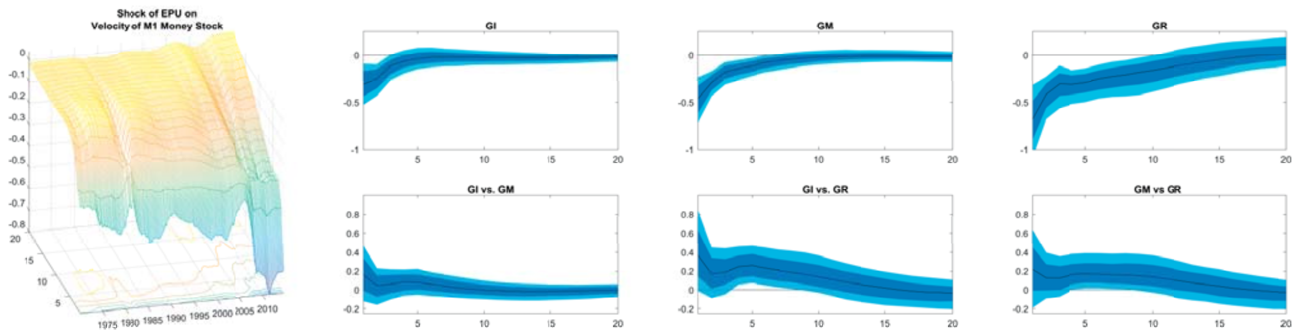
(b) *Impulse Response of Investment to an increase in Economic Policy Uncertainty by one standard deviation.*



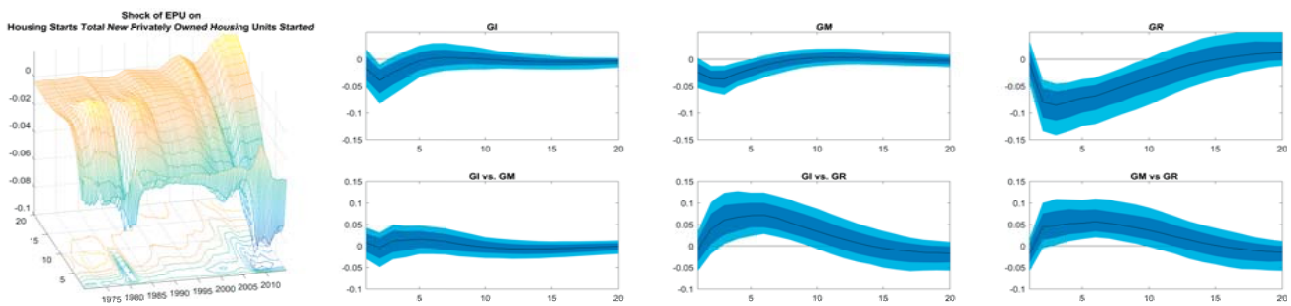
(c) *Impulse Response of Unemployment to an increase in Economic Policy Uncertainty by one standard deviation.*



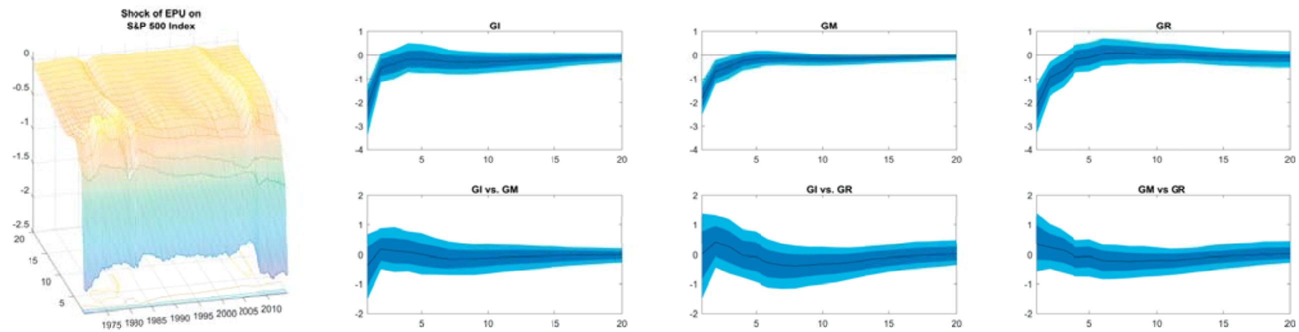
(d) *Impulse Response of Consumption to an increase in Economic Policy Uncertainty by one standard deviation.*



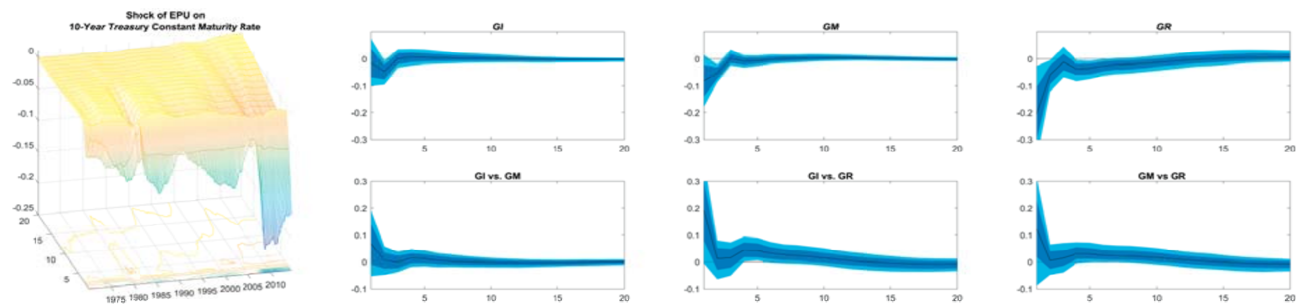
(e) *Impulse Response of Velocity of M1 to an increase in Economic Policy Uncertainty by one standard deviation.*



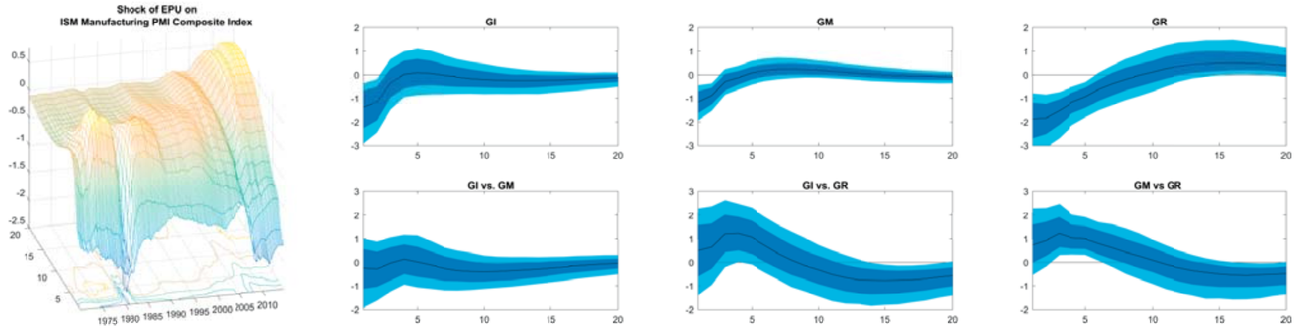
(f) *Impulse Response of Housing Starts to an increase in Economic Policy Uncertainty by one standard deviation.*



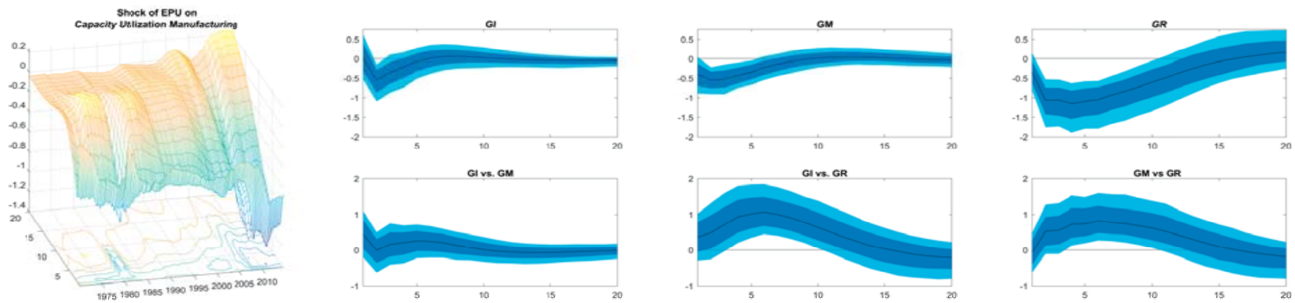
(g) *Impulse Response of S&P500 to an increase in Economic Policy Uncertainty by one standard deviation.*



(h) *Impulse Response of 10-Year Treasury Rate to an increase in Economic Policy Uncertainty by one standard deviation.*



(i) *Impulse Response of ISM Composite Index to an increase in Economic Policy Uncertainty by one standard deviation.*



(j) *Impulse Response of Capacity Utilization to an increase in Economic Policy Uncertainty by one standard deviation.*

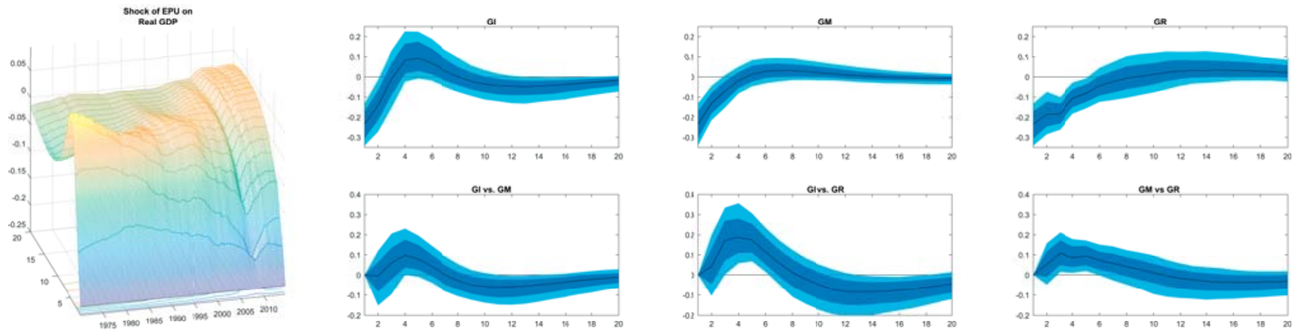
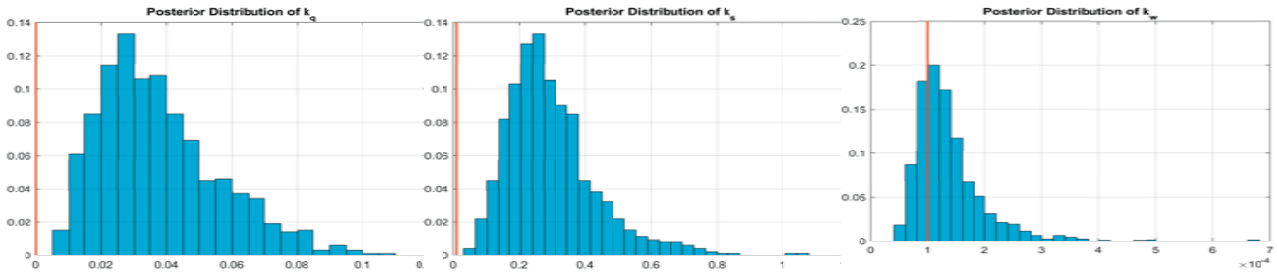


Figure 2: Response of Real GDP to a shock in Economic Policy Uncertainty if the covariance matrix $\mathbf{\Omega}_t$ is fixed at its posterior mean. 'GI' denotes Great Inflation, 'GM' Great Moderation and 'GR' Great Recession.



(a) (b) (c)

Figure 3: Posterior distributions of $k_{\boldsymbol{Q}}$, $k_{\boldsymbol{S}}$ and $k_{\boldsymbol{W}}$. The red lines correspond to the benchmark values used in Primiceri (2005).

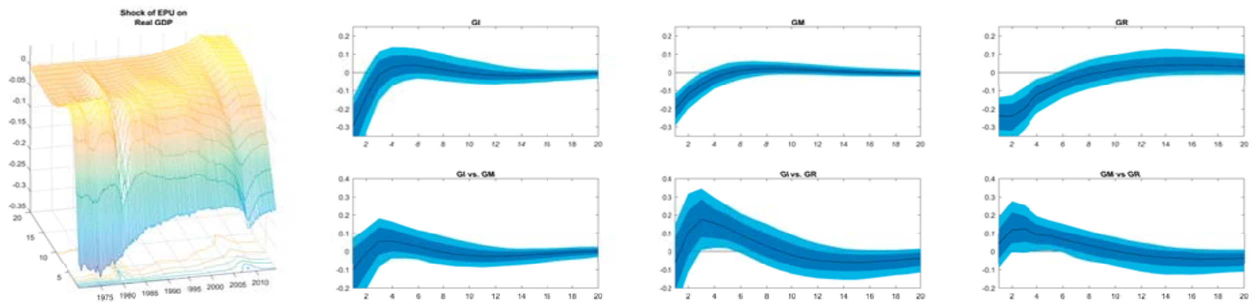


Figure 4: Response of Real GDP to a shock in Economic Policy Uncertainty estimated by using the benchmark values suggested in Primiceri (2005). 'GI' denotes Great Inflation, 'GM' Great Moderation and 'GR' Great Recession

Appendix A. Data

Table A.1: Data

No.	Name	ID	TC
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

Table A.1: Data(continued)

No.	Name	ID	TC
43	Capacity Utilization: Manufacturing	CUMFNS	1
44	Civilians Unemployed - Less Than 5 Weeks	UEMPLT5	5
45	Civilians Unemployed for 5-14 Weeks	UEMP5TO14	5
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	Effective Federal Funds Rate	FEDFUNDS	2
84	3-Month Treasury Bill: Secondary Market Rate	TB3MS	2
85	6-Month Treasury Bill: Secondary Market Rate	TB6MS	2
86	Moody's Seasoned Aaa Corporate Bond Yield	AAA	2
87	Moody's Seasoned Baa Corporate Bond Yield	BAA	2

Table A.1: Data(continued)

No.	Name	ID	TC
88	M1 Money Stock	M1SL	6
89	M2 Money Stock	M2SL	6
90	Currency Component of M1	CURRSL	6
91	Demand Deposits at Commercial Banks	DEMDEPSL	6
92	Savings Deposits - Total	SAVINGSL	6
93	Total Checkable Deposits	TCDSL	6
94	Travelers Checks Outstanding	TVCKSSL	6
95	Currency in Circulation	CURRCIR	6
96	MZM Money Stock	MZMSL	6
97	Velocity of M1 Money Stock	M1V	5
98	Velocity of M2 Money Stock	M2V	5
99	Total Nonrevolving Credit Outstanding	NONREVSL	6
100	Total Consumer Credit Outstanding	TOTALSL	6
101	Consumer Price Index for All Urban Consumers: All Items	CPIAUCSL	6
102	Consumer Price Index for All Urban Consumers: Commodities	CUSR0000SAC	6
103	Consumer Price Index for All Urban Consumers: All Items Less Energy	CPILEGSL	6
104	Consumer Price Index for All Urban Consumers: All Items Less Food	CPIULFSL	6
105	Consumer Price Index for All Urban Consumers: Energy	CPIENGSL	6
106	Consumer Price Index for All Urban Consumers: Food	CPIUFDSL	6
107	Consumer Price Index for All Urban Consumers: Apparel	CPIAPPSL	6
108	Consumer Price Index for All Urban Consumers: Medical Care	CPIMEDSL	6
109	Consumer Price Index for All Urban Consumers: Transportation	CPITRNSL	6
110	Producer Price Index: All Commodities	PPIACO	6
111	S&P 500 Index	SP500	5
112	Spot Oil Price: West Texas Intermediate	WTISPLC	5
113	U.S. / U.K Foreign Exchange Rate	EXUSUK	5
114	Switzerland / U.S. Foreign Exchange Rate	EXSZUS	5
115	Japan / U.S. Foreign Exchange Rate	EXJPUS	5
116	Canada / U.S. Foreign Exchange Rate	EXCAUS	5
117	ISM Manufacturing: PMI Composite Index	PMI	1
118	ISM Manufacturing: New Orders Index	NAPMNOI	1
119	ISM Manufacturing: Inventories Index	NAPMII	1
120	ISM Manufacturing: Employment Index	NAPMEI	1
121	ISM Manufacturing: Prices Index	NAPMPRI	1
122	ISM Manufacturing: Production Index	NAPMPI	1
123	ISM Manufacturing: Supplier Deliveries Index	NAPMSDI	1
124	Total Borrowings of Depository Institutions from the Federal Reserve	BORROW	6
125	SPOT MARKET PRICE INDEX:BLS & CRB: ALL COMMODITIES(1967=100)	PSCCOM	5

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 with the exception of series No.125 which has been retrieved from Datastream.

Appendix B. 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 ($k_{\boldsymbol{Q}}$, $k_{\boldsymbol{S}}$ and $k_{\boldsymbol{W}}$) as in Amir-Ahmadi et al. (2018). To draw from the joint posterior distributions, we draw from the following conditional posterior distributions:

1. Draw $\boldsymbol{\Sigma_t}$ from its conditional distribution $p(\boldsymbol{\Sigma_t}|\boldsymbol{y^T}, \boldsymbol{\beta^T}, \boldsymbol{\alpha^T}, \boldsymbol{I_n}, \boldsymbol{Q}, \boldsymbol{S}, \boldsymbol{W}, \boldsymbol{s^T}, k_{\boldsymbol{Q}}, k_{\boldsymbol{S}}, k_{\boldsymbol{W}})$, where $\boldsymbol{s^T}$ denotes the indicator vector needed to use the mixtures of normals approach suggested by Kim et al. (1998) to sample $\boldsymbol{\Sigma_t}$.[9]

2. Draw $\boldsymbol{\beta}^T$ from its conditional distribution $p(\boldsymbol{\beta^T}|-)$ by making use of the simulation smoother developed by Carter and Kohn (1994).[10]

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

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

5. 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. (2018):
   a) At each Gibbs iteration i, draw a candidate $k^*_{\boldsymbol{X}}$ from $N(k^{i-1}_{\boldsymbol{X}}, \sigma^2_{k\boldsymbol{X}})$.
   b) Calculate the acceptance probability $\alpha^i_{k_{\boldsymbol{X}}} = \min\left(1, \frac{p(\boldsymbol{X}|k^*_{\boldsymbol{X}})p(k^*_{\boldsymbol{X}})}{p(\boldsymbol{X}|k^{i-1}_{\boldsymbol{X}})p(k^{i-1}_{\boldsymbol{X}})}\right)$.
   c) Accept the candidate draw by setting $k^i_{\boldsymbol{X}} = k^*_{\boldsymbol{X}}$ with probability $\alpha^i_{k_{\boldsymbol{X}}}$. Otherwise set $k^i_{\boldsymbol{X}} = k^{i-1}_{\boldsymbol{X}}$.
   d) Calculate the average acceptance ratio $\overline{\alpha}_{k_{\boldsymbol{X}}}$. Adjust $\sigma_{k_{\boldsymbol{X}}}$ at every qth iteration according to $\sigma^{New}_{k_{\boldsymbol{X}}} = \sigma_{k_{\boldsymbol{X}}} \frac{\overline{\alpha}_{k_{\boldsymbol{X}}}}{\alpha^*}$, with α^* being the target average acceptance ratio. This step is not used after a pre-burn-in phase.

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

[9] T is a superscript and therefore denotes a sample from the corresponding variable for $t = 1, ..., T$.
[10] The notation $\theta|-$ represents the conditional posterior of θ conditional on the data and draws of all other coefficients.