RUHR
ECONOMIC PAPERS

Jan Prüser
Alexander Schlösser

The Effects of Economic Policy Uncertainty on European Economies: Evidence from a TVP-FAVAR

Ruhr Graduate School in Economics
UNIVERSITÄT DUISBURG ESSEN

#708

Imprint

Ruhr Economic Papers

Published by

RWI Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Editors

Editorial Office

Ruhr Economic Papers #708

Responsible Editor: Volker Clausen

ISSN 1864-4872 (online) – ISBN 978-3-86788-826-4

Ruhr Economic Papers #708

Jan Prüser and Alexander Schlösser

The Effects of Economic Policy Uncertainty on European Economies: Evidence from a TVP-FAVAR

Ruhr Graduate School in Economics
ECON
UNIVERSITÄT DUISBURG ESSEN

Bibliografische Informationen der Deutschen Nationalbibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der deutschen Nationalbibliografie; detaillierte bibliografische Daten sind im Internet über: *http://dnb.d-nb.de* abrufbar.

Das RWI wird vom Bund und vom Land Nordrhein-Westfalen gefördert.

http://dx.doi.org/10.4419/86788826
ISSN 1864-4872 (online)
ISBN 978-3-86788-826-4

Jan Prüser and Alexander Schlösser[1]

The Effects of Economic Policy Uncertainty on European Economies: Evidence from a TVP-FAVAR

Abstract

Recent events such as the financial and sovereign debt crisis have triggered an increase in European Economic Policy Uncertainty (EPU). We use a TVP-FAVAR model with hierarchical priors on the hyperparameters to investigate the effect of EPU on a wide range of macroeconomic variables for eleven European Monetary Union (EMU) countries. First, we find that EPU shocks are transmitted through various channels, such as the real options-, the precautionary savings- and the financial channel. Second, we are able to distinguish between a group of fragile countries (GIIPS-countries) and a group of stable countries (northern countries), where the former are more strongly affected by EPU shocks. Third, while the IRFs for most variables differ only in magnitude and not in sign between groups of countries, responses of long term interest rates to EPU shocks have a different sign across countries. Fourth, we discover that investors and traders react more sensitively than consumers to uncertainty. Fifth, we find that EPU shocks affect monetary policy decisions. Sixth, we provide evidence that the transmission of EPU shocks is quite stable over time. Finally, the increase in EPU can partly be explained by the state of the European economy and should therefore be treated as an endogenous variable.

JEL Classification: C11, C32, E20, E60

Keywords: TVP-FAVAR; economic policy uncertainty; fat data; hyperparameter; European Monetary Union; hierarchical prior

July 2017

---

1 Jan Prüser, RGS Econ and UDE; Alexander Schlösser, UDE. – *We thank Volker Clausen, Christoph Hanck as well as the participants of the research seminar of the Faculty of Economics and Business Administration at the University of Duisburg-Essen for valuable comments.* – *All correspondence to: Alexander Schlösser, University of Duisburg Essen, Faculty of Economics and Business Administration, Universitätsstr. 12, 45117 Essen, Germany, e-mail: alexander.schloesser@vwl.uni-due.de*

1. Introduction

Economic policy uncertainty (EPU) has recently gained increasing attention as a driving force of the business cycle. Recent events, such as the financial and sovereign debt crisis in Europe, have triggered uncertainty about a possible bailout of Greece, continuity of the Eurozone and the capacity of policy makers to solve the crisis in general. The International Monetary Fund (2012), Baker et al. (2012) and, more recently, the ECB (2016) argue that the increased EPU in Europe has hampered growth and the possibility of a faster recovery in the Eurozone. EPU influences decision making of economic agents and hence the economy, but is difficult to measure. Baker et al. (2016) develop a newspaper based index to measure EPU.[1] The index shows that EPU has increased in Europe during the financial crisis and even more during the sovereign debt crisis and until now has not returned to the pre-crisis level. Recently, many empirical studies, e.g., Österholm and Stockhammar (2014) or Scheffel (2015), used this index to quantify the effect of EPU on the economy.

Three major transmission channels have been identified in the theoretical literature and are currently under empirical investigation. The first describes how EPU affects investment, the second investigates the effect on consumption and the third explains how EPU affects the cost of finance or more general financial variables. To consider all three channels in one model a large set of variables would be needed. However, the majority of studies investigating the effect of EPU on the economy use a SVAR with only a small set of variables. Examples include Bloom (2009), Baker et al. (2012), Colombo (2013), Benati (2013), Österholm and Stockhammar (2014), Alam (2015) and Caldara et al. (2016). To consider a larger information set a FAVAR model suggested by Bernanke et al. (2005) is a useful choice. The key idea is that the VAR is augmented with k common factors extracted from a panel of macroeconomic variables. There are three studies investigating the effect of uncertainty on a panel of macroeconomic variables using a FAVAR approach. First, Mumtaz and Theodoridis (2017) focus on the effect of common and country-specific uncertainty from a global perspective. Second, Popp and Zhang (2016) use a smooth transition FAVAR with focus on the US. Third, Belke and Osowski (2017) compare the effect of US and European EPU on a small set of four variables for 18 OECD countries. Next to Popp and Zhang (2016) only two additional papers consider a possible time varying effect of EPU shocks on the economy. Caggiano et al. (2014) use a Smooth-Transition VAR to analyze the effect of uncertainty shocks on unemployment dynamics. Benati (2013) considers a possible time varying effect of EPU on aggregate Euro area variables by using a TVP-VAR. However, Benati (2013) only allows for time variation in the covariance

[1] Baker et al. (2016) ensure robustness and reliability of their index by a comparison of their algorithm based index with an index constructed from human reading of the same articles. Both indices are very similar.

matrix of the error terms.

The use of a TVP-FAVAR model permits us to contribute to the literature in at least three dimensions. First, while previous studies have focused their attention on one or two of the three channels discussed above, the TVP-FAVAR model allows us to investigate simultaneously how EPU shocks are transmitted through all three channels, which channel is relevant, which further variables are affected and which variable is most affected by EPU shocks. Second, some studies have considered the effect of EPU shocks on the European aggregate level of different macroeconomic variables. However, these studies might miss that uncertainty shocks may have a heterogeneous effect across different European economies. Also some effects may cancel out in the aggregate. For example, an uncertainty shock may hit fragile countries, like the GIIPS-countries, much harder compared to stable countries like Germany or France. Hence, we use the TVP-FAVAR model to investigate whether the European economies respond differently to uncertainty shocks. Third, previous research has mainly focused on models with constant parameters. In the light of events such as the introduction of the Euro, the financial and the debt crisis, which are all part of our sample, this assumption might not be desirable a priori and it may be useful to consider a model with time-varying parameters. Additionally, the TVP-part of our model allows us to investigate whether the transmission of uncertainty shocks or the size of shocks have changed over time.

We follow Stock and Watson (2005) and Korobilis (2013) and estimate the unobserved factors using principal components in order to avoid implausible identification restrictions (needed in a MCMC estimation scheme). Conditional on the estimated factors we use the TVP-VAR model of Primiceri (2005) to model time variation in the autoregressive coefficients and the covariance matrix of the reduced form error. In the model of Primiceri (2005) a small number of hyperparameters control the degree of time variation allowed for in the coefficients. Their choice will affect posterior inference and influence the amount of time variation in the coefficients. Various studies use benchmark values which will not always be appropriate. Given the importance of these parameters, we estimate them jointly with all other model parameters using a fully Bayesian approach as proposed by Matthes et al. (2016).

The remainder of the paper is structured as follows. Section 2 summarizes the theoretical and empirical literature, section 3 provides a brief overview of the underlying econometric model, section 4 contains empirical results and section 5 concludes.

2. Literature Review

Political uncertainty can affect the economy in several ways. A first channel is the real-options channel considered by Bernanke (1983). The premise is that investment and employment decisions are costly to revert. If decision makers are uncertain about the future of the economy, they might adopt a wait-and-see attitude and postpone investment and hiring. Thus, the option value is high when uncertainty is high and vice versa.[2] Several studies provided evidence supporting this channel, for example Bloom et al. (2007), Carrière-Swallow and Céspedes (2013) and Meinen and Röhe (2016) in terms of investment and Alexopoulos and Cohen (2009), Scheffel (2015) and Netšunajev and Glass (2017) in terms of employment.

A second channel developed by Romer (1990) explains why uncertainty affects consumption. If future income is uncertain, consumption of durable goods is subject to a similar degree of irreversibility and leads households to postpone their consumption decision until uncertainty has resolved. This channel is sometimes referred to as *precautionary savings* channel. That is, uncertainty can affect the intertemporal consumption decisions made by households. Benito (2006), Carrière-Swallow and Céspedes (2013) and Caldara et al. (2016) provide evidence on this channel.[3]

Consumption and investment constitute approximately 75% of Euro area's Gross Domestic Product (GDP). Obviously, if either one or both are negatively affected by EPU, GDP should decrease as well. This indirect effect has been documented by Donadelli (2015) and Baker et al. (2016). Furthermore, a decrease in GDP can be interpreted as a slowdown in aggregate demand, which leads, under the assumption of constant supply, to a reduction in inflation. Colombo (2013) and Belke and Osowski (2017) include inflation in their data set and both find evidence in favor of a negative relationship.

Through a third channel, uncertainty might affect financial markets. Within this third channel we differentiate between the effect of EPU on the cost of finance and the effect on the stock market. The former, known as the risk premium effect, describes that an increase in uncertainty may reduce the expected profitability of firms, which increases their perceived riskiness. Subsequently, investors require higher interest rates to be compensated for the higher risk, so that issuance of additional debt becomes more costly and adversely affects investment. Gilchrist et al. (2014) explore this hypothesis in a general equilibrium model and empirical evidence is provided by Nodari (2014) and Waisman et al. (2015). The latter study describes that, due to the effects of EPU on investment and the risk premium, stock prices are affected as well. Financial theory suggests that

[2] The empirical importance of this channel is underpinned by a statement of the FOMC of October 2001: "Several [survey] participants reported that uncertainty about the economic outlook was leading firms to defer spending projects until prospects for economic activity became clearer." A similar statement can be found in the Minutes of the FOMC from December 15-16, 2009.

[3] In order to provide further evidence that households' decisions are affected by EPU we extend the data set by the consumer confidence indicator.

stock prices are determined by the sum of expected future cash flows, discounted at the appropriate risk-adjusted discount rate. Thus, a decrease in cash flow or an increase in the risk-adjusted discount rate may lower the stock price.[4] Studies like Chang et al. (2015) or Chen et al. (2016) find empirical support for this effect.

The effect of EPU on credit is less well explored in the literature. Bordo et al. (2016, p. 90) provide a theoretical reasoning and empirical evidence on this transmission channel. They argue that "following the Great Recession, bankers complained that delays implementing financial reform under the Dodd-Frank Act created regulatory policy uncertainty that restrained lending, which, in turn, slowed economic recovery." Using a small VAR model they are able to show that EPU has a significant negative effect on bank loans.

3. Methodology

3.1. TVP-FAVAR

The VAR model introduced by Sims (1980) has become a popular tool to model dynamic relationships among macroeconomic variables and can be written in reduced form as

$$\boldsymbol{y}_t = \sum_{j=1}^{p} \boldsymbol{B}_j \boldsymbol{y}_{t-j} + \boldsymbol{u}_t, \tag{1}$$

for $t = 1, \ldots, T$, where T denotes the total number of periods, $\boldsymbol{y}_t$ is a $n \times 1$ vector of endogenous variables, $\boldsymbol{B}_j$ are $n \times n$ coefficient matrices and $\boldsymbol{u}_t \sim N(\boldsymbol{0}, \boldsymbol{\Omega})$ are reduced form errors, with $\boldsymbol{\Omega}$ a $n \times n$ covariance matrix. Because of the curse of dimensionality VAR models typically only include a small number of variables. However, more variables may be necessary to avoid an omitted variable bias and to model complex relations between macroeconomic variables. Bernanke et al. (2005) propose to increase the information set used in a VAR by augmenting it with a few factors which capture 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 economic policy uncertainty and the monetary policy rate. The use of the FAVAR model allows us to investigate through which channels an EPU shock is transmitted and how it affects European economies, which would not be possible within a standard small scale VAR.

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

[4]Expected future cash flow also depends on consumption which itself is adversely affected by EPU.

interpretation.[5] Thus, we follow Stock and Watson (2005) and Korobilis (2013) and apply a simpler two step approach. In the first step, the factors $\boldsymbol{f}_t(k \times 1)$ are estimated using the first 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, have an economic meaning and approximate the true factors in case of constant loadings. In the second step the parameters can be estimated conditional on these observed factors. Each of the observed variables x_{it} for $i = 1, \dots, m$ is linked to the k factors, to economic policy uncertainty (epu_t) and the monetary policy rate (R_t) via the factor regression

$$x_{it} = \boldsymbol{\lambda}_i^f \boldsymbol{f}_t + \lambda_i^R R_t + \lambda_i^{epu} epu_t + \epsilon_{it} \tag{2}$$

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 $\boldsymbol{y}_t = [\boldsymbol{f}'_t, R_t, epu_t]'$.

So far, we have assumed time invariant parameters and a time invariant covariance matrix of the error terms. This a priori assumption is possibly too restrictive, given that events such as the introduction of the euro or the financial crisis might have changed the transmission or the average size of shocks over time. To model time variation in the parameter matrix $\boldsymbol{B}_j$ and covariance matrix $\boldsymbol{\Omega}$, we use the TVP-VAR model of Primiceri (2005). This allows us to investigate whether the transmission of an economic policy uncertainty shock, the size or the correlation of the shocks have changed over time. By assuming that coefficients evolve as multivariate random walks the TVP-FAVAR can be written in state space form as

$$\boldsymbol{y}_t = \boldsymbol{z}'_t \boldsymbol{\beta}_t + \boldsymbol{u}_t, \tag{3}$$

$$\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \boldsymbol{\eta}_t, \tag{4}$$

where $\boldsymbol{z}'_t = \boldsymbol{I}_n \otimes [\boldsymbol{y}'_{t-1}, \dots, \boldsymbol{y}'_{t-p}]$, $\boldsymbol{\beta}_t = \text{vec}([\boldsymbol{B}_{1,t}, \dots, \boldsymbol{B}_{p,t}]')$ and $\boldsymbol{\eta}_t \sim N(\boldsymbol{0}, \boldsymbol{Q})$ is a state disturbance term with system covariance matrix $\boldsymbol{Q}$ of dimension $l \times l$, with $l = n(np+1)$. The covariance matrix $\boldsymbol{Q}$ is important in determining the amount of time-variation in the regression's coefficient. Setting this matrix to zero would lead to constant coefficients over time, nesting a constant coefficient VAR as a special case. An increased variability of the coefficients however bears the risk of overfitting the data. This suggests to impose some structure on $\boldsymbol{Q}$, as will be discussed in the next section. The covariance matrix $\boldsymbol{\Omega}_t$ is decomposed as

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

[5]For a discussion of these aspects see Korobilis (2013).

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 $\boldsymbol{\Sigma}_t$. Then the complete model can be written in state space form as

$$\boldsymbol{y}_t = \boldsymbol{z}_t'\boldsymbol{\beta}_t + \boldsymbol{A}_t^{-1}\boldsymbol{\Sigma}_t\boldsymbol{\epsilon}_t, \tag{6}$$

$$\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \boldsymbol{\eta}_t, \tag{7}$$

$$\boldsymbol{\alpha}_t = \boldsymbol{\alpha}_{t-1} + \boldsymbol{v}_t, \tag{8}$$

$$\log\boldsymbol{\sigma}_t = \log\boldsymbol{\sigma}_{t-1} + \boldsymbol{w}_t, \tag{9}$$

where $\boldsymbol{\epsilon}_t \sim N(\boldsymbol{0}, \boldsymbol{I}_n)$, $\boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{S})$ and $\boldsymbol{w}_t \sim N(\boldsymbol{0}, \boldsymbol{W})$.[6] The priors are similar to those used in Primiceri (2005),

$$\boldsymbol{\beta}_0 \sim N(\hat{\boldsymbol{\beta}}_{OLS}, V(\hat{\boldsymbol{\beta}}_{OLS})), \tag{10}$$

$$\boldsymbol{\alpha}_0 \sim N(\hat{\boldsymbol{\alpha}}_{OLS}, V(\hat{\boldsymbol{\alpha}}_{OLS})), \tag{11}$$

$$log\boldsymbol{\sigma}_0 \sim N(log\hat{\boldsymbol{\sigma}}_{OLS}, \boldsymbol{I}_n), \tag{12}$$

$$\boldsymbol{Q} \sim IW(k_Q \cdot V(\hat{\boldsymbol{\beta}}_{OLS}), v_1), \tag{13}$$

$$\boldsymbol{S} \sim IW(k_S \cdot V(\hat{\boldsymbol{\alpha}}_{OLS}), v_2), \tag{14}$$

$$\boldsymbol{W} \sim IW(k_W \cdot \boldsymbol{I}_n, v_3), \tag{15}$$

where OLS denotes the OLS estimator using the full sample[7], k_Q, k_S and k_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.

3.2. Estimation of Hyperparameters

The choice of hyperparameters k_S, k_W, and in particular of k_Q, is crucial, as it determines the amount of time variation in the autoregressive coefficients (see Primiceri, 2005). Researchers typically impose tight priors on $\boldsymbol{Q}$, thus controlling the amount of time variation, in order to avoid overfitting the data.[8] Unfortunately, the choice of the hyperparameters will affect posterior inference and influence the amount of time variation in the coefficients, a fact which is largely ignored in applications. Only a few studies, such as Primiceri (2005), select the hyperparameters over a small grid by maximizing the marginal likelihood. Inference is then conditioned on the selected hyperparameters. However, given the importance of the choice of these parameters, it may be desirable to sample the

[6] We adopted the additional assumption of $\boldsymbol{S}$ being block diagonal. This assumption is not crucial but simplifies inference and increases the efficiency of the algorithm. See Primiceri (2005) for details.

[7] The same prior specification can be found in Gambetti and Musso (2017).

[8] See, for example, the discussion in Primiceri (2005) and Cogley and Sargent (2005).

hyperparameters k_Q, k_S, k_W in a data-based fashion and take the uncertainty surrounding k_Q, k_S, k_W into account. Hence, we sample/estimate the hyperparameters k_Q, k_S, k_W jointly with all other model parameters using a fully Bayesian approach as proposed by Matthes et al. (2016). This has the additional advantage that one does not need to specify a grid. For example, the values in the grid specified in Primiceri (2005) for k_Q are not in the domain of the posterior we found for k_Q. The approach of Matthes et al. (2016) is based on the observation 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 of $k_{\boldsymbol{X}}$. Thus, the conditional posterior

$$p(k_{\boldsymbol{X}}|\boldsymbol{X}) \propto p(\boldsymbol{X}|k_{\boldsymbol{X}})p(k_{\boldsymbol{X}}), \tag{16}$$

where $p(\boldsymbol{X}|k_{\boldsymbol{X}})$ denotes the prior of $\boldsymbol{X}$ and $p(k_{\boldsymbol{X}})$ the prior of $k_{\boldsymbol{X}}$ can be obtained by a Metropolis-within-Gibbs step, as all other model densities cancel out in the acceptance probability.[9] We formulate non-informative hierarchical inverse Gamma priors for $p(k_{\boldsymbol{X}})$.

3.3. Identification

Crucially, the FAVAR allows to investigate the effect of a shock in a policy variable on a wide range of macroeconomic variables. To obtain the vector moving average (VMA) representation we rewrite equations (1) and (3) as

$$\boldsymbol{x}_t = \Lambda \boldsymbol{y}_t + \Phi(L)\boldsymbol{x}_t + \boldsymbol{\epsilon}_t^{\boldsymbol{x}} \tag{17}$$

$$\boldsymbol{y}_t = \Psi_t(L)\boldsymbol{y}_t + \boldsymbol{A}_t^{-1}\boldsymbol{\Sigma}_t\boldsymbol{\epsilon}_t^{\boldsymbol{y}} \tag{18}$$

where Λ is $m \times n$ and $\Phi(L)$ as well as $\Psi_t(L)$ are lag polynomials. Inserting (18) in (17), we obtain the VMA representation

$$\boldsymbol{x}_t = \tilde{\Phi}(L)\boldsymbol{\Lambda}\tilde{\Psi}_t(L)\boldsymbol{A}_t^{-1}\boldsymbol{\Sigma}_t\boldsymbol{\epsilon}_t^{\boldsymbol{y}} + \tilde{\Phi}(L)\boldsymbol{\epsilon}_t^{\boldsymbol{x}} \tag{19}$$

with $\tilde{\Phi}(L) = (I - \Phi(L))^{-1}$ and $\tilde{\Psi}_t(L) = (I - \Psi_t(L))^{-1}$. The model is identified in a recursive manner. The Cholesky decomposition imposes the identifying assumption that the latent factors do not respond to a policy uncertainty shock within the same period. Fortunately, we do not need to impose this assumption on all the variables in $\boldsymbol{x_t}$. Instead, in accordance with Bernanke et al. (2005), we categorize the variables in $\boldsymbol{x_t}$ to be "fast-moving" and "slow-moving".[10] Fast-moving variables are assumed to respond contemporaneously to an unanticipated change in EPU, while slow-moving variables do not. Table A.1 contains details on the classification of the variables.[11]

[9] For more details see Matthes et al. (2016).

[10] Popp and Zhang (2016) and Belke and Osowski (2017) use the same strategy to identify uncertainty shocks in a FAVAR model.

[11] We also estimate the model with two different orderings. First, $\boldsymbol{y}_t = [\boldsymbol{f}_t', epu_t, R_t]'$. Second, $\boldsymbol{y}_t = [epu_t, \boldsymbol{f}_t', R_t]'$. Our main findings are qualitatively the same for both orderings.

4. Empirical Results

4.1. Data

We estimate the model with data from eleven EMU countries which can be splitted in two groups. The first group consists of Greece, Italy, Ireland, Portugal and Spain. Those countries have been in focus in the run up of and during the sovereign debt crisis. We refer to these as the "GIIPS countries". The second group consists of the remaining countries France, Germany, Finland, Austria, Netherlands and Belgium, called "northern countries". For each country we consider nine macroeconomic variables consisting of gross domestic product, investment, consumption, the GDP deflator, the unemployment rate, credit to the non-financial privat sector, 10 year government bond yields, a stock market index and consumer confidence.[12] All variables are seasonally adjusted if necessary and standardized for the estimation of the PC. The set of further variables consists of EPU and the EURIBOR to approximate the ECB interest rate on main refinancing operations. We use quarterly data ranging from 1997:Q1 until 2016:Q1. The data sources and variable transformations can be found in Table A.1.

4.2. Model Estimation

We estimate the VAR model using two lags.[13] Furthermore, in our preferred specification, we include three factors in our model. In addition, we consider models with up to six 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 find in our estimation. Increasing the number of factors gives qualitatively similar results, but the IRFs are becoming more volatile and less smooth, suggesting that more factors overfit the data.

We initiate the Gibbs sampler with a preliminary burn-in phase of 100,000 draws in order to adjust the variance of the proposal density of $k_{\boldsymbol{X}}$ in the Metropolis-within-Gibbs step.[14] The proposal variance is adjusted to achieve a target acceptance rate of 50%. Af-

[12] These 99 macroeconomic variables form the data matrix $\boldsymbol{x}_t$ from which we extract the factors.

[13] We estimate the autocorrelation of the error term for each equation and find no evidence for serious autocorrelation.

[14] A detailed explanation of the Metropolis-within-Gibbs step as well as the whole algorithm can be found

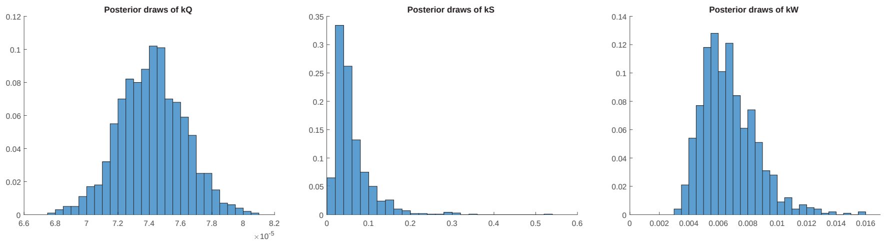

Figure 1: Posterior distributions of k_Q, k_S and k_W. The hyperparameter k_Q controls the amount of time variation in the autoregressive coefficients, k_S the amount of time variation in the contemporaneous covariance, and k_W the amount of time variation in the stochastic volatility.

ter the pre burn-in, we use a burn-in of 50,000 draws with fixed proposal variance followed by 100,000 draws to approximate the posterior, where we retained every 100th draw to deal with autocorrelation in the chain. This leaves us with 1000 draws for inference. In order to judge the mixing properties of the algorithm, the autocorrelation functions of all parameters are investigated. Therefore, we calculate the inefficiency factor (IF) for all estimated coefficients, see Figure C.1. According to Primiceri (2005), IFs ≤ 20 are regarded as satisfactory. All IFs are below 4, indicating a well mixing chain. Stability of the model has been verified by calculating the modulus of all eigenvalues for each draw.

4.3. Posterior Distributions of Hyperparameters

Prior to discussing the economic effects of EPU, we focus on the posterior distributions of k_Q, k_S and k_W and the amount of time variation in the corresponding set of coefficients. Figure 1 shows the posterior distributions of all three parameters. The posterior either mimics a normal or an inverse gamma distribution. The domains of the posterior distributions differ strongly. While the posterior median of $k_Q = 7.4061\text{e-}05$ is very small, indicating that the autoregressive parameters do not change much over time, the posterior medians of $k_S = 0.0925$ and $k_W = 0.0076$ indicate moderate time variation in the contemporaneous correlation and the stochastic volatility. Indeed, Figure 2 reveals that a small posterior of k_Q leads to fairly constant coefficients over time. While there is little time variation in the volatility of EPU, the volatility of R shows a sizeable amount of time variation.[15] Comparing our estimated hyperparameters with those used by Primiceri (2005) who sets $k_Q = 0.01^2$, $k_S = 0.1^2$ and $k_W = 0.01^2$, and which are often taken as given in other studies, highlights the importance of sampling them in a data based fash-

in Appendix B.

[15]The decline of the median volatility of EPU since 2008 may at first come as a surprise. However, this is due to the fact that a large amount of variation in EPU is explained by other shocks in the model, in particular the increase of EPU since 2008. We will discuss this issue further in the historical decomposition of EPU in Section 4.5.

ion. Those values would have yielded more time variation in the autoregressive coefficients and less time variation in the contemporaneous correlation as well as in the stochastic volatility.[16] The importance of sampling the hyperparameters, instead of using the same values as Primiceri (2005), is also documented by Matthes et al. (2016).

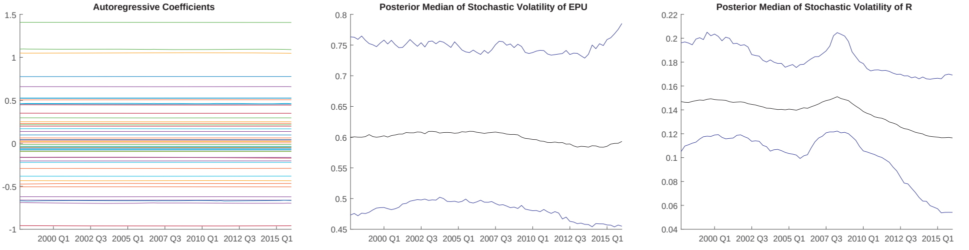

Figure 2: Posterior medians of the autoregressive coefficients, the stochastic volatility of EPU and the stochastic volatility of R along with 95% credible region.

An ex post perspective might suggest that estimating models with time variation in autoregressive coefficients is not necessary, but it should be stressed that the model discovered this fact endogenously. That is, we start with a very flexible model, allowing for time-varying autoregressive coefficients, time-varying variances and time-varying covariances, after which the model endogenously decides which aspect is supported by the data. Thereby, our econometric design can discover which part of the model is time varying. Simply starting with a constant coefficient model implies the risk to work with misspecified regression equations. In our case, the estimation process reduces the amount of time variation in the autoregressive coefficients, basically switching off this part of the model. On the other hand it allows for time varying volatility and covariances. This result is in line with empirical findings for US data. Sims and Zha (2006), for example, find that a VAR with constant coefficients and a time varying covariance matrix delivers the best fit for US data.

4.4. Impulse Response Functions

Figures D.1 to D.9 show the impulse response functions for all countries and all variables. Each figure consists of twelve subfigures. The first eleven subfigures display the response of the respective variable to a shock in EPU over the whole sample period and the 12th

[16]Estimation results with the hyperparameter values choosen by Primiceri (2005) are available upon request. The major difference appears in the stochastic volatility of R which becomes time invariant. This suggests that inappropriate benchmark values erroneously suppress or increase time variation of the model parameters.

panel contains Bayes p-values and indicates how credibly the response differs from zero.[17] We reduce for convenience the dimensionality of this plot by averaging over time. This is plausible since there is no credible time variation in the IRFs to an EPU shock. The IRFs are standardized such that the effect can be interpreted in the initial unit of measurement.

Figure D.1 contains the IRFs of GDP growth. We observe a negative effect in all countries, in line with the earlier theoretical considerations. For example in Spain, an increase in the logarithm of EPU by one standard deviation decreases GDP growth in period 1 after the shock by 0.1%. The size as well as the development of the IRFs across all countries seem reasonable to us, i.e., the effect is neither too strong nor too weak and dies off after approximately ten quarters in Greece and Spain and after approximately three quarters in all other countries. We observe that the fragile countries are on average hit more strongly by an EPU shock compared to the stable countries. The distinction between the two subgroups will become more apparent in the discussion of all other IRFs.

Turning our attention to investment, depicted in Figure D.2, a negative effect in all countries is observed, providing evidence in favor of the real options channel and highlights that business decisions are adversely affected. Comparing the effect sizes of GDP and investment reveals that investment is hit more strongly. This holds especially for the fragile countries. The IRFs of stable and fragile countries exhibit substantial heterogeneity. For example, Greek investment decreases by almost 0.4% in the period after the shock while in Germany investment decreases by only 0.1%. Furthermore, the effect dies off earlier on average in the stable countries than in the fragile countries.

The response of consumption to a shock in EPU, as summarized in Figure D.3, is negative and therefore provides evidence on the precautionary savings channel. Thus, not only business decisions are affected by EPU but also the consumption decision of households. Again the response of the fragile countries is stronger. A comparison of the effect sizes of investment and consumption shows that in many countries, e.g., Greece or the Netherlands, investment is hit harder than consumption. This suggests that investors react more sensitively than consumers.

Inflation is negatively affected as expected. Figure D.4 again reveals heterogeneity. There are three exceptions with a positive response, namely Germany, Finland and Austria. For Finland and Austria, the effect is not credibly different from zero while the effect of Germany is quite persistent. However, the effect size is very small in all countries suggesting that the effect of EPU on inflation is negligible.

The IRFs of unemployment to an increase in policy uncertainty, depicted in Figure D.5, are positive for all countries, confirming that a shock in EPU postpones hiring decisions as suggested by the "wait-and-see" attitude. Similar to the previous variables, the country set can be grouped into fragile and stable countries. Even though the effect is credible,

[17]The Bayes p-value is calculated as the frequentist p-value but has a Bayesian interpretation. For this reason we use the expression "credible" instead of "significant".

its impact is extremely small.

Figure D.6 visualizes the responses of credit. The effect is quite strong, especially in the fragile countries. For example, in Greece the credit volume decreases in period 2 after the shock by 0.4%. The effect is smaller in the stable countries but not negligible.[18]

The IRFs of the 10 year government bond, depicted in Figure D.7, provide evidence on first part of the financial channel and reveal a very interesting and intuitive pattern. While we observe an increase of the interest rate up to 1 percentage point (Greece) for the fragile countries, the stable countries experience a decrease in interest rates. That is, investors request higher risk premia for the fragile countries, while for the stable countries, a safe haven effect appears. This result indicates that caution is needed if one argues that uncertainty in general increases risk premia because this effect might be country group specific.

The effect of EPU on stock markets, the second part of the financial channel, is given in Figure D.8. The IRFs are negative and quite large, with up to -5%. The effect is short-lived and homogenous. This indicates that financial market participants do not differentiate between the current state of the economy in different countries and that the degree of financial integration between the EMU countries is high.

Finally, Figure D.9 provides an overview about the effect of EPU on consumer confidence. The pattern of the IRFs is very similar to the one of the stock market, i.e., the effect is negative, as expected, short-lived and homogenous, but weaker. This suggests that consumers are less sensitive to uncertainty compared to stock market traders.

4.5. Historical Decomposition of EPU

In this section we investigate whether EPU is exogenous or endogenous. The policy uncertainty index for various countries, depicted in the appendix of Baker et al. (2016), spikes at events that are not caused by the economy, e.g., 9/11 for the US or the German elections in 2005. But events such as the "Eurozone Stress" or the "Growth Slowdown Concern" in China at the end of 2014, are at least partially caused by economic events. To shed light on this issue, and therefore on the adequacy to treat EPU as exogenous, we use a historical shock decomposition. The historical decomposition reveals the cumulative contribution of each structural shock to the evolution of EPU. Figure 3 shows the time series and its historical decomposition. Three interesting conclusions can be drawn. First, own shocks had the largest impact on EPU and the largest shocks occur between 2001:Q3 and 2003:Q1. The first spike is due to 9/11, which can be treated as an exogenous event. Furthermore, 2002 was characterized by substantial uncertainty regarding growth perspectives of the global economy. At the end of 2002, the upcoming Iraq war led to higher

[18]Whether the effect is due to financial reforms as raised by Bordo et al. (2016) or a consequence of the decrease in investment and consumption needs to be investigated in future research and is beyond the scope of this paper.

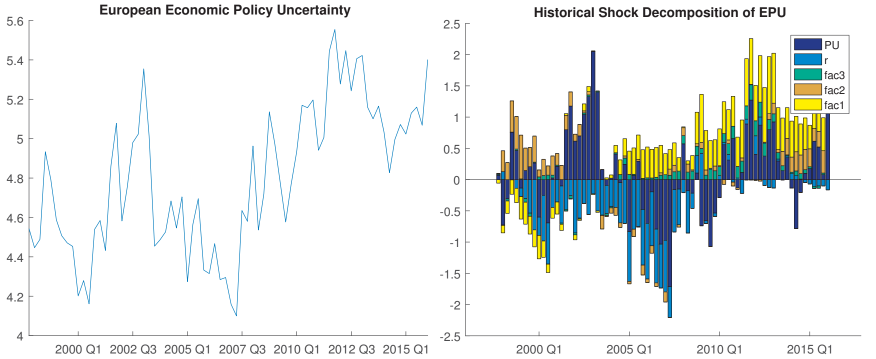

Figure 3: The *left* panel displays log EPU from 1997:Q1 until 2016:Q1. The *right* panel depicts the historical decomposition of EPU into the structural shocks. The historical decomposition reveals the cumulative effect of each structural shock on the evolution of the time series.

policy uncertainty. Second, at the beginning of the sample, monetary policy played an important role in reducing policy uncertainty, i.e., the decline of the ECB interest rate on the main refinancing operations, starting in 2001 and ending in 2005 during the stagnation period in Europe, reduced EPU in Europe.[19] This negative stimulus continued during the period of the rise in ECB interest rate, starting in 2005:Q3. Third, between 2005 and 2010 own shocks had a negative impact on EPU. In that period European countries as well as the global economy, returned to a growth path and EPU was historically low (see right panel of Figure 3). At the same time the first factor, representing one of the driving forces of the economy, started to have a positive impact on EPU. This reveals that the increase of EPU, especially since the outbreak of the financial crisis, was caused by the driving forces of the economy, plausible as the European economy was hit by the financial crisis followed by the sovereign debt crisis. Therefore, the recent high level of EPU is at least partly endogenous. Nevertheless, there are also some clearly exogenous shifts in EPU between 2011 and 2014. Those shifts are due to events such as the referendum in Greece in October 2011 or the debt cut for Greece in March 2012. Hence, the historical decomposition suggests that EPU is partly endogenous, as considerable variation is linked to the state of the European economy. Nevertheless, a large part of its variation is also linked to monetary policy decisions and own shocks, possibly related to exogenous events caused by political as well as global events. This finding is in line with Benati (2013), who also focused on the endogeneity of EPU for Europe in aggregate as well as the UK, USA and Canada. He used Granger causality tests to examine the endogeneity and was able to reject the null of no Granger causality.

[19] This period was characterized by sluggish growth of the global economy in 2003 and passed over into the Iraq war, which further affected the global economy. With the onset of the Iraq war, the ECB reduced its main interest rate by 0.5% because of expected adverse effects.

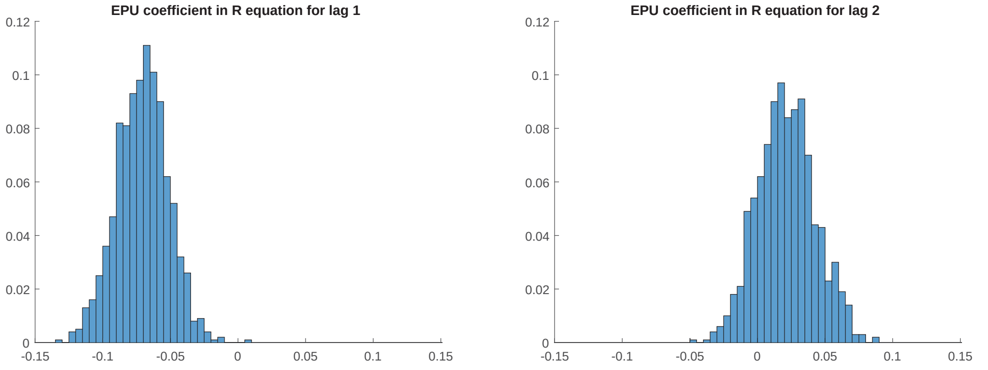

Figure 4: Posterior distributions of the two 'EPU coefficients' in the monetary policy equation.

4.6. The Role of EPU for Monetary Policy

Many studies document the usefulness of the FAVAR to conduct monetary policy analysis, see for example Bernanke et al. (2005) and Korobilis (2013). Basically, the model is capable to estimate the reaction function of monetary policy using a large information set. We will use this feature of the model to address the question whether monetary policy is affected by EPU. Evidence on this question will be given from three perspectives. First, we will investigate whether the autoregressive coefficients of EPU in the interest rate equation are credibly different from zero. Second, we will examine the IRF of R to a shock in EPU. Third, we will discuss the historical decomposition.

Starting with the autoregressive coefficients, Figure 4 shows that the coefficient of the first lag is credibly different from zero. This provides first evidence that EPU is part of the monetary policy reaction function. The IRFs (see Figure 5) reveal that a shock in EPU has a credible negative effect on R. The EPU shock dies off very slowly and lets R fall up to 0.25 percentage points. Finally, the historical decomposition reveals that from 2002 until 2005, the period of stagnation in Europe, EPU had an impact on the interest rate. From 2002 until 2005, EPU reduced R. The ECB responded to the weak economic conditions in Europe, which were partly due to the uncertainty about the global economy, and finally responded to the Iraq war by reducing the interest rate.[20]

[20] To further underline the point, note the following statement from the monthly bulletin of March 2003, p.6: "However, any judgment on future developments is overshadowed at present by the geopolitical tensions and their potential resolution. Monetary policy cannot address this kind of uncertainty. Depending on further developments which may change the medium-term outlook for price stability in any direction, the Governing Council stands ready to act decisively and in a timely manner."

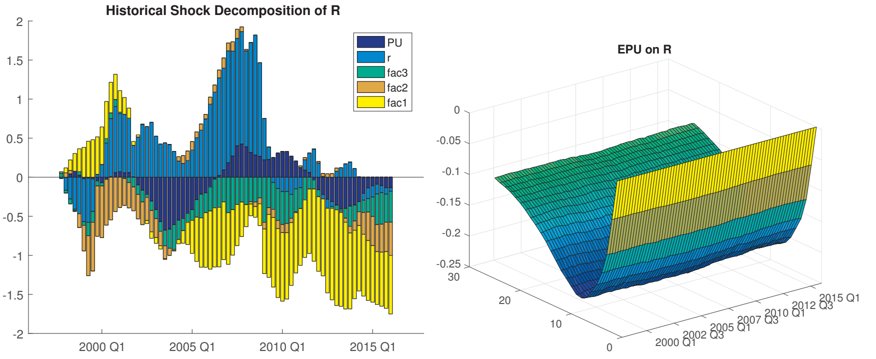

Figure 5: Historical decomposition and impulse response of R to a shock in EPU.

From 2007 until 2011 the effect was relatively small and positive before it becomes negative again during the run up of the sovereign debt crisis. However, the largest negative effect after 2009 can be attributed to the three factors representing the economy. This empirical finding shows that the majority of monetary policy decisions since the financial crisis were linked to the poor state of the economy but also that the ECB reacted to EPU. This is in line with the words of Mario Draghi in July 2012 -"Whatever it takes"-, which addressed economic as well as political uncertainty.

5. Conclusions

This study estimates a TVP-FAVAR model following Stock and Watson (2005) and Korobilis (2013) in order to avoid implausible identification restrictions (needed in a MCMC estimation scheme) and estimates the unobserved factors using principal components. Conditional on the estimated factors we use the TVP-VAR model of Primiceri (2005) to model time variation in the parameter and the covariance matrix. The majority of previous studies uses possibly inappropriate benchmark values for some hyperparameters, which control the amount of time variation in the coefficients, variances and covariances. We instead estimate the hyperparameters jointly with all other model parameters using a fully Bayesian approach as proposed by Matthes et al. (2016). We find that the hyperparameters shrink the amount of time variation in the autoregressive coefficients, but allow for time varying volatility and covariances. This finding demonstrates the importance and benefit of estimating the hyperparameters using a fully Bayesian approach.

In order to investigate the effect of EPU on the European economies it is desirable to first consider the three theoretical channels (i.e. the real options-, the precautionary savings- and the financial channel) through which EPU shocks are potentially transmitted, second to allow for heterogeneous effects between different countries and third to allow for time variation in the transmission of EPU shocks. Our TVP-FAVAR allows us to address all three points. We cater the first two points by investigating the impact of EPU shocks on 100 variables, i.e., nine macroeconomic variables consisting of the gross domestic product, investment, consumption, the GDP deflator, the unemployment rate, credit to the non-financial private sector, 10 year government bond yields, a stock market index, and consumer confidence for eleven EMU countries, namely Greece, Italy, Ireland, Portugal, Spain, France, Germany, Finland, Austria, Netherlands and Belgium. The third point is considered by using the TVP-VAR model of Primiceri (2005).

We discover that the transmission of EPU shocks is quite stable over time, but find strong evidence in favor of the first two points. The IRFs show that EPU shocks are transmitted through all three channels and hit fragile countries (GIIPS-countries) harder than more stable countries (northern countries). Furthermore, investors and financial market participants react more sensitively than consumers to uncertainty, since investment and stock prices are affected by EPU shocks more strongly than consumption and consumer confidence. While most IRFs differ only in magnitude and not in sign the response of the long term interest rates to EPU shocks has a different sign across countries. For the fragile countries we observe an increase of the interest rate up to 1 percentage point (Greece) and for the stable countries we observe a decrease in interest rates. That is, investors request a higher risk premium for the fragile countries, while for the stable countries a safe haven effect appears. This stresses that the effect of EPU on European countries is quite asymmetric. Finally, a historical variance decomposition reveals that the increase in EPU can partly be explained by the state of the European economy and EPU should thus be treated as an endogenous variable and that EPU shocks drive the EURIBOR up to 1% and thus have an important impact on monetary policy decisions.

References

Alam, M. R. (2015). Economic Policy Uncertainty in the US: Does it Matter for Canada? *Economics Bulletin*, 35(4):2725–2732.

Alexopoulos, M. and Cohen, J. (2009). Uncertain Times, Uncertain Measures. *University of Toronto, Working Papers*, 352.

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*, 131(4):1593–1636.

Belke, A. and Osowski, T. (2017). International Effects of Euro Area versus US Policy Uncertainty: A FAVAR Approach. *GLO Discussion Paper*, No. 35.

Benati, L. (2013). Economic Policy Uncertainty and the Great Recession. *Journal of Applied Econometrics*. Revise and Resubmit.

Benito, A. (2006). Does Job Insecurity affect Household Consumption? *Oxford Economic Papers*, 58(1):157–181.

Bernanke, B. S. (1983). Irreversibility, Uncertainty and Cyclical Investment. *Quarterly Journal of Economics*, 98(1):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*, 120(1):387–422.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica*, 77(3):623–685.

Bloom, N., Bond, S., and Van Reenen, J. (2007). Uncertainty and Investment Dynamics. *Review of Economic Studies*, 74(2):391–415.

Bordo, M. D., Duca, J. V., and Koch, C. (2016). Economic Policy Uncertainty and the Credit Channel: Aggregate and Bank Level U.S. Evidence over Several Decades. *Journal of Financial Stability*, 26:90–106.

Caggiano, G., Castelnuovo, E., and Groshenny, N. (2014). Uncertainty Shocks and Unemployment Dynamics in U.S. recessions. *Journal of Monetary Economics*, (67):78–92.

Caldara, D., Fuentes-Albero, C., Gilchrist, S., and Zakrajsek, E. (2016). The Macroeconomic Impact of Financial and Uncertainty Shocks. *European Economic Review*, 88:185–207.

Carrière-Swallow, Y. and Céspedes, L. F. (2013). The Impact of Uncertainty Shocks in Emerging Economies. *Journal of International Economics*, 90(2):316–325.

Carter, C. K. and Kohn, R. (1994). On Gibbs Sampling for State Space Models. *Biometrika*, 81(3):541–553.

Chang, T., Chen, W. Y., Gupta, R., and Nguyen, D. K. (2015). Are Stock Prices related to the Political Uncertainty Index in OECD Countries? Evidence from the Bootstrap Panel Causality Test. *Economic Systems*, 39(2):288–300.

Chen, J., Jiang, F., and Tong, G. (2016). Economic Policy Uncertainty in China and Stock Market Expected Returns. Available at SSRN: http://dx.doi.org/10.2139/ssrn.2808862.

Cogley, T. and Sargent, T. J. (2005). Drifts and Volatilities: Monetary Policies and Outcomes in the post WWII US. *Review of Economic Dynamics*, 8(2):262–302.

Colombo, V. (2013). Economic Policy Uncertainty in the US: Does it matter for the Euro Area? *Economics Letters*, 121(1):39–42.

Del Negro, M. and Primiceri, G. (2015). Time-varying Structural Vector Autoregressions and Monetary Policy: A Corrigendum. *Review of Economic Studies*, 82(4):1342–1345.

Donadelli, M. (2015). Google Search-Based Metrics, Policy-Related Uncertainty and Macroeconomic Conditions. *Applied Economics Letters*, 22(10):801–807.

ECB (2016). The Impact of Uncertainty on Activity in the Euro Area. Available at: `https://www.ecb.europa.eu/pub/pdf/other/eb201608_article01.en.pdf?0b0c95fcaaacf42e1e6dbb184b11d39a`.

Gambetti, L. and Musso, A. (2017). Loan Supply Shocks and the Business Cycle. *Journal of Applied Econometrics*, 32(4):764–782.

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

International Monetary Fund (2012). World Economic Outlook: Coping with High Debt and Sluggish Growth.

Kim, S., Shepard, N., and Chib, S. (1998). Stochastic Volatility: Likelihood Inference and Comparison with ARCH Models. *Review of Economic Studies*, 65(3):361–393.

Korobilis, D. (2013). Assessing the Transmission of Monetary Policy Using Time-varying Parameter Dynamic Factor Models. *Oxford Bulletin of Economics and Statistics*, 75(2):157–179.

Matthes, C., Wang, M.-C., and Amir-Ahmadi, P. (2016). Choosing Prior Hyperparameters. *Federal Reserve Bank of Richmond, Working Paper Series*, No. 16-09.

Meinen, P. and Röhe, O. (2016). On measuring Uncertainty and its Impact on Investment: Cross-country Evidence from the Euro Area. *Deutsche Bundesbank Discussion Paper*, No 48/2016.

Mumtaz, H. and Theodoridis, K. (2017). Common and Country Specific Economic Uncertainty. *Journal of International Economics*, 105:205–216.

Netšunajev, A. and Glass, K. (2017). Uncertainty and Employment Dynamics in the Euro Area and the US. *Journal of Macroeconomics*, 51:48–62.

Nodari, G. (2014). Financial Regulation Policy Uncertainty and Credit Spreads in the US. *Journal of Macroeconomics*, 41:122–132.

Österholm, P. and Stockhammar, P. (2014). The Euro Crisis and Swedish GDP growth – A Study of Spillovers. *Applied Economics Letters*, 21(16):1105–1110.

Popp, A. and Zhang, F. (2016). The Macroeconomic Effects of Uncertainty Shocks: The Role of the Financial Channel. *Journal of Economic Dynamics and Control*, 69:319–349.

Primiceri, G. E. (2005). Time Varying Structural Vector Autoregressions. *Review of Economic Studies*, 72(3):821–852.

Romer, C. D. (1990). The Great Crash and the Onset of the Great Depression. *The Quarterly Journal of Economics*, 105(3):597–624.

Scheffel, E. M. (2015). Accounting for Political Uncertainty Factor. *Journal of Applied Econometrics*, 31:1048–1064.

Sims, C. (1980). Macroeconomics and Reality. *Econometrica*, 48(1):1–48.

Sims, C. A. and Zha, T. (2006). Where There Regime Switches in US Monetary Policy? *American Economic Review*, 96(1):54–81.

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.

Waisman, M., Ye, P., and Zhu, Y. (2015). The Effect of Political Uncertainty on the Cost of Corporate Debt. *Journal of Financial Stability*, 16:106–117.

Appendix A. Data

Table A.1: Data

Variable	**Abbreviation**	**Source**	**Transformation**
Real Gross Domestic Product	GDP	Thompson Reuters	4
GDP Deflator	GDPD	Thompson Reuters	4
Credit to Non Financial Private Sector	CR	BIS	4
Long Term Government Bond yield (10 Years)*	LTI	EUROSTAT	1
Share Price Index*	SP	OECD	4
Unemployment Rate	U	EUROSTAT	2
Consumer Confidence Indicator*	CCI	OECD	4
Real Consumption of Private Households	C	EUROSTAT	4
Real Investment (Gross Fixed Capital Formation)	I	EUROSTAT	4
EURIBOR	R	EUROSTAT	1
European Economic Policy Uncertainty	EPU	http://www.policyuncertainty.com/	3

This table summarizes information regarding the time series. Variables with an asterisk are assumed to be fast-moving. Transformation code: 1-no transformation; 2-first difference, 3-logarithm; 4-first difference of logarithm.

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 Matthes et al. (2016). To draw from the joint posterior distributions, we draw from the following conditional posterior distributions:

1. Draw $\boldsymbol{\Sigma_t}$ from its conditional distribution $p(\boldsymbol{\Sigma_t}|\boldsymbol{y^T}, \boldsymbol{\beta^T}, \boldsymbol{\alpha^T}, \boldsymbol{I_n}, \boldsymbol{Q}, \boldsymbol{S}, \boldsymbol{W}, \boldsymbol{s^T}, k_Q, k_S, k_W)$, where $\boldsymbol{s^T}$ denotes the indicator vector needed to use the mixtures of normals approach suggested by Kim et al. (1998) to sample $\boldsymbol{\Sigma_t}$.[21]

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).[22]

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 Matthes et al. (2016):
   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).

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

Appendix C. Inefficiency

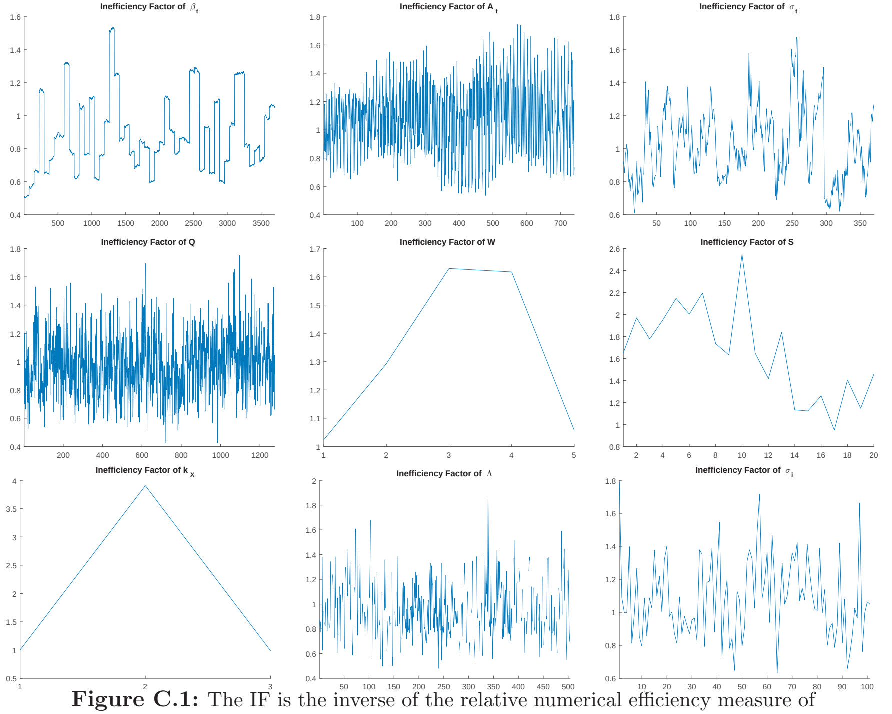

Figure C.1: The IF is the inverse of the relative numerical efficiency measure of Geweke (1992), thus an estimate of $(1 + 2\sum_{i=1}^{\infty} \rho_i)$ with ρ_i as the i-th autocorrelation of the chain. Values of the IFs ≤ 20 are typically regarded as satisfactory.

Appendix D. IRFs to EPU shock

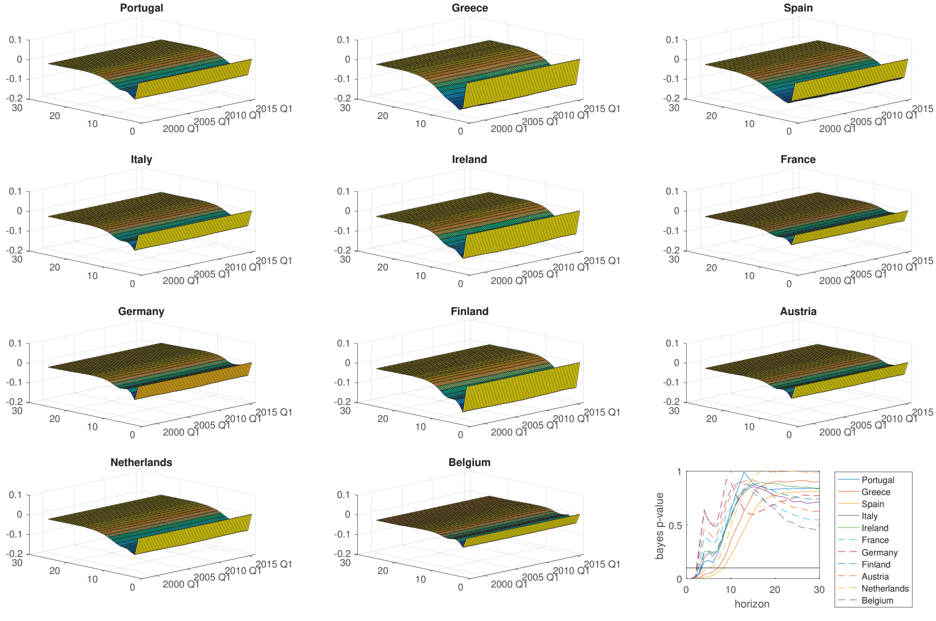

Figure D.1: *Response of GDP growth to one standard deviation shock in EPU.* The first eleven plots display the country specific response while the twelfth plot provides information about the Bayes p-value. The Bayes p-value is defined as one minus the largest coverage region of the credible bands which does not include the value zero.

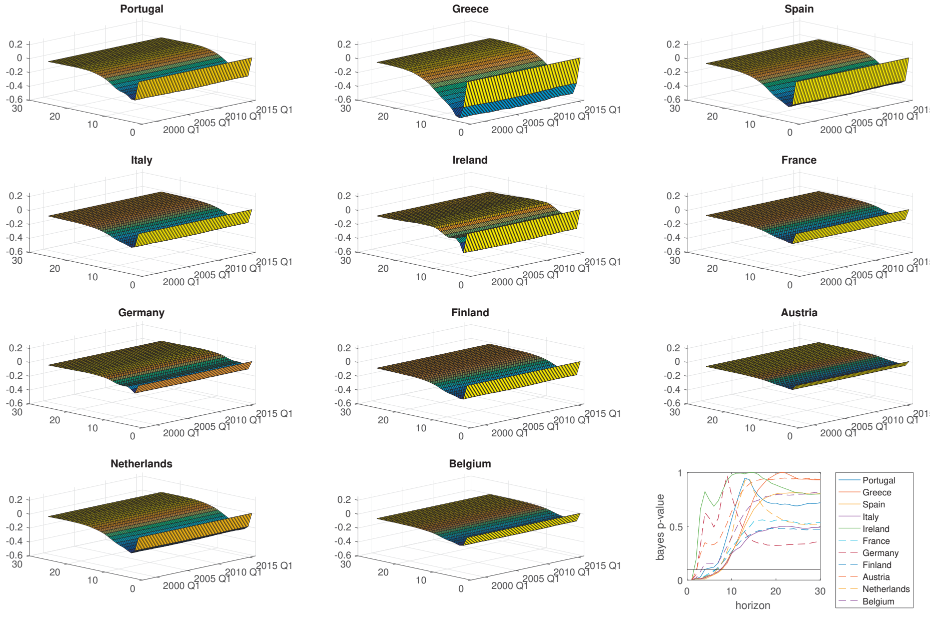

Figure D.2: *Response of investment growth to one standard deviation shock in EPU.* For details see Figure D.1.

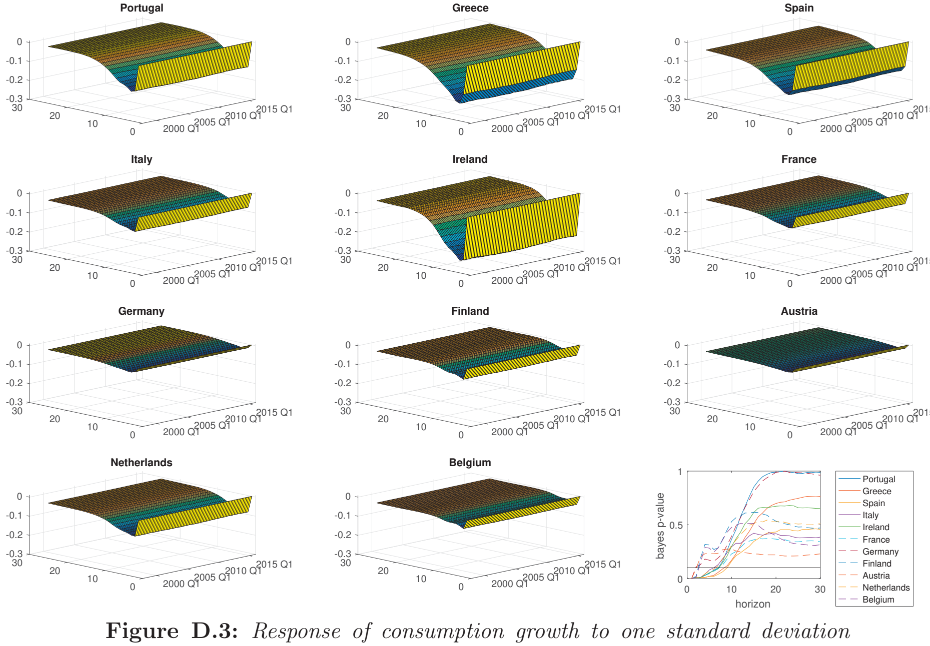

Figure D.3: *Response of consumption growth to one standard deviation shock in EPU.* For details see Figure D.1.

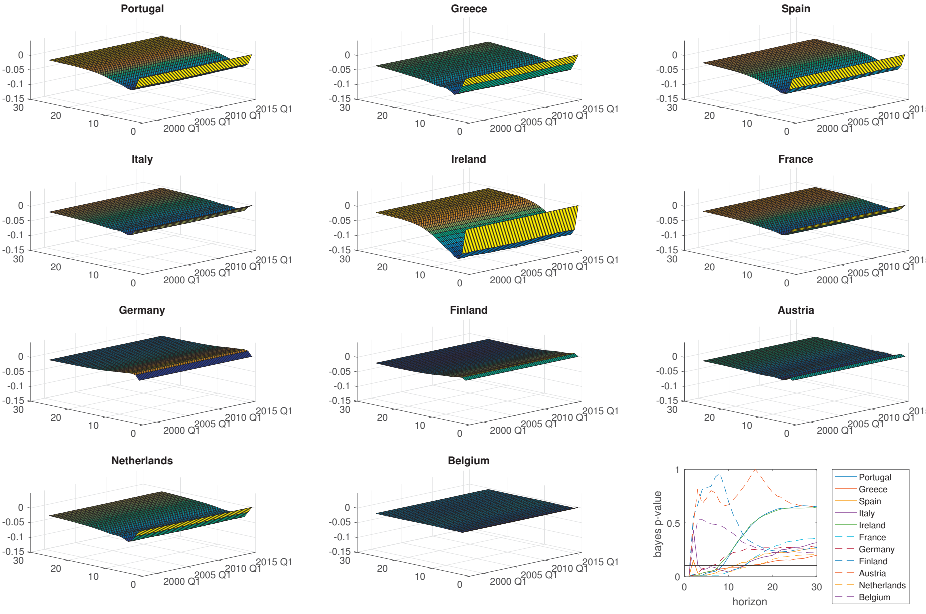

Figure D.4: *Response of inflation to one standard deviation shock in EPU.* For details see Figure D.1.

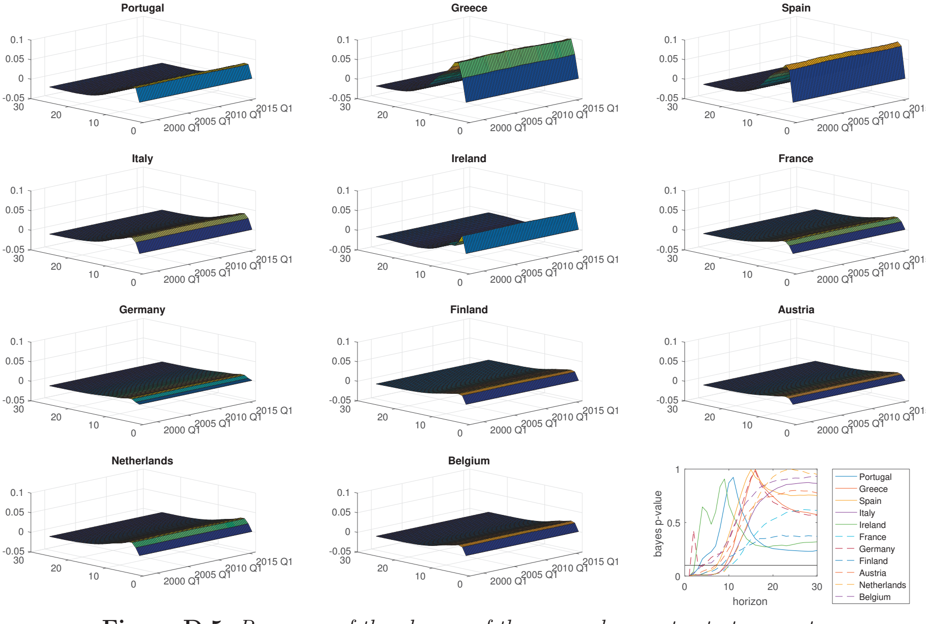

Figure D.5: *Response of the change of the unemployment rate to one standard deviation shock in EPU.* For details see Figure D.1.

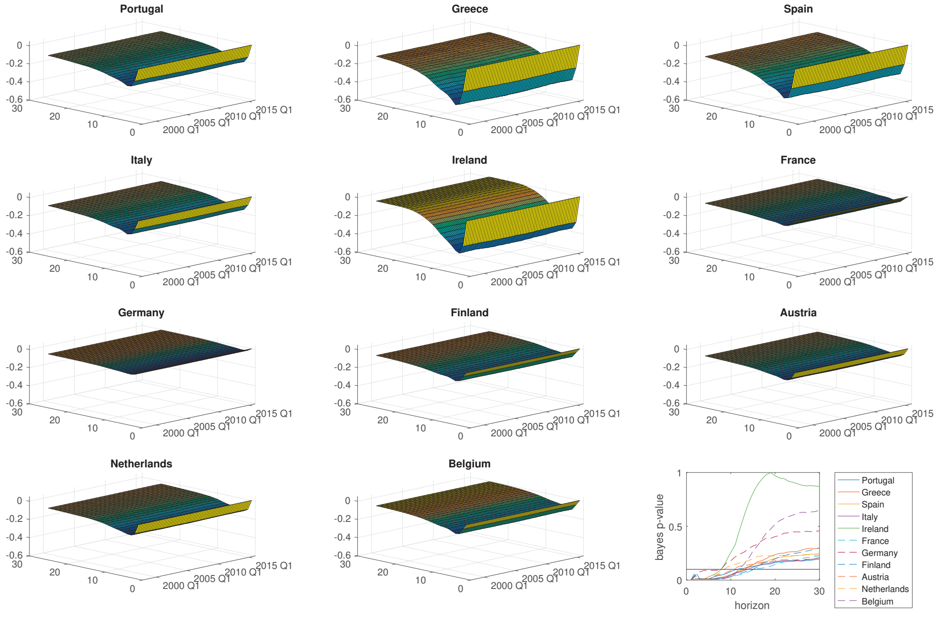

Figure D.6: *Response of credit growth to one standard deviation shock in EPU*. For details see Figure D.1.

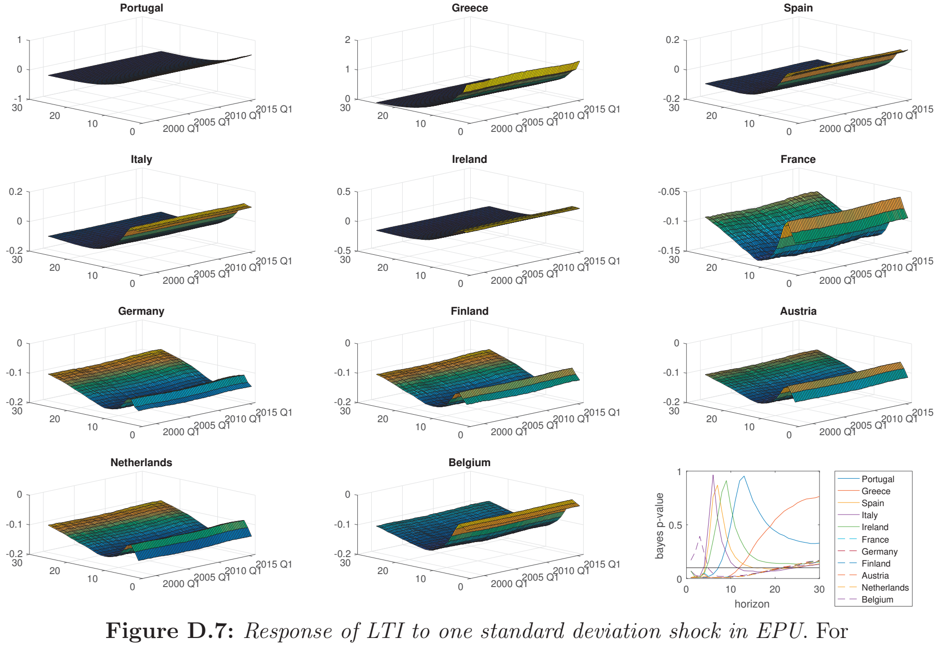

Figure D.7: *Response of LTI to one standard deviation shock in EPU*. For details see Figure D.1.

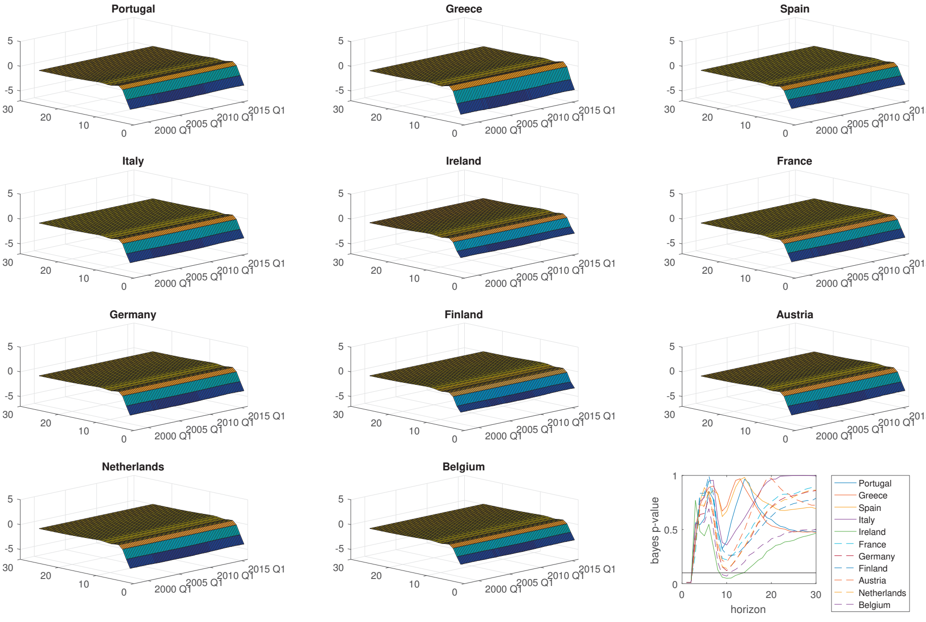

Figure D.8: *Response of stock market return to one standard deviation shock in EPU*. For details see Figure D.1.

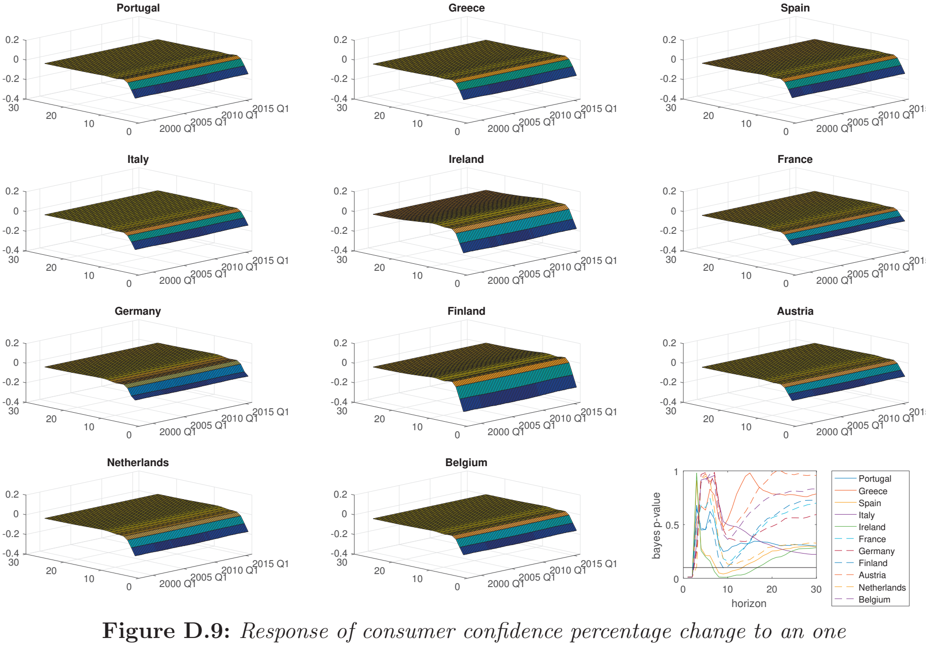

Figure D.9: *Response of consumer confidence percentage change to an one standard deviation shock in EPU*. For details see Figure D.1.