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Implications of Macroeconomic Volatility in the Euro Area*

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Abstract

In this paper, we estimate a Bayesian vector autoregressive (VAR) model with factor stochastic volatility in the error term to assess the effects of an uncertainty shock in the Euro area (EA). This allows us to incorporate uncertainty directly into the econometric framework and treat it as a latent quantity. Only a limited number of papers estimates impacts of uncertainty and macroeconomic consequences jointly, and most literature in this sphere is based on single countries. We analyze the special case of a shock restricted to the Euro area, whose countries are highly related by definition. Among other variables, we find significant results of a decrease in real activity measured by GDP in most Euro area countries over a period of roughly a year following an uncertainty shock.

JEL: C30, F41, E32
Keywords: vector autoregressive models, factor stochastic volatility, uncertainty shocks

1 Introduction

There is consistent evidence in the literature that uncertainty levels – measured by different approaches that we will discuss below – increase after major economic and political events. A specific example may be given by the Great Recession of 2007/08 and the slow economic recovery, which was greatly influenced by uncertainty (Leduc & Liu, 2016). More generally, this volatility may be due to factors resulting from increased complexity of economies based on globalization, but also conflicts, terrorism and wars. Furthermore, demographic change or changes in the economic process such as intersectoral transitions, technological progress and the distribution of income may exercise substantial influences on uncertainty levels[1]. Following the early contribution by Bloom (2009), economies are affected by uncertainty via the depression of supply-side factors such as investment and hiring numbers, implying dampened productivity growth and hence a fall in real activity. It seems reasonable to assume that aggregate demand may also be influenced by increased levels of volatility, even though this is not part of the original argument. Consequently, decreasing the level of uncertainty itself may be a policy objective, as well as considering uncertainty before using political measures such as fiscal or monetary policy. These traditional channels may be less effective to counteract unpleasant developments during periods of economic volatility. Therefore, a deepened understanding of uncertainty and its dynamic effects on the macroeconomic determinants of an economy is of great value for all the reasons cited above.

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[1]See, for example, Stockhammer (2015) for an extensive discussion on how income inequality might affect economic stability. Further treatment of the topic may be found in Galbraith (2012).

Different approaches to measuring uncertainty can be found in the literature from an empiricist's point of view. First, a great number of articles simply includes proxy variables related to uncertainty in the model. These variables may be of different origin, for instance indices such as VIX or VXO[2] are widely used. Briefly summarizing standard approaches, the usual measurements of uncertainty are the implied volatility of equity price returns, cross-sectional dispersion of firm profits, stock returns or productivity (e.g., Bloom, 2009; Caggiano, Castelnuovo, & Groshenny, 2014; Meinen & Röhe, 2017) or the occurrence of uncertainty-related key words in newspapers and online-searches (e.g., Dzielinski, 2012; Baker, Bloom, & Davis, 2016). Second, in more recent papers, uncertainty is incorporated into the model as a latent variable, in a way to simultaneously estimate arising consequences on macroeconomic variables (Carriero, Mumtaz, Theodoridis, & Theophilopoulou, 2015; Jurado, Ludvigson, & Ng, 2015; Mumtaz & Theodoridis, 2016; Crespo Cuaresma, Huber, & Onorante, 2017). This is also the the approach we take in this paper.

Theoretically, reactions of the macro economy to uncertainty shocks are often modeled in a DSGE context and business cycle models (see, for instance, Fernández-Villaverde, Guerrón-Quintana, Kuester, & Rubio-Ramírez, 2015). Empirically, uncertainty can be introduced into an econometric framework in various ways which will be summarized in the following: Bloom (2009) captures uncertainty by using the implied volatility of equity price returns employing a structural vector autoregressive model (SVAR) and finds that a large macro uncertainty shock generates a temporary drop (by the third month), rebound (usually by the sixth month) and long-run overshoot, which is different from the more persistent impact of first-moment shocks that generally take effect over at least a few quarters. In his paper, he creates a dummy variable indicating periods where the index of volatility significantly deviates from its mean. By contrast, a similar approach using a SVAR with the measure of uncertainty as an *external instrument* to the data set used by Bloom (2009), Carriero et al. (2015) find that the response to an uncertainty shock is more pronounced and more persistent, while the model is less prone to the bias mentioned above.

Similar results by Jurado et al. (2015) imply longer periods of lower real activity that are influenced by macro-level uncertainty when compared to proxies such as the VXO Index; these indices cover mostly financial uncertainty, which may not always correspond to macroeconomic uncertainty. The shocks they identify are to a large fraction due to the VAR forecast error variance in production and hours worked. Also, they are more pronounced than the ones identified when using stock market volatility shocks. Furthermore, it must be noted that induced shocks do not cause the significant *volatility-overshoot* observed by Bloom (2009), a fact that recently was found to hold true also in a study of G7 countries by Crespo Cuaresma et al. (2017). More specifically, Jurado et al. (2015) use a measure based on stochastic volatility models, an approach which drew increasing attention and has been the starting point for the treatment of uncertainty as a latent quantity. They state that the variable of interest in this literature should be *macroeconomic* uncertainty, that is, uncertainty observed in many economic time series at the same time across private and public sector, corporations and households, and multiple geographic regions. Their estimate of uncertainty indicates less periods of *real* macroeconomic uncertainty, as opposed to Bloom (2009), who identified almost 20 events inducing high uncertainty since 1960.

Carriero, Clark, and Marcellino (2016) employ a VAR model with errors where stochastic volatility is driven by two unobservable factors, reflecting both aggregate macroeconomic and financial uncertainty. Their modeling framework extends the considerations by Jurado et al. (2015). In their empirical setup, they apply these methods to estimate uncertainty and effects on macroeconomic and financial variables, concluding that pronounced and persistent reactions to uncertainty shocks exist, in line with economic theory and consistent with recent empirical contributions to the literature. A similar approach – using a factor-augmented VAR model with time-varying parameters –

[2]VIX – volatility of S&P 500 index options by Chicago Board Options Exchange (CBOE); VXO – by CBOE, S&P 100 (OEX).

enabling the estimation of a measure of uncertainty incorporating volatility from the real and the financial sector has been used by Mumtaz and Theodoridis (2016). They use their model to assess the response of real activity to uncertainty shocks and changes in this reaction over time.

Most studies discussed above consider only a single country, usually the United States. Since groups of highly synchronized clusters of economies have emerged (Stock & Watson, 2005), it appears consequent to consider joint dynamics of multiple countries simultaneously. An attempt using data for the G7 countries has been provided by Crespo Cuaresma et al. (2017). They use a Bayesian VAR with stochastic volatility, assuming the reduced form errors to feature a factor structure – uncertainty spikes are measured by using a factor structure on the one-step-ahead forecast error of the VAR. They obtain an international uncertainty factor, and find that responses are in general similar to the results in US based literature. Again, in contrast to Bloom (2009) and in line with most approaches treating *uncertainty as latent quantity*, they find that real macroeconomic uncertainty shocks induce longer periods of depressed economic variables, and do not find a significant overshoot. Furthermore, they find that reactions differ in magnitude between countries.

Our article tries to contribute to this research area by simulating a Euro area (EA) specific uncertainty shock and derives implications for the heterogeneous countries in different parts of the union with respect to numerous macroeconomic variables of interest. Thus, we can on the one hand account for the aforementioned emergence of synchronized clusters of economies and on the other hand fill a blank space in the literature which was, as mentioned before, mostly concerned with the US so far. In order to do so, we estimate a Bayesian vector autoregressive (VAR) model with factor stochastic volatility which allows us to incorporate uncertainty directly into our econometric framework. Only a limited number of papers estimate impacts of uncertainty and macroeconomic consequences jointly. Generally, our results are in line with the recent findings in this literature (Jurado et al., 2015; Crespo Cuaresma et al., 2017). We find a significant decrease in real activity in most EA countries over a period of roughly a year, but were not able to identify a significant long-run overshoot. Furthermore, we find significant effects of uncertainty on unemployment and short-term interest rates, equity prices, as well as intra-European Union (EU) exports and exports to non-EU countries. No significant results could be obtained regarding prices.

The remainder of this paper is structured as follows. section 2 contains the methodological approach used in this paper to measure uncertainty in the Euro area. The presentation of our data set and obtained empirical results and the corresponding discussion in section 3 is concluded by some closing remarks in section 4.

2 Econometric Framework

In this section, we discuss our modeling approach. We start with a standard VAR model to estimate the joint dynamics between macroeconomic and financial variables. For investigating the effects of uncertainty shocks, we assume a factor structure on the innovations of the VAR with stochastic volatility. These common latent factors allow us to analyze a common EA-specific shock by means of impulse response analysis. Our strategy strongly follows the spirit of the econometric framework presented by Crespo Cuaresma et al. (2017).

2.1 Bayesian VAR Model with Factor Stochastic Volatility

We need to model the dynamic response of an $m \times 1$ time series vector y_t, where we stack all our variables in a particular order. Moreover, we specify $m = cv$, where c is the number of countries and v the number of macroeconomic and financial variables. Assume that y_t follows a VAR(p) process,

$$y_t = c_0 + B_1 y_{t-1} + B_2 y_{t-2} + \ldots + B_p y_{t-p} + \epsilon_t. \quad (1)$$

Here $B_j (j = 1, \dots, p)$ are $m \times m$ dimensional matrices of regression coefficients and the error term ϵ_t is normally distributed, $\epsilon_t \sim \mathcal{N}(0, \Sigma_t)$. We decompose this error term in two parts: the first are common factors that capture mutual economic dynamics of variables and countries; the latter represents the idiosyncratic shock for each variable at a certain point in time (following Aguilar & West, 2000),

$$\epsilon_t = X f_t + \eta_t, \tag{2}$$

with being X is an $m \times q$ matrix of factor loadings and $f_t \sim \mathcal{N}(0, H_t)$ is a vector containing q latent common factors. This factor structure may be interpreted as zero mean risk factor, and will be used to identify the common uncertainty shock later. Its time-varying diagonal variance-covariance matrix H_t is

$$H_t = \text{diag}(h_{1,t}, \dots, h_{q,t}), \tag{3}$$

and the respective elements $h_{i,t}$ $(i = 1, \dots, q)$, the factor variances, are assumed to follow univariate stochastic volatility processes, i.e. the log-volatilities follow a centered AR(1) process,

$$\log(h_{t,i}) = \mu_i^{(h)} + \phi_i^{(h)}(\log(h_{t-1,i}) - \mu_i^{(h)}) + \xi_{t,i}^{(h)}. \tag{4}$$

We let $\mu_i^{(h)}$ denote the mean of the corresponding log volatility, $\phi_i^{(h)} \in (-1, 1)$ is the persistence parameter and $\xi_{t,i}^{(h)} \sim \mathcal{N}(0, \Xi_i^{(h)})$. Finally, $\eta_t \sim \mathcal{N}(0, \Omega_t)$ is a normally distributed idiosyncratic error term. We impose again a time-varying variance-covariance matrix,

$$\Omega_t = \text{diag}(\omega_{1,t}, \dots, \omega_{m,t}), \tag{5}$$

where we also assume that its respective elements $\omega_{k,t}$ $(k = 1, \dots, m)$, the idiosyncratic time-varying variances, follow a centered AR(1) process,

$$\log(\omega_{k,t}) = \mu_k^{(\omega)} + \phi_k^{(\omega)}(\log(\omega_{k,t-1}) - \mu_k^{(\omega)}) + \xi_{k,t}^{(\omega)}, \tag{6}$$

with the parameters defined analogously to Equation 4. The variance-covariance matrix of ϵ_t can thus be derived by taking the variance of Equation 2 and is given by

$$\Sigma_t = X H_t X^\top + \Omega_t. \tag{7}$$

Time-variation in Σ_t is not only introduced through the stochastic volatility specification of the factors in f_t, but also through the idiosyncratic error variances in Ω_t. This specification has major advantages with respect to computational gains. Conditional on X and f_t, the equations may be estimated independently, since η_t is just a diagonal matrix, enabling us to simply estimate standard univariate regression models for each $k = 1, \dots, m$.

2.2 Specification of Priors

Estimating the proposed model requires Bayesian methods. Consequently, we must specify prior distributions on each parameter of the model. Particularly, we need prior distributions for the coefficients B_j (for $j = 1, \dots, p$), the factor loadings X and the parameters in the stochastic volatility processes. For the distributions of the model-coefficients, we choose an approach in the spirit of the well-known Minnesota prior (Sims & Zha, 1996; Litterman, 1986). A slightly adapted version of this prior as proposed by Huber and Feldkircher (2017) is employed, which has advantageous properties when it comes to estimating large dimensional systems, because it avoids the tendency of the traditional Minnesota prior to overshrink significant signals. We impose a multivariate Gaussian prior distribution on each of the $m \times m$ autoregressive coefficient matrices,

$$B_j \sim \mathcal{N}_m(\Phi_j, \Theta_j) \qquad \text{for} \quad j = 1, \dots, p, \tag{8}$$

where the Φ_j is the $m \times m$ matrix of prior expected values and Θ_j is the $mm \times mm$ prior diagonal variance matrix for the j^{th} lag order. We proceed to specify the prior expected values in the spirit of the Minnesota prior, which implies the following structure on the prior means Φ_j

$$\phi_{j,st} = \mathbb{E}([B_j]_{st}) = 0 \qquad \text{for } j, s, t, \tag{9}$$

$\phi_{j,st}$ being the expected value of the s, t^{th} element of Φ_j, where $s = 1, \ldots, m$ and $t = 1, \ldots, m$. Thus, we deviate from the normal specification of the Minnesota prior and put a zero mean not only onto the off-diagonals, but also on the coefficients associated with the first own lag of a given variable[3], in order to stabilize our model.

Turning to Θ_j, we must introduce the complete specification of the prior distribution for each coefficient, where the diagonal elements $\theta_{j,l}$ (for $l = 1, \ldots, mm$) depend only on a set of local shrinkage parameters $\tau_{j,st}$ and global (or lag-specific) shrinkage parameter λ_j^2,

$$[B_j]_{st}|\tau_{j,st}, \quad \lambda_j^2 \sim \mathcal{N}\left(\phi_{j,st}, \frac{2\tau_{j,st}}{\lambda_j^2}\right). \tag{10}$$

We introduce a hierarchical prior for $\tau_{j,st}$ and λ_j^2; furthermore we impose a Gamma prior on the local shrinkage parameter,

$$\tau_{j,st} \sim G(\kappa_j, \kappa_j) \tag{11}$$

and κ_j is a hyperparameter chosen by the researcher. Griffin and Brown (2010) show that if κ_j decreases, the prior for the respective coefficient places more mass on zero, but the tails of the marginal prior density tend to be heavier at the same time. The classical Minnesota prior would result in too much shrinkage by pushing each higher order coefficient towards zero. By contrast, our specification allows for enough flexibility; if the likelihood suggests a nonzero value for the coefficient, the prior is not too informative and the data can 'speak on its own'.

The global shrinkage parameter λ_j^2 pushes each lag towards zero. Following the approach undertaken by Bhattacharya and Dunson (2011) we assume that shrinkage increases with the lag order. Thus, we assume a multiplicative Gamma process prior,

$$\lambda_j^2 = \prod_{n=1}^{j} \delta_n \quad \text{for } j = 1, \ldots, p \tag{12}$$

$$\delta_n \sim G(c_n, d_n), \tag{13}$$

where again, c_n and d_n are hyperparameters. If δ_n exceeds unity, the prior variance $\theta_{j,l}$ decreases, which means that the coefficient matrices of higher lag order tend to shrink stronger towards zero. We now proceed to briefly discuss the selection of the values of our hyper parameters. First, we must specify κ_j, where we choose an initial value of $\kappa_1 = 0.6$. For higher lags, we use $\kappa_j = \frac{0.6}{j^2}$. Second, concerning the hyper parameters of δ_n, following Crespo Cuaresma et al. (2017), we choose $c_n = 3$ and $d_n = 0.03$ that are constant for all n. Third, regarding the elements of the factor loadings matrix X we assume a relatively uninformative prior structure, given by

$$x_{k,i} \sim \mathcal{N}(0, 10) \quad \text{for } k = 1, \ldots, m \text{ and } i = 1, \ldots, q. \tag{14}$$

Finally, we need to mention the prior specification concerning the large number of stochastic volatility processes in our model. We follow the specification adopted by Kastner and Frühwirth-Schnatter

[3]The Minnesota prior puts unity on the coefficients of the first lags to induce highly persistent behavior to resemble a random walk specification.

(2014) and use Kastner (2016). Thus, for the unconditional mean, the persistence parameter of the log-volatilities and the innovation variance of the log-volatilities we have

$$\begin{aligned} \mu_i^{(s)} &\sim \mathcal{N}(0,10) \qquad \forall\, s \in \{h,\omega\} \\ \frac{\phi_i^{(s)}+1}{2} &\sim B(5,1.5) \\ \Xi_i^{(s)} &\sim G\left(\frac{1}{2},\frac{1}{2}\right). \end{aligned} \tag{15}$$

The unconditional mean is centered around zero and may be characterized as having an uninformative variance. With respect to the persistence parameter, our hyper parameter choice leads us to a prior mean of 0.54 and a standard deviation of 0.31. The exact choice of the hyper parameters for the prior variance of the log-volatilities affects mostly the smoothing of the volatility process.

2.3 Posterior Simulation

Concluding the section on the econometric framework, we now turn to the discussion of the Markov chain Monte Carlo (MCMC) algorithm we employ. The simulation of the parameters in our model follows the approach taken by Crespo Cuaresma et al. (2017). Since the posterior distribution is not tractable analytically, we set up an algorithm involving Gibbs sampling. First, we rewrite the model from Equation 1 such that we can estimate it equation-by-equation using the feature that Ω_t, the variance-covariance matrix of the idosyncratic shocks η_t, is a diagonal matrix. Thus, $\hat{y}_t = y_t - Xf_t$ is given by

$$\hat{y}_t = B_1 y_{t-1} + \ldots + B_p y_{t-p} + \eta_t. \tag{16}$$

After simulating VAR coefficients, we draw Ω_t; both steps are conditional on the latent factors f_t, the factor loadings matrix X and the variance of our coefficients Θ_j and the full history of log-volatilities. Second, we draw the latent factors from independent normal distributions. We thus must condition on the VAR coefficients, as well as on our factor loadings. Afterwards, we sample the factor loadings, where we again condition on the VAR coefficients and the latent factors. Note that we normalize each equation to enable us to estimate a full series of homoscedastic models. While estimating the latent factors we must sample scaling parameters $\tau_{j,st}$ and λ_j^2.

The local parameter $\tau_{j,st}$ is sampled from a Generalized Inverted Gaussian (GIG) distribution

$$\tau_{j,st}|\kappa_j,\lambda_j,[B_j]_{st} \sim \mathrm{GIG}(\kappa_j - 1/2, [B_j]_{st}^2, \kappa_j\lambda_j^2), \tag{17}$$

conditional on the all other parameters in the model. The global shrinkage parameter λ_j^2 is sampled from a Gamma distribution conditional on the remaining parameters,

$$\lambda_j^2|\tau_{j,st},c_n,d_n,\kappa_j \sim \begin{cases} G(c_1+\kappa_1 m^2, d_1+\kappa_1/2\sum_{s=1}^m \tau_{1,s1}) & \text{if } j=1 \\ G(c_j+\kappa_j m^2, d_j+\kappa_j/2\lambda_{j-1}\sum_{s=1}^m\sum_{t=1}^m \tau_{j,st}) & \text{if } j>1. \end{cases} \tag{18}$$

2.4 Identification

For identification, the factor loadings X must be of full rank and the number of free parameters at time t must not exceed $\frac{(m\times m+1)}{2}$ parameters in an unrestricted Σ_t to avoid overparameterization. In our setting, we assume that the common factor – macroeconomic uncertainty – is linked to the highest factor loadings of equity prices, as this is the first variable in our model. While the model was presented now in its most general form and any number of factors can be chosen, in our model, we only choose to identify one common factor in the error term. This implies that f_t is a simple scalar, the factor loadings matrix reduces to a column vector while H_t, the variance of f_t is a scalar as well. Concerning the identification of the model, we choose the first element of the vector X to be equal to 1 based on Crespo Cuaresma et al. (2017) and Aguilar and West (2000). Choosing the identification of factor and associated loadings implies that our model is sensitive to the ordering of the variables.

3 Empirical Results

This section is concerned with the presentation of the results from our analysis of uncertainty in the Euro area. First, we will briefly describe our data set. Second, we discuss the obtained common uncertainty factor and how it compares to other proposed uncertainty measures. Third, we analyze the respective explained shares of the variances. Finally, we present the reaction of various macroeconomic quantities to a common uncertainty shock in the Euro area, namely GDP as proxy for real activity, the unemployment rate, short-term interest rates, the price-level, equity prices and exports among the Euro area members, as well as exports with other partners not included in the EU.

3.1 Data

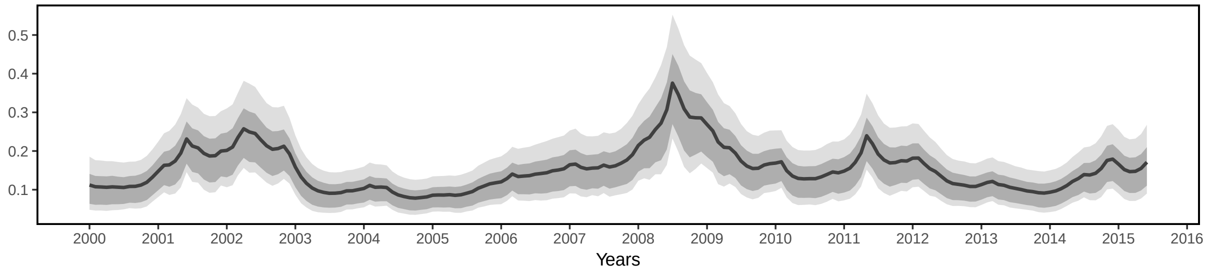
Our data set covers 12 out of 19 Euro Area countries, i.e. Austria, Belgium, Germany, Greece, Spain, Finland, France, Ireland, Italy, the Netherlands, Portugal and Slovakia. We exclude the Baltic states, Malta, Cyprus, Slovenia and Luxembourg because of bad data quality and/or a general lack of appropriate time series. In addition, the data set contains most of the country-specific time series aggregated on the level of the whole Euro Area (EA19). The data set covers 189 time points on a monthly basis starting in January 2000 and ending in September 2015.

We use primarily standard macroeconomic variables – e.g. gross domestic product (GDP), consumer prices, unemployment rates and interest rates – to conduct our analysis. However, we also include two distinct trade variables capturing exports within Europe and outside of Europe. This allows us to analyse the different effects of an uncertainty shock both on a common market trade area and on the "world market". Moreover, we include oil prices as exogenous variable to control for changes in the structure of the global economy. We gather our data from various sources including Eurostat, the European Commission, the OECD and the Austrian National Bank (OeNB). A comprehensive description of the time series in use and their sources can be found in Appendix A.

3.2 Measures of Uncertainty

An overview of volatility in Euro area economies is given in Figure 1. The plot of the variance of the uncertainty factor gives an idea of how volatility in the Euro area evolved over time. The millennium starts off with the burst of the dot-com bubble reaching Europe. Roughly at the same time, the devastating 9/11 terror attack adversely impacts the economic environment and its financial markets, causing the Dow Jones to fall 1.370 points and a loss of $1.4 trillion of market value. After that, a few years of relative tranquility follow. However, in 2008/09 the global financial crisis hits Europe, followed by the European Debt Crisis two years later. This storyline is supported strongly by our model. Thus, we are confident to capture a substantial amount of economic uncertainty in our estimation framework.

To assess how well we capture macroeconomic uncertainty, we compare our own measure to a few commonly known and accepted proxies of (mostly financial market) volatility and economic stability. We would for example expect that the confidence in the economy of both consumers and business owners will decrease in times of high uncertainty. Indeed, as can be seen in Figure 2a we find that the Consumer Confidence Index (CCI) and Business Confidence Index (BCI) published by the European Commission show a lagged countercyclical behavior when uncertainty peaks. This is

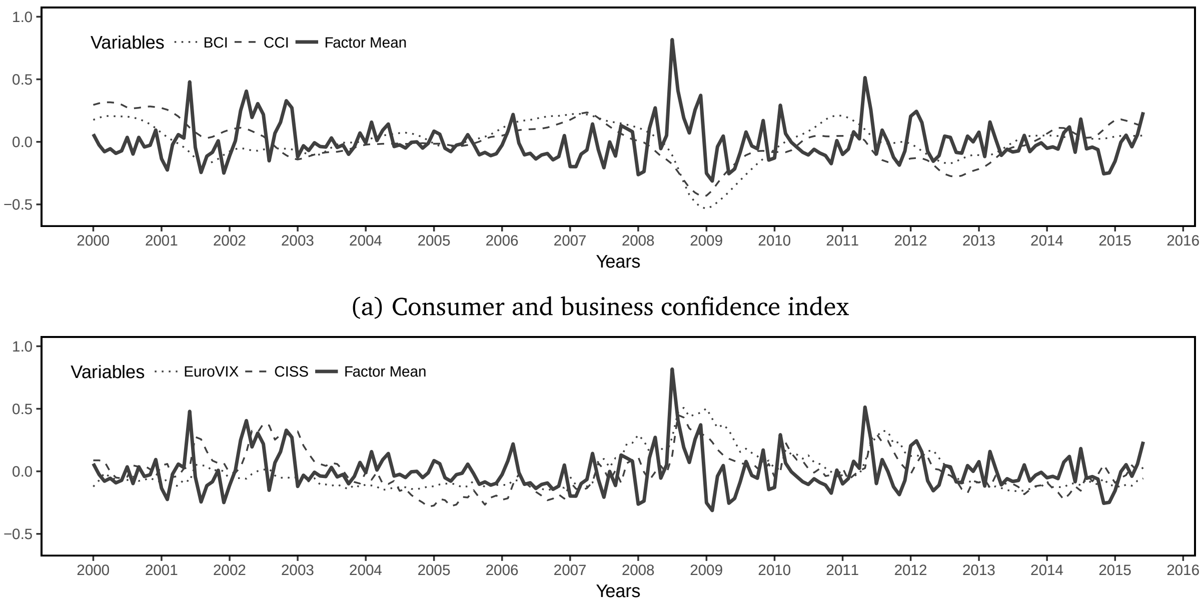


Note: The obtained measure is depicted by the dark grey line, indicated confidence bands are the 16th and 84th (grey area), and 5th and 95th percentiles (light grey area), respectively.

Figure 1: Corresponding volatility of posterior median of the latent factor.

a strong indicator that uncertainty has real, measurable impacts on the economy; if both consumers and businesses react, the chance to observe changes in macroeconomic behavior is high.

Figure 2b compares the uncertainty in our model with two more rather common proxies of volatility. On the one hand, we have the EuroVIX, which is the official volatility index of the EUROSTOXX stock markets; on the other hand, we compare our measure of uncertainty to the Composite Indicator of Systemic Stress, which is an indicator constructed by the European Central Bank (ECB) to capture the exposure of the European economic system to macroeconomic volatility. Again, we capture the trend and peaks quite well. The two chosen indices mostly reflect the situation on the financial markets, which may imply that our measure of uncertainty, the common factor in the error term, is highly related to financial uncertainty. However, our estimated quantity deviates from the other measures in the years before the global financial crisis.[4]



(a) Consumer and business confidence index

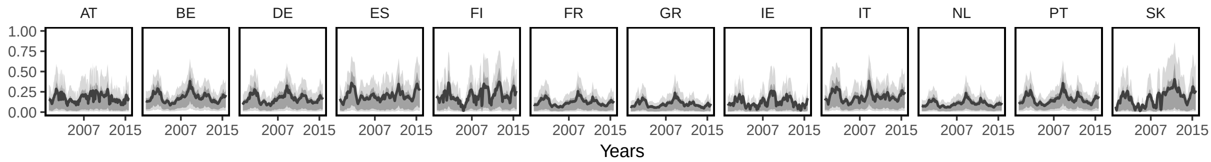
(b) Proxies for uncertainty

Figure 2: Comparison of the estimated uncertainty factor and other measures.

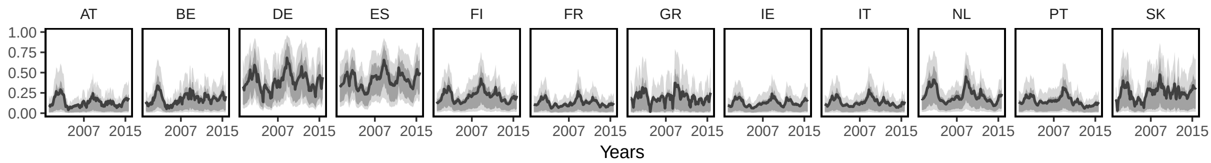
[4]This indicates that our uncertainty measure is in fact able to capture more than just financial uncertainty. Furthermore, our framework would allow for a greater number of factors, thus offering higher flexibility than the use of observable proxies.

3.3 Explaining Innovation Variance by the Uncertainty Factor

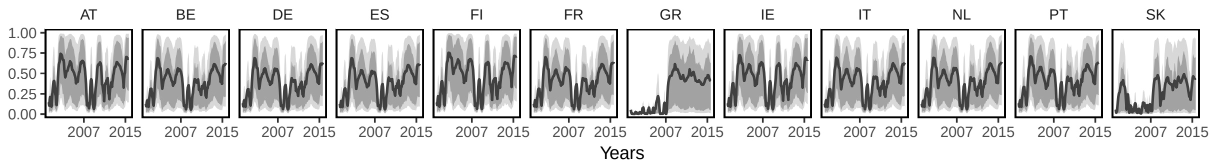
Following the comparison of our global uncertainty factor with various other proxies, we want to investigate how much of the forecast error variance of the different variables can be explained by our latent factor. Figure 3 displays all proportions of the explained innovation variance over time for all variables except for extra-EU exports. The exclusion of those shares is due to the similarity with intra-EU exports and to space limitations within this paper.



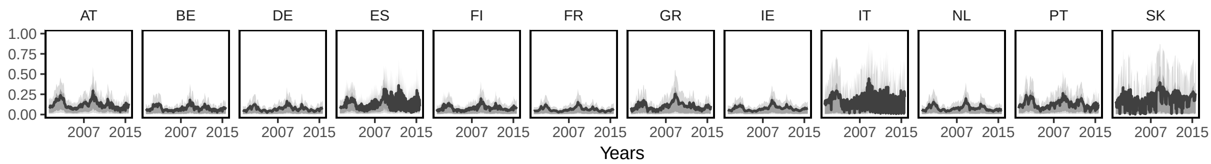
(a) Real gross domestic product (GDP)



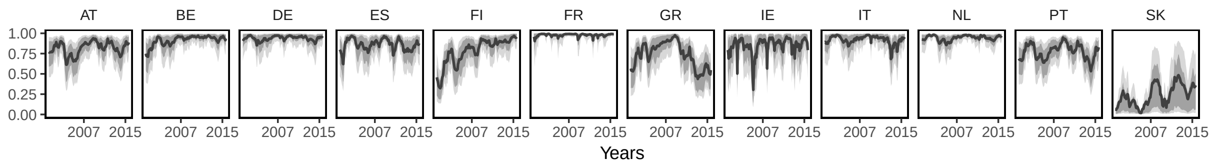
(b) Unemployment



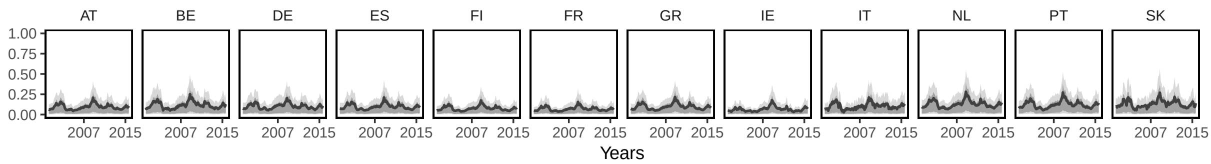
(c) Short-term interest rates



(d) Prices



(e) Equity Prices



(f) Intra-EU exports

Note: The obtained measure is depicted by the dark grey line, indicated confidence bands are the 16$^{\text{th}}$ and 84$^{\text{th}}$ (grey area), and 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles (light grey area), respectively. Country codes may be found in Appendix A.

Figure 3: Share of innovation variance explained by uncertainty factor

Figure 3a shows the decomposition of real GDP. The uncertainty factor plays a rather limited role in explaining the forecast error variance of GDP. Only about 15% to 30% of the innovation variance is explained by the latent factor. However, an interesting pattern arises, as the explained variance due to our uncertainty factor increases in times of economic or financial crisis. This supports our claim that our latent uncertainty factor captures the latest crises in the Euro area. This is particularly visible in Belgium, Germany, France, Greece, Italy, the Netherlands as well as in Portugal. In these plots, we can clearly recognize the dot-com bubble and the global financial crisis due to a higher share of explained forecast error variance. We conjecture that the reason why the European sovereign debt crisis is not observable to a great extent is because our uncertainty factor is linked to financial uncertainty and not entirely to pure macroeconomic uncertainty. Clearly, the visible crises – the dot-com bubble and the Great Recession – emerged from the financial markets, whereas the European sovereign debt crisis was rather a macroeconomic, but not a financial, crisis.

For most of the countries in Figure 3b the same pattern is visible. The plots depict the explained forecast error variance of unemployment over time for all countries. Again, on average only about 15% to 25% of the innovation variance can be explained. Germany and Spain represent two outliers with more variation in explained shares. A plausible explanation might be a more severe reaction of the labor market due to financial uncertainty.

The share of explained variance for short-term interest rates in Figure 3c appears to have fierce movements, varying from 10% to 75%. Interestingly, the pattern described for the last two variables seems somehow reversed. While the explained variance of short-term interest rates is quite high during times of economic prosperity, it dramatically drops in economic downturns. A lower share implies that the role of uncertainty is smaller in the unsystematic component.

In Figure 3d the low shares of explained innovation variance of prices by the uncertainty factor can be seen. The shares are under 15% for almost all countries. We conjecture that price forecast variance is mostly driven by other factors. Since all countries in our sample are dependent on ECB monetary policy, the similarity across countries is not surprising. Moreover, the primary objective of the ECB is to maintain price stability, which might explain the low variability of prices during economic downturns.

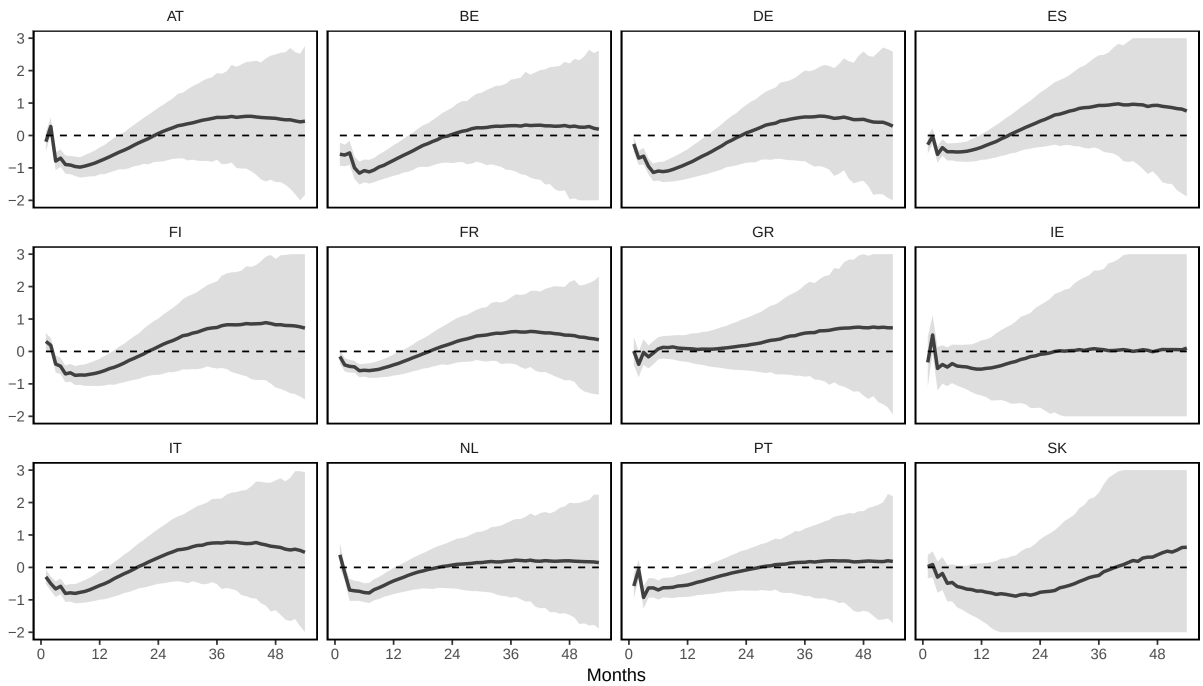
Concerning equity prices, our latent factor can explain almost all the forecast error variance as can be seen in Figure 3e. This was to be expected when considering our chosen model identification. The only exceptions are Greece and Slovakia, where Greece is arguably a special case based on various crisis related events. For Slovakia, this may be due to the lower dependence of CEE countries on the global financial market. For intra-EU exports (as well as extra-EU exports) we see only a low level of explained forecast error variance in Figure 3f. The level of the shares is not changing much, thus we conclude that there is no great influence. Summing up, the uncertainty factor explains a large fraction of forecast error variance for real GDP, unemployment rates and short-term interest rates. A general pattern is visible: the fractions increase in periods of financial market turmoil. This supports the notion that our latent factor captures European financial uncertainty, a finding also obtained by (Crespo Cuaresma et al., 2017).

3.4 Impulse Responses of Uncertainty Shocks

Now we present impulse response functions (IRFs) of the variables in the model. Specifically, we use a shock to the common uncertainty factor to assess reactions of all variables in the model. As already mentioned above, an uncertainty shock is identified as affecting all macroeconomic and financial time series in the model simultaneously. A shock, or any change in f_t is transmitted to the other variables through the respective factor loadings. Thus, the impulse response on impact of a shock is given by the variables' respective factor loadings, i.e., $\Delta y_{t,i} = x_i \Delta f_t$.

This indicates clearly that the factor loadings X can be interpreted as multiplicators or translators of a common unforeseeable shock. We experience different amplitudes on impact for different time series depending on the loadings. The higher the loading x_i of the corresponding time series, the more exposed this variable is to a common uncertainty shock (i.e. the higher is the impulse response on impact). Additionally, fast moving variables are supposed to be equipped with relatively large loadings, as they are expected to react to a shock immediately. Following the approach by Crespo Cuaresma et al. (2017), we scale the shock – for better imaginability – to represent a 10% decline of equity prices.

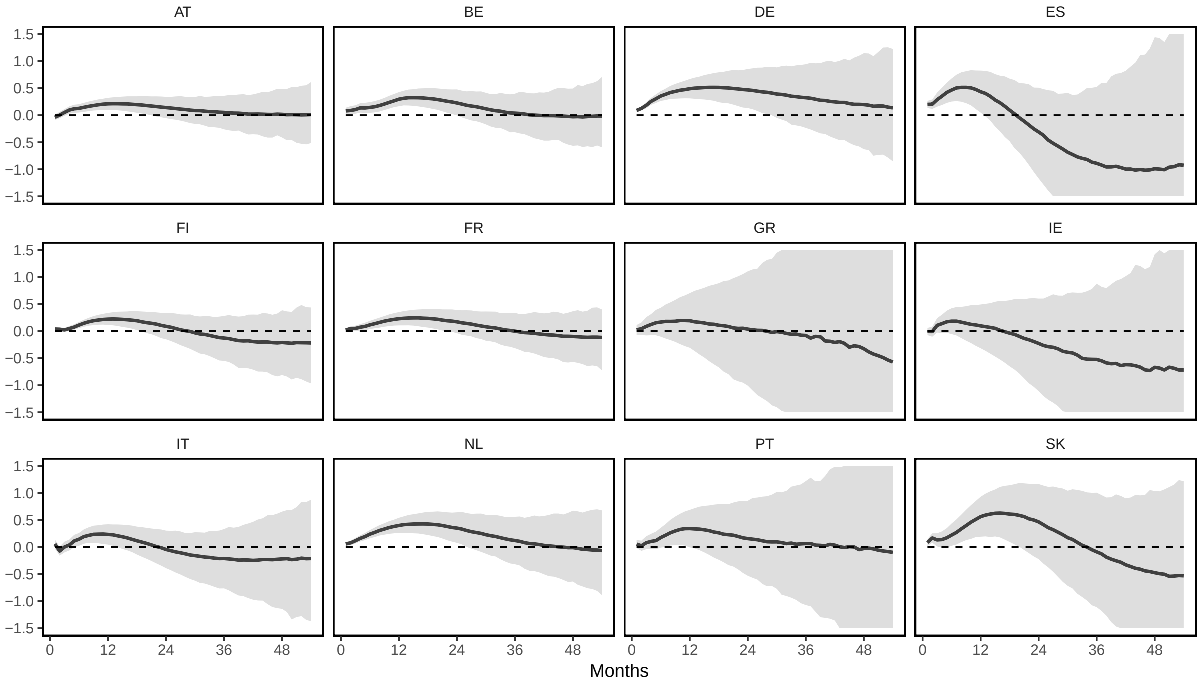
Consequently, the scales and responses may be interpreted as follows. For variables in logarithms, the scale represents deviations from the level at the time of the shock in percent. This is the case for all variables except short-term interest rates and the unemployment rate. The scale regarding these variables constitutes a deviation from the rate at the time of the shock in percentage points. The red line marks the zero line, the dark grey line is the estimated median value, whereas the light grey area denotes the confidence band with respect to the 16th and 84th percentile. The results are based on 35.000 posterior draws with a burn-in period of 15.000 draws.



Note: Posterior distribution of impulse responses in percent. The median is depicted in grey, the 16th and 84th percentile are indicated by the light grey area. The dashed line indicates zero. Country codes may be found in Appendix A.

Figure 4: Impulse response functions of GDP as measure for real activity in Euro area countries.

The observed behavior of real activity in terms of GDP – which can be found in Figure 4 – in most of the countries is consistent with recent findings in Jurado et al. (2015) and Crespo Cuaresma et al. (2017) and in line with the theoretical reasoning in the original paper by Bloom (2009). Most countries exhibit a significant drop on impact. This is caused by the wait-and-see attitude of enterprises in times of uncertainty and risk. Consequently, we observe lower hiring-rates, which in term lead to a decrease in the reallocation of workers from less productive units to more productive ones – a major channel of productivity growth. Furthermore, investment rates decrease, and usually a drop of consumption can be observed as well. This period of decreased GDP in percent relative to the time of the shock lasts for roughly 10 to 12 months, where from that point onward responses turn insignificant. This is a major difference to the empirical findings of Bloom (2009), who presents evidence for a statistically significant medium-run real activity overshoot. Hence, our empirical results regarding GDP provide further evidence for the absence of a significant rebound effect. A puzzle emerges for Greece, which shows no significant results over the calculated period of 48 months. It also deviates in the sense that positive real activity effects occur.

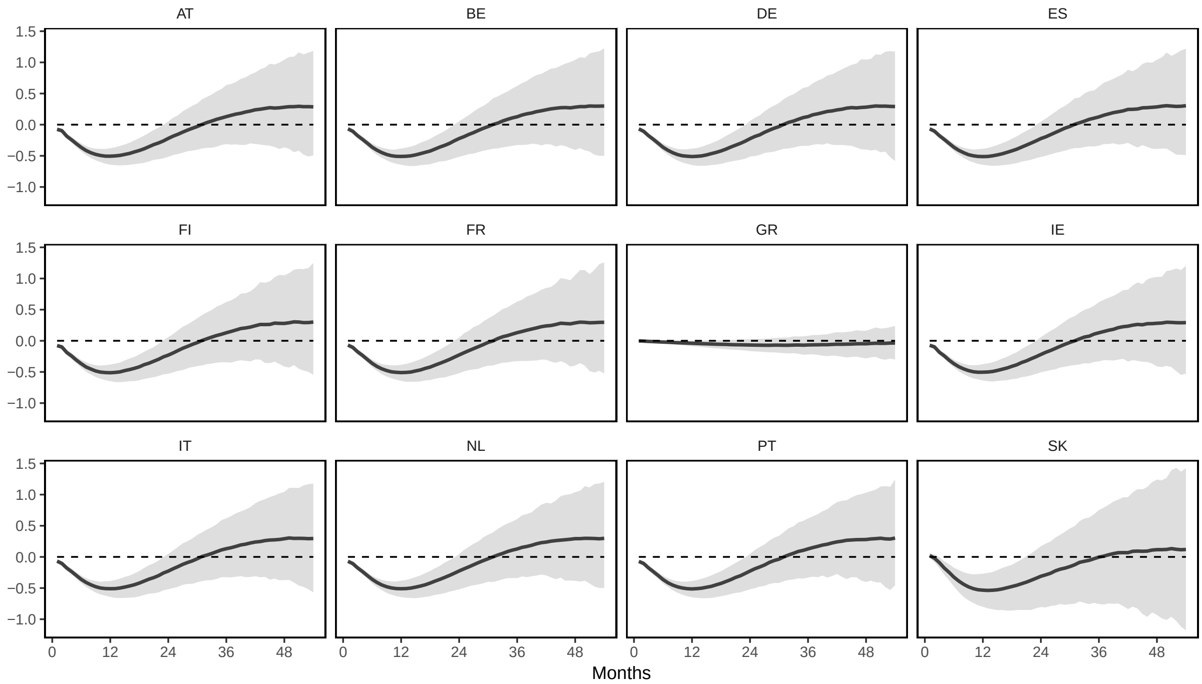


Note: Posterior distribution of impulse responses in percentage points. The median is depicted in grey, the 16th and 84th percentile are indicated by the light grey area. The dashed line indicates zero. Country codes may be found in Appendix A.

Figure 5: Impulse response functions of the unemployment rate in Euro area countries.

Our second variable, depicted in Figure 5, is the unemployment rate. The theoretical channel follows the reasoning with respect to real activity; uncertainty causes firms to stop hiring of new employees, hence there is almost no effect on impact. Over the course of time people will then be laid off, corresponding to profit maximization considerations of enterprises. As we observe different patterns, we will discuss the countries by groups. Note that the interpretation for this variable is different, since we deal with a percentage point response in this case, i.e. the scale represents a percentage point change in the unemployment rate. Compared with already established research results from Jurado et al. (2015), we found similar responses, even though it must be acknowledged that the effects we observe are less persistent. Generally, employment decreases, which implies a significant increase of the unemployment rate between 12 to 24 months. Longest lasting effects are observed in Germany, Slovakia and the Netherlands, where the unemployment rate increases by 0.5 to roughly 1 percentage points. This behavior can be found also in the cases of Spain and Portugal, with the difference that these estimated parameters are not significant. A less pronounced, but still significant increase of unemployment occurs in Austria, Belgium, Finland and France, where it increases approximately by 0.1 percentage points. It must be acknowledged that the results from Greece, Italy and Ireland are not significant over the period considered and much broader confidence bounds were estimated for these three countries alongside Slovakia.

Impulse responses of the short-term interest rate can be found in Figure 6. Generally, the dynamic response of short-term interest rates is common to all countries but Greece, where again a different reaction – not a significant one at all, even though the sign is negative and thus consistent with the other countries – is observable. The shape, magnitude and duration of the lowered interest



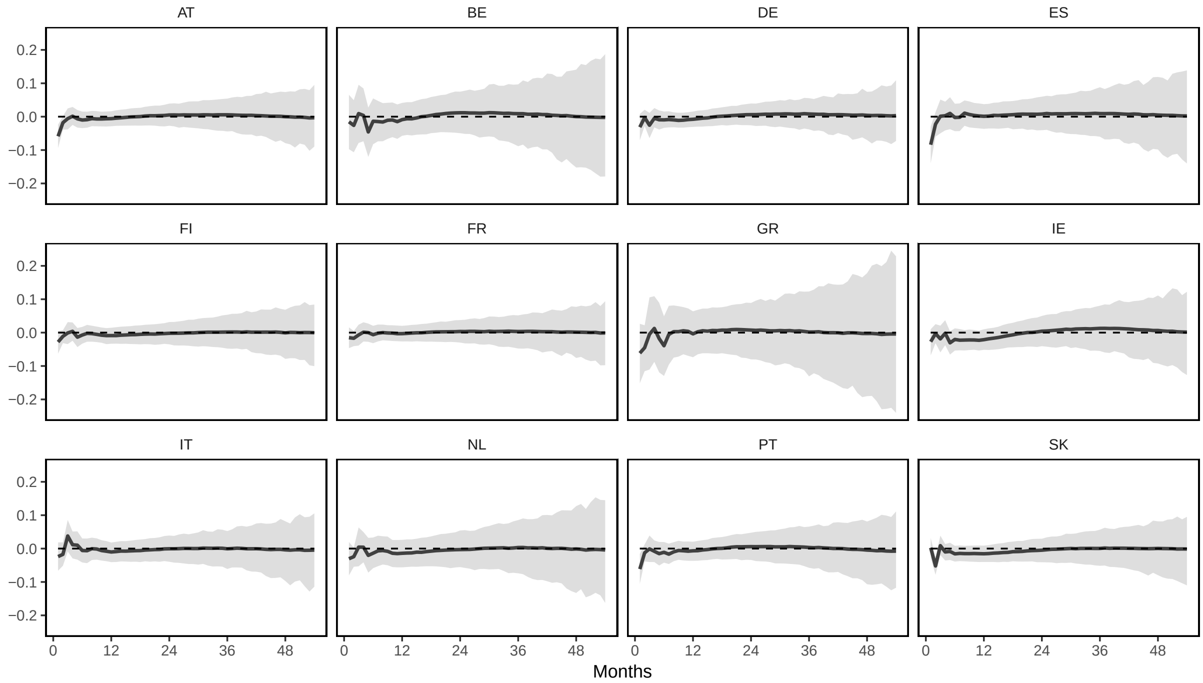
Note: Posterior distribution of impulse responses in percentage points. The median is depicted in grey, the 16th and 84th percentile are indicated by the light grey area. The dashed line indicates zero. Country codes may be found in Appendix A.

Figure 6: Impulse response functions of the short-term interest rate in Euro area countries.

rates, reaching their peak at −0.5 percentage points after roughly 12 months is thus shared by all other countries we considered; after two years, the short-term interest rate change based on the uncertainty shock is insignificant. Comparing these results to previous studies, this response is more persistent than calculated by previous researchers, but the main findings are consistent (Bekaert, Hoerova, & Duca, 2013; Crespo Cuaresma et al., 2017). It appears reasonable that central banks respond to an uncertainty shock by lowering interest rates to foster investment and restore economic prosperity and growth. As all the countries are dependent on the same central bank, the ECB, it is not surprising that the reaction is similar. However, the curious case of Greece would require further attention; it may be that standard transmission channels of monetary policy were impeded by special circumstances, rendering the policy ineffective.

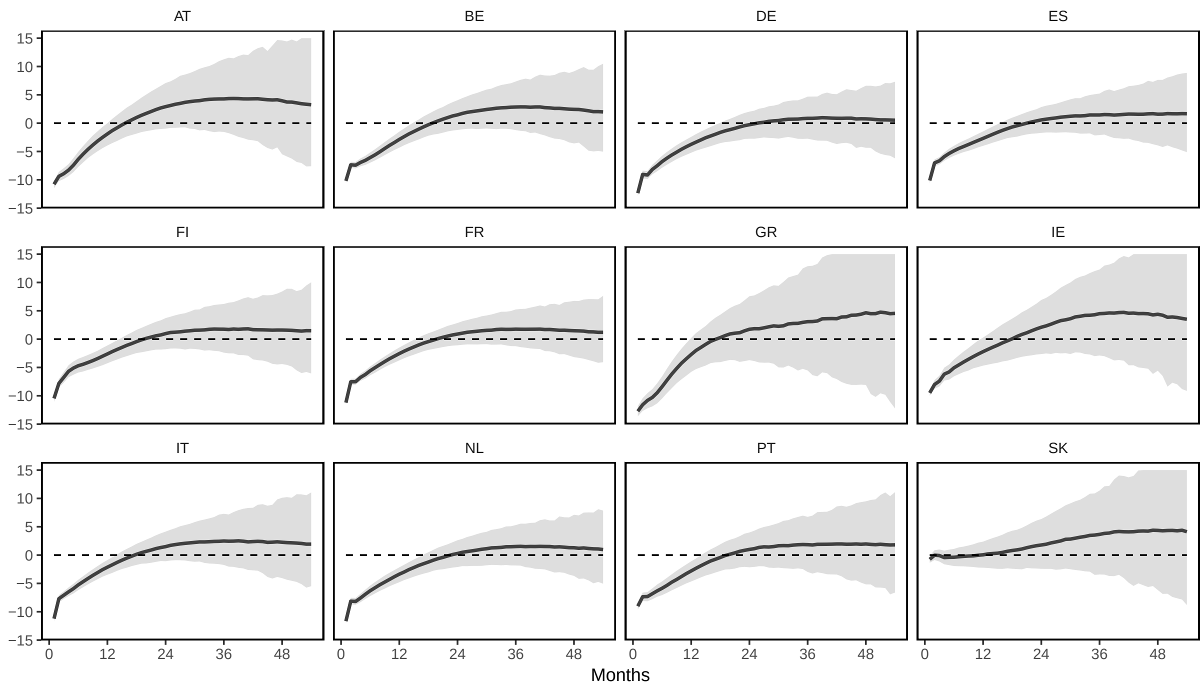
No significant results concerning prices were obtained within our model framework (see Figure 7). This may be because the main theoretical channels counteract each other, canceling out as a consequence for the set of countries considered here. Fernández-Villaverde, Guerrón-Quintana, Rubio-Ramírez, and Uribe (2011) identify the channels as follows; on the one hand, there is the *aggregate demand channel*, where uncertainty implies reduced consumption of households, thereby decreasing prices in a market-based economy. On the other hand, via the *upward pricing bias channel*, because firms may increase prices to maximize their profits, thereby increasing the overall price level.

The impulse responses of equity prices to an uncertainty shock, which can be seen in Figure 8 are consistent in light of the model identification. Apart from Slovakia, equity prices in all countries react with a sharp decrease to an uncertainty shock, which can be attributed to the high factor loadings of equity prices. The fall is exactly 10% (as this was our definition of an uncertainty shock) and the response is significantly different from zero for at least 12 months in most countries and up to 18 months in some. Another reason which might explain the high impact of uncertainty on



Note: Posterior distribution of impulse responses in percent. The median is depicted in grey, the 16th and 84th percentile are indicated by the light grey area. The dashed line denotes zero. Country codes may be found in Appendix A.

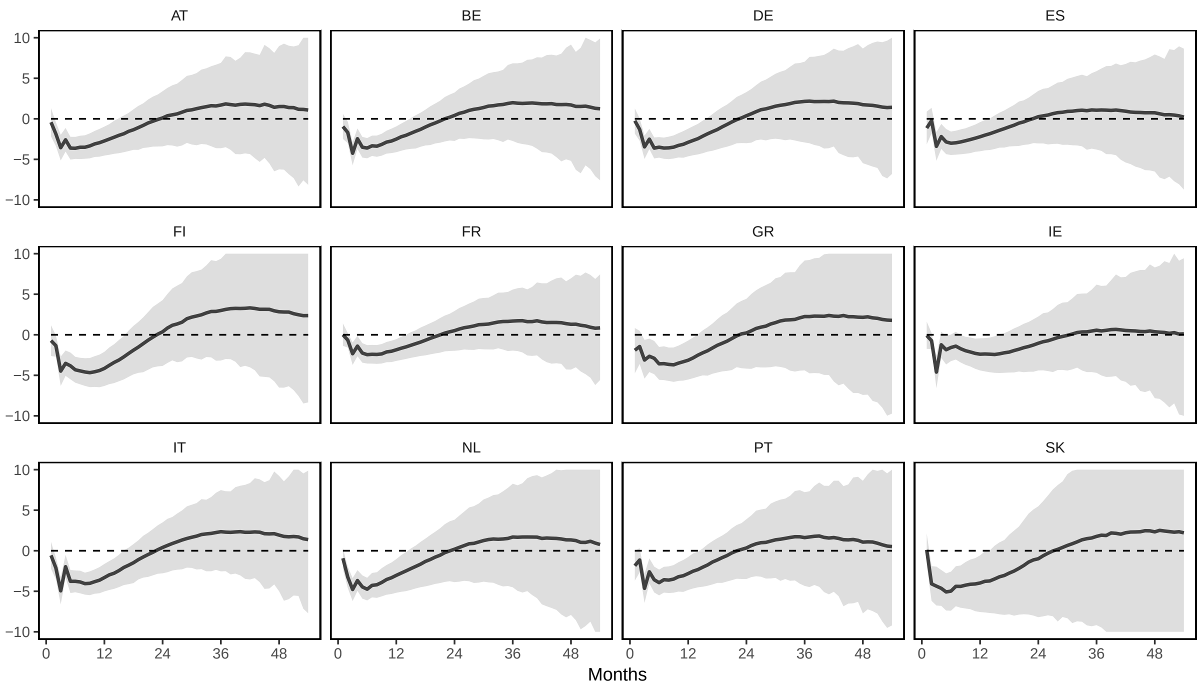
Figure 7: Impulse response functions of price level in Euro area countries.



Note: Posterior distribution of impulse responses in percent. The median is depicted in grey, the 16th and 84th percentile are indicated by the light grey area. The dashed line indicates zero. Country codes may be found in Appendix A.

Figure 8: Impulse response functions of equity prices in Euro area countries.

equity prices could be that it is a fast moving variable, meaning that it reacts quickly to changing economic circumstances. As such, equity prices react faster and to a bigger extent than other, slower moving variables. Overall, the result of our analysis of equity prices is consistent with our model identification and with other findings from the literature, as for example in Crespo Cuaresma et al. (2017) or Carriero et al. (2016).



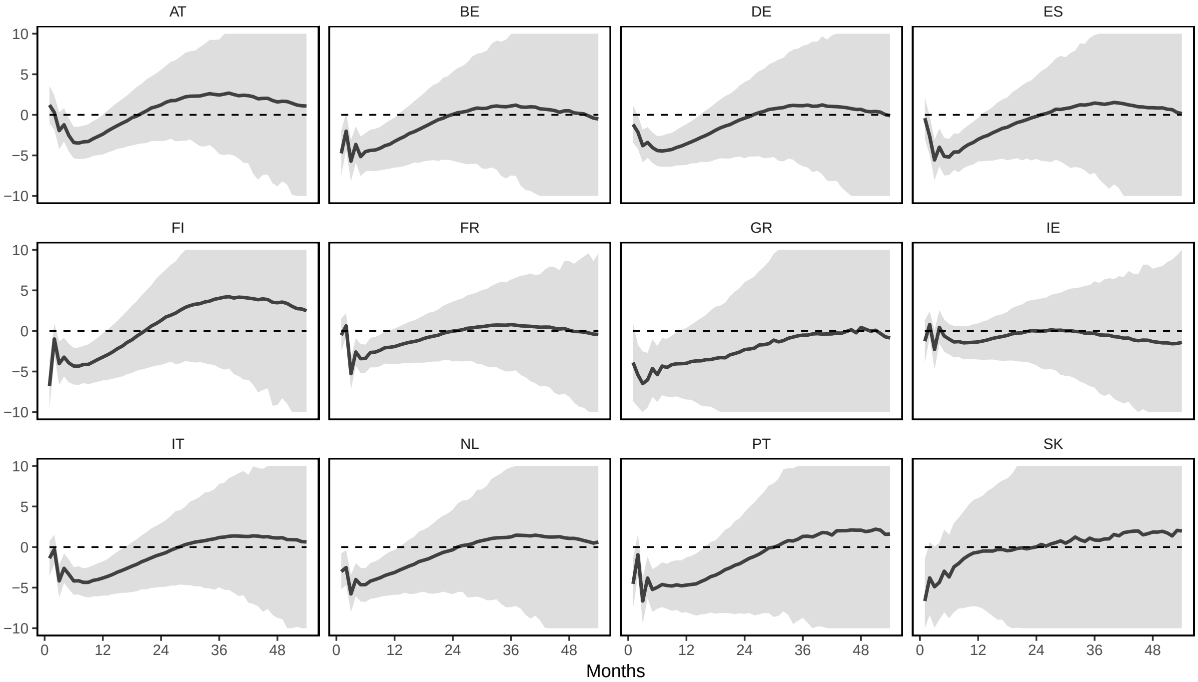
Note: Posterior distribution of impulse responses in percent. The median is depicted in grey, the 16th and 84th percentile are indicated by the light grey area. The dashed line indicates zero. Country codes may be found in Appendix A.

Figure 9: Impulse response functions of exports among EU countries.

Figure 9 shows the impact of an uncertainty shock on the exports within the EU. On impact the effect is relatively modest, but it reaches its maximum of about 5% decline in exports after 6 to 8 months. This suggests a tight link between (intra-EU) trade and European uncertainty. The drop in within-EU exports is remarkably long lasting. After 12-15 months, exports begin to increase again, but we cannot observe a significant rebound effect, although it is visible for the median. The movements are completely the same for all countries, but vary slightly in magnitude and length. The strongest effects can be seen for Finland, Italy and the Netherlands. The weakest effect is in Ireland, where the drop of exports in between gets insignificant. This may be due to the special role of Ireland within the EU – it is popular as hosting country for headquarters of multinationals since the corporate tax rates are one of the lowest in the whole EU – and thus may react slightly different than other Euro area countries.

When looking at the impulse responses with respect to exports outside of the EU area, we see a similar picture as with exports within the EU. Unfortunately, the impulse responses do not look as clear as exports within the EU, which may be due to fact that most EU countries trade more than 80% of their entire goods and services within the EU. Therefore, the data can be characterized by large leaps and bounds, which yields less smooth plots. Nevertheless, in Figure 10 a significant drop after a few months can be observed. The amplitude of the decline is again at 5%, but it is not significant for all countries. After 12-15 months, the decline mitigates and becomes insignificant afterwards.

To assess the robustness of our results, we calculated various other specifications that shall be



Note: Posterior distribution of impulse responses in percent. The median is depicted in grey, the 16th and 84th percentile are indicated by the light grey area. The dashed line indicates zero. Country codes may be found in Appendix A.

Figure 10: Impulse response functions of exports outbound from EU countries.

briefly mentioned at this point. One alternative specification that was estimated was a country subset of the original sample. Namely, we choose the five countries with the highest GDP in the Euro area, that is, Germany, Spain, France, Italy and the Netherlands. Here we can see that our common factor in the error term still depicts macroeconomic uncertainty quite well when compared to alternative measures of uncertainty. Considering the impulse responses in this specification shows that responses have slightly different amplitudes compared to the bigger model, but the direction of change stays consistent, thus the main implications of our model hold. Considering our model identification which we achieve by identifying the uncertainty factor as the factor that loads most heavily on one-step-ahead forecast errors of equity prices, we base our claim of robustness on the checks of Crespo Cuaresma et al. (2017), who conduct robustness checks concerning model identification. Using an alternative identification scheme, almost identical results were obtained. As our model is based rather closely on the one by Crespo Cuaresma et al. (2017), we are quite confident that the same holds for our results.

4 Concluding Remarks

In this article, we estimated a Bayesian vector autoregressive (VAR) model with factor stochastic volatility. Previously, only a limited number of papers estimate impacts of uncertainty and macroeconomic consequences jointly and most literature in this sphere is based on US data. We contribute to the research area by analyzing the special case of a shock restricted to a certain area, the Euro area. Generally, our results are in line with the recent findings in this literature. After presenting the main specification of our model which closely resembles the work by Crespo Cuaresma et al. (2017), we also extensively discuss the Bayesian methods required to estimate all regressions. Furthermore, we compare the latent quantity – the uncertainty factor we obtained – to other measures of uncertainty like the EuroVIX or business and consumer confidence indices. It must be acknowledged that our factor mostly covers financial uncertainty; further differentiation between different types of uncertainty may be an interesting research avenue in the future. Before finally considering the impacts of second-moment shocks on macroeconomic quantities, we also indicate shares of innovation variance explained by the global uncertainty factor. Regarding impulse responses of various variables to an uncertainty shock, we obtain significant results of a decrease in real activity in most Euro area (EA) countries over a period of roughly a year, but were not able to identify a significant long-run overshoot. Furthermore, we found significant effects of uncertainty considering rising unemployment, decreases in the short-term interest rate, equity prices, as well as intra Euro area exports and Exports to non-Euro area countries. No significant results could be obtained for prices.

Greece, Ireland and Slovakia are often affected slightly different by the shock than other countries. This may be related to different effects in subsets of countries. Consequently, two distinct objectives may be identified for future research considerations. First, additional factors of uncertainty may be used to differentiate between different kinds of uncertainty, such as financial volatility, fiscal uncertainty or more specifically, 'real' macroeconomic uncertainty besides financial uncertainty. Second, depending on interdependences of economies and the magnitude of business cycle synchronization, clusters of countries and cluster-specific reactions might be of interest. Considering empirical evidence from previous articles and results presented in *this* paper – in light of the recent Great Recession and related theories of global imbalances and instability – it appears of utmost importance to thoroughly examine effects stemming from macroeconomic volatility with respect to economic policy.

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A Data

The variables are grouped as follows: Euro Area Aggregate (EA19), Austria (AT), Belgium (BE), Germany (DE), Greece (GR), Spain (ES), Finland (FI), France (FR), Ireland (IE), Italy (IT), the Netherlands (NL), Portugal (PT), Slovakia (SK) and exogenous variables (exo).

Variable	**Description**	**Transformation**	**Source**	**Comments**
y	Real GDP	Logs	OeNB	—
p	Consumer Price Index	LogDiffs	OeNB	—
stir	Short-Term Interest	—	OeNB	—
eq	EUROSTOXX Main Index	Logs	stoxx.com	—
cci	Consumer Confidence Index	Logs	OECD	EA19 specific
bci	Business Confidence Index	Logs	OECD	EA19 specific
unemp.r	Unemployment Rate	Season. Adjusted	Eurostat	—
ciss	Stress Index*	Logs	ECB	EA19 specific
ex.intra	Intra EU Exports	Deseason. Logs	Eurostat/Comext	in mio. EUR
ex.extra	Extra EU Exports	Deseason. Logs	Eurostat/Comext	in mio. EUR
poil	Oil Price Index	Logs	OeNB	Exogenous
eurovix	EUROSTOXX Volatility Index	Logs	stoxx.com	EA19 specific

Note: ECB – European Central Bank; OeNB – Oesterreichische Nationalbank; OECD – Organisation for Economic Co-operation and Development; *Composite Indicator of Systemic Stress. Logs – Natural Logarithm, Diffs – Differences.

Table 1: Description of variables used in this article and their source.