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Ansgar Belke and Thomas Osowski[1]

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Abstract

Building on the growing evidence on the importance of large data sets for empirical macroeconomic modeling, we estimate a large-scale FAVAR model for 18 OECD member countries. We quantify the global effects of economic policy uncertainty shocks and check whether the signs, the magnitude, and the persistence profile are consistent with the literature on the real and financial sector effects of uncertainty. In that respect, we compare the impacts of a US and a Euro area uncertainty shock. According to our results, an increase in uncertainty has a strong negative impact on economic activity, consumer prices, equity prices, and interest rates. Uncertainty shocks cause deeper recessions in Continental Europe (except Germany) than in Anglo-Saxon countries. This pattern is compatible with the view that continental Europe still suffers from institutions which prevent flexible markets. And US uncertainty shocks have a bigger impact than their European counterparts. Uncertainty does not only impact that country where the shock originates but also has large cross-border effects. In that respect, Switzerland turns out to be the most affected non-Euro area European country. We also find a high degree of synchronization among the responses of national variables to a (foreign) uncertainty shock, indicating evidence of an international business cycle. With respect to the responses of national long-term interest rates to an uncertainty shock, our results reveal a strong "North-South" divide within EMU with rates decreasing less significantly in the South. Another important result is that uncertainty shocks emerging in one region quickly raise uncertainty outside the region of origin which appears to be an important transmission channel of uncertainty.

JEL Classification: C32, F42, D80

Keywords: Economic policy uncertainty; Europe; FAVAR analysis; large-scale econometric models; option value of waiting; uncertainty effects; international uncertainty spillovers; United States

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1. Introduction

Uncertainty has gained much attention as one of the main drivers of the depth and duration of the Great Recession (Bloom et al., 2013, Caggiano et al. 2017). For example, the Federal Open Market Committee minutes repeatedly emphasize uncertainty as a key factor driving the 2001 and 2007-2009 recessions. Financial and uncertainty shocks are generally interpreted as the main factors behind the decline in output and employment during the 2007-2009 US recessions (Stock and Watson, 2012). Bordo et al. (2016), for instance, find negative effects of policy uncertainty on bank credit growth in the United States. The results of other studies which have found important macroeconomic effects of bank lending growth on the economy are consistent with the interpretation that high economic uncertainty has slowed down the U.S. recovery by limiting overall credit growth through the bank lending channel.

But also the European Central Bank (ECB) argues that uncertainty in the Euro area rose substantially during the Great Recession and the sovereign debt crisis and that a high degree of uncertainty has the potential to significantly dampen economic activity, above all investment (ECB, 2016).[1] However, there is no consensus yet about what the sign of the impact of uncertainty is on economic and financial activities and how the international spillovers of uncertainty look like. Via business cycle correlations, the possibility arises that the impact of an uncertainty shock originating in the US may influence global business cycles (Kamber et al., 2013). This view is supported by the rapid and accelerating process of financial globalization and new technologies (Kang et al., 2017). Our study is directly geared towards an empirical assessment of these emanating issues.

The study closest to ours is Colombo (2013) who investigates the effects of uncertainty shocks from the US to the Euro area by using aggregated data for the Euro area. Colombo (2013) uses standard VARs and obtains the results that an uncertainty shock in the US has large domestic and cross-border effects. Our Factor-augmented Vector Autoregression (FAVAR) approach attempts to generate more detailed evidence about the cross-border effects and is a natural extension of Colombo (2013) as we extend her research in several aspects. By using a FAVAR and not a two-country SVAR as she employs, we put a larger emphasis on cross-border effects on individual national economies. We focus on US and Euro area economic policy uncertainty whereas Colombo (2013) solely estimates the effects of US uncertainty and then continues with a variance decomposition exercise in order to compare the effects of US and European uncertainty. However, her impulse-responses and specifications only consider US uncertainty

[1] Similar views have been shared and propagated by the IMF, the OECD and other international institutions.

shocks. In addition, throughout the study she puts US uncertainty before European uncertainty in her Cholesky orderings. Having said this, we would like to argue that the results would change significantly if one would in turn put European uncertainty before US uncertainty. In the end, the ordering of both uncertainty measures depends on the assumed transmission of the uncertainty shock. Taking this as the starting point, we will change the ordering dependent on the shocked variable in our paper because we would otherwise determine our estimation result a priori. Another motivation to proceed like that is that we find a strong contemporaneous bilateral correlation between Euro area and US uncertainty and thus question the usefulness of a variance decomposition exercise in our context.[2] This is because Colombo (2013) imposes that US uncertainty can impact Euro area uncertainty contemporaneously but not the other way around (for more details see section 3.3).

Other than Colombo (2013), we do not use aggregated data for the Euro area as a whole in order to evaluate uncertainty effects on and uncertainty transmission to individual national economies, a topic extremely relevant in the euro area debt crisis. Furthermore, we include additional industrialized economies, such as European EMU-outs and Canada, into our analysis. This increases the variety in our sample and allows us to draw some conclusions about specific institutional drivers behind different impacts of uncertainty. Furthermore, we use a much longer time span for our estimations. Finally, we include additional financial variables such as equity prices, exchange rates, and long-term interest rates because uncertainty is quickly transmitted via financial variables (see in more detail section 2.1 below).

In line with Colombo (2013), we argue that the VAR methodology is well suited to capture the effects of uncertainty. As impulse responses only estimate the effect of an unexpected change (a "shock") in a specific variable, this procedure appears especially useful for the evaluation of uncertainty effects. While monetary policy contains unanticipated changes as well systematic changes, uncertainty measures should not contain such a systematic component (Bernanke et al., 2005). Therefore, the general critique that impulse response functions (IRFs) only estimate the effect of unexpected changes is not valid for the evaluation of uncertainty effects.

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[2] By means of a variance decomposition, the effects of several exogenous shocks (i.e. their contributions) are compared. In this context, the ordering of the variables is decisive if they are correlating as strongly as in our case. Accordingly and Colombo (2013) endows US uncertainty with a higher impact ex ante due to her specific ordering. If US uncertainty is shocked and the Euro area uncertainty is able to react on it contemporaneously (corresponding with Colombo's chosen ordering), the impact of US uncertainty is larger, because US uncertainty is now impacting all variables also through its impact on the Euro area uncertainty. If, however, the ordering were the other way round and US uncertainty is shocked, one would find only a smaller effect of US uncertainty on the Euro area uncertainty variable and, hence, smaller impacts on all other variables as well.

One important drawback of standard VARs is the curse of dimensionality which limits the number of endogenous variables and therefore the scope of the analysis. As we are interested in the effects of uncertainty on various countries, we use the FAVAR approach presented by Bernanke et al. (2005). The FAVAR approach enables us to estimate country-specific responses to an uncertainty shock in a feasible specification and to overcome the curse of dimensionality. Our study differs from a couple of other FAVAR-based studies with respect to, among others, the dimension of the analysis (country data vs. cross-country data). Many studies confine themselves to data for one single country. We treat the dimension issue differently by turning away from the country-specific view but are employing the same variables across 18 countries and then drawing the principal components from them (see, for instance, Belke and Rees, 2014).

The basic idea of a FAVAR model rests on merging a large amount of macroeconomic data into a sufficiently small number of factors which are subsequently used for the sparingly estimation of a VAR model. Therefore, we extract the information about common components of business cycle movements from a large cross section of national time series. As a stylized fact from the literature, common components play a larger role for business cycles in advanced economies which are the focus of our paper than for emerging economies (Kose et al., 2003). Many emerging market economies have, in contrast to industrialized countries, only reached intermediate levels of financial integration, i.e. they have not been able to achieve improved risk sharing over the globalization period (Kose et al. 2007). The common components approach thus allows us to model business cycles without pretending to have too much a priori economic theory (Sargent and Sims, 1977).

The FAVAR approach is applied to augment the information content in a VAR through a two-step procedure. First, the common dynamics in our large panel consisting of a multitude of time series is identified employing a dynamic factor model (DFM) techniques (Geweke, 1977, Sims and Sargent, 1977). In a second step, the causality between uncertainty and some suitable measures of economic activity is assessed using a traditional VAR which includes the factors as the relevant description of the underlying economic dynamics.

We use this framework to answer the following research questions: Is the FAVAR approach an adequate framework to model cross-country developments? What are the global effects of uncertainty shocks? What is the sign of the estimated uncertainty impact coefficient? What are the channels of uncertainty transmission between Euro area and the US in both directions? For this purpose, we compare a US and a Euro area uncertainty shock and put a special focus on non-EMU countries in Europe.

The remainder of our paper proceeds as follows: Section 2 reviews the literature on the impact of uncertainty on the real economy. In section 3, the data and the empirical approach are introduced. The empirical results are delivered and discussed in section 4. In section 4.1, the impact of a shock to Euro area economic policy uncertainty is investigated. For reasons of comparison, Section 4.2 then derives the impacts of a shock to US economic policy uncertainty. In section 4.3, we present some robustness checks. In section 4.4 we summarize and discuss our results and confront the latter with the pertinent literature. Section 5 finally concludes.

2. Impacts of uncertainty on the economy – A review

2.1 On the sign of uncertainty impacts on macroeconomic variables

In the academic literature, the impact of uncertainty on the real and the financial sector is a constantly recurring topic. Some intriguing questions that typically emerge in this context: How does uncertainty affect the economy (Belke and Goecke, 2005)? What are the transmission channels of uncertainty (Bloom, 2013)? What exactly is the magnitude and the sign of these impacts on a variety of variables such as GDP, the consumer price index, the long-term interest rate, equity, the monetary policy stance, and the exchange rate and their common components?

It was US economist Frank Knight (1921), who in his book "Risk, Uncertainty and Profit" built his analysis on the distinction between risk and uncertainty. He defined uncertainty as peoples' inability to forecast the likelihood of events taking place. On the contrary, Knight defined risk as "peoples known probability distribution over known events" (Bloom, 2013). In this paper, we primarily focus our analysis on a specific concept of uncertainty (i.e. economic policy uncertainty), which embraces both risk and uncertainty.

Focusing on impacts of uncertainty on investment-type variables, we take up an idea originally proposed by Dornbusch (1987), Dixit (1989), Bentolila and Bertola (1990), and Pindyck (1991). Option price effects are modeled in a technically sophisticated way in these references. These models typically abstract from risk aversion. These models are based on a risk-neutral (dis)investment decision under revenue uncertainty caused by revenue volatility and fixed sunk (i.e. irreversible) hiring and firing costs. It is comparable to a group of models incorporating irreversible investment decisions. This mechanism relies on the asymmetry of adjustment costs (Caballero, 1991) and on scrapping values (Darby et al., 1998). In addition, the degree of competition in the output market and economies of scale (Caballero, 1991) do sometimes play a predominant role in this strand of literature.

As seen from theory, the sign of the impact of uncertainty on investment-type decisions is ambiguous. As far as general investment is concerned, the sign might be *positive* because it pays off to be able to react to different states of the world in the future. Closely following Caballero (1991), Bloom (2013) underscores two variants of positive effects of uncertainty on growth: firstly, he addresses growth options through which higher uncertainty fosters investment by expanding the "upside of future outcomes". Secondly, firms may expand when reacting to positive shocks and contract as a reaction to negative shocks and, hence, a mean-preserving spread in outcomes has the potential to raise the average output (Oi 1961, Hartman 1972, and Abel 1983).

But regarding specific "investment" the sign is often expected to be *negative* in order to cut off the negative part of the distribution of the potential realization of the variable which is vulnerable to uncertainty ("option value of waiting under uncertainty", Leduc and Zheng, 2016). These *real options* effects make firms more cautious about hiring and investing, and consumers more cautious about buying durables and through both avenues, lower growth (Caggiano et al. 2017).

A third possibility is an effect of uncertainty on the relation among different variables, for instance between exports or employment and the exchange rate. For example, a so-called "band of inaction" which emerges due to hiring and firing costs on the microeconomic level is widened by option value effects of exchange rate uncertainty (Belke and Goecke, 2005). Based on this micro foundation, an aggregation approach can be applied. Under uncertainty, intervals of weak response to exchange rate reversals (called 'play' areas) are introduced on the macro level. 'Spurts' in new employment or firing may occur after an initially weak response. Since these mechanisms may apply to other 'investment' cases where the aggregation of microeconomic real options effects under uncertainty are relevant, they may even be of a more general interest (Belke and Goecke, 2005). As a result, the sign of the impact of uncertainty on the real economy is *ambiguous*. Higher uncertainty implies less structural change in the economy because it prevents investment and de-investment.[3]

Models *with risk aversion* typically lead to negative effects of uncertainty. For instance, in this case, *risk-premium* effects emerge which act to raise the cost of finance (Bloom, 2013) and thus, may have a dampening impact on asset prices as well. Accordingly, Chen and Tong (2016) find that economic policy uncertainty predicts negatively future stock market returns at various

[3] Aastveit et al. (2013) estimate that investment reacts two to five times weaker when uncertainty is in its upper instead of its lower decile.

horizons. In the same vein, Jiang and Tong (2016) show that uncertainty of monetary policy (MPU) induces a risk premium in the US Treasury bond market. They come up with the robust result that MPU forecasts significantly and positively future monthly Treasury bond excess returns. Finally, *precautionary savings* effects may emerge which act to reduce consumption spending (Bloom, 2013).

Seen on the whole, thus, the literature finds that uncertainty is hampering growth (Ramey and Ramey, 1995, Engle and Rangel, 2008, and Baker and Bloom, 2013a), credit (Bordo et al., 2016), thus reducing investment and output (Aastveit et al., 2013, Bloom, 2009, and Bloom et al., 2013), hiring of labor and thus employment (Bloom, 2009, Leduc and Zheng, 2016), consumption (Romer, 1990), trade (Belke and Goecke, 2005, Handley and Limao, 2012, and Novy and Taylor, 2012) and inflation (because uncertainty acts as a demand shock, Leduc and Zheng, 2016). [4,5] However, empirical evidence that uncertainty stimulates R&D spending driven by growth options effects and, hence, uncertainty has a positive effect on longer-run growth is more ambiguous.

Concerning the impact of uncertainty *on monetary policy* the literature comes up with the notion of „wait-and-see“ monetary policy (Lei and Tseng, 2016) which implies that the impact of monetary policy is lower under uncertainty (Aastveit et al., 2013) and that considering uncertainty in the monetary policy context means "a journey into non-linear territory" (Pellegrino, 2017). Moreover, in some cases, the impact of uncertainty on real economy variables may interact with the monetary policy stance and tend to be greater when the economy is, as in the current years, close to the zero lower bound (Caggiano et al. Pellegrino, 2017).[6] This again underlines the importance and timeliness of our study.

Regarding the exchange rate, political uncertainty is often viewed to lead to a depreciation of the domestic currency and a higher volatility of its exchange rate. As an example, the EUR-USD exchange rate skyrocketed as the US political uncertainty weighed on the US-Dollar: Democratic presidential candidate Hillary Clinton was only a couple points ahead of her Republican rival Donald Trump after having led the polls for quite a while before.[7]

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[4] A good and comprehensive survey is IMF (2016), p. 41.
[5] For a survey see Bloom (2013).
[6] See Caggiano et al. (2017). For the underlying theoretical foundations see Basu and Bundick (2016).
[7]See http://www.euroexchangeratenews.co.uk/eur-usd-exchange-rate-skyrockets-us-political-uncertainty-weighs-us-dollar-21586.

A second wave of literature analyzing macroeconomic impacts of uncertainty shocks started along with significant progress in handling general equilibrium analysis. In some cases, endogenous uncertainty is stressed and (micro) uncertainty appears to be systematically rising in recessions (Bloom, 2013). A seminal contribution here is Bloom (2009) who offers a structural framework to analyze the impact of uncertainty shocks. [8]

2.2 VAR-type studies assessing the impacts of uncertainty

There are a few VAR-type studies related to ours which assess the impacts of uncertainty on macroeconomic variables. As mentioned already in the introduction, the study closest to ours is Colombo (2013) who quantifies spillovers directed from the US to the Euro area via a two-country Structural VAR and also uses policy uncertainty indicators presented by Bloom et al. (2013). She focuses on shocks to US economic policy uncertainty which induce a negative and significant reaction of Euro area price and quantity indicators. Furthermore, she finds strong co-movements between US and euro uncertainty indicators. According to her estimations, the Fed but also the ECB reacts to uncertainty shocks originating in the US by reducing their policy rate. In contrast to our approach, the author only uses US and aggregated Euro area variables and only focuses on the effects of a US uncertainty shock.

Different from us, de Wind and Grabska (2016) do not estimate a FAVAR model interconnecting different regions of the world but separate structural VARs with a similar specification as Bloom (2009) for the various countries in their data set. In contrast to our approach, they focus on the domestic effects of an uncertainty shock. They include eleven countries from Europe and North America in their sample and put a large emphasis on differences of uncertainty effects between continental European and Anglo-Saxon countries. Their choice of uncertainty focuses more on financial markets as they primarily use equity volatility indicators.

The authors find that uncertainty shocks cause deeper recessions in Continental Europe than in Anglo-Saxon countries. According to the results of their variance decomposition, the conditional variance of economic activity relative to uncertainty shocks is much smaller for Anglo-Saxon countries. The authors explain their findings with country heterogeneity in labor and capital market flexibility. As continental European countries have a larger amount of labor and capital market restrictions, the authors conclude that these restrictions enhance the effects of

[8] Further references of specific effects of uncertainty on a variety of macro variables can be found at http://www.policyuncertainty.com/research.html (2016).

uncertainty shocks, since firms are less capable of dealing with uncertain situations when investment and hiring decisions are less easy to reverse, as suggested by Bloom (2009).

Kang et al. (2017) use FAVAR as well as factor-augmented Bayesian VAR (FABVAR) estimation techniques to analyze the effects of global uncertainty shocks. Although their country sample is smaller than ours (15 countries), they also include several emerging markets. Their research focus is more on the effects of a *global* rise in uncertainty, while we focus more on cross-country spillovers. In contrast to our study ("national on national") they estimate the impact of global uncertainty on key global macroeconomic variables („global on global") and national variables ("global on national"). They find that global uncertainty shocks cause a strong reduction in global output, prices, and interest rates. Similar effects are identified at the country level.

As we do in our study, Kamber et al. (2016) utilize a FAVAR model to estimate the impact of US economic uncertainty on several developed economies and New Zealand as a small open economy in particular. In other words, they analyze international spillover effects of (US) uncertainty shocks just as we do. For the Euro area, the authors use aggregated Euro area variables which do not allow for individual country analyses for Euro area countries. Besides the indicator presented by Jurado et al. (2015), they also employ the VIX (S&P 500 Volatility) and the economic policy uncertainty index developed by Bloom et al. (2013). In contrast to our study in which we compare the effects of US and Euro area uncertainty shocks, the authors are solely interested in the effects of a US uncertainty shock. They find that an increase in US uncertainty leads to strong adverse domestic effects in the US and other developed countries. Among developed countries, they observe a rather high degree of synchronization in the response of national variables (especially stock markets).

In the following, we empirically assess the sign, magnitude, and significance of the economic policy uncertainty (in the following sometimes abbreviated as "uncertainty") effects in a FAVAR framework. For this purpose, we assess the impact of uncertainty shocks in the Euro area and the US on real economic and financial market variables in Europe and North America for a sample of 18 countries and the period ranging from 1996:01 to 2015:12. What is more, we also check whether economic uncertainty has cross-border effects and not only domestically impacts the country where the shock originates. Finally, we strive to identify some of the before-mentioned transmission channels of uncertainty shocks to the economy.

3. Data and empirical approach

3.1 Empirical approach

In order to use a coherent and appropriate framework, we estimate a Factor-augmented Vector Autoregressive Model (FAVAR) as proposed by Bernanke et al. (2005). In this regard, we use the FAVAR as a multi-country framework, assuming that developments of economic variables share strong similarities which can be approximated by common factors. Our empirical approach is also motivated and encouraged by the results of Georgiadis (2015). His results show that multi-country models such as the FAVAR (and GVAR) are, in contrast to bilateral VARs, more appropriate to model global and regional shocks as well as cross-country spillovers, because these models are capable of modeling higher-order spillovers.

As we include at least four variables for each of the 18 countries in our sample, the FAVAR appears to be a sufficient solution to the curse of dimensionality (Chudik and Pesaran, 2009). As mentioned in the introduction, the main advantage of the FAVAR is the possibility to simultaneously model a large amount of time series and thereby including a large amount of economic information. The curse of dimensionality is handled by generating principal components and thereby reducing the number of endogenous variables (Chudik and Pesaran, 2009). The principal components represent "unobservable" factors F_t which are supposed to explain a sufficient amount of variance in the data set. Besides the factors in F_t, the model also contains a set of "observable" factors Y_t.

While variables in Y_t are directly observable, the elements of F_t need to be estimated. The unobservable factors are estimated based on an informational data set X_t containing N variables while accounting for the impact of the observable factors Y_t:

$$X_t = \lambda^f F_t + \lambda^y Y_t + e_t \tag{1}$$

where λ^f is an $N \times K$ matrix of factor loadings, λ^y is $N \times M$, and the $N \times 1$ vector of (idiosyncratic) error terms e_t are mean zero and assumed to be either weakly correlated or uncorrelated. K represents the number of unobserved factors and M equals the number of variables in Y_t.

In essence, Y_t and F_t are common forces that drive the dynamics of X_t. The elements of F_t may also be regarded as the primary common drivers of international economic developments while e_t contains idiosyncratic or variable/country specific components. The number of (unobservable) factors is generally assumed to be small ($K \ll N$). Factors are orthogonal to each other and factors and idiosyncratic components are orthogonal. Furthermore, it is important to note that, if equation (1) and (2) adequately describe the data generation process, omitting F_t from the system will result in biased estimates.

Although equation (1) indicates that X_t only depends on current values of the factors, it can be interpreted as *dynamic* factor model because F_t can include lags of the fundamental factors. Altogether, a FAVAR is a standard VAR in which some of the variables are factors taken from a dynamic factor model:

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \varepsilon_t \quad (2)$$

where $\phi(L)$ is a polynomial in the lag operator. The error term ε_t is mean zero with covariance matrix Q. It is important to note that if (1) and (2) correctly describe the data-generating process, omitting F_t from the system will result in biased estimates.

Equation (1) and (2) are jointly estimated by likelihood-based Gibbs sampling techniques presented by Geman and Geman (1984), Gelman and Rubin (1992), and Carter and Kohn (1994). We use the single-step Bayesian likelihood approach developed by Bernanke et al. (2005) which is a multi-move version of the Gibbs sampling technique.[9] In setting the prior distributions, we use a "Minnesota"-type prior but with a zero mean for all coefficients. We estimate the model based on monthly data for the period 1996:01-2015:12. Additionally, and consistent with other studies as, for instance, Bernanke et al. (2005), we divide our economic data set X_t into two subgroups. While the first group contains measures of economic activity and price developments which are supposed to react slowly to shocks in the system, the second subgroup includes financial data which immediately react to innovations. The split between slow- and fast-moving helps to identify the unobservable factors and to identify the model using a Cholesky decomposition. Since one of our aims is to analyze possible heterogeneity in the responses of economic variables of the different countries in our sample, we decided not to impose more structural restrictions for the factor extractions and on the individual series.[10] We use six lags

[9] See Bernanke et al. (2005) for further details and mathematical derivations of the estimator. They also present an additional two-step estimation procedure where the factors in X_t are extracted and estimated according to Stock and Watson (2002) and afterwards included in a VAR. From an econometric perspective, it is difficult to discriminate between both. Furthermore, Bernanke et al. (2005) show that both procedures generate similar results. Therefore, our choice to use the Bayesian approach is primarily based on convenience.

[10] See, for instance, Vasisthta and Maier (2013) and Fernald et al. (2014) who generate one factor for a given subset of variables instead of jointly generating the factors from the entire sample. Their approach enables them to better interpret the estimated factors which is important for their research question and estimation procedure as both studies use two-step estimation procedure instead of the Bayesian approach. In our approach, we do not put emphasis on the interpretation of the factors as we are not explicitly interested in the estimation of common factors but in the effects on individual country variables and therefore the elements of X_t. Thus, we decided not to impose further restrictions on the factor estimation.

and employ 50,000 Gibbs replications while discarding the first 10,000 as burn-in sample for the Gibbs sampler.

As common in VAR literature, we use impulse response analysis in order to examine the international impact of uncertainty in the Euro area. We present 10%-significance bands in order to interpret the significance of our (median) impulse responses. Because a lot of variables in X_t enter in growth rates (or first differences in case of the interest rates) rather than levels (see section 3.3), we plot cumulated impulse responses for those variables.[11]

Regarding the statistical identification of economic shocks, we use a Cholesky decomposition. Although the Cholesky decomposition is the standard identification scheme which has been used by nearly every FAVAR study in the literature, its appropriateness can be questioned in principle (see Christiano et al., 2005). However, we argue that in particular the division between slow and fast-reacting variables helps with the identification of shocks and supports this choice. In this regard, we follow Bernanke et al. (2005) and use a standard recursive ordering in which factors representing output and inflation are ordered first, followed by the factors of the "fast-moving" variables – in our case interest rates and stock prices. Afterward, the stances of monetary policy and eventually uncertainty in the Euro area and the USA are ordered last. Thereby, we assume that uncertainty responds endogenously and immediately to changes in other variables, but that innovations in uncertainty affect the remaining variables with a lag of at least one month – depending on the position of the ordering.

The most crucial step of our analysis is to determine the number of factors to be included in our models. Although there are several procedures for this choice available, Bernanke et al. (2005) argue, that these criteria may not be useful for the FAVAR as these do not address the question of how many factors to include in the VAR specification. In general, the empirical literature does not (yet) generate a final solution to the determination of the number of factors. This is especially true for the Bayesian FAVAR approach used in this study. Therefore, several authors simply chose their number of factors in a more or less ad hoc fashion (see, for instance, Bernanke et al. 2005, Shibamoto, 2007, and McCallum and Smets, 2007).

We base our choice on two aspects: Firstly, we determine the number by examining the cumulative amount of variance explained by a predefined number of factors. As a lower bound for

[11] For a derivation of impulse responses for the elements of X_t, see Gupta and Kabundi (2010), Blaes (2009) and Bernanke et al. (2005).

the amount of variance explained, we set 80% as a common threshold in the empirical literature.[12] In our context, this procedure only gives a first indication which can be expected to be (too) high, as it does not consider that we also include observable factors (Y_t) in the model.

Secondly, we evaluate the amount of variance in X_t which is explained by our (unobserved and observed) factors. For the second method, we obtain the adjusted R^2 values by regressing the respective series on the common factors $\widehat{F}_t$ and Y_t. If the variation of the variables in X_t is to a large extent explained by our factors, we can assume that the estimated factors summarize the information contained in these series well which enables us to put more confidence in the results of our impulse responses (Blaes, 2009). However, both procedures can at best generate evidence of the adequate choice of factors, because especially the first method does not incorporate all features of the FAVAR approach. The findings by Forni and Gambetti (2014) in the context of fundamental information embedded in VAR models also show that there is no silver bullet when it comes to identify the optimal number of principal components.

It is important to underline that the space spanned by the factors is still estimated consistently when the number of factors is overestimated although efficiency is reduced. On the other hand, an underestimation of factors results in an inconsistent model as potentially important dynamics won't be captured by the factor set (Stock and Watson, 1998). This argument can be used to check the adequacy of the number of factors. If the number of factors was chosen to be too low and important dynamics of X_t were left out, results based on a larger number of factors might reveal fundamentally different results. Therefore, even if we start with too many unobserved factors, the estimation is still unbiased. Bernanke and Boivin (2003) argue "it is important to note 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." Our robustness checks in section 4.2 also contain re-estimations of the benchmark models with a higher number of factors.

3.2 Data

Our sample includes data between 1996:01 and 2015:12 for the following 18 countries: Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Italy, Ireland, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, UK, and the US. We have chosen 1996 as the starting point of our estimation due to data constraints. As other contributions in the field which

[12] Alternatively, one may also use the criteria presented by Bai and Ng (2002) or the Kaiser criterion (all factors with eigenvalues greater than one). However, according to our results, the Kaiser criterion tends to propose rather large factor numbers (see Table 4).

include Euro area member countries (Kang et al., 2017, Kamber et al., 2016, and others), we do not set a dummy for the start of European Monetary Union in 1999.[13]

For each country, we include the following variables into the dataset of X_t: a proxy of economic activity, an indicator of the price development, nominal equity prices, and 10-year interest yields[14]. Additionally, we include the nominal effective exchange rate for the Euro area with an increase of this index implying an appreciation of the home currency. Regarding the indicator of economic activity, we choose two indicators in separate specifications: (Monthly) real GDP[15] and industrial production. As our price indicator we use the CPI and core price indices.[16] Overall, every specification of X_t contains 72 time series. Table 1 summarizes the data used in our study.

[Insert Table 1]

As observed factors (Y_t), we include two sets of variables for the Euro area and the US: first, an indicator of economic uncertainty and secondly, a variable which tries to measure the monetary stance of the central bank. The inclusion of US and Euro area variables as observed factors does not only enable us to simulate uncertainty shocks originating from both currency areas. Both regions are economically powerful and can be considered as “large” in comparison to the other countries which can be considered to be “small” in our empirical model. Therefore, US and Euro area variables – especially those measuring monetary policy – can be seen as important global factors themselves and probably explain a large amount of variation in national variables. Therefore, their inclusion in Y_t further increases the probability that our FAVAR model captures all relevant dynamics in X_t.

Furthermore, even if one is merely interested in analyzing the effects of a shock to Euro area (US) uncertainty including US (Euro area) variables in Y_t appears to be important (especially in a framework similar to ours). As uncertainty in both currency areas is highly correlated (see section 3.3), our framework (and, more specifically, the IRFs) might attribute too large impacts to a Euro area uncertainty shock if we do not explicitly control for developments in the US.

[13] Moreover, the probability and technical possibility to identify a break at around 1999 would be not very high because the break would be located at the very beginning of the sample. And we would be forced to start our Granger-causality tests not earlier than in 1999 for technical reasons. What is more, some variants of our FAVAR are in the end estimated from 1999 on anyway. For instance, data about the VSTOXX is only available from 1999:01 onwards. The same is valid for the composite indicator of systematic stress in the financial system (FUI_t^{EA}) published by the ECB.

[14] Due to data limitations, Greek interest yields are not included in the baseline model.

[15] We use the procedure of Litterman (1983) to construct monthly realizations of GDP. Industrial production, retail sales and nominal export data are used as high(er)-frequency data.

[16] In contrast to CPI, core price indices exclude developments of energy and food prices

This is because in that case effects of US uncertainty would be attributed to the Euro area shock.[17] This aspect is especially relevant for our international perspective as we analyze the effects on countries outside both economic powers.

As indicators of monetary policy, we employ shadow rates (SR_t^i). As policy rates cannot significantly drop below zero, common short term interest rates like the Federal Funds Rate and the Euro OverNight Index Average (EONIA) do not correctly reflect the general stance of monetary policy in times of unconventional monetary policies anymore. In this regard, the use of shadow rates appears to be a necessary and sufficient solution. It eliminates statistical problems, as the shadow rate cannot, like the policy rate, be regarded as+ a truncated variable at the zero lower bound and it is supposed to include information about unconventional monetary policies used during the recent crisis. So far, however, there is no commonly agreed way to construct a shadow rate available in the empirical literature. Hence, we decided to use the widely used shadow rates proposed by Krippner (2016).

As an indicator of uncertainty, we employ *economic policy uncertainty* (EPU_t^i), an indicator developed and provided online by Baker et al. (2013). The authors create a newspaper-based economic policy uncertainty variable. While an indicator for the US is already available, the authors have not (yet) published a measure of uncertainty for the Euro area. Instead, only a measure of *European* uncertainty is available which is based on the respective single-country indicators for France, Germany, Italy, Spain, and the United Kingdom. In analogy with the measure of European economic policy uncertainty, we construct an economic policy uncertainty index for the Euro area based on the individual indicators of the four members (France, Germany, Italy, and Spain) which are weighted by their share of GDP.[18] We feel legitimized to follow this approach, as the inventors of the indicators use an (almost) identical approach to construct their European and their "global" indicator of uncertainty.

In our study, we decided to use the indicators of Baker et al. (2013) also for several other reasons. Although there is a variety of different indicators available which put emphasis on different forms of economic uncertainty, we argue that especially in the recent years of the sovereign debt crisis the largest amount of uncertainty was related to economic policy in the Euro area. However, the main advantage of using the indicators of Baker et al. is that the authors publish

[17] This is exactly what we find if we exclude the US uncertainty variables from Y_t.

[18] At the start of the sample period (1996:01) only values for Germany and France are available. The Italian indicator is available from 1997:01 and the Spanish one from 2001:01. Unfortunately, indicators for other Euro area countries are currently not available.

indicators for a large variety of countries, a relatively large time period, and – especially relevant in our context – based on a single estimation procedure. It would be clearly problematic to compare the effects of uncertainty originating from different regions, if the indicators would alternatively be based on different procedures and if one would put emphasis on different types of uncertainty. Obviously, this is relevant in our case as we attempt to compare the sign and magnitude of the impact of uncertainty originating from the US and the Euro area. Therefore, we primarily focus our analysis on newspaper-based uncertainty measures.

Finally, as shown by Caldara et al. (2016), shocks to uncertainty have an especially large macroeconomic effect if they signal a worsening of financial conditions. Their robust finding that uncertainty increases immediately as a reaction to an adverse financial shock (which is corroborated by Belke et al. (2016), in the context of Brexit) makes it possible that changes in uncertainty are driven by fluctuations in financial conditions. This suggests that an increase in economic policy uncertainty (the variable implemented by us in this paper) may be a "general symptom of financial market volatility" (Caldara et al., 2016). Hence, we alternatively substitute policy uncertainty by financial volatility and test for robustness of our results by using monthly averaged values of stock exchange volatility ($EQVol_t^i$). In this regard, we use the VIX for the US and VSTOXX for the Euro area. We choose this measure instead of the others also presented in section 3.3, because both measures are comparable regarding construction and the specific uncertainty component analyzed. By using these indicators, we put more emphasis on financial (equity) uncertainty in comparison to the news-based measures. Data about the VSTOXX is only available from 1999:01 onwards.

3.3 Preliminary findings, diagnostics, and VAR specification

Every variable has been investigated for non-stationary behavior and, as expected, we find a lot of evidence that several variables are non-stationary in levels. In this regard, Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are employed. As both our approach and the regular Principal Components (PCA) approach cannot handle non-stationary variables well, every variable in X_t enters in month-on-month growth rates[19] except for interest rate variables which enter as first differences.[20] While our uncertainty indicator is clearly I(0), both shadow rates turn out to be I(1). As theses variables are included into the Y_t vector and are therefore not part of the factor estimation, we include both shadow rates in levels.

[19] The growth rates have been tested again for non-stationarity.

[20] We are aware of the empirical discussion whether interest rates can contain a unit roots. In our specification, we do not explicitly reject this assumption and therefore include interest rate variables in first differences.

Additionally, we tested for seasonality. In case of evidence of seasonality, we used the common X-12 ARIMA procedure to eliminate seasonal patterns.

As a starting point of our analysis, we focus on the relationship between uncertainty in the US and uncertainty in the Euro area as indicated by our measures. Since we are not only interested in the economic effects of uncertainty but also in the transmission of uncertainty, we use simple Granger-causality tests in order to obtain first evidence in this regard (see Table 2).

[Insert Table 2]

We observe no clear pattern regarding a Granger-causality between both variables, independent on the sample period used (1996 to 2015 or 1999, the start of EMU, to 2015).

Empirical realizations of the SBC and HQ information criteria uniformly suggest a lag length of 1. For a lag length of one, we find significant support that the EPU variables Granger-cause each other. However, this result does not prove to be robust to variations of the lag length. Evidence of Granger-causality is throughout larger for the equity price volatility variables. Especially equity volatility in the US appears to improve explanation of equity price volatility in the Euro area. Overall, we find moderate evidence that US uncertainty and Euro area uncertainty Granger-cause each other.

Although a Granger-causality exercise can be used as a preliminary step for a deeper VAR analysis, it does not include the possibility of contemporaneous effects or relationships. Therefore, before we turn to the estimation of our FAVAR model, we want to take a further look at the relationships between the indicators used in this study. Furthermore, we present several other indicators suggested by the literature.[21] ECB (2013) proposes two additional indicators to measure uncertainty which are available on a monthly basis: firstly, a composite indicator of systematic stress in the financial system (FUI_t^{EA})[22] published by the ECB for a period starting 1999:01 and, secondly, an indicator based on a forward-looking questionnaire of the Business and Consumer Survey (BCS_t^{EA}) of the European Commission.[23] While the first indicator is focusing on financial market developments and is therefore primarily based on financial data, the second one relies on expectations of businesses and consumers about the economic development within the next year. The latter is based on monthly survey data. For the United States,

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[21] We only present evidence for a selective amount of indicators. Additional indicators relevant in this context are presented by Ludvigson et al. (2014) and Jurado et al. (2015).

[22] See Hollo et al. (2012) for further details.

[23] See European Commission (2013) for details.

we include financial indicators provided by the Federal Reserve Bank of Kansas (FUI_t^{US}).[24] Table 3 presents a first correlation analysis among the indicators selected by us.

[Insert Table 3]

We find a large and expected amount of correlation. Looking at the correlations among indicators from each region individually, we observe overall strong correlations. Regarding cross-country correlations, we observe very strong correlations for indicators whose conceptions are similar. For the economic policy uncertainty (EPU) variables, we observe a very strong correlation of 0.716 between the US and the Euro area EPU indicator. For the equity volatility indicators, the correlation turns out to be even higher (0.830).

Additionally, Figure 1 sheds further light on the evolution of the indicators over time in order to examine differences and similarities. Comparing indicators for each region separately, we observe that the indicators tend to follow a similar pattern but we also detect a certain amount of heterogeneity across the indicators. Figure 2 compares the developments of EPU and $EQVol$ in both region. As expected, we see even stronger similarities and co-movements without clear evidence of a leader-follower relationship. Overall, we argue that the commonalities across indicators are relatively high despite the fact that the indicators put different emphasizes on specific uncertainty aspects and are based on different methods.

[Insert Figure 1]

[Insert Figure 2]

Before we turn to our FAVAR results, the preliminary results are relevant for the specifications used in section 4. As we use a Cholesky decomposition, the ordering of our factors in general and especially of the observable factors in Y_t is of importance. Regarding the ordering of Y_t, Colombo (2013) and Giavazzi and Favero (2008) assume that shocks hitting the Euro area do not exert contemporaneous effects on the US variables. In Colombo (2013), US uncertainty is therefore ordered before Euro area uncertainty. This ordering appears appropriate for the research question addressed by Colombo (2013), because she mainly focuses on the effects of a shock to US uncertainty.

In our study, however, we are interested in the effects of uncertainty shocks originating from both economic regions. As shown above, we observe a strong contemporary correlation and co-movements between each pair of variables. By choosing an ordering which prohibits Euro area

[24] Both indicators are conceptually close to the composite indicator of the ECB. See Hakkio and Keeton (2009).

uncertainty to have a contemporary effect on US uncertainty we would ex ante exclude a potentially important transmission channel. As we also aim to compare the effects of both shocks, this might drive our results and the subsequent interpretation. Therefore, we choose two different orderings for both shocks in order to make sure that the uncertainty variable shocked can have a contemporary effect on uncertainty of the other region. We feel legitimized to do so with an eye on the results in this section and our results in section 4 which clearly show that uncertainty shocks spread very quickly into the entire system.

4. Empirical Results

4.1 Shocking Euro area economic policy uncertainty

Our benchmark specification $Z_t^1 = (X_t^1, Y_t^1)$ contains the following set of variables:

X_t^1: $(GDP_t^i, CPI_t^i, Equity_t^i, LTIR_t^i, EXR_t^{EA})$ and Y_t^1: $(SR_t^{EA}, SR_t^{US}, EPU_t^{EA}, EPU_t^{US})$.

The results of our principal component analysis suggest that six factors are explaining roughly 80 percent of the total variation of X_t. We take this as a first indication of the adequate number of factors and proceed by evaluating the amount of variation explained by our factors.

[Insert Table 4]

Table 5 presents the R^2 based on regressions of X_t and the observed and unobserved factors. We observe that in general a large and sufficient amount of variation is explained by our factors. For national GDP and CPI, we explain 79 percent respectively 77 percent. The Norwegian and the Greek CPI are important outliers which are explained to a lesser extent.[25] Our results are even better for financial variables, as the average R^2 of equity variables is almost 90 percent and for the long-term interest rate it is around 81 percent. This pattern came quite expected, because it is well known that interlinkages or common movements of financial data are generally higher than for GDP or CPI. Overall, the combination of six unobserved factors and four observed factors in Y_t explain 81.6 percent of the total variance. When we increase the number of factors to 7, the average R^2 only increases very slightly to 83.7 percent (GDP: 80.2 percent; CPI: 80.2 percent; equity: 91.2 percent, long-term interest rate: 83.5 percent). Due to the apparently small amount of additional explanation power of the seventh factor, we decided to proceed by including only six factors. Overall, the reasonably high R^2 values endow us with a fair

[25] In general, we find that the Norwegian economic variables are least explained by our model – independent of the specification. This may be explained by structural differences between the Norwegian and the other European economies due to Norway's international role as exporting country of primary products (e.g. oil).

amount of confidence that our FAVAR framework is capturing the most important dynamics in X_t.

[Insert Table 5]

In the following, we interpret the impulse responses of a positive shock to EPU_t^{EA} (one standard deviation) presented in Figure 3. One standard deviation roughly equals an increase of 50 percent of the uncertainty index.[26] However, the interpretation of an uncertainty shock itself is inherently difficult because the variable has no dimension. Nevertheless, we focus our analysis and interpretation on qualitative aspects as well as quantitative effects as we attempt to compare the overall effects of an uncertainty shock in the Euro area and a shock to US uncertainty. Our estimation period is 1996:01 to 2015:12. We include 6 lags in the VAR model. The dotted lines indicate the 15 percent confidence intervals.

[Figure 4]

We start by analyzing the effect on the other observable factors in Y_t and Exr_t^{EA}. The response of EPU_t^{EA} over time shows that the effects quickly vanish over time and are only insignificant for the first periods. Regarding the spillover effect of Euro area uncertainty on US uncertainty, we observe a moderate increase of roughly 18 percent which is highly significant, but quickly vanishes over time. Both central banks react to an uncertainty shock in the Euro area by taking a more expansionary stance. As expected, the shadow rate of the ECB shows a stronger reduction (up to 20bp)[27] than the Fed's (up to 10bp). Equally as expected, the Euro significantly depreciates by approximately 0.25 percent.

Regarding the effects on GDP, our results indicate a universally negative effect on economic activity which is highly significant for the majority of countries. However, the size of the uncertainty impact highly depends on the individual countries. In general, the effect stabilizes and therefore reaches its maximum after around 10 to 15 periods.[28] For the North American economies, we observe low but significant effects of a GDP reduction of 0.5 percent for the US and 0.6 percent for Canada.

We find the largest effects for EMU countries which is not surprising given the origin of the shock. We find the largest effects (approximately 0.7 to 1.2 percent) for Austria, Belgium,

[26] This roughly equals the increase of uncertainty at the beginning of 2010 in the Euro area.

[27] From the perspective of the ECB, these results might be explained by an expected decrease in the CPI as indicated by our results.

[28] The stabilization of the median impulse responses over time also indicates that our VAR model is stable.

Greece, the Netherlands, Portugal, and Spain. Therefore, large effects are observable for many countries which have been at the epicenter of the sovereign debt crisis (Greece, Portugal, and Spain). For Germany and Ireland, however, the effects on GDP are not significant. And for non-EMU member countries in Europe, we observe overall smaller effects (0.25 to 0.5 percent). However, we find one except

ion as Swiss GDP is highly affected by a Euro area uncertainty shock (up to one percent).

In contrast with the results of the other – especially financial – variables, the CPI responses display a larger share of insignificant results and overall heterogeneity. The median impulses, however, show a negative response for almost every country. For EMU countries, we observe the strongest effects for Spain, Greece, Italy, Germany, and Italy (up to 1 percent). For several countries of the EMU, we do not observe significant responses (Austria, Belgium, Finland, the Netherlands, and Portugal). Except for Denmark and Switzerland, there is only small and partly even no significant response for the non-EMU countries in Europe. Again, we observe a very large effect for Switzerland (1.5 percent). A shock to Euro area uncertainty appears to be highly significant for the US CPI.

The effects on equity are, as expected, negative and significant. We observe similar reductions in terms of size and duration of nominal equity prices in all countries. In contrast to the real economy variables, we observe an even larger amount of commonalities across countries indicating a very large degree of financial integration and interdependencies. The average reduction in equity prices as a response to an uncertainty shock amounts to roughly 0.8 percent. The responses are significant over the entire 60 periods for a large majority of countries, indicating that uncertainty has especially large and persistent effects on financial markets.

Regarding the uncertainty impacts on the long-term interest rates, we observe a clear division between Portugal, Spain, Italy, Ireland, and the remaining countries.[29] For the latter, we observe decreases of up to 1 percentage point. The strongest decrease is observed for Switzerland (up to 150bp) followed by Germany, the Netherlands, and the US (up to 125bp). The decrease is strong but expected because several factors might cause a reduction in nominal yields. While the reduction in the monetary policy rate in the EMU is only moderate (around 20bp), we observe a negative impact on economic growth as well as an overall negative effect on the CPI which might have negative effects on inflation expectations. Furthermore, during times of crisis

[29] We do not include the Greek interest rate. However, due to the evidence generated, we would expect the Greek interest rate to behave similar to or even stronger than the Portuguese yield.

and uncertainty, an increase of risk-aversion might lead investors to shift out of high-risk towards low-risk investments. Furthermore, central banks of smaller European countries might mimic the policy of the ECB to a certain extent[30] and might become targets for capital inflows. Thereby, the ECB policy might influence interest rates outside the EMU. All effects mentioned would contribute to a very strong effect on sovereign bond yields as indicated by our results.

The estimated effects on Italian, Irish, Portuguese, and Spanish yields are not significant and close to zero. As the GIIPS countries are at the heart of the sovereign debt crisis and experienced strong increases in yields in recent years, our results do not come unexpected. We would like to argue that an increase in the risk premia is the most probable explanation for our result as observed since 2010. We conclude that the effects of uncertainty on these countries cancel out the impacts of several mechanisms mentioned above which should reduce yields in theory. According to the "flight to quality" argument, investors might have also reduced their amount of exposure to the GIIPS, as these bonds have been regarded as increasingly risky during the sovereign debt crisis.

Regarding the uncertainty effects on Switzerland, we find very strong evidence. We argue that this finding is mainly driven by country-specific effects. While the Euro area is the main trading partner of Switzerland, the Swiss Franc has strongly appreciated against the Euro especially due to large capital inflows. As Euro area products get relatively cheaper, the CPI in Switzerland decreases in reaction to the uncertainty shocks. This aspect is also highly relevant for the strong reduction of the Swiss long-term interest rates. Trade relationships alone are not capable of explaining the large effects on Swiss variables, especially if compared to a country like the UK with equally strong economic ties (see, for instance, De Carvalho Filho, 2013).

4.2 Shocking US economic policy uncertainty

As a next step, we compare the effects of a shock to Euro area uncertainty to the impact of a similar size shock originating in the US. For this purpose, we slightly change our specification (or rather the ordering) to $Z_t^2 = (X_t^1, Y_t^2)$ which now contains the following set of variables:

X_t^1: $(GDP_t^i, CPI_t^i, Equity_t^i, LTIR_t^i, EXR_t^{EA})$ and Y_t^2: $(SR_t^{US}, SR_t^{EA}, EPU_t^{US}, EPU_t^{EA})$.

Figure 4 presents the estimated impulse responses of a positive shock to EPU_t^{US}. The shock size is set to equal the size of the shock to EPU_t^{EA} in order to ensure comparability.

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[30] This might be most relevant for Denmark which is part of the ERM II.

[Figure 4]

We again start by analyzing the effect on the other observable factors in Y_t and Exr_t^{EA}. Similar to the shock in the Euro area, US uncertainty decreases quickly after the shock. Monetary policy in the US and Euro area responds immediately by taking a more expansive stance as indicated by reductions of the shadow rates (US: up to 20bp). As before, we observe that an increase in uncertainty quickly leads to a large increase of uncertainty in the other region.

For national GDP, we find uniformly negative and significant effects. For the US, we observe a decrease of roughly 0.7 percent. The size of the effects is overall comparable. The most obvious differences versus their reactions to a shock to Euro area uncertainty emerge for the responses of German and Irish GDP. Both are significant and larger (Germany: approximately 0.7 percent, Ireland: 0.5 percent). Both countries react stronger to a US uncertainty shock (a result also gained by Colombo, 2013). In contrast to before, we do not observe a clear pattern between EMU and non-EMU countries.

As before, the responses of the CPIs are more difficult to interpret. Overall, we observe decreases in national CPIs for most countries, although they are only partly significant. The United States are heavily affected as the CPI decreases by approximately one percent. We find only limited evidence of the "price puzzle" which has often been observed in VAR applications, although mostly for a monetary policy shock (see, for instance, Belke et al., 2010). In this regard, we only find evidence for the Netherlands and Norway as the CPIs of both countries show an unexpected positive response. However, the response of the latter has to be interpreted with caution as only a small amount of the Norwegian CPI is explained by our factors. Comparing the effects to those of an uncertainty shock originating from the Euro area, the effects are of similar size but we partly observe strong differences between individual countries.

As before, we find very strong commonalities between responses of national equity variables. All responses indicate a large and significant reduction. The reduction of US equity amounts to about 0.9 percent after one year. For other countries, we observe similar reductions in size and significance alike indicating that equity markets are highly connected. In comparison to the Euro area economic policy uncertainty shock, the effects are rather similar in size, significance, and duration. For long-term interest rates, the effects are negative and significant for the majority of countries. Again, we observe no reduction for Italy, Portugal, and Spain and no significant effect on Irish yields.

4.3 Robustness tests

As common in empirical literature, we performed several robustness tests in order to confirm that our results do not depend on a specific specification.[31] As a first step, we experimented with the number of lags in the VAR model and the number of factors. Regarding the number of lags, the results are quantitatively and also quantitatively identical. We employed lag orders of four to eight. We only observe a few changes when the number of lags is increased to eight as few impulse-responses lose their significance.

Next, we proceeded by increasing the number of factors up to eight factors. We argue that qualitative and strong quantitative changes may indicate that our dynamic factor model (using 6 factors) is not capable of capturing all relevant dynamics in X_t. Changing the number of factors to 7 or 8 does not appear to change our results or interpretation qualitatively. While the median impulses are very similar, the inclusion of further factors (especially in the case of 8 factors) strongly increases the number of insignificant responses at the 15 percent significance level. In our opinion, these results indicate that we have used a sufficient number of factors (and lags), and that a further inclusion strongly reduces the efficiency of our estimations.

In our study, we use a Cholesky decomposition. Also, we argue that the subdivision of the variables in X_t into fast and slow-moving variables of the Gipps sampling is theoretically reasonable; the ordering of the variables in Y_t is less obvious. Therefore, we changed the ordering in two respects. Firstly, we changed the ordering by putting the shadow rates before the uncertainty variables in each specification. We obtain very similar results compared to our results presented in sections 4.1 and 4.2. Secondly, we switch the positions of the uncertainty variables set earlier in section 4.1. As explained before, this prohibits a contemporary effect of the Euro area uncertainty variable on US uncertainty. Qualitatively, we arrive at an identical interpretation although the effects are lower, but still largely significant. In this setting, the US uncertainty variable does not respond significantly anymore and thus the overall reduction of effects does not come unexpected.

In addition, we check the robustness of our results for the variable measuring economic activity. Although the temporal disaggregation of Litterman (1983) is used in several papers to obtain monthly estimates of GDP, the time series are not (directly) observed and are based on an empirical relationship between GDP and monthly economic indicators. Therefore, we slightly

[31] The results presented in this section are available on request.

change our X_t-dataset and include industrial production (IP_t^i) instead of our monthly GDP estimates.[32] For the shock to Euro area uncertainty, we use the specification $Z_t^3 = (X_t^2, Y_t^1)$ which contains the following set of variables and the corresponding ordering:

X_t^2: $(IP_t^i, CPI_t^i, Equity_t^i, LTIR_t^i, EXR_t^{EA})$ and Y_t^1: $(SR_t^{US}, SR_t^{EA}, EPU_t^{UEA}, EPU_t^{US})$.

For the shock to US uncertainty, we use the specification $Z_t^4 = (X_t^2, Y_t^2)$. We present the results for IP_t^i in Figures 5 and 6.

[Figure 5]

[Figure 6]

While the responses of IP_t^i to uncertainty shocks are qualitatively similar to the responses of GDP_t^i, there are some country-specific differences especially regarding the size of the effects.[33] However, the effects are difficult to compare as IP_t^i only focuses on one specific part of the economy. With an eye on the overall similarity, we argue that our results are generally robust with regard to the variable used as indicator of economic activity. The responses for the other variables $(Equity_t^i, LTIR_t^i, EXR_t^{EA})$ are omitted as they are almost identical to the ones presented before.

As an additional robustness check, we substitute our price index CPI_t^i with a core price index ($CORE_t^i$). We can only explain a small and not sufficient amount of variation of the core price variables (on average: < 60 percent, large discrepancy between country variables) even if we use up to 8 factors. Apparently, core price indices only share a limited (smaller) amount of commonalities or common developments which can be used to construct unobserved factors.[34] This shows that the FAVAR approach has specific limitations – especially if used in an international context – when the variables in the information set do not share a large amount of similarities.

As a final check of robustness, we changed the operationalization of our uncertainty variable. Instead of EPU_t^i we included $EQVol_t^i$ in the specifications used in 4.1 and 4.2. As this indicator

[32] We again use 6 factors and 6 lags.

[33] As an example, we find stronger and significant effects for economic activity in Germany when IP is used instead of GDP.

[34] This observation does not come unexpected, as core price indices are excluding developments of energy and food prices which are known to be settled on the global stage and therefore are very similar on the national level.

of uncertainty does not only put emphasis on another aspect of uncertainty, but is also constructed differently, it is overall difficult to directly compare the results with those presented before (especially in the quantitative dimension). We observe that the responses of GDP_t^i are qualitatively identical, as every response is negative and significant. Furthermore and in contrast to our benchmark results for EPU_t^{US} and EPU_t^{EA}, a shock to $EQVol_t^{US}$ and $EQVol_t^{EA}$ has larger effects on the equity markets relative to the effects on GDP. As $EQVol_t^i$ measures uncertainty on equity markets, this results does not come unexpected. For long-term interest rates, we again find a large reduction in most yields as a reaction to an uncertainty shock. Again, the yields of Italy, Spain, Ireland, Portugal, and Spain do not respond significantly with a negative sign. Instead, we find an increase in yields for the countries mentioned. The effects on the CPI are again difficult to interpret. Most of the responses are not significant and we find larger evidence of a “price puzzle”.

4.4 Discussion

In the following, we put all our empirical results together and compare them with our priors from theory formulated in section 2.1 and similar studies presented in section 2.2. We expected a priori that uncertainty hampers growth, credit, thus reducing investment and output, employment, consumption, trade, and inflation. What is more, uncertainty is often viewed to lead to a depreciation of the domestic currency. Finally, uncertainty should have a dampening impact on asset prices as well. In other words, the *sign* of uncertainty should be *negative* in all these cases (Caggiano et al., 2017). Hence, it turns out to be rather easy to compare our results with these priors. Seen overall, our priors are in general corroborated by our FAVAR estimation results. Our results also indicate that uncertainty shocks emerging in the US have larger impacts in terms of size and duration.

For national *GDP*, we find uniformly negative and significant effects of Euro area policy uncertainty for most countries of the Euro area, with the notable exception of Germany. As expected, the effects on the peripheral countries’ GDP (Greece, Portugal, and Spain) but also on one EMU- and EU-out country, namely Switzerland, are the largest. Less significant and permanent effects emerge in the case of the other countries in the sample. If we employ US instead of Euro area uncertainty, the results become even more significant and enduring. This mirrors the fact the US is much more relevant for the world economy and world financial markets than Europe (also outside the countries under investigation here). The number of countries, for which persistent uncertainty effects with the theoretically expected sign emerge, increases. Most notably, persistently negative GDP effects are now indicated for Germany as well. US economic policy uncertainty thus appears so dominant on a global scale that it makes the lack of an “option value of waiting under uncertainty” irrelevant also for Germany.

With respect to the national *CPIs*, effects of Euro area uncertainty turn out to be significantly negative but only temporary for France, Germany, Greece, Ireland, Italy, Spain (even persistently), Switzerland, and the US. The impacts of US policy uncertainty on the CPIs are temporarily significant and negative for France and Spain and permanently negative for Germany, Greece, Switzerland, and the United States.

For country-specific *equity* as a financial variable, the negative effects of both policy uncertainty variables are very strong as expected from theory (see section 2). In all cases with Euro area policy uncertainty as the uncertainty variable, however, it is temporary but not persistent in accordance with the Fama hypothesis. If US policy uncertainty is used, the estimates even suggest a persistent negative impact of uncertainty on equity prices in nearly every country.

Regarding *long-term interest rates*, the effect of Euro area uncertainty on country-specific rates is impressive as well. Significant permanent effects with the expected negative sign emerge for the vast majority of the countries under investigation. Only the impulse responses for Ireland, Italy, and Portugal turn out to be insignificant. If one considers the results prevailing if US policy uncertainty is implemented, the results change in a way that temporary effects emerge for a higher share of countries. In this case, only the impulse responses for Ireland, Italy, Portugal, and Spain turn out to be insignificant.

Euro area monetary *policy rates* measured by shadow rates go down significantly but temporarily in the wake of a Euro area policy shock (which is consistent with an inflation-targeting approach), whereas US rates show the same pattern but to a lesser extent. The reverse pattern emerges if a shock to US policy uncertainty is considered.

The external value of effective nominal Euro *exchange rate* decreases temporarily in the case of a Euro area policy uncertainty shock and increases in the case of a US policy uncertainty shock. Finally, US policy uncertainty increases temporarily if Euro area *policy uncertainty* increases and vice versa. Hence, there seems to exist a bilateral policy uncertainty spillover across the Atlantic.

Interestingly enough, in most of our cases (Figures 3 to 5) the effects of uncertainty are lower and *less persistent in the Anglo-Saxon World* (United States, United Kingdom, and Canada) *than in Europe*. According to Figure 6, the effects on both sides of the Atlantic appear equally as large. In other words, uncertainty appears to cause deeper recessions in Continental Europe than in the Anglo-Saxon world.[35] This result seems to underline the traditional story that adjustment costs are generally larger in Continental Europe, except Germany where the flexibility-enhancing Hartz reforms took effect around 2005. This represents the "hysteresis under uncertainty" type of explanation that firms are less capable of dealing with uncertainty in Continental Europe due to too rigid institutions (see section 2.1).[36] Maybe it also reflects that the euro area is considerably more open than the US and is thus more exposed to (foreign) uncertainty (Belke and Gros, 2002).

That said, we now roughly compare our results qualitatively with those in the literature, although the methods, the data, and the magnitude of shocks cannot be compared directly (as became clear in section 2.2). The results of Colombo (2013) are very similar to ours. Her results indicate that a US uncertainty shock has negative and significant effects on prices, real economic variables, and policy rates. Furthermore, Colombo (2013) also finds evidence of a very fast and strong transatlantic transmission of uncertainty. Overall and in line with our results, a US uncertainty shock has similar effects in terms of magnitude on US and Euro area variables. Based on the results of forecast error variance decompositions, Colombo (2013) also generates evidence that US uncertainty is even more relevant for Euro area variables than Euro area uncertainty itself.

Our results also parallel the results gained by Kang and Vespignani (2015) and Kamber et al. (2016). Both studies find strong evidence that uncertainty has negative effects on output and prices as real economy variables and on interest rates as a financial variable. What is more, both studies find large evidence that national variables respond similarly to (foreign/global) uncertainty shocks. Both studies support our result of a strong synchronicity of the responses of national variables to an (foreign/global) uncertainty shock. Therefore, our results might also be interpreted as evidence of an international business cycle affecting financial variables and real economic variables alike.

As a reaction to a positive US uncertainty shock, domestic currencies depreciate in all countries except the United States, Japan, and Switzerland in the Kamber et al. (2016) study. The authors argue that this pattern of exchange rate reactions corresponds with the reserve currency status

[35] Accordingly, Belke and Gros (2002) find that the variability of the euro (i.e. exchange rate uncertainty) has a statistically significant negative impact on labor markets in the Euro area. In the US a similar effect seems to be operating, but it is statistically less strong. According to the authors who have the option value of waiting with investment-type decisions in mind, these results fit the general observation that US labor markets are more flexible and that the euro area is considerably more open than the US. See also Bentolila and Bertola (1990).

[36] Note, however, that this strong pattern for Germany only emerges in the case of European uncertainty but not for US uncertainty.

of the US-dollar, the Yen, and the Swiss Franc and the flight to safety usually observed during uncertain times. However, in our case, the euro depreciates as a reaction to a Euro area uncertainty shock but appreciates in the case of a US uncertainty shock suggesting that from the perspective of Europe the dollar is no safe haven if the uncertainty emerges in the US. As far as the spread of corporate yields over bond yields is concerned, Kamber et al. (2016) find a strong positive impact. This result is consistent with our finding that equity prices are significantly negatively affected by an increase in uncertainty.

Finally, with respect to the sign of the uncertainty impact, we corroborate the findings of de Wind and Grabska (2016). Contrary to us, they only assess the impact of domestic uncertainty shocks on industrial production. Like us, they come up with a significantly negative sign of the uncertainty-industrial production relationship.

5. Conclusions

The research questions tackled within this paper have been the following ones. Is the FAVAR approach an adequate framework to model cross-country developments? What are the global effects of uncertainty shocks? What is the sign of the estimated uncertainty impact coefficient? What are the channels of uncertainty transmission between Euro area and the US in both directions? For this purpose, we compare a US and a Euro area policy shock and put a special focus on non-EMU countries in Europe.

For this purpose, this paper assessed the impact of uncertainty shocks in the Euro area and the US on real economic and financial market variables in Europe and North America. We used 76 variables in total in every specification of our FAVAR model estimated for 18 countries and the sample period from January 1996 to December 2015 (monthly data).

Our results indicate that economic policy uncertainty has large cross-border effects and not only impacts the country where the shock originates. This argument appears to be especially valid for financial variables. Our results show that uncertainty shocks emerging in one region quickly raise uncertainty outside the region of origin which appears to be an important transmission channel. In our case, shocks to either US or Euro area uncertainty contemporaneously affect uncertainty in the other region. However, this result raises the question whether uncertainty (in general and also in our model) is purely regional, as we cannot differentiate between a spillover or a “pure” global shock in our framework.

Based on the experiences of the financial crisis which originated in the US and the sovereign debt crisis which originated in the Euro area, we support the former hypothesis. Therefore, due to the strong co-movements of uncertainty, it is difficult to strictly compare a US and Euro area policy shock in terms of the size of the effects. However, we find evidence that US uncertainty shocks have slightly larger cross-border effects compared to a Euro area shock. Our results overall reveal strong and significant adverse effects on economic activity and especially equity which are similar across countries, while the impact on prices is more ambiguous.

But seen on the whole, thus, uncertainty has a strong negative impact on economic activity, consumer prices, equity prices and interest rates. Uncertainty shocks cause deeper recessions in Continental Europe than in Anglo-Saxon countries. Economic policy uncertainty does not only impact that country where the shock originates but also has large cross-border effects. In that respect, Switzerland is the most affected non-Euro area member country. In this regard, we find a strong synchronization of the responses of national variables to a (foreign) uncertainty shock, indicating evidence of international business cycles. Regarding the response of long-term yields, we find a clear “North-South” divide in the Euro area with rates decreasing less in the South. Another important result is that uncertainty shocks emerging in one region quickly raise uncertainty outside the region of origin which appears to be an important transmission channel of uncertainty.

With respect to our modeling approach, we conclude that the FAVAR is capable of jointly modeling economic developments in a lot of countries. Each specification explains a very large amount of the overall variation in our data set. Therefore, we feel legitimized to argue that our model (or the factors extracted) most probably includes all relevant dynamics in our dataset. Therefore, we conclude that the FAVAR is not only capable of jointly analyzing a lot of economic information (i.e. a very large amount of variables) for a specific country, but it can also be used to analyze cross-country developments.

In order to generate further evidence on the effects of different specifications of uncertainty, we see further potential for research. The most obvious approach is to check the robustness of our results by using alternative indicators of uncertainty. As mentioned, there is no commonly accepted measure of uncertainty. Furthermore, the use of other multi-equational models like global vector autoregressive (GVAR) models, Panel-VAR models, and Bayesian VARs, developed by Banbura et al. (2008).

Additionally, our approach might be expanded in several other ways. In our opinion, the most promising way is to drop the underlying assumption of linearity (because it contradicts some of the transmission mechanisms of uncertainty mentioned in section 2 and non-linearity may become relevant especially in crisis times which are covered by parts of our sample period) in our model. Firstly, the effect of uncertainty might be regime-dependent, indicating that uncertainty shocks have different effects when uncertainty is already high or when uncertainty is low or moderate (Belke and Goecke, 2005). Regime-dependency may also emerge with respect to the monetary policy stance, if the economy is close to the zero lower bound or is, for instance, bound to an inflation targeting regime (Mumtaz et al., 2011). And, secondly, uncertainty impacts might be time-varying in general.

References

Aastveit, K.A., G. J. Natvik, and S. Sola (2013): Economic Uncertainty and the Effectiveness of Monetary Policy. Working Paper No. 2013/17, Norges Bank Research, Oslo.

Abel, A.B. (1983): Optimal Investment under Uncertainty, American Economic Review, Vol. 73(1), pp. 228-233.

Bai, J. and S. Ng (2002): Determining the Number of Factors in Approximate Factor Models, Econometrica, Vol. 60, pp. 191-221.

Baker, S.R., N. Bloom, and S.J. Davis (2015): Measuring Economic Policy Uncertainty, NBER Working Paper, No. 21633.

Banbura, M., D. Gianonne, D., and L. Reichlin (2008): Large Bayesian VARs, Journal of Applied Econometrics, Vol. 25, pp. 71-92.

Basu, S. and B. Bundick (2016): Uncertainty Shocks in a Model of Effective Demand, Econometrica, forthcoming.

Belke, A. and M. Goecke (2005): Real Options Effects on Employment: Does Exchange Rate Uncertainty Matter for Aggregation?, German Economic Review, Vol. 6(2), pp. 185-203.

Belke, A. and D. Gros (2002): Designing EU-US Monetary Relations: The Impact of Exchange Rate Variability on Labor Markets on Both Sides of the Atlantic, The World Economy, Vol. 25/6, pp. 789-813.

Belke, A. and A. Rees (2014): Globalization and Monetary Policy – A FAVAR Analysis for the G7 and the Euro Area, North American Journal of Economics and Finance, Vol. 29(C), pp. 306-321.

Belke, A., I. Dubova, and T. Osowski (2016): Policy Uncertainty and International Financial Markets: The Case of Brexit, CEPS Working Document, No. 429, Centre for European Policy Studies (CEPS), Brussels, November.

Belke, A., W. Orth, and R. Setzer (2010): Liquidity and the Dynamic Pattern of Asset Price Adjustment: A Global View, in: Journal of Banking and Finance, Vol. 34, pp. 1933-1945.

Bentolila, S. and G. Bertola (1990): Firing Costs and Labour Demand: How Bad Is Eurosclerosis?, Review of Economic Studies, Vol. 57, pp. 381-402.

Bernanke, B. and J. Boivin (2003): Monetary Policy in a Data-Rich Environment, Journal of Monetary Economics, Vol. 50, pp. 525-546.

Bernanke, B., J. Boivin, and P.Eliasz (2005): Measuring the Effects of Monetary Policy: A factor-augmented Vector Autoregressive (FAVAR) Approach, Quarterly Journal of Economics, Vol. 120(1), pp. 387-422.

Blaes, B. (2009): Money and Monetary Policy Transmission in the Euro Area: Evidence from FAVAR- and VAR Approaches, Discussion Paper Series 1: Economic Studies No. 18/2009, Deutsche Bundesbank, Frankfurt/Main.

- (2009): The Impact of Uncertainty Shocks, Econometrica, Vol. 77(3), pp. 623-685.

(2013): Fluctuations in Uncertainty, Occasional Paper 38, Centre for Economic Performance, London School of Economics and Political Science, December.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S.J. Terry (2013): Really Uncertain Business Cycles CEP Discussion Paper No. 1195, Centre for Economic Performance, London School of Economics and Political Science, March.

Bordo, M.D., J.V. Duca, and C. Koch (2016): Economic Policy Uncertainty and the Credit Channel: Aggregate and Bank Level U.S. Evidence over Several Decades, NBER Working Paper 22021, National Bureau of Economic Research. Cambridge/MA.

Caballero, R.J. (1991): On the Sign of the Investment-Uncertainty Relationship, American Economic Review, Vol. 81, pp. 279-288.

Caggiano, G., E. Castelnuovo, and G. Pellegrino (2017): Estimating the Real Effects of Uncertainty Shocks at the Zero Lower Bound, Bank of Finland Research Discussion Paper 6, Helsinki.

Caldara, D., C. Fuentes-Albero, S. Gilchrist, and E. Zakrajsek (2016): The Macroeconomic Impact of Financial and Uncertainty Shocks, NBER Working Paper No. 22058, National Bureau of Economic Research, Cambridge/MA.

Carter, C.K. and P. Kohn (1994): On Gibbs Sampling for State Space Models, Biometrika, Vol. 8, pp. 541-553.

Chen, J., F. Jiang, and G. Tong (2016): Economic Policy Uncertainty in China and Stock Market Expected Returns, Beijing, mimeo.

Christiano, L.J., M. Eichenbaum, and C.L. Evans (2005): Nominal Rigidities and the Dynamic Effects of a Shock to Monetary Policy, Journal of Political Economy, Vol. 113(1), pp. 1-45.

Chudik, A. and H.M. Pesaran (2009): Infinite Dimensional VARs and Factor Models, ECB Working Papers 998, European Central Bank, Frankfurt/Main.

Colombo, V. (2013): Economic Policy Uncertainty in the US: Does it Matter for the Euro Area?, Economics Letters Vol. 121, No. 1, pp. 39-42.

Darby, J., A. Hughes Hallet, J. Ireland, and L. Piscitelli (1998): The Impact of Exchange Rate Uncertainty on the Level of Investment, CEPR Discussion Paper No. 1896, Center for Economic Policy Research, London.

De Carvalho Filho, I. (2013): Risk-off Episodes and Swiss Franc Appreciation: the Role of Capital Flows, Working Paper No. 13.07, Study Center Gerzensee, Switzerland.

De Wind, J. and K. Grabska (2016): The Impact of Uncertainty Shocks: Continental versus the Anglo-Saxon World, CPB Discussion Paper 335, CPB, Netherlands Bureau for Economic Policy Analysis, Rotterdam, September.

Dixit, A. (1989): Entry and Exit Decisions under Uncertainty, Journal of Political Economy, Vol. 97, pp. 620-638.

Dornbusch, R. (1987): Open Economy Macroeconomics: New Directions, NBER Working Paper No. 2372, National Bureau of Economic Research, Cambridge/MA.

Engle, R. and J.G. Rangel (2008): The Spline-GARCH Model for Low-Frequency Volatility and Its Global Macroeconomic Causes, Review of Financial Studies, Vol. 21, No. 3, pp. 1187-1222.

European Commission (2013): Quarterly Report on the Euro Area, Economic and Financial Affairs, Vol. 12(2), Brussels.

European Central Bank (2013): Monthly Bulletin, Frankfurt/Main, October.

- (2016): The Impact of Uncertainty on Activity in the Euro Area, Economic Bulletin 08/2016, European Central Bank, Frankfurt/Main.

Fernald, J.G., M.M. Spiegel, and E.T. Swanson (2014): Monetary Policy Effectiveness in China: Evidence from a FAVAR Model, Journal of International Money and Finance, Vol. 49, pp. 83-103.

Forni, M. and L. Gambetti (2014): Sufficient Information in Structural VARs, Journal of Monetary Economics Vol. 66, pp. 124-136.

Geman, S. and D. Geman (1984): Stochastic Relaxation, Gibbs Distributions and the Bayesian Restoration of Images, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 6, pp. 721–741.

Gelman, A. and D.B. Rubin (1992): A Single Sequence from the Gibbs Sampler Gives a False Sense of Security, in J.M. Bernardo, J.O. Berger, A.P. Dawid, and A.F.M. Smith, eds., Bayesian Statistics, Oxford, UK: Oxford University Press.

Georgiadis, G. (2015): To Bi, or Not to Bi? Differences in Spillover Estimates from Bilateral and Multilateral Multi-country Models, ECB Working Paper, No. 1868, European Central Bank/Frankfurt.

Geweke, J. (1977): The Dynamic Factor Analysis of Economic Time Series, in Dennis Aigner, D., and Goldberger, A. (eds.) Latent Variables in Socio-Economic Models, Amsterdam: North-Holland.

Giavazzi, C. and F. Favero (2008): Should the Euro Area Be Run as a Closed Economy?, American Economic Review, Vol. 98(2), pp. 138-145.

Gupta, R. and A. Kabundi (2010): The Effect of Monetary Policy on House Price Inflation: A Factor Augmented Vector Autoregression (FAVAR) Approach, Journal of Economic Studies, Vol. 37(6), pp. 616-626.

Handley, K. and N. Limao (2012): Trade and Investment under Policy Uncertainty: Theory and Firm Evidence, NBER Working Paper No. 17790, National Bureau of Economic Research, Cambridge/MA.

Hakkio, C.S. and R. Keeton (2009): Financial Stress: What Is It, How Can It Be Measured, and Why Does It Matter?, Federal Reserve Bank of Kansas City Economic Review, 2nd quarter, pp. 5-50.

Hartman, R. (1972): The Effects of Price and Cost Uncertainty on Investment, Journal of Economic Theory, Vol. 5(2), pp. 258-266.

Hollo, D., M. Kremer, and M. Lo Duca (2012): CISS – A Composite Indicator of Systemic Stress in the Financial System, ECB Working Paper, No. 1426, European Central Bank, Frankfurt/Main.

IMF (2016): United Kingdom - Selected Issues, IMF Country Report No. 16/169, International Monetary Fund, Washington/DC, June.

Jiang, F. and G. Tong (2016): Monetary Policy Uncertainty and Bond Risk Premium, Beijing, mimeo.

Jurado, K., S.C. Ludvigson, and S. Ng (2015): Measuring Uncertainty, American Economic Review, Vol. 105(3), pp. 1177-1216.

Kamber, G., O. Karagedikli, M. Ryan, and T. Vehbi (2016): International Spill-overs of Uncertainty Shocks: Evidence from a FAVAR, mimeo, Reserve Bank of New Zealand and New Zealand Treasury.

Kang, W., R.A. Ratti and R. Vespignani (2017): The Impact of Global Uncertainty on the Global Economy, and Large Developed and Developing Economies, CAMA Working Paper 9/2017, Centre for Applied Macroeconomic Analysis, Australian National University, Crawford School of Public Policy, January.

Knight, F. H. (1921): Risk, Uncertainty and Profit. Hart, Schaffner and Marx, New York.

Kose, M.A., C. Otrok, and C.H. Whiteman (2003): International Business Cycles - World, Region and Country-specific Factors, American Economic Review, Vol. 93, pp. 1216-1239.

Kose, M.A., E.S. Prasad, and M. Terrones (2007): How Does Financial Globalization Affect Risk Sharing? Patterns and Channels, IMF Working Paper No. 07/238, International Monetary Fund, Washington/DC, October.

Krippner, L. (2016): Documentation for Measures of Monetary Policy, source; http://www.rbnz.govt.nz/-/media/ReserveBank/Files/Publications/Research/Additionalresearch/Leo Krippner/5892888.pdf?la=en.

Leduc, S. and L. Zheng (2016): Uncertainty Shocks Are Aggregate Demand Shocks, Journal of Monetary Economics, Vol. 28, pp. 20-35.

Lei, X. and M.C. Tseng (2016): “Wait and See" Monetary Policy, Department of Economics, Simon Fraser University, British Columbia, Canada.

Litterman, R.B (1983): A Random Walk, Markov Model for the Distribution of Time Series, Journal of Business & Economic Statistics, Vol.1(2), pp. 169-173.

Ludvigson, S.C., S. Ma, and S. Ng (2015): Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response?, NBER Working Papers, No.21803.

Lutz, C. (2014): Unconventional Monetary Policy and Uncertainty, Copenhagen Business School, October 6, available at SSRN: https://ssrn.com/abstract=2505943 or http://dx.doi.org/10.2139/ssrn.2505943.

McCallum, A.H. and F. Smets (2007): Real Wages and Monetary Policy Transmission in the Euro Area, Kiel Working Paper, No.1360, Kiel Institute for the World Economy, Kiel.

Mumtaz, H., P. Zabczyk, and C. Ellis (2011): What Lies Beneath? A Time-varying FAVAR Model for the UK Transmission Mechanism, ECB Working Paper, No. 1320, European Central Bank, Frankfurt/Main.

Oi, W. (1961): The Desirability of Price Instability under Perfect Competition, Econometrica, Vol. 29, pp. 58-64.

Pellegrino, G. (2017): Uncertainty and Monetary Policy in the US: A Journey into Non-Linear Territory, Melbourne Institute Working Paper Series Working Paper No. 6/17, Melbourne.

Pindyck, R. S. (1991): Irreversibility, Uncertainty, and Investment, Journal of Economic Literature, Vol. 29, 1110-1148.

Ramey, G. and V. Ramey (1995): Cross-country Evidence on the Link between Volatility and Growth, American Economic Review, Vol. 85(5), pp. 1138-1151.

Romer, C. (1990): The Great Crash and the Onset of the Great Depression, Quarterly Journal of Economics, Vol. 105(3), pp. 597-624.

Shibamoto, M. (2007): An Analysis of Monetary Policy Shocks in Japan: A Factor Augmented Vector Autoregressive Approach, Japanese Economic Review, Vol. 58(4), pp. 484-503.

Sargent, T. and C. Sims (1977): Business Cycle Modeling without Pretending to Have Too Much A Priori Economic Theory, in: Sims, C. (ed.), New Methods in Business Research, Minneapolis: Federal Reserve Bank of Minneapolis.

Stock, J.H. and M. Watson (1998): Diffusion Indexes, NBER Working Paper No. 6702. National Bureau of Economic Research, Cambridge/MA.

- (2002): Macroeconomic Forecasting Using Diffusion Indexes, Journal of Business Economics and Statistics, Vol. 22, pp. 147-162.

- (2005): Implications of Dynamic Factor Models for VAR Analysis, NBER Working Paper 11467, National Bureau of Economic Research, Cambridge/MA.

- (2012): Disentangling the Channels of the 2007-2009 Recession, NBER Working Paper No.18094, National Bureau of Economic Research, Cambridge/MA.

Vasisthta, G. and P. Maier (2013): The Impact of the Global Business Cycle on Small Open Economies: A FAVAR Approach for Canada, North American Journal of Economics and Finance, Vol. 24, pp. 191-207.

Tables

Table 1: Overview of variables

Variable	Name	Source	Subgroup	Treat-ment
Real GDP	GDP_t^i	Own calculations	Slow	5
Industrial production	IP_t^i	OECD/IMF	Slow	5
Consumer price index	CPI_t^i	OECD	Slow	5
Core price index	$CORE_t^i$	OECD	Slow	5
Equity Prices	EQ_t^i	MSCI	Fast	5
Long-Term Interest Rate (10y Government Bonds)	$LTIR_t^i$	Thomson Reuters Datastream	Fast	2
Nominal effective exchange rate of the Euro area	EXR_t^{EA}	Bank for International Settlements	Fast	5
Shadow rates as proposed by Krippner (2016)	SR_t^i	Reserve Bank of New Zealand		1
Economic policy uncertainty	EPU_t^i	http://www.policyuncer-tainty.com/; own calculations		4
Equity volatility (VSTOXX / VIX)	$EQVol_t^i$	Thomson Reuters Datastream		4

Source: Own calculations.
Notes: The transformation codes are: 1 – no transformation; 2 – first difference; 4 – logarithm; 5 – first difference of logarithm.

Table 2: Granger-causality tests

	Sample: 1996–2015		Sample: 1999-2015	
Lag-length	EPU_t^{US} does not GC EPU_t^{EA}	EPU_t^{EA} does not GC EPU_t^{US}	$EQVol_i^{US}$ does not GC $EQVol_i^{EA}$	$EQVol_i^{EA}$ does not GC $EQVol_i^{US}$
1	0.037	0.031	0.003	0.122
2	0.266	0.132	0.003	0.022
3	0.359	0.336	0.008	0.045
6	0.113	0.268	0.052	0.119

Source: Own calculations.
Notes: Schwarz-Bayes and Hannan-Quinn information criteria indicate a lag length of one for both specifications.

Table 3: Correlation matrix of uncertainty indicators

	EPU_t^{EA}	$EQVol_t^{EA}$	FUI_t^{EA}	BCS_t^{EA}	EPU_t^{US}	$EQVol_t^{US}$	FUI_t^{US}
EPU_t^{EA}	1	**0.293**	0.348	0.488	**0.716**	0.216	0.087
$EQVol_t^{EA}$		1	0.660	-0.023	0.572	**0.830**	0.679
FUI_t^{EA}			1	0.345	0.486	0.683	0.773
BCS_t^{EA}				1	0.205	-0.145	-0.173
EPU_t^{US}					1	**0.532**	0.411
$EQVol_t^{US}$						1	0.798
FUI_t^{US}							1

Source: Own Calculations. Sample: 1996:01 to 2015:12.
Notes: If FUI_t^{EA} or $EQVol^{EA}$ is considered, the time period is reduced to 1999:01 to 2015:12

Table 4: Principal Components Analysis (X_t^1)

Factors	Eigenvalue	Proportion	Cumulative
1	24.071	0.339	0.339
2	15.139	0.213	0.552
3	9.345	0.131	0.683
4	4.335	0.061	0.744
5	2.897	0.040	0.785
6	2.187	0.030	0.816**
7	1.718	0.024	0.840
8	1.356*	0.019	0.859
9	0.927	0.015	0.875
10	0.675	0.015	0.891

Source: Own Calculations. * Factor number proposed by the Kaiser criterion.
** Factor number which explains at least 80% of the variance in X_t

Table 5: Fraction of X_t^1 explained by common factors (R^2 (Z_t^1, Z_t^2)

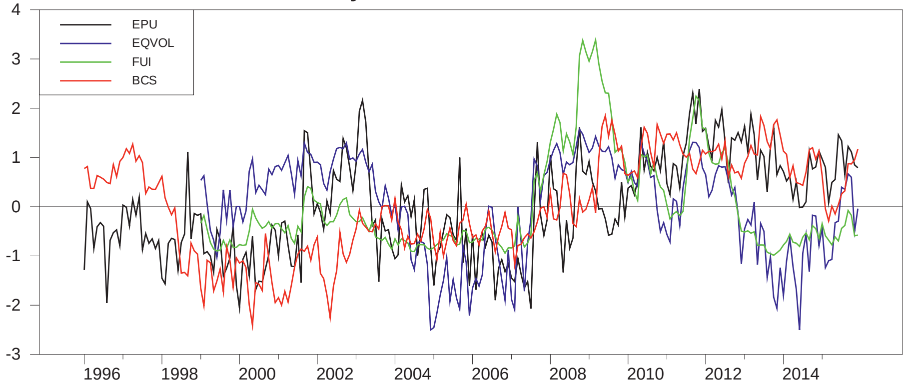
Variable	R^2	Variable	R^2	Variable	R^2	Variable	R^2
GDP AUST	80,5	CPI AUST	82,6	EQ AUST	90	LTIR AUST	92,8
GDP BEL	76,8	CPI BEL	89,0	EQ BEL	91,5	LTIR BEL	87,3
GDP CAN	83,6	CPI CAN	66,6	EQ CAN	86,1	LTIR CAN	74,7
GDP DEN	68,6	CPI DEN	83,5	EQ DEN	93,3	LTIR DEN	92,0
GDP FIN	82,1	CPI FIN	77,4	EQ FIN	91,1	LTIR FIN	84,2
GDP FRA	91,2	CPI FRA	87,4	EQ FRA	96,2	LTIR FRA	91,0
GDP GER	82,1	CPI GER	85,0	EQ GER	95,3	LTIR GER	94,2
GDP GRE	79,1	CPI GRE	57,7	EQ GRE	87,2	LTIR ITA	78,2
GDP ITA	88,4	CPI ITA	71,5	EQ ITA	90,9	LTIR IRE	55,6
GDP IRE	66,5	CPI IRE	84,0	EQ IRE	84,4	LTIR NET	93,5
GDP NET	89,1	CPI NET	59,2	EQ NET	94,1	LTIR NOR	73,1
GDP NOR	33,1	CPI NOR	41,1	EQ NOR	91,4	LTIR POR	70,8
GDP POR	72,3	CPI POR	83,1	EQ POR	84,0	LTIR SWE	79,8
GDP SWE	83,3	CPI SWE	81,3	EQ SWE	89,8	LTIR SWI	83,8
GDP SWI	82,1	CPI SWI	81,9	EQ SWI	89,2	LTIR SPA	74,5
GDP SPA	95,0	CPI SPA	87,4	EQ SPA	91,0	LTIR UK	85,5
GDP UK	85,1	CPI UK	72,3	EQ UK	91,9	LTIR US	78,1
GDP US	86,5	CPI US	87,3	EQ US	90,1	EXR EURO	57,5

Source: Own Calculations. “R^2” refers to the fraction of the variance of the variable explained by the common factors, $(\hat{F}_t,\ Y_t)$.

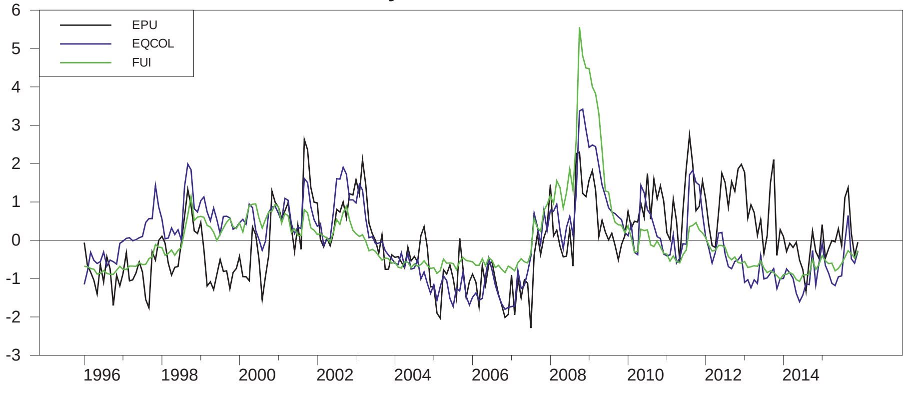
Graphs

Figure 1: Development of uncertainty by economic region

Uncertainty Indicators for the Euro area

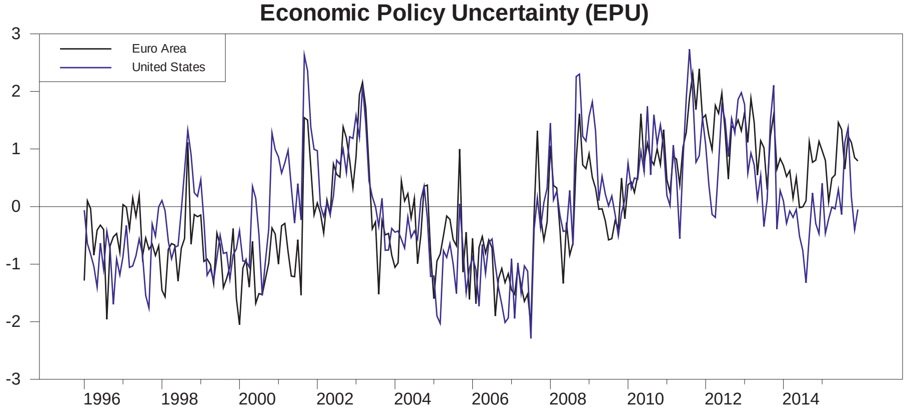


Uncertainty Indicators for the US



Source: www.policyuncertainty.com, ECB, European Commission, Fed of Kansas and Fed of Cleveland. Own calculations.

Figure 2: Development of uncertainty by indicator



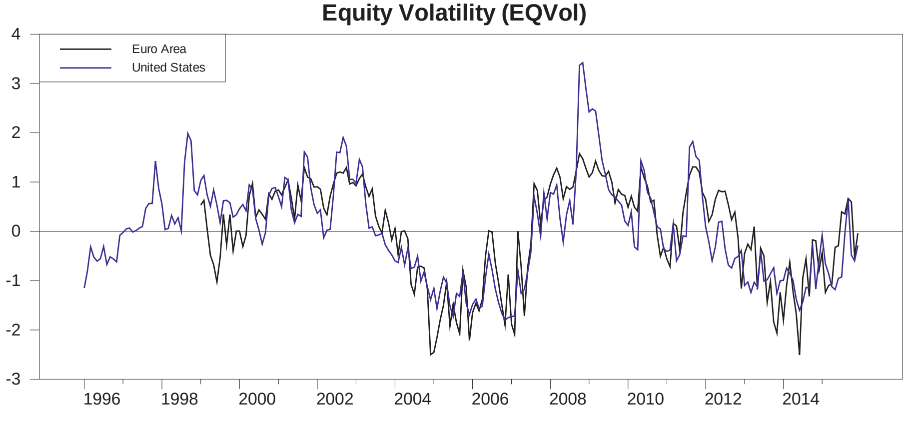
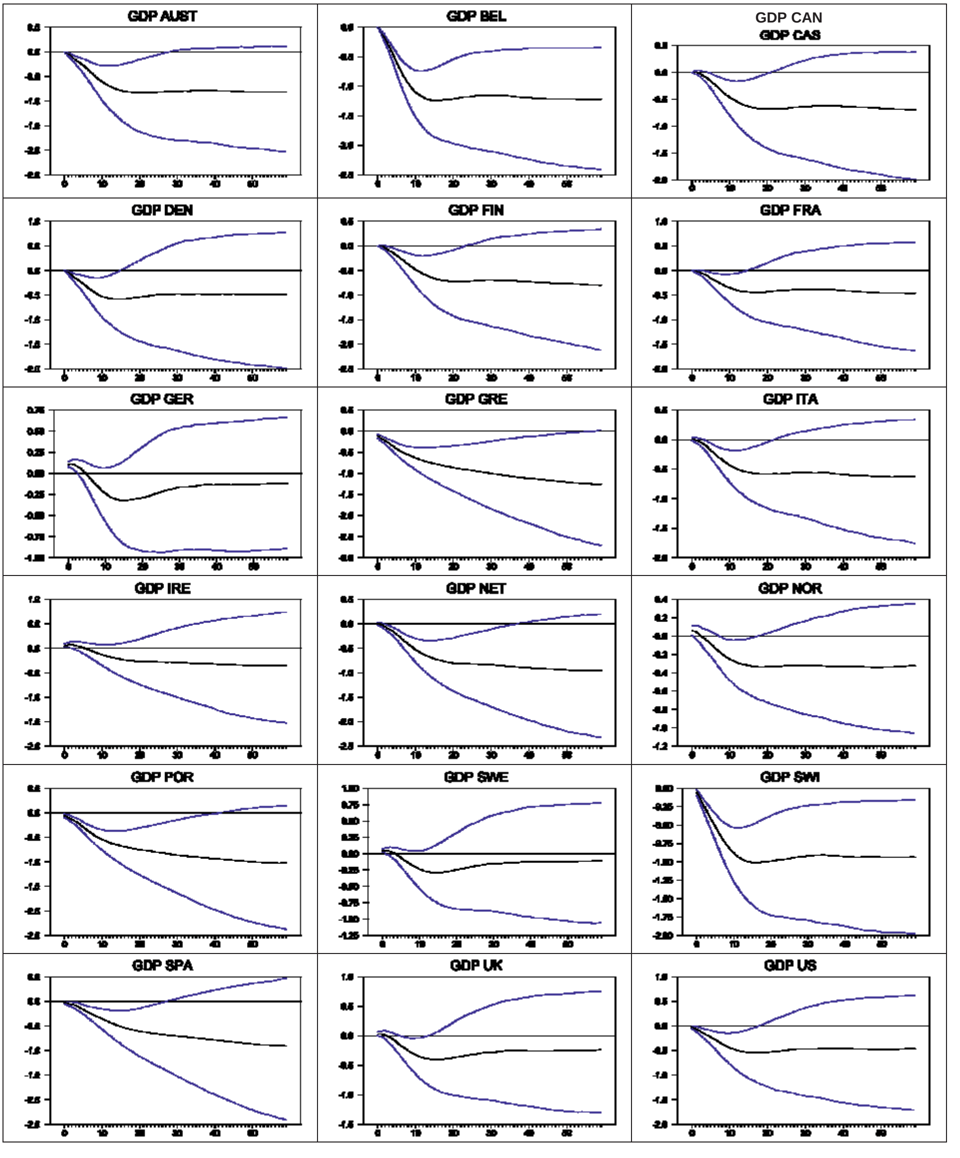
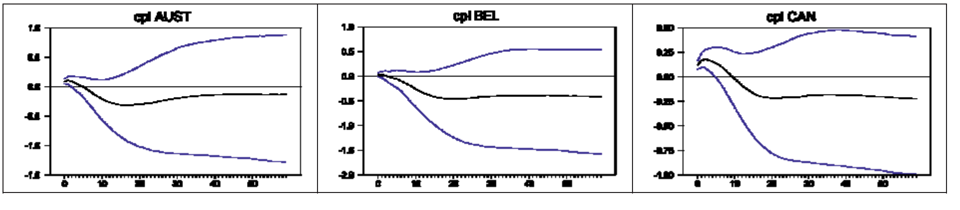
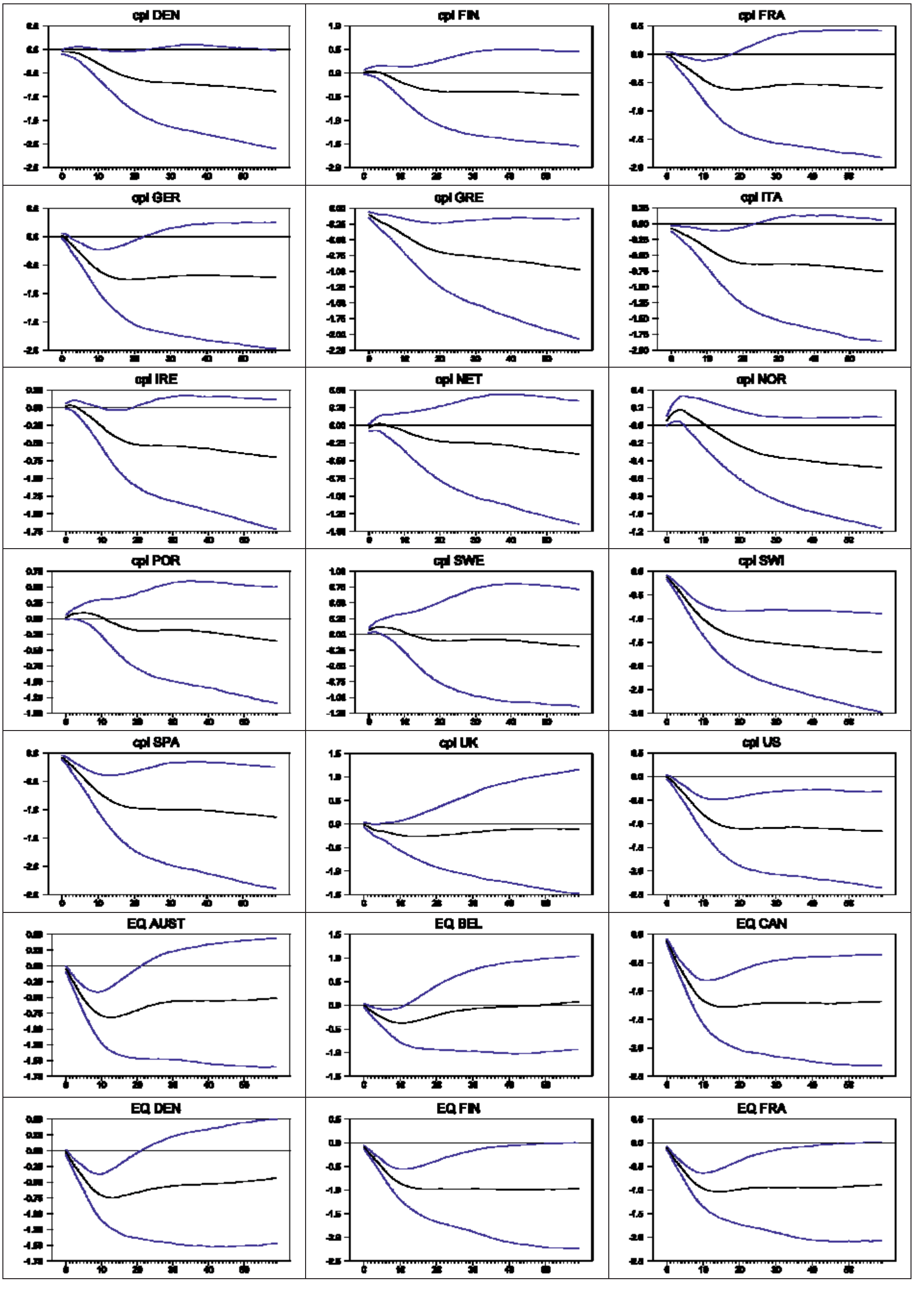


Figure 3: Impulse-responses (Z_t^1) – Shock to Euro area uncertainty (EPU_t^{EA})



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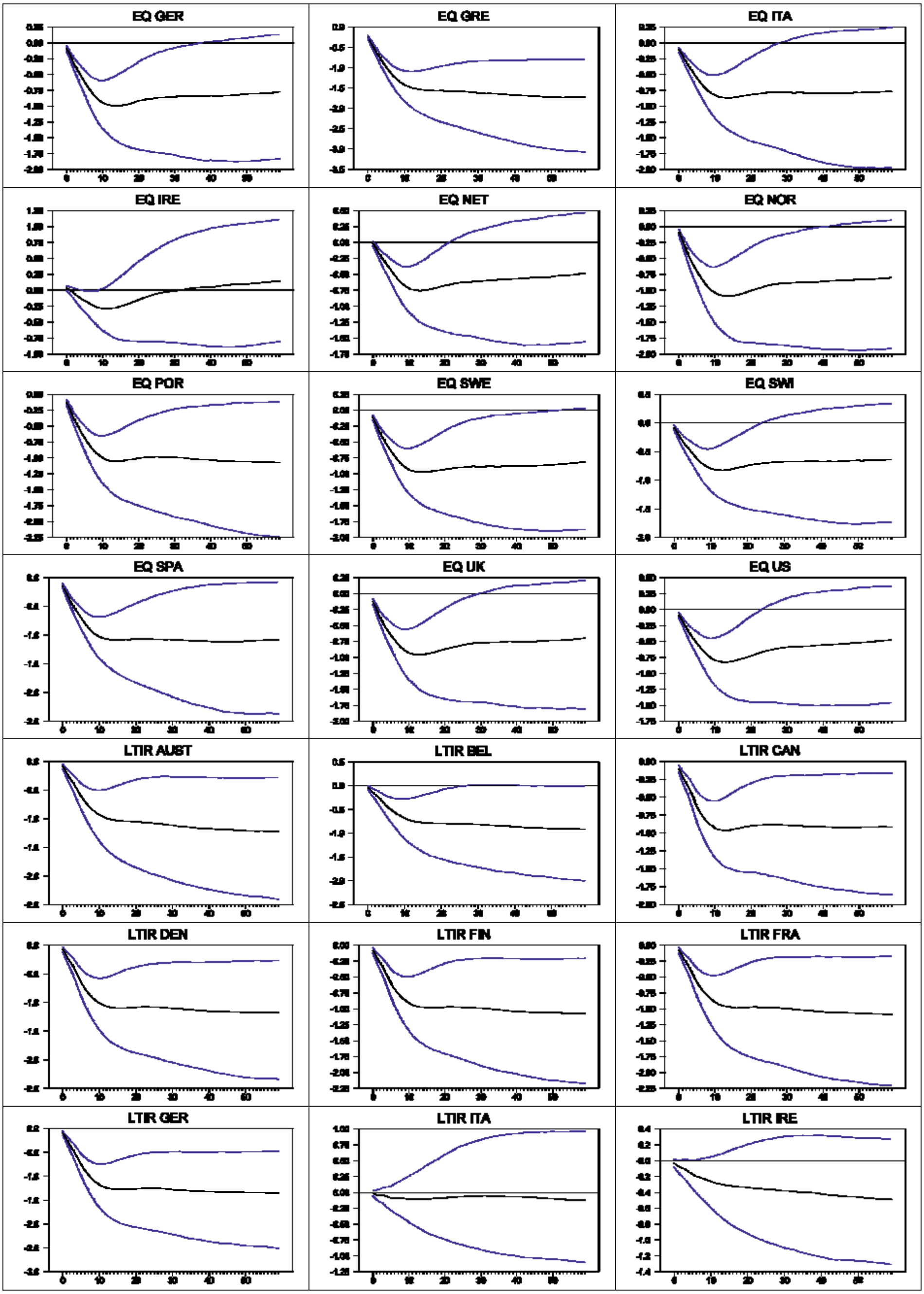
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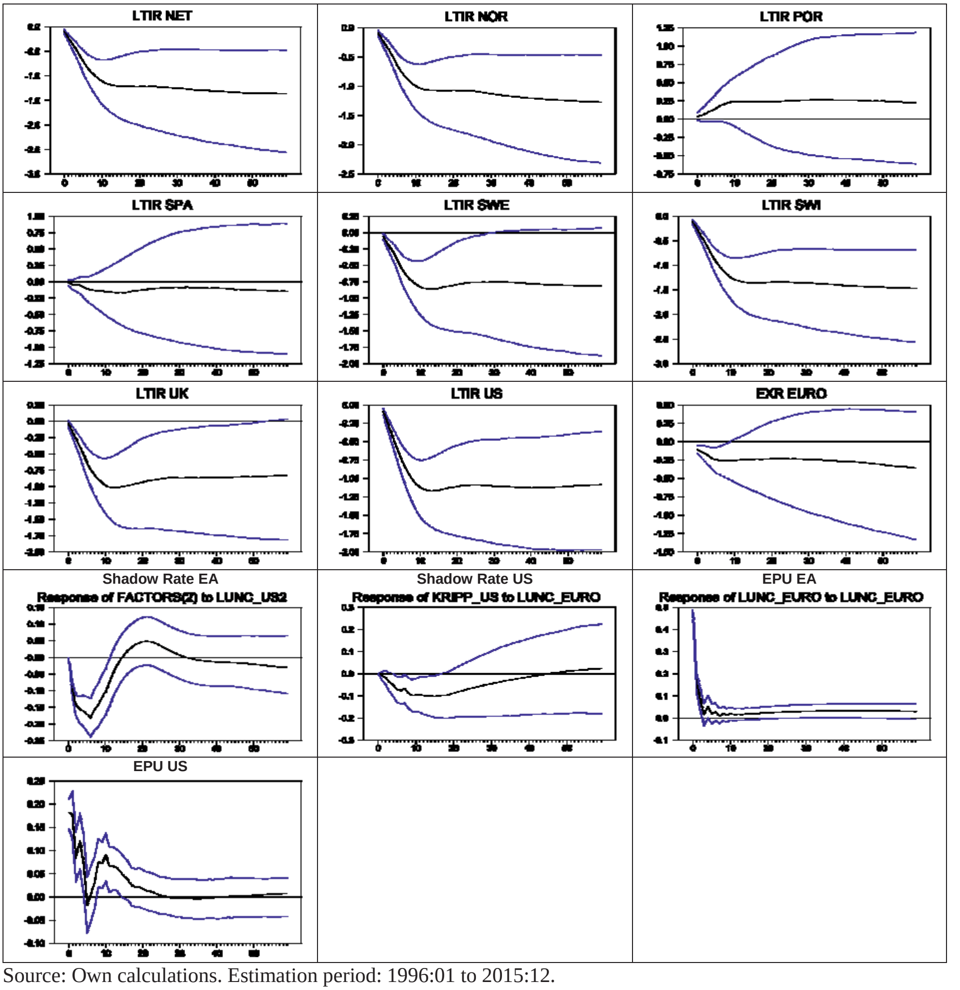
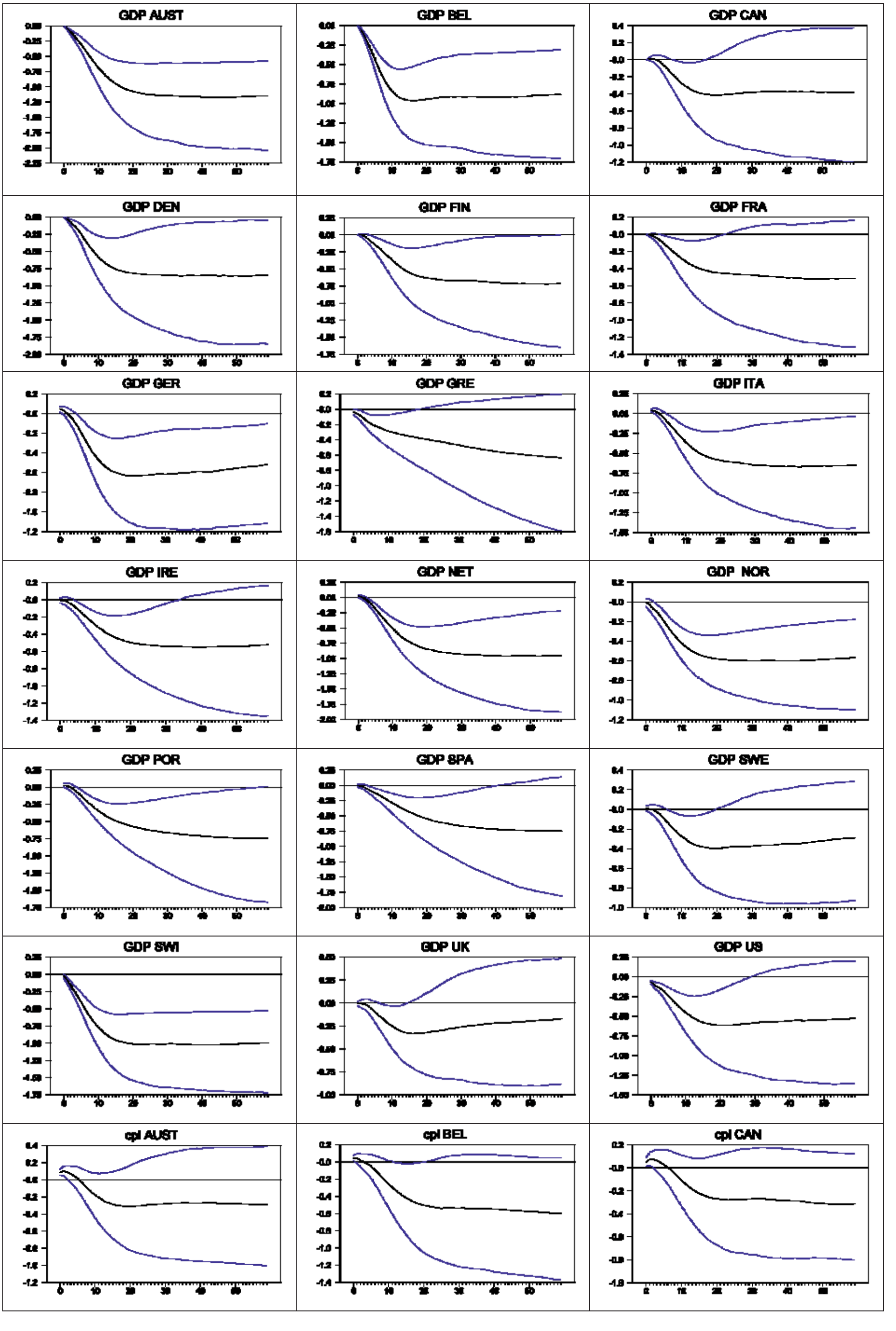
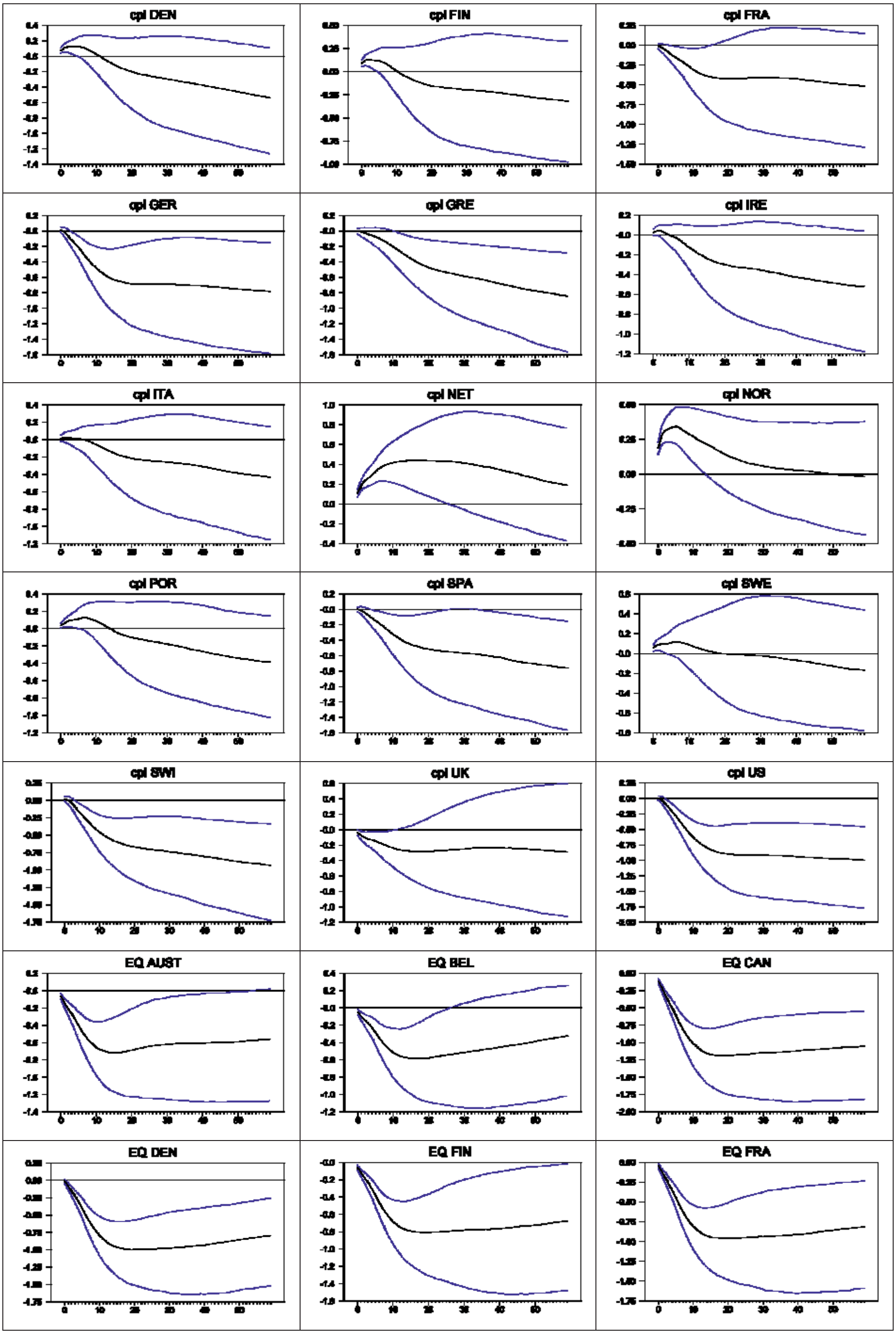


Source: Own calculations. Estimation period: 1996:01 to 2015:12.

Figure 4: Impulse-responses (Z_t^2) – Shock to US uncertainty (EPU_t^{US})

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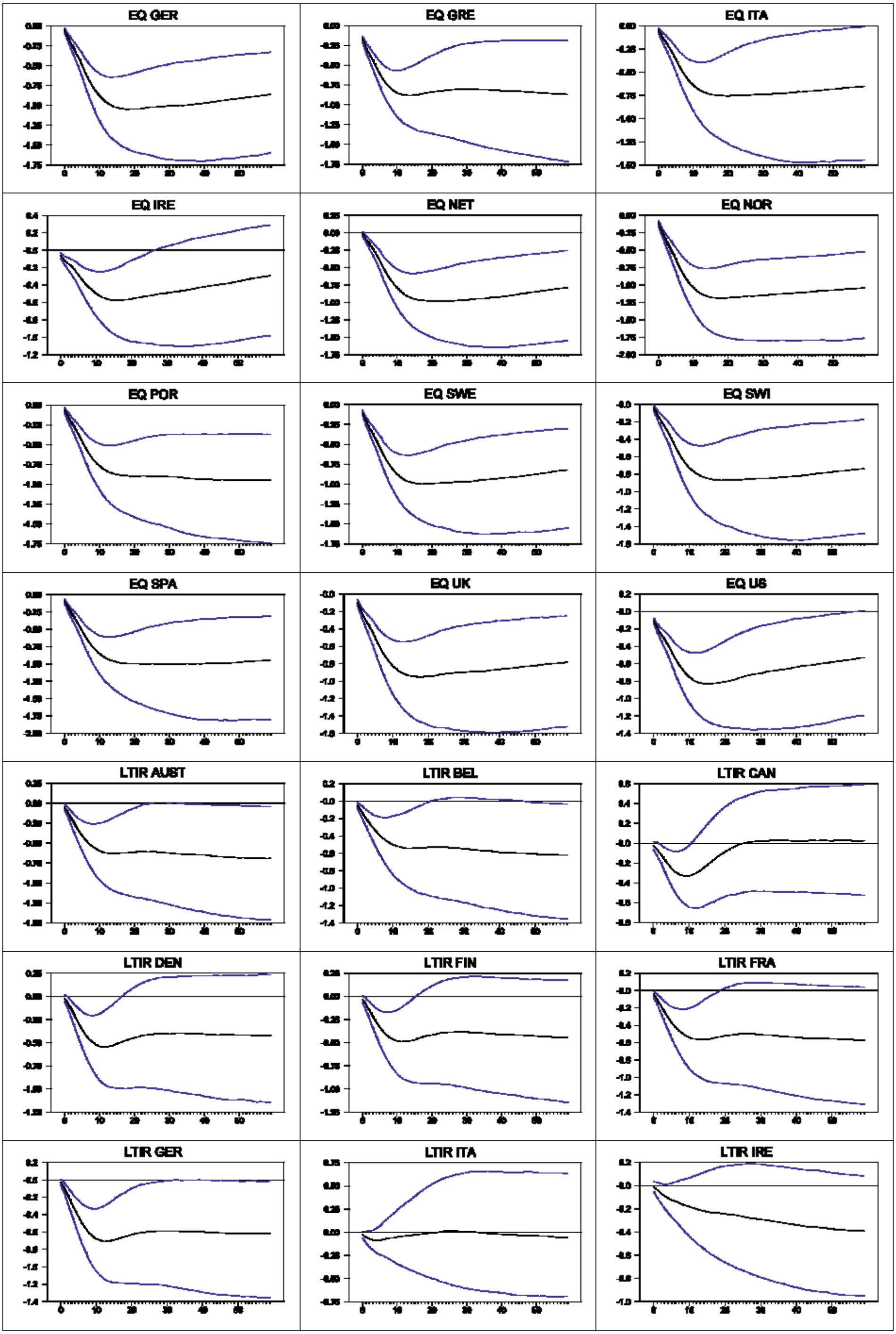
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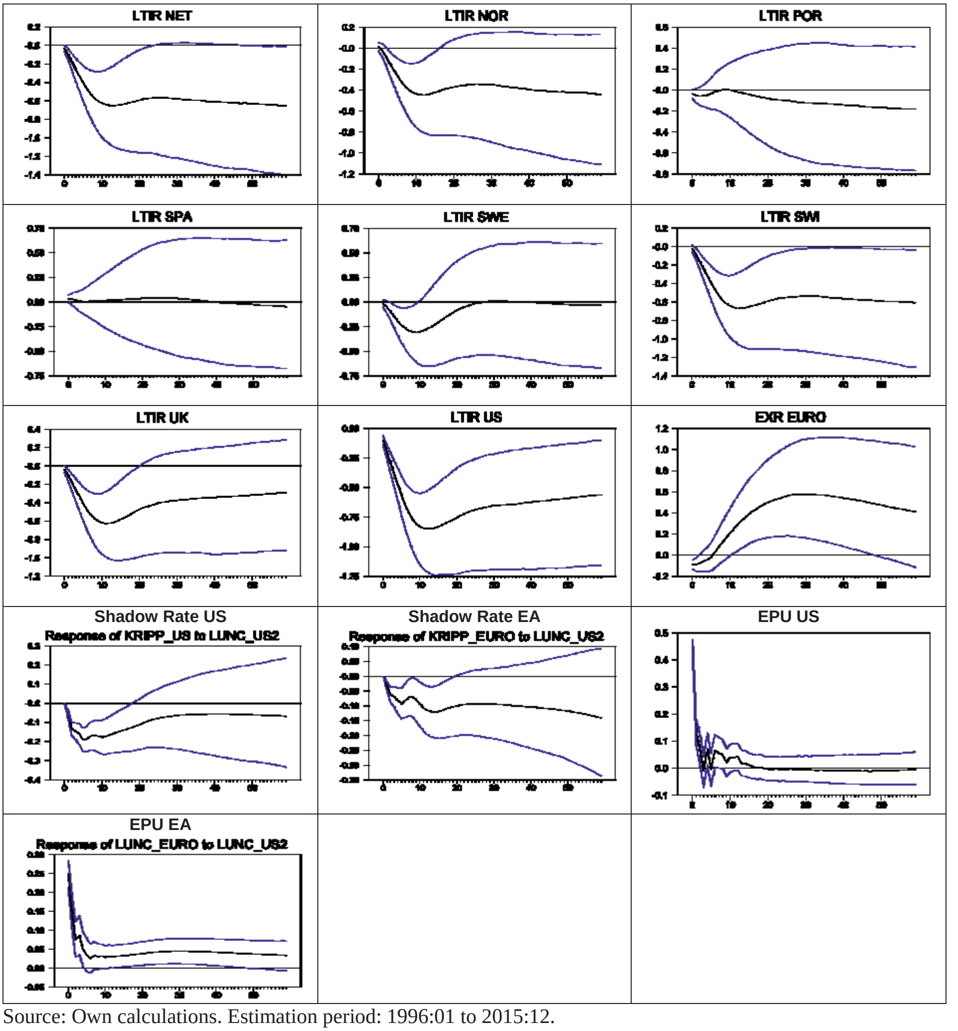
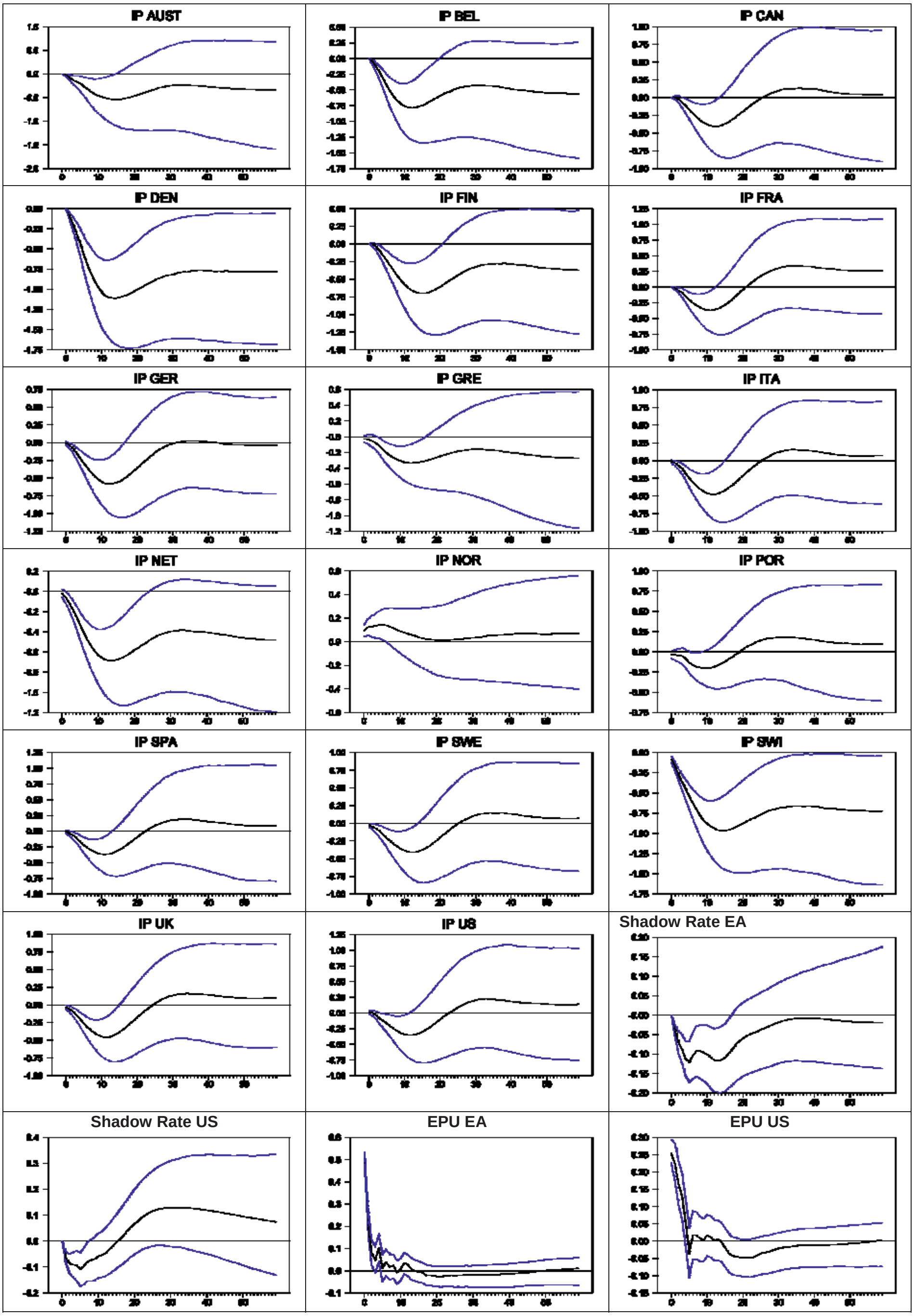


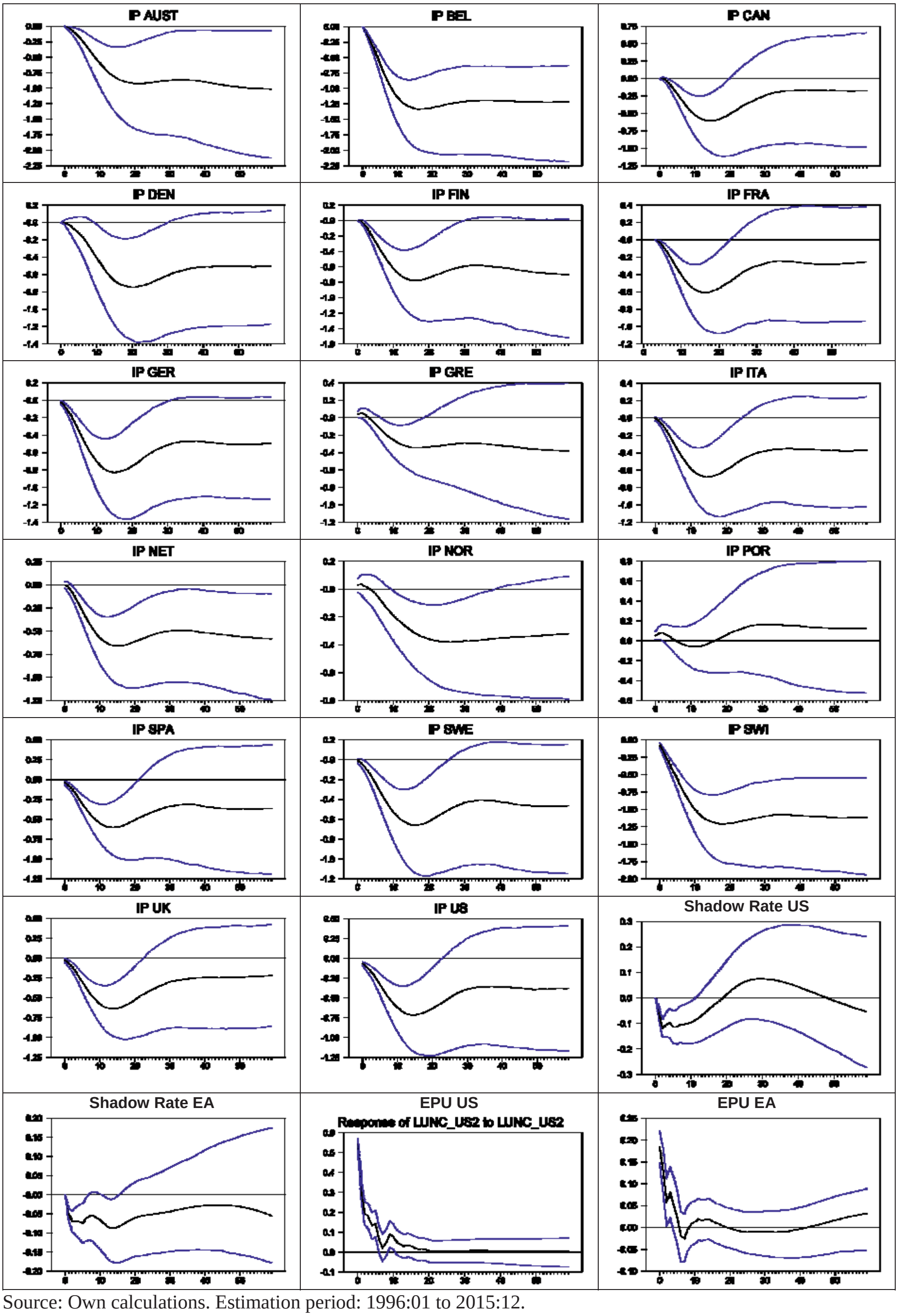
Source: Own calculations. Estimation period: 1996:01 to 2015:12.

Figure 5: Selected impulse-responses (Z_t^3) – Shock to US uncertainty (EPU_t^{US})



Source: Own calculations. Estimation period: 1996:01 to 2015:12.

Figure 6: Selected impulse-responses (Z_t^4) – Shock to US uncertainty (EPU_t^{US})



Source: Own calculations. Estimation period: 1996:01 to 2015:12.