Transmission of uncertainty shocks: learning from the hetereogenous response on a panel of EU countries

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Abstract

Numerous recent studies, starting with Bloom (2009), highlight the impact of varying uncertainty levels on economic activity. Studies mostly aim at individual countries and cross-country evidence is scarce. In this paper we use a set of (panel) BVAR models to study the effect of uncertainty shocks on economic developments in EU Member States. We explicitly distinguish between domestic, common and global uncertainty shocks employing new proxies of uncertainty. The domestic uncertainty indicators are derived from the Business and Consumer Surveys administered by the European Commission. The common EU-wide uncertainty is consequently derived by a factor model. Finally, the global uncertainty indicator - inspired by Jurado et al. (2015) - is extracted as a common factor from a broad set of forecast indicators that is not driven by the business cycle. Results suggest that real output in EU countries drops after spikes in uncertainty, mainly as a result of lower investment. Unlike for the US, there is little evidence for activity overshooting following this initial fall. The responses to uncertainty shocks vary across Member States, and these differences cannot be attributed to the different size of shock but rather to cross-country structural characteristics. Member States with more flexible labour markets and product markets seems to better weather uncertainty shocks. Likewise, higher manufacturing share and higher economic diversification help dampen the impact of uncertainty shocks. The role of economic openness is more ambiguous.

JEL Codes: E32, G12, G35.

Keywords: Bayesian VAR, Economic activity, Uncertainty.

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1. Introduction

Over the last decade, numerous events have caused major fluctuations in perceived uncertainty on a global scale. Since the global financial crisis, the concept of uncertainty has also become an integral part of policy discussions and a booming economic literature has analysed the impact of uncertainty shocks on the real economy. Whereas there is no single theory describing the impact of uncertainty shocks on economic activity, it can be expected that a rise in perceived uncertainty, by affecting the capability of economic agents to assess future prospects, influences their behaviour at present. When uncertainty is high, consumers, for instance, might postpone consumption of durable goods and increase their precautionary savings (Caballero, 1990). Firms may adopt a similar 'wait-and-see' approach and make firms keep investment on hold until the uncertainty is resolved, even if the investment project has a positive net present value (Bernanke, 1983). This ‘wait-and-see’ effect initially depresses investment, but once uncertainty is resolved, should create an investment boom as firms catch-up on executing planned projects. The financial sector may find difficult to evaluate the riskiness of the projects, which results in credit rationing, especially for firms with weaker balance sheets. Banks as financial intermediaries might suffer problems themselves with external financing.[1] *Risk aversion* of economic agents, perceived *irreversibility* of some decisions (investment for instance) and *financial frictions* cause real impacts of uncertainty.

Different indicators of uncertainty have been suggested in the literature, and applied to many different countries. This paper assesses the impact of uncertainty on real economic developments in EU countries. We explicitly distinguish between domestic, European and global uncertainty shocks employing new proxies of uncertainty. The domestic uncertainty measures for individual EU countries are derived from the Business and Consumer Surveys (BCS) administered by the European Commission following Girardi and Reuter (2016). Inspired by Bachmann et al. (2013), they propose a set of uncertainty measures based on the dispersion of responses in the BCS. The common EU uncertainty can consequently be derived from a factor model on these indicators. Finally, the global uncertainty indicator - inspired by Dovern (2015) and Jurado et al. (2015) - is extracted as a common factor from broad set of forecast indicators that is not driven by the business cycle.

Most of the analysis examines the impact of domestic uncertainty shocks on real economic variables, mostly consumption or investment, in single-country studies. The focus of our analysis is on (a) the structural characteristics that may explain differences in country-specific responses to (b) uncertainty shocks that come from different sources. Differences can arise as the transmission of uncertainty shocks works via financial channels, so that different financial structures can give rise to different responses. In addition, uncertainty that is imported via external channels could potentially have a different impact on economic variables.

The rest of the paper is organised as follows. Section 2 provides a selective survey of related literature. Section 3 briefly gives an overview of existing indicators of uncertainty and presents the new uncertainty indicators used for the empirical analysis. Section 4 describes the empirical methodlogy. The empirical results tracking impact of uncertainty shocks on real economy by means of (panel) BVARs are presented in Section 5. The analysis provides evidence (i) for some individual EU countries, (ii) for groups of EU countries by their structural features (namely, labour market flexibility, product market flexibility, economic openness, export concentration, share of manufacturing on the GDP and economy diversification), (iii) on differences between impacts of idiosyncratic, common and global shocks uncertainty shocks, and (iv) on the nexus between uncertainty and other shocks. Section 6 concludes.

[1] Bonciani et al. (2016) develop a stylized DSGE model for the euro area that links uncertainty shocks with financial frictions and economic aktivity.

2. Related literature

Sudden changes to the level of aggregate uncertainty facing economic agents have been shown to be an important shock driving the US business cycle. Using a simple reduced-form VAR, Bloom (2009) estimates on firm level data that US industrial production is reduced by approximately 1% in response to an uncertainty shock. The initial drop is followed by a swift recovery and subsequent overshoot in production that surpasses its trend by approximately 1%. The role of uncertainty shocks in driving business cycles is surprisingly large: changes in the level of uncertainty contribute to about a quarter of overall variance of economic series. Other studies have come to very similar conclusions for other G7-countries (Popescu and Smets, 2010; Gourio et al., 2013; Benati, 2014). The evidence has also survived scrutiny with a set of more advanced identification techniques in VAR models, such as Mumtaz and Surico (2013), who append a stochastic volatility specification for the VAR's time-varying covariance matrix, Caggiano et al. (2013), who use smooth-transition VARs, or Benati (2014), who applies sign-restrictions on Bayesian time-varying parameters structural VARs with stochastic volatility.

Some papers look at the impact of uncertainty shocks from a cross-country perspective. These results show quite some differences in the effects of uncertainty. Stock and Watson (2012) estimate a large dynamic common factor model and identify a prominent role for financial disturbances during the Global financial crisis, and associate it with increased uncertainty. Claessens et al. (2011) carry out a comprehensive business-cycle analysis of recessions and recoveries for a sample of 45 countries. One of their findings is that recessions in emerging market countries are more often accompanied by financial market disruptions than is the case in developed economies. Carriere-Swallow and Cespedes (2013) find substantial heterogeneity in reactions to uncertainty shocks – based on the option-implied uncertainty VXO index of the U.S. stock market – across 40 countries. In contrast to the response in G7-economies, emerging economies suffer much more severe falls in investment and private consumption, take significantly longer to recover, and do not experience a subsequent overshoot in activity. They attribute the difference in responses between industrialized and emerging markets mostly to the depth of financial markets, an index of business-related institutional quality, and the degree of financial dollarization. Similar analysis has been carried out in Claeys (2017) who also stresses the role of financial development alongside with fiscal policy and fixed exchange rate regimes as sources that dampen the transmission of uncertainty to the real economy in advanced countries.

Other studies test explicitly the uncertainty shocks spillover across countries. Mumtaz and Theodoridis (2015) look at how U.S. GDP growth volatility shocks spill over to the U.K. (in a SVAR model with time-varying volatility), and find the effect to be sizeable. Colombo (2013) focuses on mutual spillover of U.S. and euro area policy uncertainty and the effect on economic activity. He finds that the effect of U.S. policy uncertainty shocks dominates those of euro area policy uncertainty. Klösner and Sekkel (2014) find spillovers between G7 countries (measured by the Diebold-Yilmaz spillover index) and explains up to one half of all movements in policy uncertainty at the height of Global financial crisis. Cesa-Bianchi et al. (2014) use a Global VAR to identify the effects of a volatility shock. Their measure covers a broad range of asset over 33 countries, and is driven by financial prices of over 109 assets worldwide. They assume that both volatility and real economic activity are determined by unobserved common factors, and derive then a global volatility shock. They find that exogenous changes to volatility have no significant impact on economic activity, once the model is conditioned on some country-specific and global macro-financial factors.

In the EU – and particularly in the euro area – there have been numerous events inducing high uncertainty in recent years. Yet, the empirical evidence documenting the economic impact of such uncertainty shocks is still rather scarce, especially when it comes to cross-country evidence for Member States. Some evidence for the euro-area is provided by Balta et al. (2013), Gieseck and Largent (2016) and Girardi and Reuter (2016) and evidence for the four largest EA countries (Germany, France, Italy Spain) using diverse measures of uncertainty in Meinen and Röhe (2017). These studies confirm the detrimental impact of uncertainty shocks on the real economy, especially investment. However, they also put in doubt the common finding for the US that after some time the economic activity rebounded strongly offsetting its original decline (overshooting). However, little is known abound the differential impact of uncertainty shocks across EU Member States.

Although these empirical results demonstrate the first order impact on economic activity of uncertainty shocks, they are only suggestive as to the reasons for its impact. In a standard RBC model, more uncertainty should not induce dampened activity as households expand labour supply in response to lower wealth, and hence boosting economic activity (Gilchrist and Williams, 2005). For uncertainty shocks to keep investment on hold requires real frictions in the economy. Leduc and Liu (2016), for example, show this by adding search frictions in the labour market. Firms are hesitant to fill vacancies when economic conditions are uncertain, and as a result, do not accomplish investment plans. This conclusion holds even stronger with sticky prices, as prolonged falls in demand make investment in additional capacity less valuable, leading to a protracted drop in activity (Basu and Bundick, 2017).

An alternative strand of the literature use either calibrated or estimated DSGE models to explore the role played by uncertainty shocks in macroeconomic fluctuations. Fernandez-Villaverde et al. (2015) estimate stochastic processes with time-varying volatilities for US government's tax and spending policies, and then feed the estimated processes into a calibrated standard New Keynesian model. Their main finding is that fiscal volatility shocks can have a sizable adverse effect on economic activity. Bachmann and Bayer (2013) use a heterogeneous-firm DSGE model, where firms face fixed capital adjustment costs. Surprise increases in idiosyncratic risk lead firms to adopt a 'wait-and-see' policy for investment. Calibration of the model shows 'wait-and-see' dynamics are not a major source of business cycle fluctuations.[2]

3. How to measure uncertainty

3.1 Different proxies for uncertainty

There is substantial disagreement about how to objectively measure the level of uncertainty perceived by economic agents. Capturing a latent process that reflects agents' uncertainty about what types of events might occur requires imposing substantial assumptions. The economic literature comes with different methods how to proxy *unobservable* level of uncertainty, typically at a country level. Namely, five classes of *observable* indicators have been employed:

(i) **Financial market indicators** are most commonly given by the second moments, i.e. implied or historical volatility of stock market or volatility of bond market or the exchange rate. Examples of such indicators are the indices of implied volatility of stock market VIX or VSTOXX. This type of as uncertainty proxies was popularized by Bloom (2009) using VXO, the implied volatility index based on trading of S&P 100 (OEX) options.

(ii) **News-based indicators** use the frequency of certain key words in selected newspapers. The most famous is the Economic policy uncertainty index by Baker et al. (2016), which is based on the relative frequency of newspaper articles that refer to of the terms 'uncertainty', 'economic' policy' (and their variations) but also the number of expiring tax provisions, and the dispersion in economists' forecasts about government spending and inflation levels. They showed that inovations to this index cause statistically significant declines in both employment and industrial production. In a follow-up paper, Baker and Bloom (2013) look at the variation in natural catastrophes, terroristic attacks, etc. across countries and again find a negative impact on both output growth and its volatility.

[2] Other studies include Bianchi and Melosi (2013), Bachmann et al. (2013), Christiano et al. (2014).

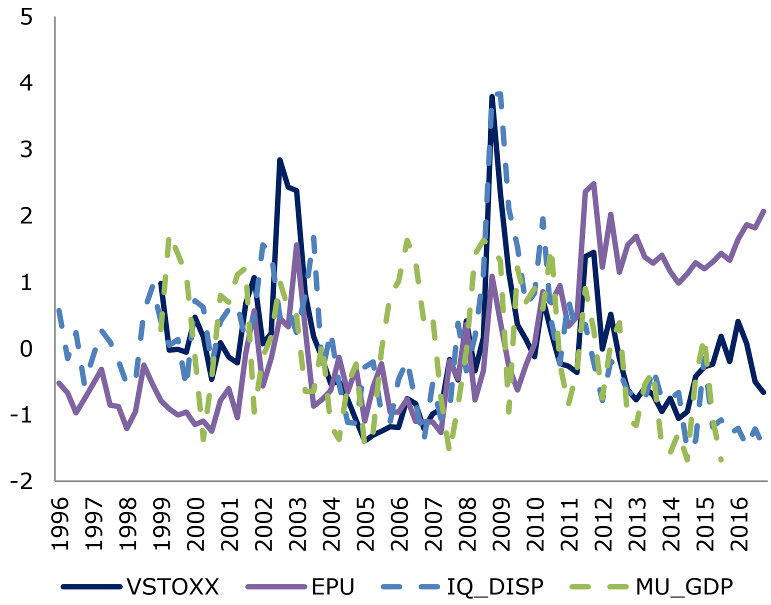
(iii) **Micro-based indicators** use cross-sectional dispersion of profits or productivity across firms or industries (Bloom et al., 2012).

(iv) **Survey-based indicators** are also micro-based but have a subjective nature, like the dispersion of answers regarding expectations for the future in surveys such as the Business and Consumer Survey (BCS) of the European Commission.

(v) **Macroeconomic data sets and forecasts** are used to infer uncertainty by means of forecast disagreement (Dovern, 2015), forecast errors (Rossi and Sekhposyan, 2015), or the unforecastable component of large sets of macroeconomic and financial variables (Jurado et al., 2015). For example, Dovern (2015) develops different measures to track multivariate disagreement between forecasters. For example, a single forecaster's projection on inflation might be correlated with consistent views on output growth. Forecasters needn't make consistent predictions for themselves. Jurado et al. (2015) instead use data on hundreds of monthly economic series in a system of forecasting equations and look at the implied forecast errors. Rossi and Sekhposyan (2015) in turn propose to infer uncertainty based on the ex-post comparison of the forecast using the unconditional likelihood of observed outcome.

Figure 1 plots examples of each of these indicators for the euro area aggregate,[3] namely the implied volatility of the stock market (VSTOXX), the economic policy uncertainty index (EPU), the BCS-based dispersion indicator (IQ_DISP) and macroeconomic uncertainty inferred from forecast errors of GDP from the Survey of Professional Forecasters (MU_GDP). Indications based on the different measures tend to coincide around the most pronounced peaks such as the years 2001-03 (dot-com bubble burst, World Trade Centre attacks, and Iraq war), the beginning of the global financial crisis in 2008-09 and the euro area debt crisis in 2012. For 2016, substantial dispersion between economic policy uncertainty and other indicators is observed, which has gradually faded away during 2017.

Figure 1: Different uncertainty indicators for the euro area



Notes: VSTOXX - implied volatility of the EURO STOXX 50 index (source: Bloomerg), EPU - economic policy uncertainty (source: www.policyundertainty.com), IQ_DISP - intraquestion dispersion from the BCS (source: authors' calculations based on Girardi and Reuter, 2015), MU_GDP - macroeconomic uncertainty derived from forecast error from the SPF (source: Rossi and Sekhposyan, 2016)

[3] Except for firms' profit / productivity dispersion, which is not available for the euro area.

Unfortunatelly, there is no single generally indicator of uncertainty as each indicator has advantages and pitfalls:

(i) Some indicators can be relatively easily calculated, while derivation of others is more complex. The *real-time availability* of the indicators differs: most data used for their calculation, except for the financial ones, are subject to publication lags, and macroeconomic data tend to be subject to revisions.

(ii) None of the indicators is fully *representative* for the whole economy and each of them may *reflect other concepts* unrelated to uncertainty. For example, stock market volatility fluctuates with in risk aversion or economic confidence, which are different concepts than uncertainty. Bekaert et al. (2013) use a decomposition of the VIX index to distinguish between true uncertainty shock and swings in general risk aversion. Dovern (2015) and Jurado et al. (2015) criticize the most common proxies as unrepresentative of macroeconomic uncertainty. In fact, most proxies focus on the volatility of a single series, like stock prices, whereas 'true' uncertainty should probably be reflected in a broader set of indicators. Forecast or survey dispersion might on the other hand reflect heterogeneity of agents, who evaluate economic prospects differently because they possess different information or because the same information might have different implications for them or because they interpret information with different analytical tools.

(iii) *The availability* of indicators *at country level* represents an important constraint in the EU context. Namely, financial market indicators and news-based indicators are available only for the largest EU countries and the euro area as a whole and the micro-based indicators only for a few EU countries. On the contrary, survey-based indicators and macroeconomic-forecast based indicators can be constructed for most EU Member States, and these are the ones we use for the empirical analysis.

Interestingly, this literature is not always explicit whether the different indicators shall be understood as proxies of more generalized unobservable uncertainty, or whether they track one specific type of uncertainty related to a specific type of events (as for economic policy uncertainty). For example, Duca and Saving (2018) find that both economic policy and macroeconomic uncertainty as measured in Jurado et al. (2015) matter. This suggests that different types of uncertainty shocks may not be mutually exclusive.

3.2 Country-level indicators of uncertainty

The Business and Consumer Surveys (BCS) administered by the European Commission[4] represent a unique source of information that has not yet been explored for the construction of country-specific uncertainty indicators. The BCS are run in all EU countries, albeit the time span and coverage may differ somewhat. The biggest advantage of the survey-based uncertainty indicators is their representativeness as they cover a wide range of businesses (industry, services, retail trade and construction) as well as opinions of consumers. Decisions by businesses and consumers are directly affected by the uncertainty they perceive and they, in turn, determine overall macroeconomic activity. However, as noted above, dispersion of answers to the surveys may also be driven by other forces than perceived uncertainty, namely the heterogeneity of agents that affect their opinions.

BCS inquire on a monthly basis around 120,000 businesses with questions about production, orders and employment and around 40,000 consumers on their financial situation and their evaluation of macroeconomic developments. The replies to each question in BCS are summarized in terms of share of respondents giving positive answers minus those giving negative answers. The questions are related to the present situation, the recent past (3 months for business and 12 months for consumers) and the expectation for the near future (again in 3 and 12 months respectively). Importantly, some questions are asked both related to the past (backward-looking) and the future (forward-looking).

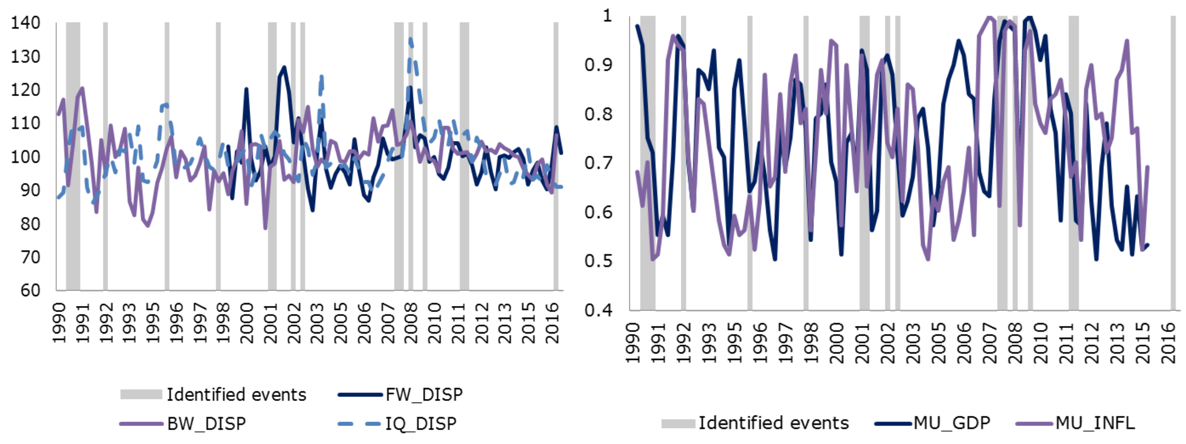
[4] See https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en

Building on Bachmann et al. (2013) who proposed to measure uncertainty as the dispersion of businesses‘ expectations about the future, Girardi and Reuter (2015) developed three uncertainty indicators using fully scope of the BCS datasets. The first indicator (FW_DISP) is based on the dispersion of responses to 22 forward-looking questions (monthly and quarterly). The second indicator (BW_DISP) also accounts for the backward-looking versions of the questions (i.e. opinions on developments in recent past rather than those expected in near future), which allows comparison between the ex-ante and ex-post dispersion. In this way the indicators mute the impact of heterogeneity as driven by different background of agents or information sets available to them. Finally, the third indicator (IQ_DISP) is based on the dispersion of scores across different questions rather than dispersion of answers to a single question. The underlying assumption is that uncertainty is related to dynamic changes in the economy. If the economic situation changes, the responses to different questions (related to past, present and future) can evolve in different directions and the dispersion of scores across questions increases. Therefore, while the first two indicators (FW_DISP and BW_DISP) use question-specific dispersions (i.e. the standard deviation of positive and negative answers to a specific question in the survey), the third indicator (IQ_DISP) proxies uncertainty by dispersion of changes of the shares across several survey questions.

Graph 2 (left panel) plots these three indicators at country level, using France as an example (indicators for other countries are in the Appendix I), and suggests that most peaks of the indicators are clearly related to some well-identified events but also some important differences exist between the three indicators. In the case of France, the FW_DISP indicator captures well the 2001-2003 uncertainty period (dot-com bubble burst, World Trade Centre attacks, and Iraq war). It increases (albeit only moderately) during the Great Recession and temporarily spikes after the Brexit vote (2016, Q3). The BW_DISP is very flat and does not increase much during the Great Recession (2008-2009) and even decreases during the euro area debt crisis (2011). Finally, the IQ_DISP indicator identifies a number of significant events: the Gulf war (1991), the important strikes in 1995 in France, the dot-com bubble burst and WTC attacks (2001), the Iraq war and the strikes in France in 2003, and the Lehman brothers collapse (2008, Q4). However, this measure does not increase significantly during the euro area debt crisis (2011).

Confronting these three indicators with events that can be deemed to trigger spikes in uncertainty in several EU countries, the IQ_DISP indicator appears as the most reliable in that for most countries it peaks at the time of such events (such as the global financial crisis). Therefore, this indicator will be used in our further analysis as the BCS-based indicator of uncertainty.

Figure 2: Uncertainty indicators constructed from and SPF - example for France

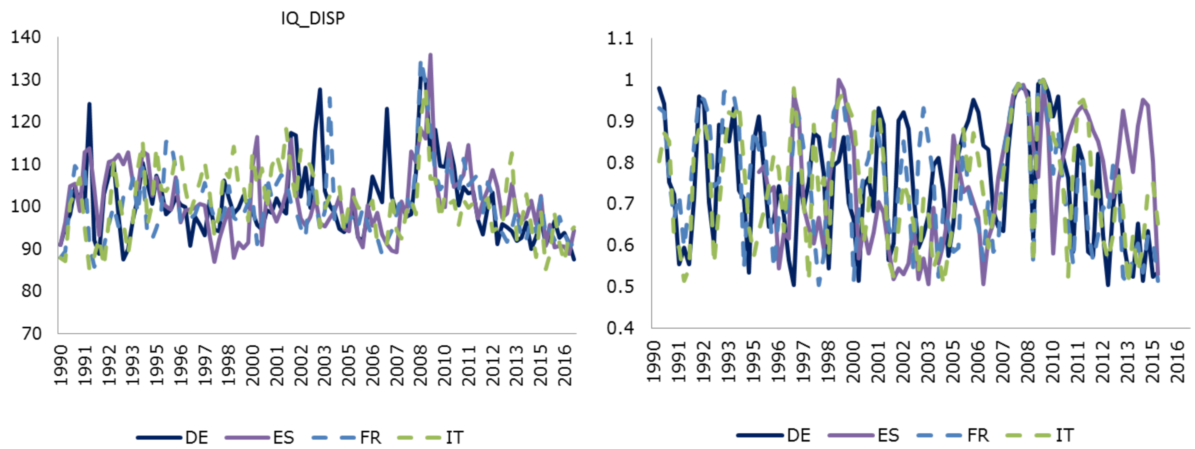


The second option to derive country-level uncertainty indicators is the information in broad cross-country macroeconomic forecast. Namely, Rossi and Sekhposyan (2016) calculate forecast-error based uncertainty measure originally developed in Rossi and Sekhposyan (2015) from the Survey of professional forecasts (SPF) administered by the ECB. Therefore, the indicators are *limited only to the euro area* members. Unlike uncertainty indicators based on forecast dispersion (e.g. Jurado et al., 2015) this indicator does not require a large cross section of forecasts but only a point forecast and the actual realization of macroeconomic variables. Given their aggregated and ex-post nature, this indictor does not suffer from the problem of heterogeneity. On the other hand, the SPF relies on opinions of a very specific group of agents (professional forecasters) and may therefore not be representative of the economy as a whole.

Figure 2 (right panel) plots two macroeconomic uncertainty indicators developed by Rossi and Sekhposyan (2016), viz. forecast errors in quarterly forecast of GDP (MU_GDP) and inflation (MU_INFL). The indicators are based on the comparison of the realized forecast error with the unconditional distribution of forecast errors for each variable. If the forecast error is in the tail of the distribution, it means that the realization was very difficult to predict, and therefore the macroeconomic environment was very uncertain. Based on inspection across euro area countries (similar as for the BSC-based measures), the GDP-based forecast error (MU_GDP) seems to be more related to identifiable events and will be used in the consecutive analysis.[5]

It seems that when there was major political, economic or financial distress both uncertainty indicators peaked. However, there are also numerous spikes, especially for the forecast-error based indicator, which cannot be reasonably related to any known uncertainty-generating event. In any case, these indicators shall be rather understood as proxies of uncertainty rather than direct measures. Consequently, it seems appropriate to use various available uncertainty indicators for robustness of empirical analysis whenever possible. While there are apparent differences in dynamics between the BCS-based and forecast-based uncertainty indicators, there is also substantial co-movement of indicators across Member States. This is apparent in Figure 3 that plots both selected indicators (IQ_DISP and MU_GDP) for the four largest euro area countries.

Figure 3: Uncertainty indicators constructed from BCS (IQ_DISP) and SPF (MU_GDP) for four largest EA countries



Formal statistical factor analysis confirms that over 70 % of the dynamics of the IQ_DISP indicator across the EU Member States can be explained by a single common factor, 82 % for the euro area countries, and in case of MU_GDP indicator (avilable only for the euro area countries) only one factor is necesary to explain 100 % of the the variance. This suggests that uncertainty in the EU, and the euro area in particular, arises mainly from common rather than idiosyncratic factors. Among the euro area countries, Cyprus, Greece, Ireland and Portugal in turn feature the strongest idiosyncratic components,

[5] The indicators are by construction bounded on the interval [0.5, 1].

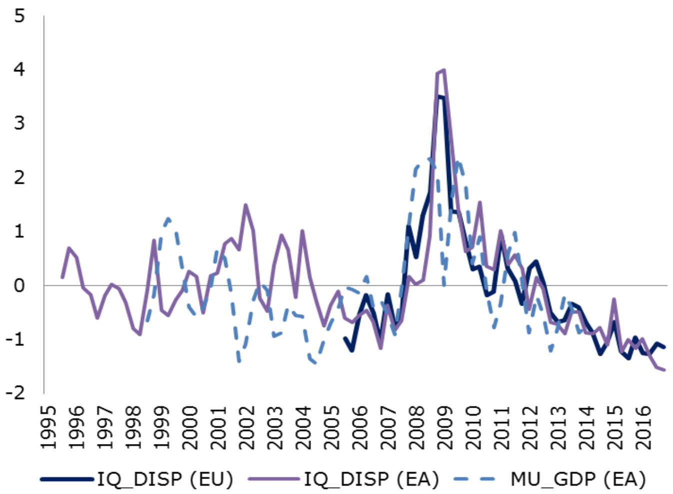
which is consistent with the economic priors about specific uncertainty-generating events in these countries,[6] and from non-EA countries, such as Hungary and the UK.

Table 1: Factor model estimates

EU					
Factor	Variance	Cumulative	Difference	Proportion	Cumulative
Factor 1	20.44	20.44	11.66	0.70	0.70
Factor 2	8.78	29.22	---	0.30	1.00
Total	29.22	29.22		1.00	
EA					
Factor	Variance	Cumulative	Difference	Proportion	Cumulative
Factor 1	6.33	6.33	4.90	0.82	0.82
Factor 2	1.43	7.76	---	0.18	1.00
Total	7.76	7.76		1.00	

Figure 4 plots the first common factor of the IQ_DISP and MU_GDP indicators. While the common factors of both indicators attain their highest value during the global financial crisis (2007-2009), the common factor behind the IQ_DISP indicator seems to be more consistent with common wisdom about other potentially uncertainty producing events, especially in the pre-crisis area. Namely, the period between 2001 and 2003 when the dot-com bubble burst, and the World Trade Centre attacks and the Iraq war occurred. Both indicators point to an increase in uncertainty since 2008 peaking at the height of the global financial crisis in 2009, after which it started to fade away with local peaks during the euro area debt crisis in 2012.

Figure 4: Uncertainty indicators constructed from BCS (IQ_DISP) and SPF (MU_GDP) for four largest EA countries



3.3 Measure of global uncertainty

Macroeconomic uncertainty is a broad phenomenon that is not only the result of domestic developments. It reflects also changes in global economic conditions. Gourio et al. (2013) find that country-level risk indices constructed with domestic financial indicators are highly correlated across countries. Cesa-Bianchi et al. (2014) compute realized volatility using daily returns on 92 asset prices, in 33 advanced and emerging economies, and 17 commodity indices, and find these volatility measures are importantly driven by global factors. Dovern (2015) finds that his measure of

[6] The decoupling of these countries has been most apparent in terms of sovereign bond yields, which were often deemed to be related to redenomination risk. See for example: Klose and Weigert (2014).

multivariate disagreement is positively correlated with the economic policy uncertainty index of Baker et al. (2015) and with the principal component of three financial market volatility indicators. The measure of Jurado et al. (2015) instead moves rather independently from other uncertainty proxies. They find spells of uncertainty are not occurring frequently, but only at a few points in time when large economic shifts occurred, such as the OPEC recession of 1973, the Volcker shift in monetary policy (1982), and the Great Recession (2008).

Following Dovern (2015) and Jurado et al. (2015), we develop a broad macro index that captures global uncertainty.[7] To that end, we collect data from many different forecasters on different projections, and on a broad set of countries. These data come from Consensus Economics (CE) data. CE conducts a survey—mainly based on OECD countries—among professional economists working for commercial or investment banks, government agencies, research centers and university departments. Most of the surveyed experts provide forecasts for their own country only. However, there are also a few experts working for international financial institutions or research institutes that provide forecasts for several countries simultaneously. The survey queries respondents every first week of each month about current and future developments for a number of macroeconomic and financial variables, including the yields on 10-year benchmark government bonds. The forecasts are then published early in the second week of the same month.[8]

Evidence shows that CE forecasts are less biased and more accurate than forecasts of some international institutions.[9] CE data are public, which helps to prevent a participant from reproducing others' forecasts and limits the possibility of herding (Trueman, 1994). Moreover, forecasters are bound in their survey answers by their recommendations to their clients, and discrepancies between the survey and their private recommendation would be hard to justify (Keane and Runkle, 1990). Overall, we can reasonably argue that the CE survey data broadly reflects the spectrum of expectations of market experts.

We focus on forecasts of inflation, economic growth, unemployment in the US, Japan, Germany, France, U.K. and Italy with data covering the period from 1990 to 2016. Overall, the dataset contains a large number of expert forecasters in each country (Table 2). However, we can only use a subset of these respondents. In fact, despite the gradual expansion of the dataset, some forecasts have not always received the same attention from forecasters over time. Some forecasters stopped producing projections, while others that were initially included left the sample owing to closures, mergers or other reasons. Moreover, new forecasters joined the CE survey only at a later stage. Therefore, we apply a double criterion to select our sample. First, we do not consider those forecasters that have participated for fewer than 12 consecutive months in the CE survey. Second, among those forecasters, we select only those with no gaps between two consecutive forecasts that are larger than 36 months. This reduces the number of forecasters as indicated in Table 1 to about 40% of the total available number.

[7] This measure is also used and further details on it provided in an accompanying paper (Claeys, 2017).

[8] Further information on how the survey is conducted is available at www.consensuseconomics.com

[9] Batchelor (2001) shows that CE forecasts are less biased and more accurate in terms of mean absolute error and root mean square error than OECD and IMF forecasts.

Table 2: Number of forecasters in CE, January 1990-December2015.

country	total	maximum	selection
US	120	76	56
Japan	95	74	60
Germany	52	40	32
France	48	36	18
UK	111	68	60
Italy	54	42	33
total	480	336	259

Notes: total number of forecasters in CE database; the maximum number in a single month, and the number of forecasters that satisfy the double criterion (continued forecasting with no gaps).

We now derive the uncertainty indicator from these year-ahead forecasts. Each forecaster is asked to make projections of inflation, economic growth, and unemployment for the year ahead. We can then compute each forecaster's forecast error. We collect data for the six economies on standard measures of inflation, economic growth and unemployment to compute these errors. We are not so much interested in assessing forecast performance (which has been extensively studied in Batchelor, 2001), but from the total number of 259 forecasts we have in our dataset, we extract instead a few factors employing the method of principal factors (Stock and Watson, 2005). The Minimum Partial Average (MPA) method determines that three factors (alternative statistical criteria point to the same number of factors) are able to explain close to 90 per cent of the original series' variability. Table 3 provides details on the factors' unrotated loadings. The first factor explains around 55 per cent of the total variability. This factor is related to the business cycle, calculated as the average growth rate across G7 economies. The correlation is close to 0.90. Periods of high growth are associated with a rise in the first main driver in forecast errors.[10] The second factor explains around 32 per cent of total variability. It is not related to cyclical developments. Hence, it seems that dispersion in the opinions of forecasters has an important cyclical component, but once this cyclical co-movement has been taken into account, the second factor seems to capture the uncertainty that forecasters face.

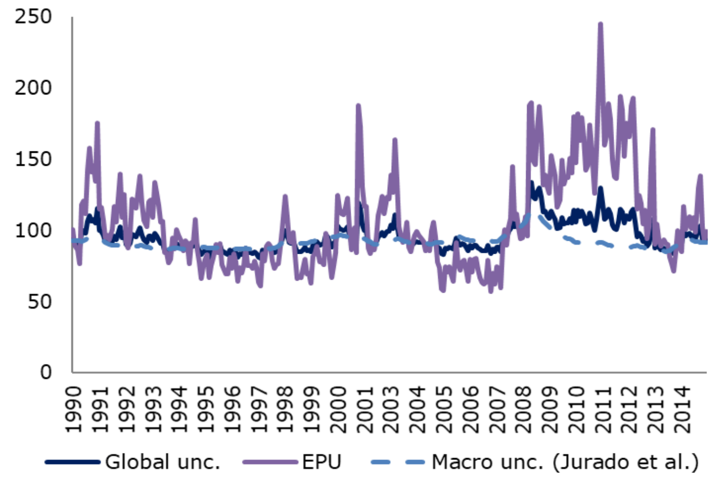
Table 3: Factor model estimates

Factor	Variance	Cumulative	Difference	Proportion	Cumulative
Factor 1	5.76	5.76	3.72	0.55	0.55
Factor 2	2.04	7.80	0.52	0.32	0.87
Factor 3	1.52	9.32	-	0.10	0.97
Total	9.32	9.32		0.97	

We plot this second factor together with the proxies that Jurado et al. (2015) suggest in Figure 5, and find that the factor-based measure displays somewhat more variation outside of the three episodes that they find to be important spells of uncertainty (2001, 2008). The reason is that by decomposing forecast errors into a notable cyclical component, we clean the dispersion of forecast errors from any strong recessionary effect. We do nevertheless find important rises in the index in these episodes too. If we compare the factor based measure to the news index of Baker et al. (2016) then the opposite result holds. Their measure displays more variation over time than the factor-based uncertainty indicator.

[10] The factor model also filters out any seasonal pattern in the forecast errors that could result from the shrinking forecast horizon.

Figure 5: Global uncertainty measure comparison



Notes: Baker's loom measure of political uncertainty; JLN is the macro-uncertainty measure of Jurado *et al.* (2015) at 12 months (scaled by 100 to fit the Bloom index), and the factor-based measure based on CE forecasts.

4. Empirical setting

The impact of uncertainty shocks on the real economy is evaluated by means of Bayesian Vector Autoregression (BVAR) models estimated on quarterly data for 1996-2016. We employ both standard country-level BVARs and panel BVARs. The Bayesian shrinkage allows estimating model with several endogeneous variables in face of limited data sample. The model includes 6 variables (next to a constant term and a linear trend to control for nonstationarity of some variables) in the following ordering: (log of) stock prices, the Economic Sentiment Indicator (ESI), the uncertainty indicator (IQ_DISP, common factor of the IQ_DISP country-level indicators, global uncertainty indicator, and in country-specific VAR also MU_GDP and EPU), short-term interest rate, log HICP and log real GDP, consumption or investment respectively. The ESI and the other indicators needed for construction of IQ_DISP come from the Busienss and Consumer Surveys of the EC, the macroeconomic data come from Eurostat, the ECB and the OECD. As we work with quarterly data, we include four lags of each variables.

The country-level estimates come from standard BVAR that can be written as:

$$Y = (XA + E)$$

with Y and E being $T \times m$ matrices and X is $T \times (mp + 1)$ matrix. This can be also written as:

$$y = (Im \otimes X)\theta + e$$

For the derivation of the likelyhood funcation, a standard Litterman/Minnesota prior is used, i.e. a normal prior on θ and Σ_e is replaced by its estimate and the hyperparametes are also standard, i.e. $\mu_1 = 0$ (zero mean of θ), $\lambda_1 = 0.1$ (overal tightness), $\lambda_2 = 0.99$ (relative cross-variable weight), $\lambda_3 = 1$ (lag decay).

The panel (B)VAR model in general form can be written as:

$$yi = (Im \otimes Xi)\theta i + ei$$

where i stands for $i = 1, 2, . . ,N$ cross-sectional units. The dynamic equation for each variable in cross-sectional unit i at period t contains of $k = Nnp + m$ coefficients to estimate. Therefore, there are $q = n(Nnp+m)$ coefficients to estimate for each unit. In order to account for the dynamics of the quarterly series, we use 4 lags in each BVAR model.

There are different types of panel BVAR ranging from a very general model that allows for cross-sectional heterogeneity as well as static and dynamic linkages across the cross-sectional units to more restricted models that relax some of these properites, which (if deemed reasonable) allows loosing additional degrees of freedom and in turn gain more accurate estimates. Given that we are mainly interested in average responses for certain subgroup of the EU countries we use the Bayesian pooled estimator,[11] which is the Bayesian counterpart of the classical the mean-group estimator. With this approach, each cross-sectional unit (country) is independent of other units and the dynamic coefficients are homogeneous across units. While this implies relaxing properties such as static and dynamic linkages between cross-sectional units, we deeem it appropiate as we mostly work with subsamples of EU countries that share certain structural features (e.g. labour market flexibility) but it does not imply that such subsample include countries that share especially strong linkages that needs to be taken into account. As noted before we are interested only in the average response in each group of EU countries to uncertainty shocks rather than the cross-country linkages.[12] The standard normal-Wishart prior is used for estimation and 5,000 iteractions (with 1,000 as burn-in) are used.

While we are mainly interested in the impact of uncertainty shocks on economic activity, the presence of other variables included in the BVAR is needed to distinguish the impact of *uncertainty shocks* from other similar shocks likely affecting economic activity. This applies especially to *confidence shocks* and *financial shocks*.[13] Firstly, confidence can affect consumer and investment decisions. Whereas confidence shocks shall be understood as changes in *the level* of confidence about future outcomes (first moment shocks), uncertainty shocks are rather the changes *in the dispersions* of opinions about the future (second moment shocks).[14] Secondly, adverse developments on financial markets often *coincide* with periods of increasing uncertainty, and financial and uncertainty shocks can *reinforce* each other, but remain separate shocks in nature. Financial shocks can be measured as unexpected changes in asset prices, housing prices, price or volume of banking credit (see for example Gilchrist et al., 2014).

The implementation of country-level BVAR allows for different identification schemes for impulse-response analysis and we use both Choleski factorization and generalized impulse-response analysis, which both provide largarly similar results. Therefore, for the panel BVAR, we rely on the Choleski factorization only.[15] For robustness, we tested also other ordering, which did not materially alter the impulse-response functions. On the contrary, the variance decomposition (not reported further) featured some discrepancies, namely alternative ordering the stock prices, ESI and uncertainty indicator changed the relative importance of financial, confidence and uncertainty shocks for explantion of real economic developments. In this context, we need ordering uncertainty indicator only after the stock prices and ESI as a conservative choice.

While the IQ_DISP uncertainty indicator can be calculated for most EU countries, the availability of other variables reduce the dataset used for empirical analysis to 18 EU Member States, namely Austria

[11] We use BEAR toolbox developed by the ECB for the panel estimations.

[12] For example, the Czech Republic shares very strong financial and trade linkages with Germany and it would be very appropriate to allow for static and dynamic interdependencies. However, the Czech Republic is often allocated to a different subgroup than Germany.

[13] News shock is another type of shock studies recently. However, unlike the other shocks, these shocks that shall be undestrood as news about future total factor productivity, which affect the real economy only in longer term (e.g. Jaimovich and Rebelo, 2008 or Barsky and Sims, 2011)

[14] There is also booming economic literature that studies the role of confidence as an autonomous driver of business cycle fluctuations (e.g. Bacchetta and Van Wincoop, 2013 or Angeletos and La'O, 2013).

[15] The BEAR toolbox used for the panel BVAR estimations allows only for Choleski and triangular factorization, whhich provide in our case very similar results.

(AT), Belgium (BE), the Czech Republic (CZ), Germany (DE), Denmark (DK), Estonia (EE), Spain (ES), Greece (EL), Finland (FI), France (FR), Hungary (HU), Italy (IT), Netherlands (NL), Portugal (PT), Sweden (SE), Slovenia (SI), Slovakia (SK) and the United Kingdom (UK).

5. Empirical Results

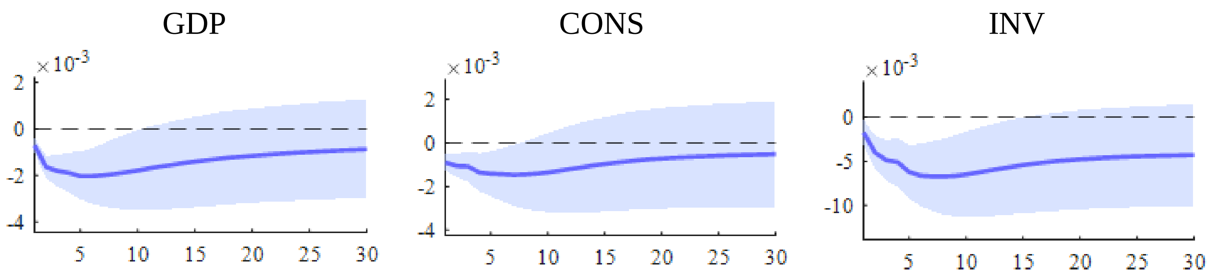
This section provides an empirical evidence on the impact of uncertainty shocks across in the EU countries using the (panel) BVAR models. In some cases, we refer only to the EU countries where additional uncertainty indicators are available. We usually report the impact of an unexpected uncertainty shocks on the GDP, in some cases also on consumption and investments. First, we present the EU-wide evidence comparing overall impact of idisyncratic, EU-wide common and global uncertainty shocks on the real economy. In addition, we provide also some evidence on the linkages between uncertainty and other shocks. Second, we present selective country-level evidence to demonstrate the scope of heterogeneity in responses to uncertainty shocks across the EU countries. Third, we split the EU countries across diverse structural characterstics and test their potential relevance in the transmission of uncertainty shocks. In doing so, we focus on the charactersitics of flexibility, openess, specialization and diversification of the EU economies.

5.1 The EU-wide evidence on impact of uncertainty shocks

The evidence on the overall impact of uncertainty shocks in the EU countries is provided in Figure 6. The uncertainty is proxied by the country-level uncertainty indicator IQ_DISP derived from the BCS (see subsection 3.2 and Appendix I). The results suggest that following an unexpected spike in uncertainty, EU output suffers a significant decline, drops for around six quarters and gradually returns to baseline. The impact is especially pronounced for investment, which represents the most volatile part of GDP. While the response of consumption is significant as well, the decline is substantially less pronounced and more short-lived than for investment. Importantly, there is no evidence of overshooting when economies recover from the shocks, suggesting that the temporal decline in economic activity is not consequently compensated.

The identified uncertainty shocks from this panel BVAR are reported in Appendix II. While they suggest that during the Global financial crisis, uncertainty hit numerous countries, there were other periods when the uncertainty spiked in several countries such as during the 2001-2003 period (dot-com bubble burst, World Trade Centre attacks, and Iraq war).

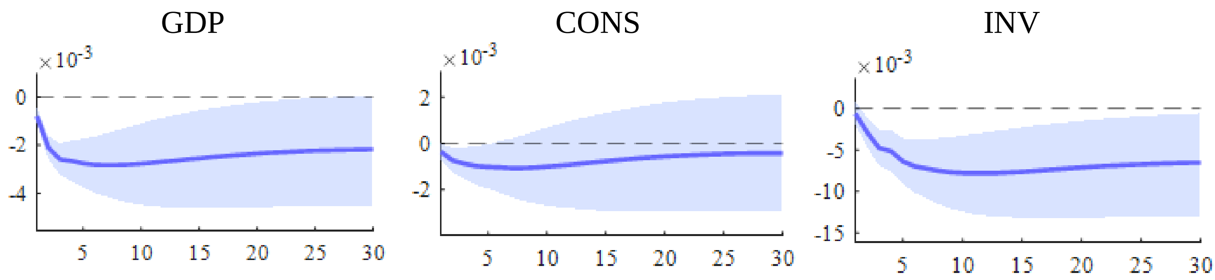
Figure 6: Impact of domestic uncertainty shocks on GDP, consumption and investment – panel of 18 EU countries



Notes: The graph represents the estimated response of GDP following an unexpected (idiosyncratic) uncertainty shock (of one standard deviation) in the panel BVAR model incuding 18 EU countries. Uncertainty is proxied by the IQ_DISP indicator. The x-axis represents quarters. The values on y-axis represent (when multiplied by 100) percentage points. Confidence bounds are of 90 %.

As the EU economies are tied by strong trade and financial linkages, they may be also subject to common shocks. Indeed, the country-level uncertainty indicators IQ_DISP (and for the EA countries also MU_GDP) were found to share a strong common component. Figure 7 shows the responses of the EU countries to such common uncertainty shock with uncertainty being proxied by the first principal component of the country-level IQ_DISP measures. The estimated impact of such synchronized uncertainty shock is even more pronounced, especially for investment whose decline turn out to be very persistent.

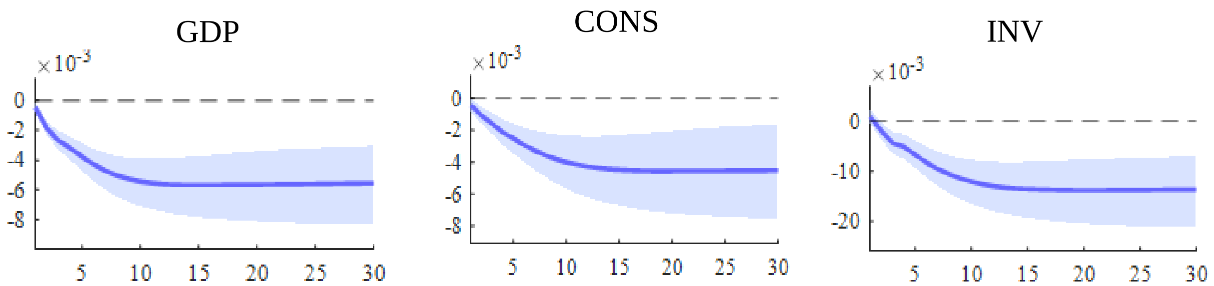
Figure 7: Impact of common EU uncertainty shock on GDP, consumption and investment – panel of 18 EU countries



Notes: The graph represents the estimated response of GDP following an unexpected (common) uncertainty shock (of one standard deviation) in the panel BVAR model incuding 18 EU countries. Uncertainty is proxied by the first principal factor derived from country-level IQ_DISP indicators. The x-axis represents quarters. The values on y-axis represent (when multiplied by 100) percentage points. Confidence bounds are of 90 %.

With globalization, spikes in uncertainty may even attain a global dimension (Berger et al., 2017). In subsection 3.3 we developed a global uncertainty indicator as a common factor extracted from broad set of forecast indicators. Figure 8 reports the impact of a global uncertainty shock. The graph suggests that EU output suffers a major decline, which is even of a larger magnitude than after the EU-wide uncertainty shock. Besides the very persistent impact on investment, consumption suffers a significant and very long-lived decline as well. These results are confirmed when we use the EPU for the US (Baker et al., 2016) and original macroeconomic uncertainty indicators by Jurado et al. (2015).[16] The spells of global uncertainty (as reported in Figure 5) occur only infrequency during major events such as the global financial crisis. Therefore, the response of real economy shall be also seen as rather extraordinary.

Figure 8: Impact of global uncertainty shock on GDP, consumption and investment – panel of 18 EU countries



Notes: The graph represents the estimated response of GDP following an unexpected (common) uncertainty shock (of one standard deviation) in the panel BVAR model incuding 18 EU countries. Uncertainty is proxied by the first principal factor derived from country-level IQ_DISP indicators. The values on y-axis represent (when multiplied by 100) percentage points. The y-axis represents percentage points. Confidence bounds are of 90 %.

[16] These results are not reported here to save the space but are available from the authors.

When we use annual growth rates of GDP instead of its log level (as in Figure 6-8), there is some minor evidence for overshooting (see Appendix IV), especially in the case of an idiosyncratic uncertainty shock. Still, the conclusion that inial decline of economic activity after the uncertainty shock is not consequenty compenstated – and hence the output loss is permanent – still holds.

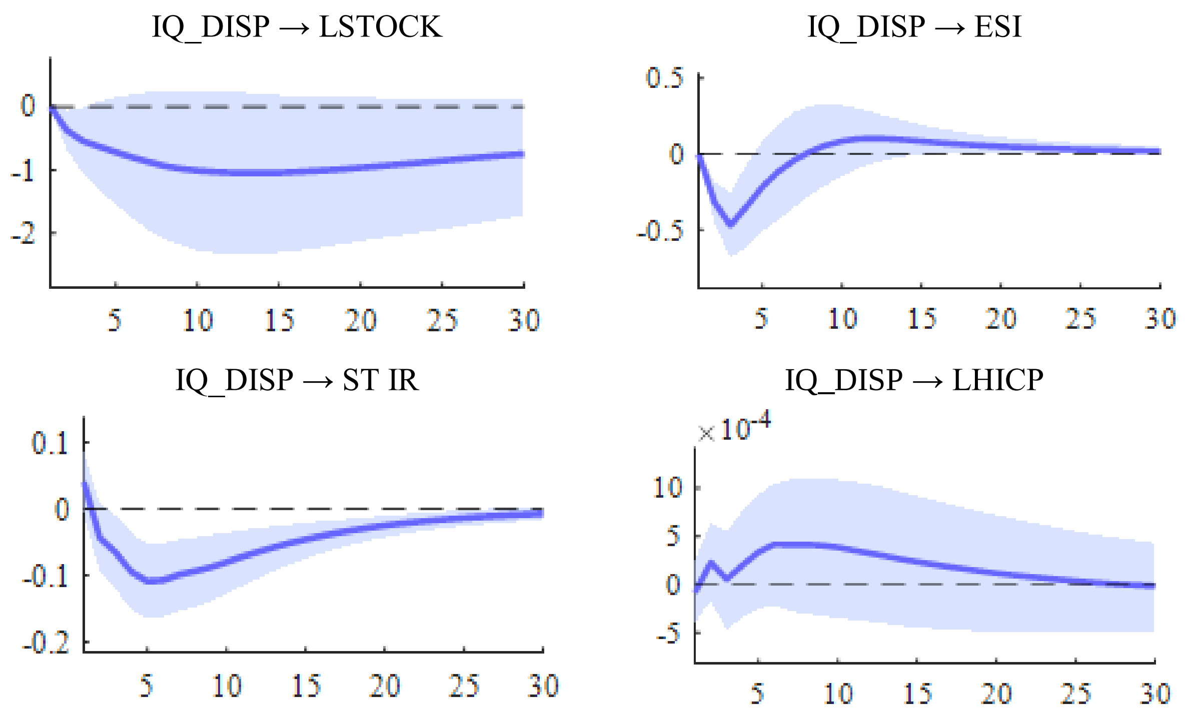
The Global Financial Crisis of 2008/09 is often seen as a period in which political and economic uncertainty contributed much to a financial meltdown and generalised economic collapse. However, from the point of view of individual EU Member States this was rather a global rather than idiosyncratic uncertainty.[17] A historical decomposition (reported for three sample countries, Germany, Spain and the UK in Appendix V) from a panel BVAR for the 18 countries where uncertainty is proxied by the global uncertainty indicators shows that over that period, the uncertainty shock amounted for about a quarter to a third of total variability in GDP. For example, GDP in Germany, Spain or the UK fell by almost 4-5% and around 1%-1,5% can be attributed to uncertainty shocks. Besides the negative impact of uncertainty dragged GDP growth of EU countries until 2011. At that time global uncertainty peaked again arguably also because of internal EU problems. The historical decomposition also stress role of other shock closely related to uncertaninty shocks, namely financial and confidence shocks.

Beyond the analysis of the impact of uncertainty shocks on the real economy, it is interesting to evaluate what is the impact of uncertainty shocks on other macroeconomic and financial variables. Given the significant diversity in model settings across empirical studies, with regard to both the indicators used for uncertainty and the choice of other variables, there is no consensus on how uncertainty affects other variables. Figure 9 plots the responses of the other four variables, which were included in the panel BVAR model, to an uncertainty shock. The results show that stock prices experience a protracted decline, the economic sentiment drops quickly but only for a short period, short-term interest rates decline and there is no significant response of prices.

While the country-level IQ_DISP indicators were used for this estimation, the use of common or global uncertainty indicators does not largely change the picture. The only discrepancy is in the response of prices. Namely, when our global measure of uncertainty is used prices respond positively, which is confirmed when Baker's EPU indicator is used. On the contrary, when the original macroeconmic uncertainty by Jurado et al. (2015) is employed, the prices record a significant decline. The direction of the economy's responses following an uncertainty shock can be useful to understand the nature of the shock. Leduc and Liu (2016) and Basu and Bundick (2017) recently argued that uncertainty shocks act very much like conctractionary aggregate demand shocks (as the shock induces a rise in unemployment and declines in inflation and the nominal interest rate) and point to nominal price rigidity and search frictions in the labour market to represent the key link between the increase of uncertainty and economic activity.

[17] Appendix II reports the identified idiosyncratic uncertainty shocks (when country-specific IQ_DISP measure described in section 3.2 is used in the panel BVAR for all 18 EU countries). It is evident that for some EU countries, there were no idiosyncratic uncertainty shocks in that period. Appendix III in turn reports the identified global uncertainty shocks (when common global uncertainty measure described in section 3.3 is used) for three sample countries. As expected given that the other endogeneous variable differ across the countries, the identified uncertainty shock is not identical albeir almost identical for all the countries.

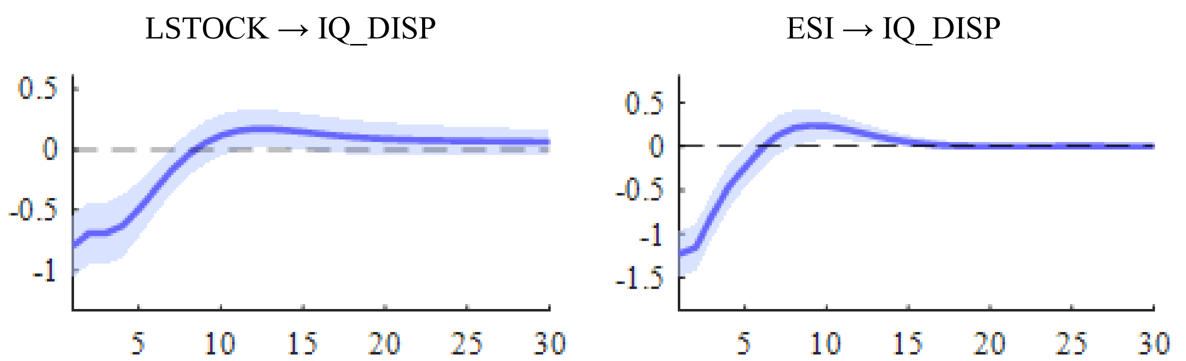
Figure 9: Impact of uncertainty shock on other variables – panel of 18 EU countries



Notes: The graph represents estimated response of stock prices, ESI, EONIA and HICP following unexpected uncertainty shock (of one standard deviation) in the panel BVAR models including 13 EA countries (AT, BE, DE, EE, EL, ES, FI, FR, IT, NL, PT, SE, SK). Uncertainty is proxied by IQ_DISP. The x-axis represents quarters. The value on y-axis represent units of each variable. Confidence bounds are of 90 %.

So far, we have looked at impact of uncertainty shocks on other variables. However, uncertainty may also increase as a consequence of other shocks. We have pointed to confidence and financial shocks, which we aim to explicitly control for in our BVAR model. While Figure 9 demonstrated that an increase in uncertainty had a negative impact on financial markets and economic confidence, Figure 10 confirms that uncertainty (as proxied by IQ_DISP indicator) also increases following a drop in stock market prices (proxy of financial shock) and the Economic Sentiment Indicator (proxy of confidence shocks). These results in overall suggest a two-sided relation between uncertainty and other adverse shocks in the EU countries: i.e., an increase in perceived uncertainty about the future may decrease economic confidence and hurt the financial sector today. This can, in turn, feed back into higher uncertainty.

Figure 10: Impact of other shocks on uncertainty – panel of 18 EU countries

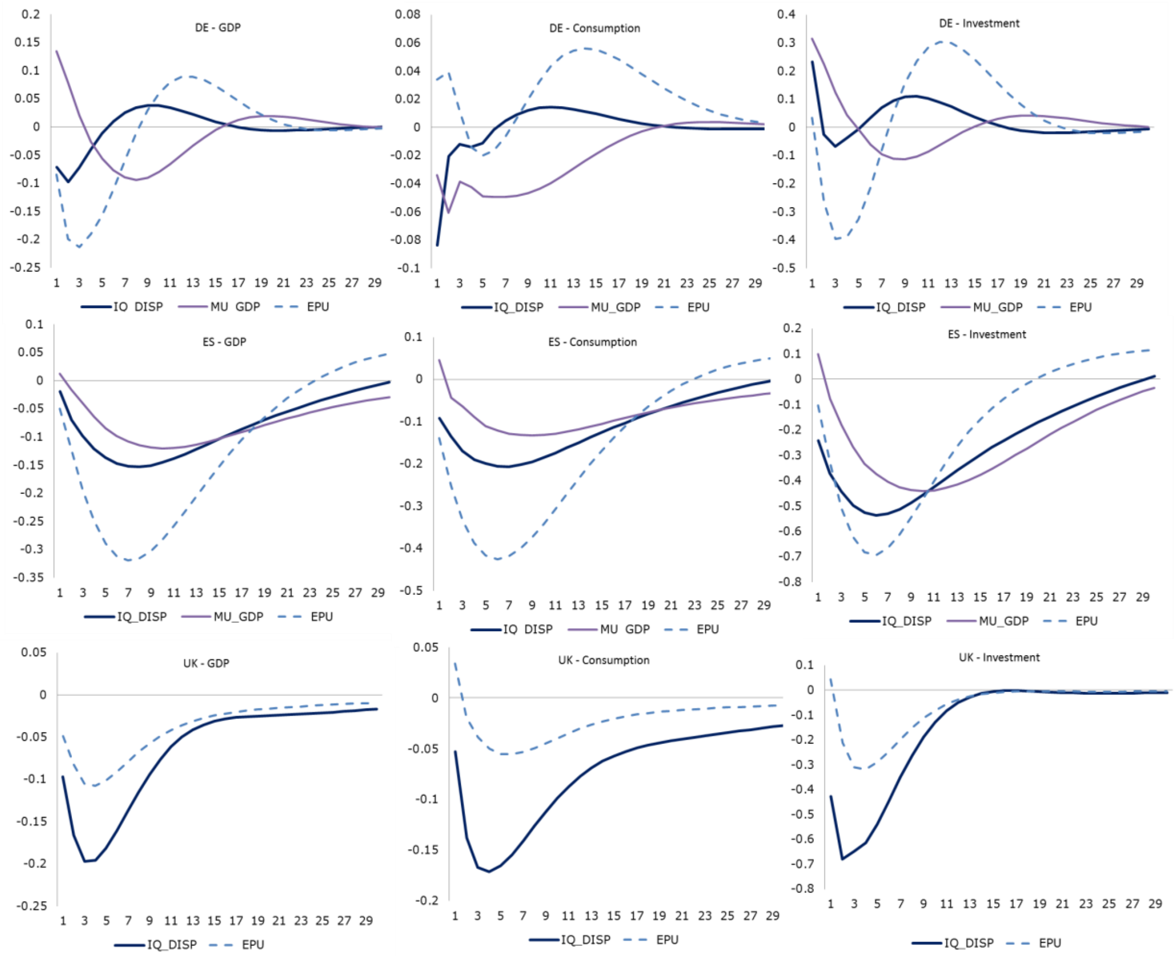


Notes: The graph represents estimated response of uncertainty indicator GDP following unexpected financial shock and sentiment shock (of one standard deviation) in the panel BVAR model incuding 18 EU countries. The x-axis represents quarters. The values on y-axis represent units of uncertainty indicator IQ_DISP. Confidence bounds are of 90 %.

5.2 The heterogeneous impact of uncertainty shocks across the EU countries

Figure 11 provides a first glimpse at the heterogeneity of responses across the EU countries. We use the example of three large Member States, namely Germany, Spain and the UK, for which several uncertainty proxies are available. Besides the IQ_DISP indicator derived from the BCS, there is the aformentioned MU_GDP indicator derived from the SPF forecast errors and the EPU indicator of Baker et al. (2016). The results show that the impact of the uncertainty shock is much weaker in Germany than in Spain and the UK, irrespective of the uncertainty measure used. The responses of German GDP, consumption and investment are not statistically significant. By contrast,[18] Spanish GDP – and mainly investment – suffers a statistically significant decline after a shock to any of the three uncertainty indicators). Even consumption falls significantly (when the EPU is used). The impact of uncertainty shocks in the UK is very pronounced in the short term, as the GDP and investment suffers statistically significant decline (consumption as well but only when the IQ_DISP indicator is used) but unlike in Spain where the impact of uncertainty on real economy fades away only after several years, the UK economy recovers within two years.

Figure 11: Impact of domestic uncertainty shock on GDP, consumption and investment – Germany, Spain and the UK

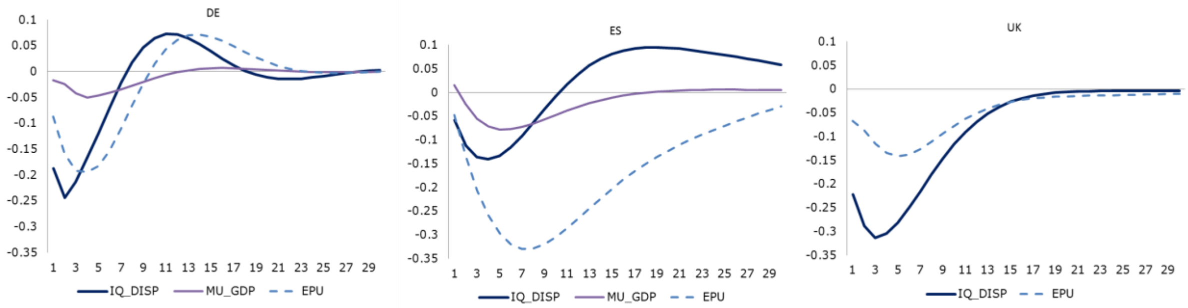


Notes: The graph represents estimated response of GDP, consumption and investment following unexpected uncertainty shock (of one standard deviation) in the BVAR model. Uncertainty is proxied by three alternative indicators: IQ_DISP, MU_GDP, EPU. The x-axis represents quarters. The values on y-axis represent percentage points.

[18] The confidence intervals along the point estimates are not plotted to save the space.

The differential impact of domestic uncertainty shocks on the economy, as from the results presented above, can be driven not only by the different *severity* of the uncertainty shocks hitting each country but also by differences in economic *resilience* across Member States. As the common EU uncertainty is relevant in driving domestic uncertainty, it is interesting to assess how Member State economies respond to common uncertainty shocks. This allos us to abstract from the different size of uncertainty shocks. Figure 12 compares the impact of such a euro-area wide uncertainty shock (the common factor of country-level measures) on the GDP of the three countries. The results suggest that GDP declines (at statistically significant levels) as a consequence of the uncertainty shock in all three economies (for IQ_DISP and EPU). However, the impact on German GDP is less persistent than on Spanish and UK GDP.

Figure 12: Impact of common EU uncertainty shocks (three alternative measures of uncertainty) on GDP of Germany, Spain and the UK



Notes: The graph represents estimated response of GDP following unexpected uncertainty shock (of one standard deviation) in the BVAR model. Uncertainty is proxied by three alternative indicators: IQ_DISP, MU_GDP, EPU. The x-axis represents quarters. The values on y-axis represent percentage points.

This preliminary evidence suggests that (i) the different indicators of uncertainty provide largely a similar picture at country level, (i) the EU countries suffer from both idiosyncratic and common uncertainty shocks, which reflect the high degree of interconnectedness of their economies, and (iii) the response to uncertainty shocks differs across Member States, reflecting both the different severity of uncertainty shocks but also differences in economic resilience.

5.3 Uncertainty shocks and structural characteristics of EU countries

Whereas it is impossible to prevent the occurrence of uncertainty shocks, it is important to uncover the factors affecting the impact of uncertainty shocks on the real economy, so as to design policies and implement structural reforms that make the economies resilient. Previous empirical evidence based on large country samples (Carrière-Swallow and Céspedes, 2013; Claeys, 2017) points to financial structures, labour and product market characteristics and even macroeconomic policies as determinants of how economies react to uncertainty shocks. A similar analysis can be carried out for EU countries across some characteristics. These can be broadly assigned to three large categories, (i) economic flexibility, (ii) economic openess, and (iii) economic structure.

(i) Economic flexibility refers mainly to the flexibility of labour and product markets. We consider labour market differences across the EU countries in wage bargaining systems and in the degrees of wage flexibility and labour mobility. *Labour market flexibility* is generally deemed as important for shock absorption capacity and recovery after shocks. *Product market flexibility* is, in turn, determined by the quality of business regulation and the degree of competition and plays an important role too in strengthening economic resilience in that it determines the flexibility of price adjustment. We proxy the labour and product market flexibility by corresponding measures from *World Economic Forum Competitiveness Database*.[19]

(ii) While trade and financial linkages across the euro area are generally very strong, the degree of *economic openness* is not the same for all the Member States. While economic openness makes an economy more vulnerable to external shocks, it may also improve its shock-absorption capacity through cross-border risk sharing (via cross-border holdings of financial assets). We use trade on GDP from the *World Development Indicators* by the World Bank. However, there is another characteristic describing the trading pattern, namely *export concentration*. Export concentration is also related to degree of product diversification and more diversified economies are likely to be more resilient. In terms of trade this means being able to substitute one export product for another. The degree of product concentration (Herfindahl-Hirschmann index) comes from UNCTAD.

(iii) The economic structure of Member States differs in terms of the contribution of different economic sectors to overall output. The share of industry and services determines the share of tradable output. *The share of value added in manufacturing* out of total GDP shall be understood as a proxy of output tradability, integration to global value chains. In addition, manufacturing is usually characterised by faster productivity growth. Therefore, higher share of manufacturing may incude greater shock absorption capacity. Another category is economic diversification. The more diversified an economy, the better it can withstand uncertainty shocks as these are unlikely to affect all the sectors equally. While there is no readily available measure of *internal economic diversification*, we proxy it by the standard deviation of the relative contribution of different productive sectors (NACE10) on the gross value added (Quarterly National Accounts from Eurostat). We assume that the more even the contribution of the ten broad sectors to overall value added, the higher is economic diversification.

We use the time average of each indicator and country including data from 1995 till 2016. Figure 13 plots these structural characteristics for the 18 EU countries. The indicators are normalized to have zero mean and bars in the graph represent the (positive or negative) deviation from the mean EU value for each indicator.

There appears to be positive correlation across the labour market flexibility and product market flexibility, i. e. countries that feature more flexible labour markets tend to have also relatively more flexible product markets (i.e., the first two bars point to the same, positive or negative, direction). However, there seems to be more cross-country dispersion in terms of labour market flexibility then product market flexibility as potentially result of increased convergence in product market stardards across the EU countries. While Denmark and the UK stand up as countries with most flexible labour and product markets, the euro area peripheral countries are well below the EU avarage.

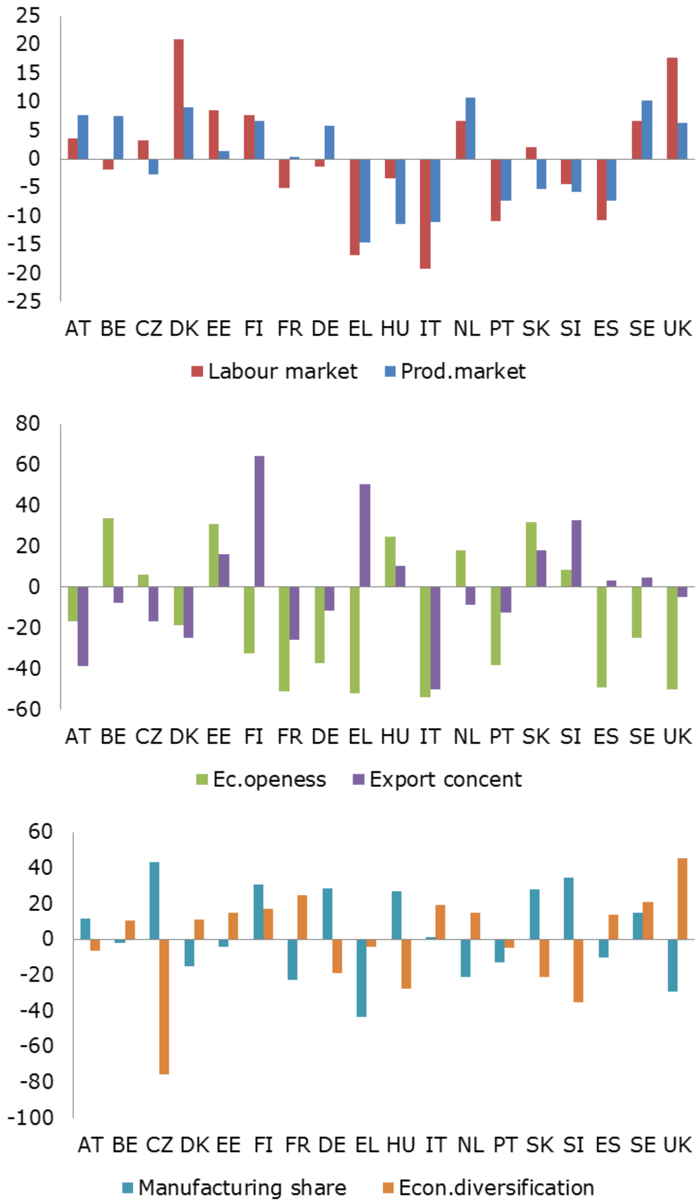
Economic openness and export concentration feature even larger dispersion across the EU countries and there seems to little relation between these two characteristics. Unsurprisingly, large EU countries are less open, which holds also for Finland, Greece and Portugal. Finland and Greece turn out to be the countries with most concentrated exports, while Austria and Italy the least.

Finally, the manufacturing share and economy diversification mostly point to opposite directions given that a large share of manufacturing is common in countries where the economic structure is skewed towards industrial sectors. While the Czech Republic and Slovenia have economies that feature relativelly large manufacturing sector and low diversification,[20] the UK has a small manufacturing share with a high diversification.

[19] These indicators are labelled in this database as pillars 7. (labour market) and 6. (product market) of the World Competitiveness Index. The score corresponding to each pillar is an average of scores related to several underlying indicators. This dataset covers period 2006-2016.

[20] The very low diversification of the Czech economy (as measured by the standard deviation of the relative share of different sectors on the gross value added) is a result of a very high share of manufacturing (26% vs. 17% average for the EU-18) and

Figure 13: Six structural charactertistics for EU countries



Notes: The graph represents devation of each structural characterstics from the sample (18 EU countries) mean value (normalized to zero).

The empirical analysis uses panel BVAR models. The panel setting accounts for country-level information while addressing the issue of the relatively short data series for individual EU countries.[21] We look at different groups of Member States according to the structural characteristics defined above. Specifically, the EU countries are split according to the scores attained for each of the characteristics. A sub-panel is constructed with Member States having more flexible labour markets versus a sub-panel of Member States with less flexible labour markets. The panel BVAR model is estimated for each group separately. As each cross-section unit contributes evenly to the overall results, results are driven relatively more by individual country experiences rather than being skewed towards larger EU countries. The reported results come from a panel BVAR with country-specific uncertainty indicators

a relatively small share of some other sectors such as real estate (8% vs. 11% for the EU-18), professional, scientific and technical activities (6.5% vs. 10% for the EU-18) or arts, entertainement and recreation (2% vs. 3% for the EU-18).

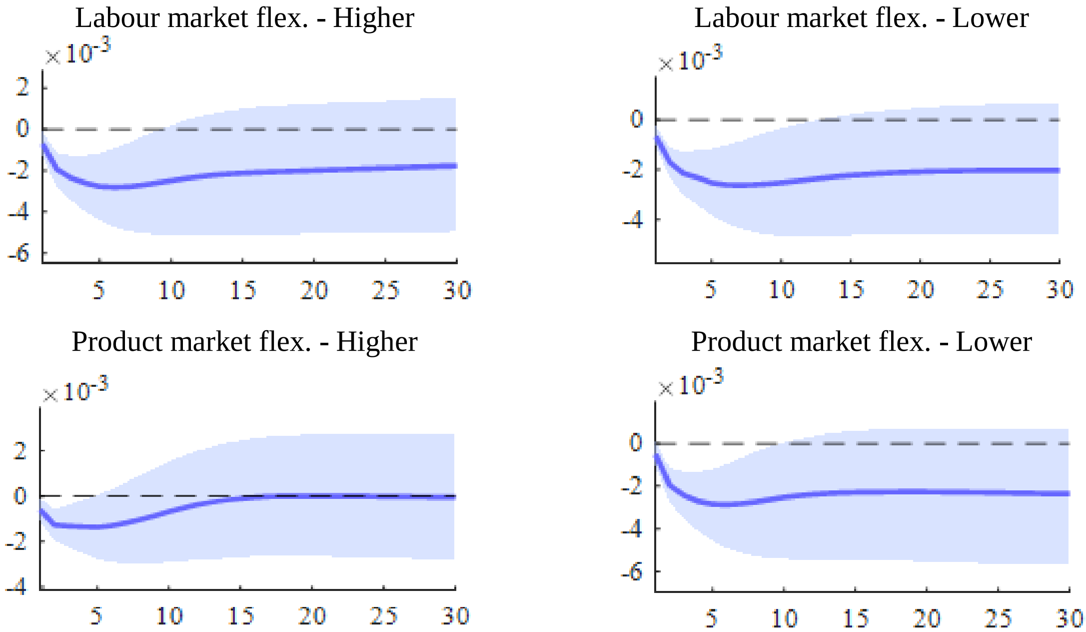
[21] Pooled estimator is used and report impulse-response functions come from the Cholesky factorization.

IQ_DISP but very similar results are obtained when the common uncertainty indicator (a common factor from country-level IQ_DISP indators, see subsection 3.2) or the global uncertainty indicator (a common factor from broad set of forecast indicators, see subsection 3.3) is used. The same holds when the sample is reduced from 18 EU countries to 13 euro area Member States, which allows additionally to employ the SPF forecast-error-based measure MU_GDP.

Figure 14 reports the impact of uncertainty shocks on GDP using impulse-response functions from the estimated panel BVAR for EU according to labour and product market flexibility respectively. While the 90 % confidence interval around the mean estimate is rather wide (which may reflect further heterogeneity of responses within each sub-group), the impact of an uncertainty shock visibly differs between the two groups. The difference is less pronounced in the case of labour markets: the negative impact on countries with less flexibile labour market is statistically significant for around a year longer than for countries with more flexible labour market. Moreover, when the sample is reduced to the EA countries and the MU_GDP measure is used,[22] the difference is much more pronounced.

Product market flexibility seems to matter more as the impact of the uncertainty shock is only marginally significant for a group of EU countries with flexible product markets, while it is clearly significant for those with less flexible product markets. The difference is driven mainly by the response of investment, but consumption seems to be (at least temporarily) affected too in countries with low labour market flexibility.[23] More flexible product markets allow, for example, for faster adjustment in prices that may be needed when the economy is hit by adverse shocks.

Figure 14: Impact of uncertainty shock on GDP in EU countries according to economic flexibility

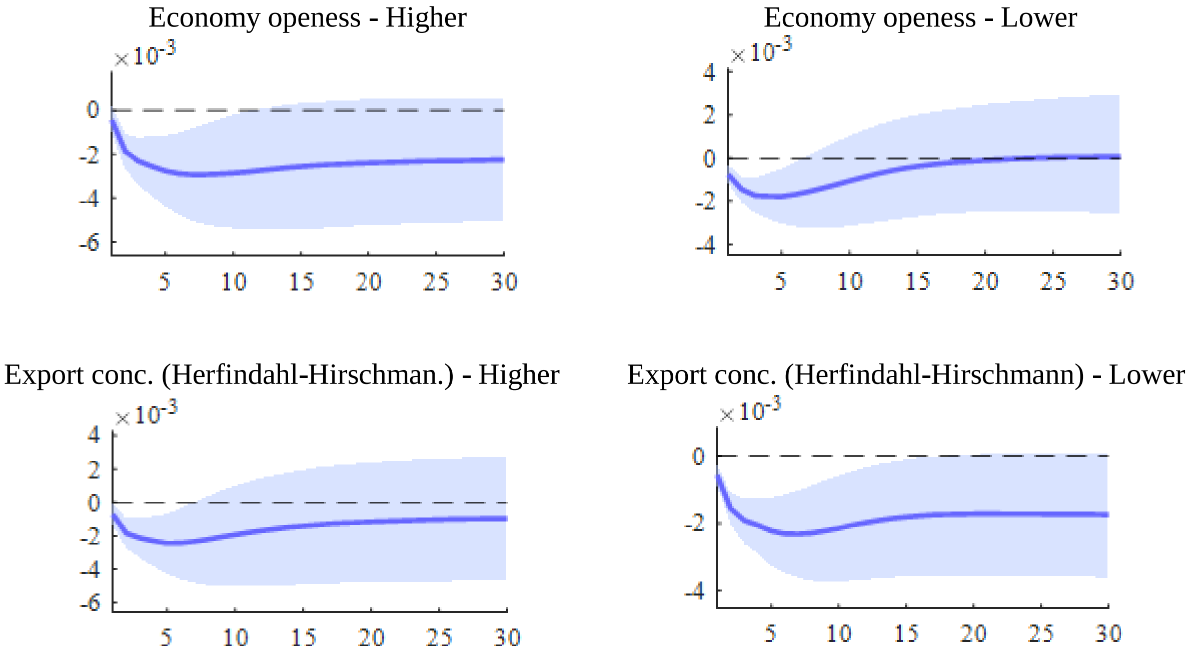


Notes: The graph represents estimated response of GDP following unexpected uncertainty shock (of one standard deviation) in the panel BVAR models. The EU countries are split into two subpanels according to labour and product market flexibility. Labour market flexibility, higher: AT, CZ, DK, EE, FI, NL, SE, SK, UK, lower: BE, DE, EL, ES, FR, HU, IT, PT, SI. Product market flexibility, higher: AT, BE, DK, DE, EE, FI, NL, SE, UK, lower: CZ, EE, ES, FR, HU, IT, PT, SI, SK. The x-axis represents quarters. The values on y-axis represent (when multiplied by 100) percentage points. Confidence bounds are of 90 %.

[22] These results are not reported here due to space constrains.
[23] These results are not reported here due to space constrains.

When we split the EU countries by economic openness, unsurprisingly, the Member States with a higher degree of openness are smaller economies, whereas the group with lower economic openness includes all large Member States (Germany, France, Italy, and Spain). Figure 15 confirms that impact of uncertainty shocks is slightly more persistent in countries that are more open than in relatively more closed economies. Given that economic openness is closely related to economic size, it can be also claimed that relativelly larger economies cushion better for uncertainty shocks. However, this results does not seem to be very robust because when we limit the sample to the EA countries and use also the other uncertainty indicator (MU_GDP), the result is just the opposite (i.e. more open economies are less effected by uncertainty shocks). Therefore, while openness can on the one hand make countries more vulnerable to external shocks, international trade, namely in the form of intra-industry trade (Krugman, 1981) and financial linkages can smooth the impact of shocks through cross-border risk sharing. The final outcome dements on the relative strenght to these two factors. However, there is more than economic openess, namely it may be importat how diversified is the export, which in turn often reflect the domestic diversification of the economy. On the other hand, stand there is an argument of comparative advantage, which is more likely hold for economies with specialized exports and for developed countries like the EU Member States, which do not rely on exports on a few raw materials as many emerging countries does (see Claeys, 2017).

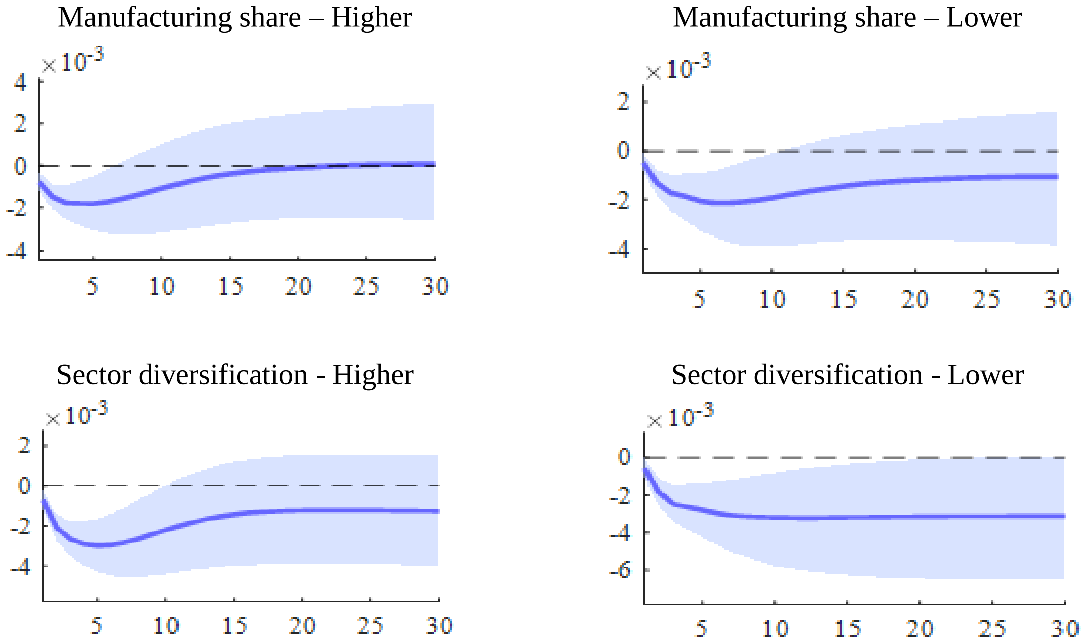
Figure 15: Impact of uncertainty shock on GDP in EU countries according to economic openness and trade characteristics



Notes: The graph represents estimated response of GDP following unexpected uncertainty shock (of one standard deviation) in the panel BVAR models. The EU countries are split into two subpanels according to economic openess, trade differentiation and export concetrantion. Economic openess, higher: AT, BE, CZ, DK, EE, HU, NL, SI, SK, lower: DE, EL, ES, FI, FR, IT, PT, SE, UK. Export concentration, higher: DK, EE, EL, ES, FI, SK, SE, SI, UK, lower: AT, BE, CZ, DE, DK, FR, IT, NL, PT. The x-axis represents quarters. The values on y-axis represent (when multiplied by 100) percentage points. Confidence bounds are of 90 %.

Finally, Figure 16 reports effects of uncertainty shocks for the Member States according to their share of value added in manufacturing. This characteristic appears relevant too: countries with higher manufacturing shares turn out to be better able to cushion uncertainty shocks. Here the share of value added in manufacturing out of total GDP shall be understood mainly as a proxy for both output tradability but manufacturing is usually characterised by faster productivity growth. However, manufacturing represents only a minor part of total output, and it may be also important how the overal production is diversified. When we split the country according to the diversification in terms of share of individual industries (NACE10) on overall output (lower standard deviation means that there are not large differences in the shares of individual industries and the economy is more diversified), it appears that more diversified economies suffer from uncertainty shocks as well but the impact is much less persistent.

Figure 16: Impact of uncertainty shock on GDP in EU countries according to economic structure



Notes: The graph represents estimated response of GDP following unexpected uncertainty shock (of one standard deviation) in the panel BVAR models. The EU countries are split into two subpanels according to manufacturing share and sectoral diversification. Manufacturing share, higher: AT, CZ, EE, FI, DE, HU, SE, SI, SK, lower: BE, DK, EL, ES, FR, IT, NL, PT, UK. Sectoral diversification, higher: DK, EE, ES, FI, FR, IT, NL, SE, UK, lower: AT, BE, CZ, DE, EL, HU, PT, SI, SK. The x-axis represents quarters. The values on y-axis represent (when multiplied by 100) percentage points. Confidence bounds are of 90 %.

6. Concluding Remarks

Spells of uncertainty are argued to drive rapid drops in economic activity. Wait-and-see behavior and risk aversion in combination with other frictions can make these periods of increased uncertainty an important driver of the business cycle. These effects can be present in European countries, and even reinforced in those where diverse frictions (labour market, product market, financial system) are particularly strong. However, there can be other structural features of countries (economic openness, product diversification) that may mitigate how an economy responds to uncertainty shock. Besides, the EU countries are small and open, and hence likely undergo the effect not just of domestic uncertainty but also the effect of uncertainty spilling over from the EU level or even from global economy.

This paper employs novel proxies of uncertainty both at the country and international level and use them to test the differential impact of domestic, common European and global uncertainty shocks. Domestic uncertainty is derived from dispersion in the Business and Consumer Surveys, administered by the European Commission, and the the EU-wide uncertainty is derived as the main common factor underlying the domestic measures. This common component is quite strong, which suggests that unexpected spikes in uncertainty (uncertainty shocks) are often common rather than idiosyncratic events. Finally, as a measure of global uncertainty, we use the common factor behind forecaster errors in G7 countries as in Jurado et al. (2015) or Claeys (2017).

We then estimate a Bayesian (panel) VAR over the period 1996-2016 to test the impact of uncertainty shocks on the real GDP, consumption and investment. Overall results suggest that the real output in the EU countries is negatively affected by spikes in uncertainty, which is driven mainly by investment. Unlike for the US, there is little evidence that after initially declining, economic activity termporarily overshoots during recoveries thereby making up for earlier output declines. We also find a two-sided relationship between uncertainty shocks and confidence / financial shocks, whereby shocks feedback and amplify each other.

The responses to uncertainty shocks vary across Member States, which cannot be only attributed to different size of shock, but also importantly reflect differences in the structural characteristics of countries. Specifically, we test responses to uncertainty shocks for diverse subsamples of EU countries, which are also assessed across groupings with several structural characteristics. Namely, the Member States with more flexible labour markets and product markets seem to better weather uncertainty shocks. Likewise, higher manufacturing share and higher economic diversification contribute to dampening the impact of uncertainty. The role of economic openness, however, is more ambiguous.

The distinction between the subsample is not always very sharp. It may be because that the differences across EU countries are not that glaring as when one considers large and very heterogeneous country panel (Carrière-Swallow and Céspedes, 2013, Clayes, 2017). Moreover, indicators imperfectly measure the degree of rigidity of flexibility by which an economy can cope with uncertainty shocks. Finally, we simply assume a split into two even group of countries but a proper transition model with a latent threshold at which the economic responses differ, as in Claeys (2017), would allow splitting the groups of countries in less rudimentary ways. Unfortunatelly, the country sample is too small to allow for a very asymmetric split.

Spikes in subjective perception of uncertainty cannot be entirely avoided as they can originate outside the economic system, and economic theory suggests that psychological factors such as perceived uncertainty represent an inherent driver of economic behaviour. However, as our analysis confirmed there are certain features of economies that make them more prone to suffer the effects of an uncertainty shock. Moreover, the aforementioned structural features may also affect the subjective perception of risk and uncertainty by economic agents, thus reinforcing the link between structural characteristics and uncertainty shocks. On the positive side, the analysis presented in this paper points to some areas where structural reforms might prove particularly useful to strengthen resilience, therefore dampening the effects of adverse shocks.

References

Angeletos, G.M. and J. La'O (2013). ‘Sentiments’, *Econometrica*, No 81(2), pp. 739-779.

Bacchetta, P. and E. Van Wincoop (2013). ‘Sudden spikes in global risk’, *Journal of International Economics*, No 89(2), pp. 511-521.

Bachmann, R., S. Elstner and E.R. Sims (2013). ‘Uncertainty and economic activity: Evidence from business survey data’. *American Economic Journal: Macroeconomics*, No. 5(2), pp. 217-249.

Bachmann, R. and C. Bayer, C. (2013). ‘Wait-and-See’business cycles?’, *Journal of Monetary Economics*, No 60(6), 704-719.

Balta, N, I. Valdes Fernandez and E. Ruscher (2013). 'Assessing the impact of uncertainty on consumption and investment', *Quarterly Report on the Euro Area*, Vol. 12, No 2, pp. 7-16;

Baker, S.R., N. Bloom and S.J. Davis (2016). 'Measuring economic policy uncertainty', *The Quarterly Journal of Economics*, No. 131(4), pp. 1593-1636.

Baker, S.R. and N. Bloom (2013). 'Does uncertainty reduce growth? Using disasters as natural experiments', National Bureau of Economic Research Working Paper No. 19475.

Barsky, R.B. and E.R. Sims (2011). 'News shocks and business cycles', *Journal of Monetary Economics*, No 58(3), pp. 273-289.

Basu, S. and B. Bundick (2017). 'Uncertainty shocks in a model of effective demand', *Econometrica*, No. 85 (3), pp. 937-958.

Batchelor, R. (2001). 'How useful are the forecasts of intergovernmental agencies? The IMF and OECD versus the consensus', *Applied Economics*, No. 33(2), pp. 225-235.

Benati, L. (2014). 'Economic policy uncertainty and the Great recession', University of Bern, mimeo.

Berger, T., S. Grabert, and B. Kempa (2017). 'Global macroeconomic uncertainty', *Journal of Macroeconomics*, No 53, pp. 42–56;

Bernanke, B.S. (1983). 'Irreversibility, uncertainty, and cyclical investment', *The Quarterly Journal of Economics*, No 98(1), pp. 85-106.

Bianchi, F., and L. Melosi (2014) 'Dormant shocks and Fiscal virtue', *NBER Macroeconomics Annual*, No 28(1), 1-46.

Bloom, N. (2009). 'The impact of uncertainty shocks', *Econometrica*, No. 77(3), pp. 623-685.

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S.J. Terry (2012). 'Really uncertain business cycles', *National Bureau of Economic Research Working Paper*, No. 18245.

Bonciani, D. and B. van Roye (2016). 'Uncertainty shocks, banking frictions and economic activity', *Journal of Economic Dynamics and Control*, No. 73, pp. 200-219.

Caballero, R.J. (1990). 'Consumption puzzles and precautionary savings', *Journal of Monetary Economics*, No. 25(1), pp. 113-136.

Caggiano, G., E. Castelnuovo and N. Groshenny (2014). 'Uncertainty shocks and unemployment dynamics in US recessions', *Journal of Monetary Economics*, No 67, pp 78-92.

Carrière-Swallow, Y. and L.F. Céspedes (2013). 'The impact of uncertainty shocks in emerging economies', *Journal of International Economics*, No. 90(2), pp. 316-325.

Cesa-Bianchi, A., Pesaran, M., & Rebucci, A. (2014). 'Uncertainty and economic activity: A global perspective', CESifo Working Paper Series, No 4736.

Christiano, L., R. Motto, and M. Rostagno (2014). 'Risk shocks', *American Economic Review*, No 104(1), pp. 27-65.

Claeys, P. (2017). 'Uncertainty spillover and policy reactions', *Ensayos sobre Política Económica*, No 35(82), pp. 64-77.

Claessens, S., K.A. Kose and M.E. Terrones, M. E. (2011). 'Recessions and financial disruptions in emerging markets: A bird's eye view', *Central Banking, Analysis, and Economic Policies Book Series*, No 16, 59-104.

Colombo, V. (2013). 'Economic policy uncertainty in the US: Does it matter for the euro area?', *Economics Letters*, 121(1), 39-42.

Dovern, J. (2015). 'A multivariate analysis of forecast disagreement: Confronting models of disagreement with survey data', *European Economic Review*, 80, 16-35.

Duca, J.V. and J.L. Saving (2018). 'What drives economic policy uncertainty in the long and short runs: European and U.S. evidence over several decades', *Journal of Macroeconomics*, Vol. 55, 128-145

Fernandez-Villaverde, J., P. Guerron-Quintana, K. Kuester, and J. Rubio-Ramirez (2015). 'Fiscal volatility shocks and economic activity', *The American Economic Review*, No 105(11), pp. 3352-3384.

Gieseck, A. and Y. Largent (2016). 'The Impact of Macroeconomic Uncertainty on Activity in the Euro Area', *Review of Economics*, No 67(1), pp. 25-52;

Gilchrist, S., J.W. Sim, and E. Zakrajšek (2014). 'Uncertainty, financial frictions, and investment dynamics', *National Bureau of Economic Research Working Paper*, No. 20038.

Gilchrist, S., and J. Williams (2005). 'Investment, capacity, and uncertainty: A putty-clay approach', *Review of Economic Dynamics*, No. 8(1), pp. 1-27.

Girardi, A. and A. Reuter (2016), 'New uncertainty measures for the euro area using survey data', *Oxford Economic Papers*, No. 69(1), pp. 278-300.

Gourio, F., M. Siemer and A. Verdelhan (2013). 'International risk cycles', *Journal of International Economics*, No 89(2), pp. 471–484.

Jaimovich, N. and S. Rebelo (2008). 'News and business cycles in open economies', *Journal of Money, Credit and Banking*, No. 40(8), pp. 1699-1711.

Jurado, K., S.C. Ludvigson, and S. Ng (2015). 'Measuring uncertainty', *The American Economic Review*, No. 105(3), pp. 1177-1216.

Keane, M.P. and D.E. Runkle (1990). 'Testing the rationality of price forecasts: New evidence from panel data', *The American Economic Review*, 714-735.

Klose, J. and B. Weigert (2014). 'Sovereign yield spreads during the euro crisis: Fundamental factors versus redenomination risk', *International Finance*, no 17(1), pp. 25-50.

Klößner, S., and R. Sekkel (2014). 'International spillovers of policy uncertainty', *Economics Letters*, No 124(3), 508-512.

Krugman, P.R. (1981), 'Intraindustry specialization and the gains from trade', *Journal of Political Economy*, No 89(5), pp. 959-973.

Leduc, S. and Z. Liu (2016). 'Uncertainty shocks are aggregate demand shocks', *Journal of Monetary Economics*, No 82, pp. 20-35.

Meinen, P. And O. Röhe (2017). 'On measuring uncertainty and its impact on investment: Cross-country evidence from the euro area', *European Economic Review*, No 92, pp. 161-179.

Mumtaz, H., and P. Surico (2013). 'Policy uncertainty and aggregate fluctuations', London Business School and Queen Mary University of London, mimeo.

Mumtaz, H. and K. Theodoridis (2015). 'The international transmission of volatility shocks: An empirical analysis', *Journal of the European Economic Association*, No 13(3), pp. 512-533.

Popescu, A., and F.R. Smets (2010). 'Uncertainty, risk-taking, and the business-cycle in Germany', *CESifo Economic Studies*, No 56, pp. 596-626.

Rossi, B. and T. Sekhposyan (2015), 'Macroeconomic uncertainty indices based on nowcast and forecast error distributions', *The American Economic Review*, No. 105(5), pp. 650-655.

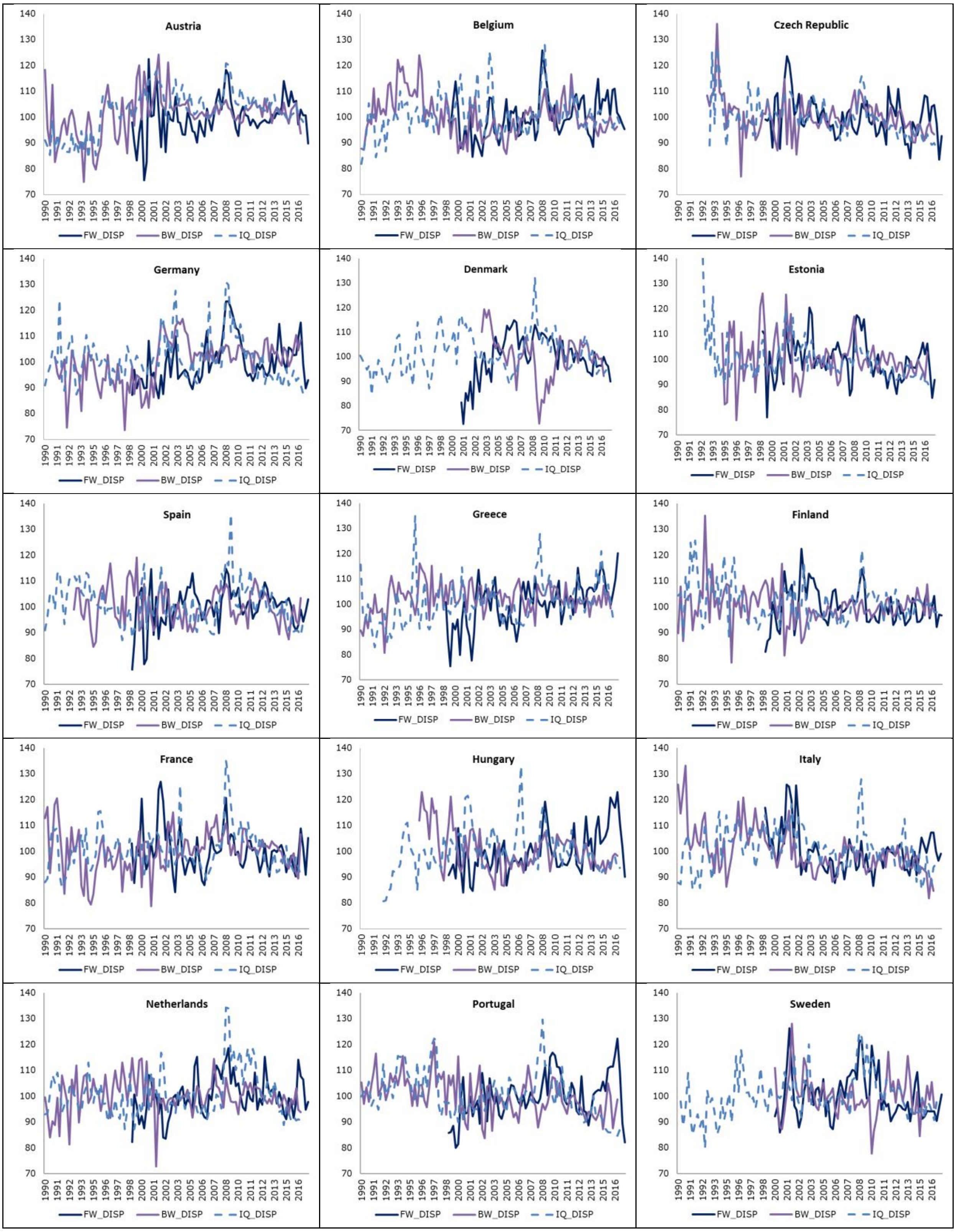
Rossi, B. and T. Sekhposyan (2016). 'Macroeconomic uncertainty indices for the euro area and its individual member countries', *Empirical Economics*, No 53(1), pp. 1-22.

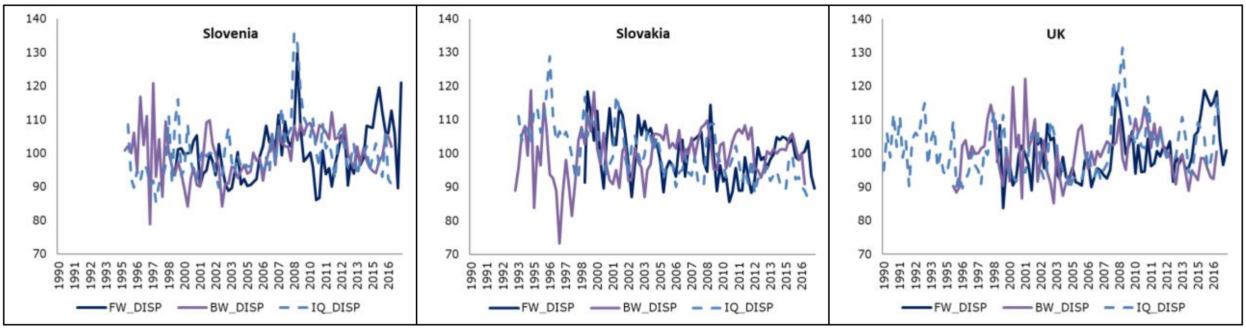
Stock, J.H. and M.W. Watson (2005). 'Implications of dynamic factor models for VAR analysis', No. National Bureau of Economic Research Working Paper, No 11467.

Stock, J. H. and M.W. Watson (2012). 'Disentangling the channels of the 2007-2009 recession', National Bureau of Economic Research Working Paper, No 18094.

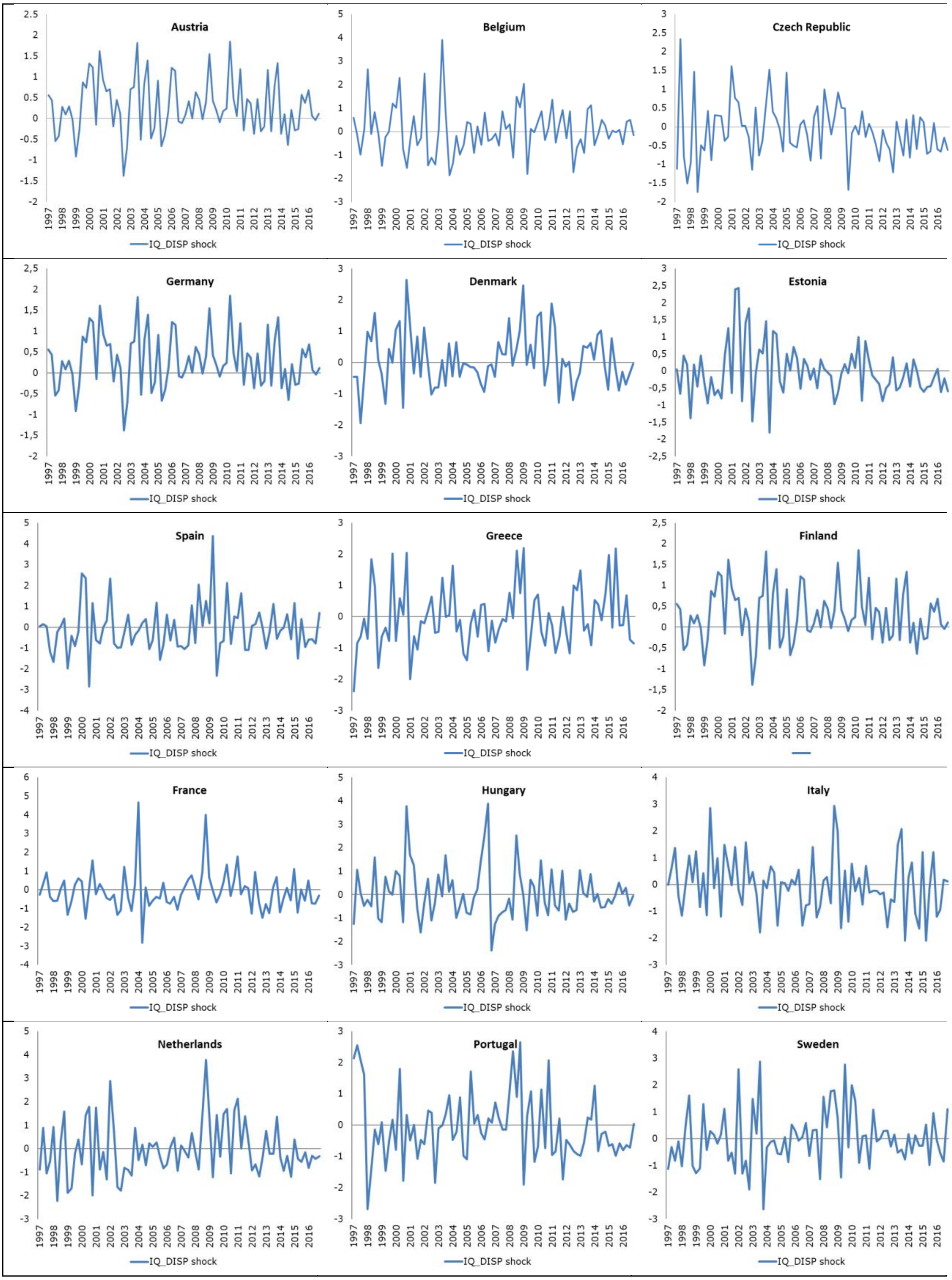
Trueman, B. (1994). 'Analyst forecasts and herding behavior', *Review of Financial Studies*, No 7(1), pp 97-124.

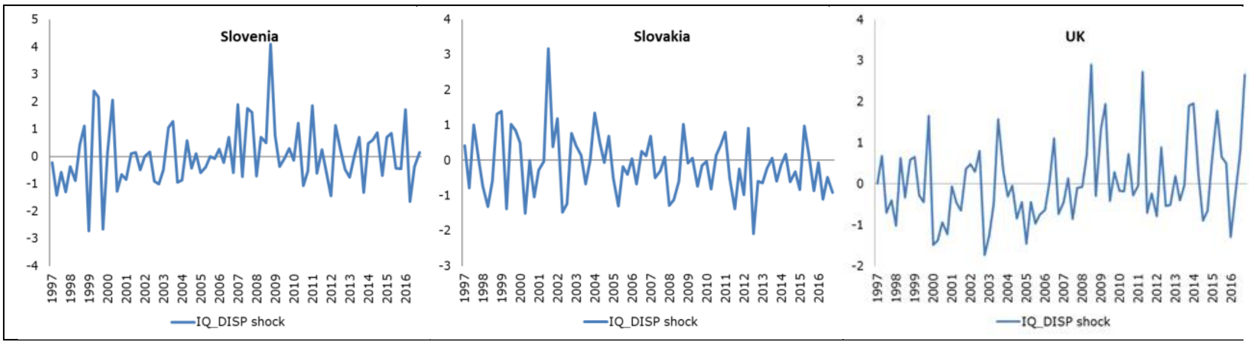
Appendix I: Uncertaintly measures derived from the BCS



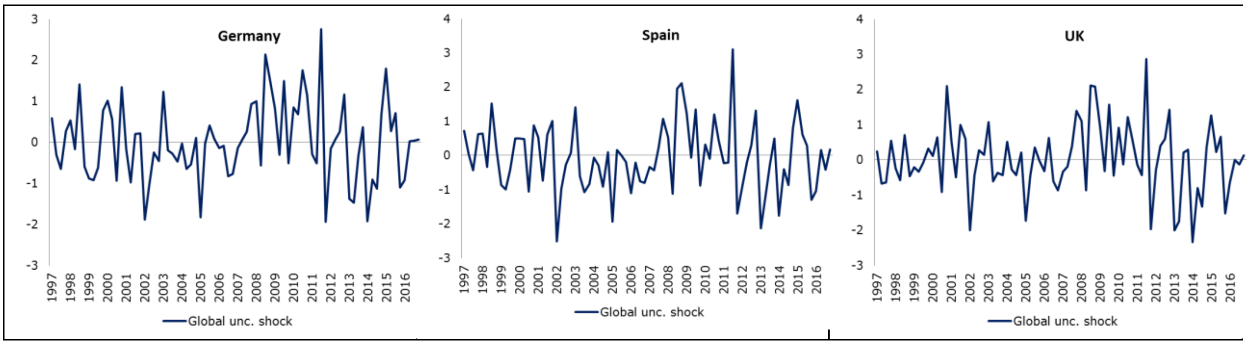

Slovenia
Slovakia
UK
FW_DISP
BW_DISP
IQ_DISP

Appendix II: Uncertaintly shocks indentified in panel VAR of 18 EU countries (IQ_DISP variable)

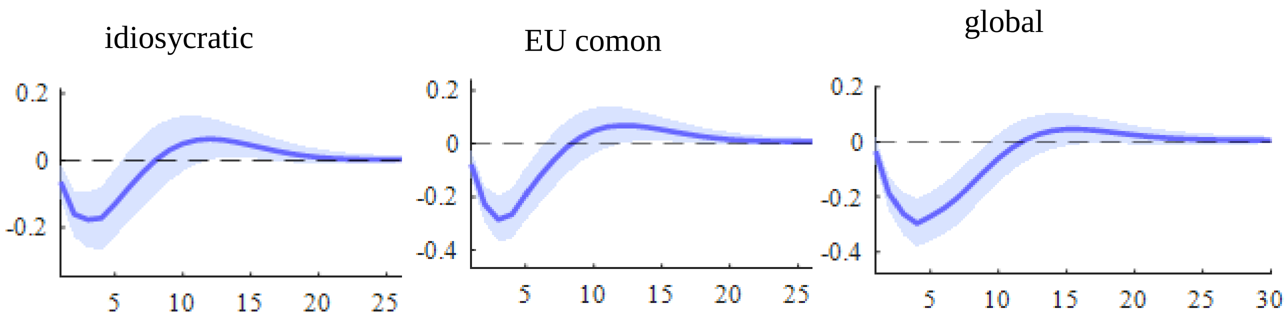




Appendix III: Global shock indentified in panel VAR of 18 EU countries



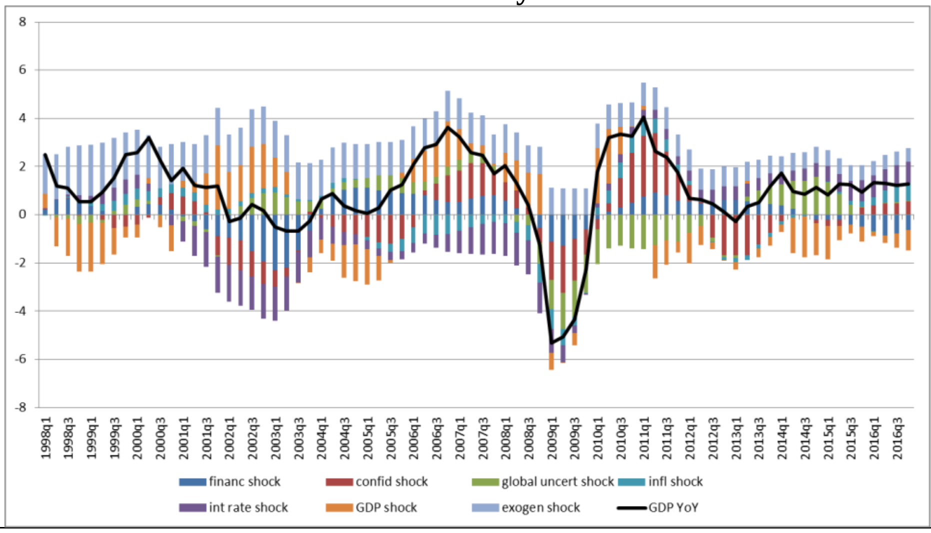
Appendix IV: Impact of uncertainty shocks on GDP (YoY growth rates)



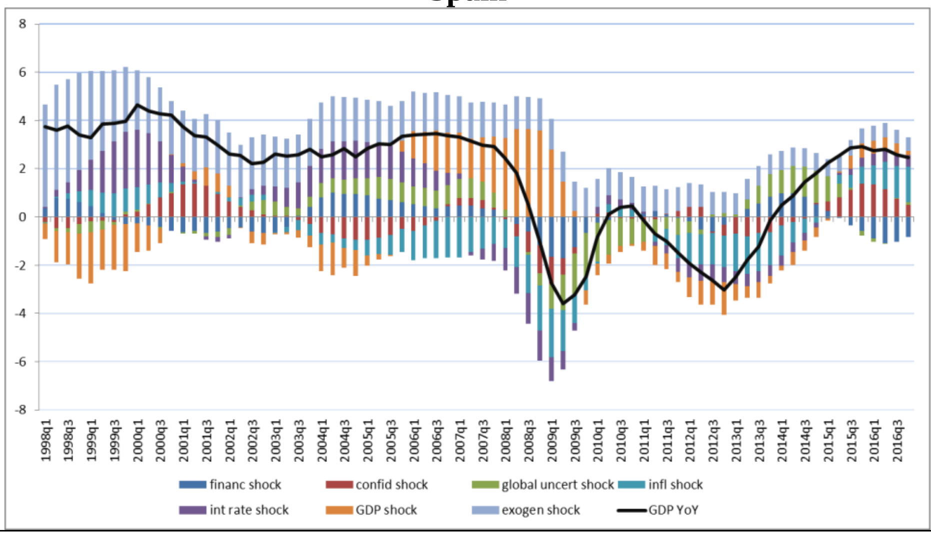
Notes: The graph represents estimated response of GDP following unexpected (idiosyncratic, EU common and global) uncertainty shock (of one standard deviation) in the panel BVAR model incuding 18 EU countries. The x-axis represents quarters. The values on y-axis represent percentage points of GDP growth. Confidence bounds are of 90 %.

Appendix V: Historical decomposition of GDP (YoY growth rates)

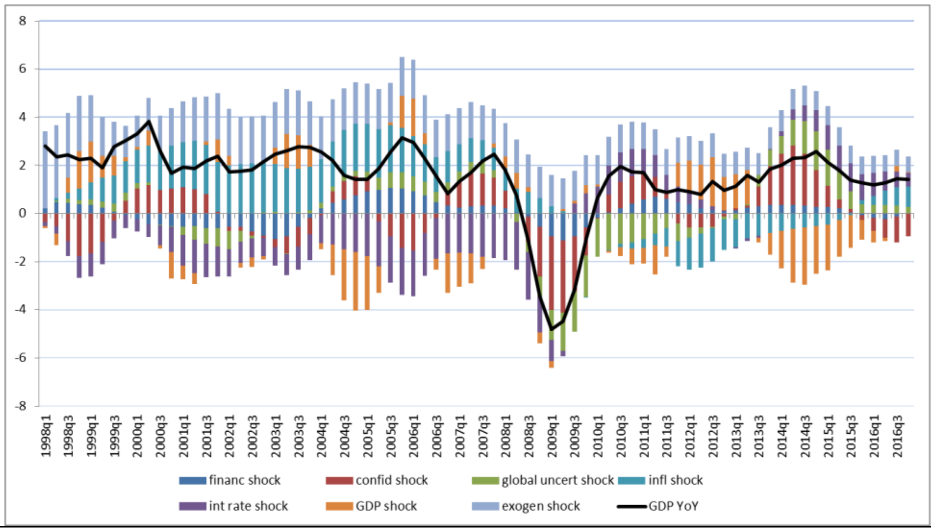
Germany



Spain



the UK



Notes: The graph represents estimated historical variance decomposition of GDP growth as attributed to shocks in endogeneous variables included in the BVAR model including 18 EU countries as well as to exogeneous shocksck (of one standard deviation) in the panel BVAR model incuding 18 EU countries.