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Claeys, Peter; Vašíček, Bořek
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Responses on a Panel of EU Countries

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Oxana Babecká Kucharčuková (Czech National Bank)

Project Coordinator: Michal Franta

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Peter Claeys, Bořek Vašíček

Transmission of Uncertainty Shocks: Learning from Heterogeneous Responses on a Panel of EU Countries

Peter Claeys and Bořek Vašíček *

Abstract

Numerous recent studies, starting with Bloom (2009), highlight the impact of varying uncertainty levels on economic activity. These studies mostly focus on 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 and employ 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 subsequently derived by means of 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 are not driven by the business cycle. The results suggest that real output in EU countries drops after spikes in uncertainty, mainly as a result of lower investment. Unlike for the U.S., there is little evidence of activity overshooting following this initial fall. The responses to uncertainty shocks vary across Member States. These differences can be attributed not mainly to different shock sizes, but rather to cross-country structural characteristics. Member States with more flexible labour markets and product markets seem to weather uncertainty shocks better. Likewise, a higher manufacturing share and higher economic diversification help dampen the impact of uncertainty shocks. The role of economic openness is more ambiguous.

* Peter Claeys, Faculty of Economics and Social Sciences, Vrije Universiteit Brussel, Department of Applied Economics, Pleinlaan 2, 1050 Brussels, Belgium. Email: peter.claeys@vub.be.
Bořek Vašíček, European Commission, DG Economic and Financial Affairs, Rue de la Loi 170, 1047 Brussels, Belgium, Email: borek.vasicek@gmail.com.

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Abstrakt

Počínaje příspěvkem Blooma (2009) mnoho empirických prací posledních let potvrdilo význam nejistoty, resp. jejích změn v čase, na ekonomickou aktivitu. Tyto práce se obvykle zaměřují na jednotlivé země a poznatků pro širší skupiny zemí je dosud velmi málo. Cílem tohoto článku je analýza dopadů šoků nejistoty na ekonomický vývoj členských zemí EU při využití (panelových) modelů BVAR. Analýza využívá nových indikátorů nejistoty a explicitně rozlišuje mezi šoky domácími, celoevropskými a globálními. Indikátory domácí nejistoty vycházejí z dat z Business and Consumer Surveys administrovaných Evropskou komisí. Indikátor společné evropské nejistoty je pak odvozen z národních indikátorů pomocí faktorového modelu. Indikátor globální nejistoty, který je inspirován prací Jurado et al. (2015), je extrahován jako společný faktor z širokého vzorku indikátorů v prognózách, přičemž tento společný faktor není ovlivněn fází hospodářského cyklu. Výsledky analýzy naznačují, že reálný hospodářský výstup zemí EU v důsledku nárůstu nejistoty klesá, což se děje především prostřednictvím poklesu investic. Na rozdíl od výsledků pro USA naše výsledky pro EU nenaznačují, že by po původním poklesu ekonomické aktivity docházelo jejímu k přestřelení. Dopad šokových změn nejistoty do reálné ekonomiky se výrazně liší napříč členskými zeměmi, přičemž vysvětlení této heterogenity nelze hledat v různé intenzitě domácích šoků, ale spíše v strukturálních rozdílech mezi zeměmi. Členské země EU, které disponují flexibilnějšími pracovními a produktovými trhy, jsou schopny šokovým změnám nejistoty odolávat lépe. Podobně vyšší podíl zpracovatelského průmyslu a vyšší diverzifikace ekonomiky pomáhají dopad šokových změn nejistoty tlumit. Význam otevřenosti ekonomiky je méně jednoznačný.

JEL Codes: E32, G12, G35.

Keywords: Bayesian VAR, economic activity, uncertainty.

Nontechnical Summary

Rising uncertainty levels affect households and firms. When uncertainty is high, consumers, for instance, might postpone consumption of durable goods and increase precautionary savings. Firms may adopt a similar ‘wait-and-see’ approach and keep investment on hold until the uncertainty is resolved. This ‘wait-and-see’ effect initially depresses investment, but, once the uncertainty is resolved, it should create an investment boom as firms catch up on executing planned projects. The financial sector may find it difficult to evaluate the riskiness of projects, resulting in credit rationing, especially for firms with weaker balance sheets. Banks as financial intermediaries might themselves suffer problems with external financing. Risk aversion of economic agents, perceived irreversibility of some decisions and financial frictions cause uncertainty to have real impacts.

The source of uncertainty is not always obvious. First, uncertainty can be due to political, economic or financial uncertainty and can therefore easily be confused with other types of shocks, related to policymaking itself, the behaviour of financial markets or fluctuations in the business cycle. We therefore control for different sources of uncertainty in the empirical analysis, applying panel BVAR models including alternative shocks. Second, uncertainty is a phenomenon that domestic agents increasingly face as a result of external events. We therefore explicitly distinguish between domestic, common and global uncertainty shocks and employ 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 subsequently derived by means of a factor model. The global uncertainty indicator is taken from forecast indicators in G7 countries.

Empirical studies find that shocks to uncertainty result in relevant and significant drops in economic activity. We confirm similar effects across EU countries, in particular on investment. Unlike for the U.S., there is little evidence of activity overshooting following this initial fall.

The transmission of these shocks is less clear. Not all EU countries see a similarly strong reaction. These differences can be attributed not to different shock sizes, but rather to cross-country structural characteristics. Financial structure, labour and product market characteristics and even macroeconomic policies determine 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 openness and (iii) economic structure.

Member States with more flexible labour markets and product markets seem to weather uncertainty shocks better. Likewise, a higher manufacturing share and higher economic diversification help dampen the impact of uncertainty shocks. The role of economic openness is more ambiguous.

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 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 the uncertainty is resolved, it should create an investment boom as firms catch up on planned projects. The financial sector may find it difficult to evaluate the riskiness of projects, resulting in credit rationing, especially for firms with weaker balance sheets. Banks as financial intermediaries might themselves suffer problems with external financing.¹ *Risk aversion* of economic agents, perceived *irreversibility* of some decisions (investment, for instance) and *financial frictions* cause uncertainty to have real impacts.

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 and employ 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 subsequently be derived from a factor model of these indicators. Finally, the global uncertainty indicator – inspired by Dovern (2015) and Jurado et al. (2015) – is extracted as a common factor from a broad set of forecast indicators that are 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 (i) the structural characteristics that may explain differences in country-specific responses to (ii) uncertainty shocks that come from different sources. Differences can arise because the transmission of uncertainty shocks works via financial channels, so 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 organized 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 methodology. The empirical results tracking the impact of uncertainty shocks on the real economy by means of (panel) BVARs are presented in Section 5. The analysis provides evidence (i) for

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

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 in GDP and economic diversification), (iii) on the differences between the impacts of idiosyncratic, common and global uncertainty shocks, and (iv) on the nexus between uncertainty and other shocks. Section 6 concludes.

2. Related Literature

Sudden changes in the level of aggregate uncertainty facing economic agents have been shown to be an important shock driving the U.S. business cycle. Using a simple reduced-form VAR, Bloom (2009) estimates on firm-level data that U.S. industrial production is reduced by approximately 1% in response to an uncertainty shock. The initial drop is followed by a swift recovery and a subsequent overshoot in production, which surpasses its trend by around 1%. The role of uncertainty shocks in driving business cycles is surprisingly large: changes in the level of uncertainty contribute about a quarter of the overall variance in 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 in Mumtaz and Surico (2013), who append a stochastic volatility specification to the VAR time-varying covariance matrix, Caggiano et al. (2013), who use smooth-transition VARs, and Benati (2014), who applies sign restrictions to 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 large 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. Carrière-Swallow and Céspedes (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. Relative 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. A similar analysis has been carried out in Claeys (2017), who also stresses the role of financial development alongside fiscal policy and fixed exchange rate regimes as sources that dampen the transmission of uncertainty to the real economy in advanced countries.

Other studies explicitly test the spillover of uncertainty shocks across countries. Mumtaz and Theodoridis (2015) look at how U.S. GDP growth volatility shocks spill over to the UK (in an 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 that of euro area policy uncertainty. Klößner and Sekkel (2014) find that spillovers between G7 countries

(measured by the Diebold-Yilmaz spillover index) explain up to one half of all the movements in policy uncertainty recorded at the height of the 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 assets over 33 countries and is driven by the financial prices of over 109 assets worldwide. They assume that both volatility and real economic activity are determined by unobserved common factors and then derive 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 the Member States. Some evidence for the euro area is provided by Balta et al. (2013), Gieseck and Largent (2016) and Girardi and Reuter (2016). Meinen and Röhe (2017) offer evidence for the four largest EA countries (Germany, France, Italy and Spain) using diverse measures of uncertainty. 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 U.S. that after some time economic activity rebounded and strongly offset its original decline (overshooting). However, little is known about the differential impact of uncertainty shocks across EU Member States.

Although these empirical results demonstrate the first-order impact of uncertainty shocks on economic activity, 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 boost 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 their investment plans. This conclusion holds even more strongly 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 uses 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 the U.S. 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 sizeable 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 that 'wait-and-see' dynamics are not a major source of business cycle fluctuations.²

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

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 offers various methods for proxying the *unobservable* level of uncertainty, typically at country level. Specifically, five classes of *observable* indicators have been employed.

(i) **Financial market indicators** are most commonly given by the second moments, i.e. the implied or historical volatility of the stock market, the bond market or the exchange rate. Examples of such indicators include the VIX and VSTOXX indices of implied stock market volatility. This type of uncertainty proxy was popularized by Bloom (2009) using the VXO, an implied volatility index based on trading in 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 the terms 'uncertainty' and 'economic policy' (and variations thereof) and on the number of expiring tax provisions and the dispersion in economists' forecasts about government spending and inflation levels. They showed that innovations to this index cause statistically significant declines in both employment and industrial production. In an earlier paper, Baker and Bloom (2013) looked at the variation in natural disasters, terrorist attacks and so on across countries and likewise found a negative impact on both output growth and its volatility.

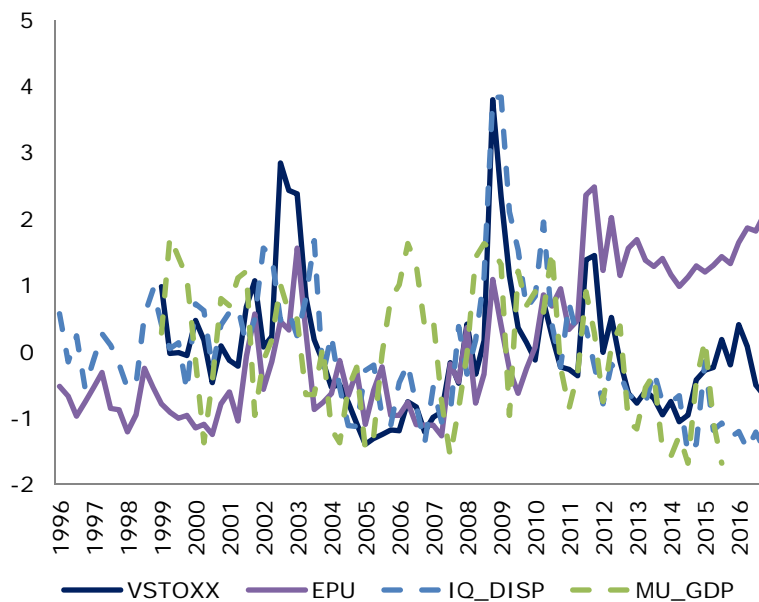
(iii) **Micro-based indicators** use the cross-sectional dispersion of profits or productivity across firms or industries (Bloom et al., 2012).

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

(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). Dovern (2015) develops different measures to track multivariate disagreement between forecasters. For example, a single forecaster's projection for inflation might be correlated with consistent views on output growth. Forecasters may not 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 an ex-post comparison of the forecast using the unconditional likelihood of the observed outcome.

Figure 1 plots examples of each of these indicators for the euro area aggregate,³ namely implied stock market volatility (VSTOXX), the economic policy uncertainty index (EPU), the BCS-based dispersion indicator (IQ_DISP) and macroeconomic uncertainty inferred from GDP forecast errors from the Survey of Professional Forecasters (MU_GDP). The indications based on the different measures tend to coincide around the most pronounced peaks, such as the period of 2001–2003 (the dot-com bubble burst, the World Trade Centre attacks and the Iraq War), the beginning of the global financial crisis in 2008–2009 and the euro area debt crisis in 2012. Substantial dispersion between economic policy uncertainty and other indicators is observed for 2016, but this gradually faded away during 2017.

Figure 1: Different Uncertainty Indicators for Euro Area



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

Unfortunately, there is no single general indicator of uncertainty, as each indicator has its advantages and pitfalls.

(i) Some indicators can be calculated relatively easily, while others are more complex to derive. The *real-time availability* of the indicators differs: the data used to calculate them, 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* of the whole economy and each of them may reflect *other concepts* unrelated to uncertainty. For example, stock market volatility fluctuates with 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 shocks and swings in general risk aversion. Dovern (2015) and Jurado et al. (2015) criticize the most

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

common proxies as being unrepresentative of macroeconomic uncertainty. In fact, most proxies focus on the volatility of a single series, such as 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, 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. Financial market indicators and news-based indicators are available only for the largest EU countries and the euro area as a whole and micro-based indicators only for a few EU countries. Conversely, 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 on whether the different indicators should be understood as proxies for more generalized unobservable uncertainty, or whether they track one specific type of uncertainty related to a specific type of event (such as 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 Commission⁴ 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, although the time span and coverage may differ somewhat. The biggest advantage of survey-based uncertainty indicators is their representativeness, as they cover a wide range of businesses (industry, services, retail trade and construction) as well as the 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, the dispersion in the answers to the surveys may also be driven by forces other than perceived uncertainty, specifically the heterogeneity of agents, which affects their opinions.

The monthly BCS asks around 120,000 businesses about production, orders and employment and around 40,000 consumers about their financial situation and their evaluation of macroeconomic developments. The replies to each question in the BCS are summarized in terms of the 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 expectations for the near future (again 3 and 12 months respectively). Importantly, some of the questions relate to both the past (backward-looking) and the future (forward-looking).

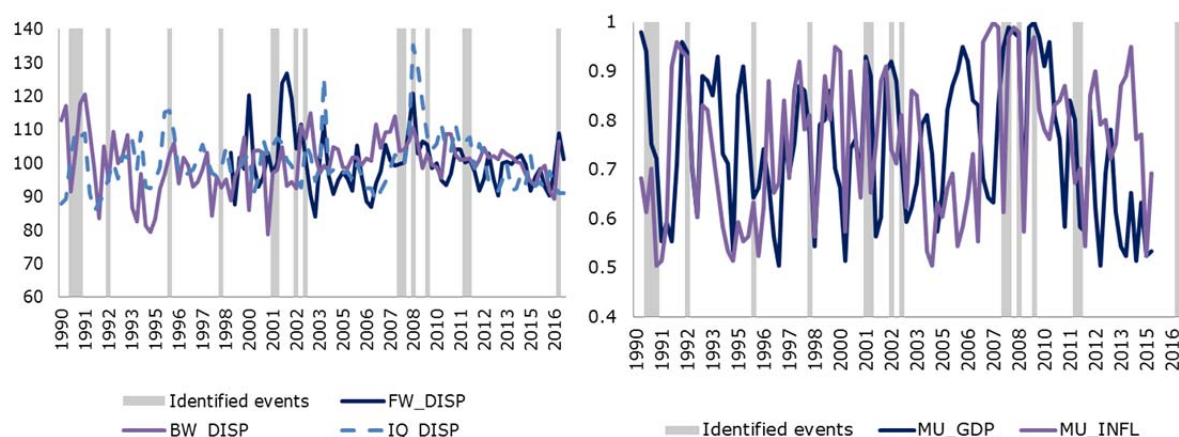
⁴ See https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en.

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 the full scope of the BCS datasets. The first indicator (FW_DISP) is based on the dispersion of the responses to 22 forward-looking questions (monthly and quarterly). The second indicator (BW_DISP) accounts for the backward-looking versions of the questions (i.e. opinions on developments in the recent past rather than those expected in the near future), which allows for comparison between the ex-ante and ex-post dispersion. In this way, the indicators mute the impact of heterogeneity as driven by the different backgrounds of agents or the information sets available to them. Finally, the third indicator (IQ_DISP) is based on the dispersion of the scores across different questions rather than the dispersion of the 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 the past, the present and the future) can evolve in different directions and the dispersion of the 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 the positive and negative answers to a specific question in the survey), the third indicator (IQ_DISP) proxies uncertainty with the dispersion of changes of the shares across several survey questions.

Figure 2 (left panel) plots these three indicators at country level, using France as an example (indicators for other countries are given in Appendix A), and suggests that most peaks of the indicators are clearly related to some well-identified events, but also that some important differences exist between the three indicators. In the case of France, the FW_DISP indicator captures well the 2001–2003 period of uncertainty (the dot-com bubble burst, the World Trade Centre attacks and the 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 major strikes in France in 1995, the dot-com bubble burst and the 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).

When these three indicators are confronted with events that can be deemed to trigger spikes in uncertainty in several EU countries, the IQ_DISP indicator emerges 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 SPF – Example for France



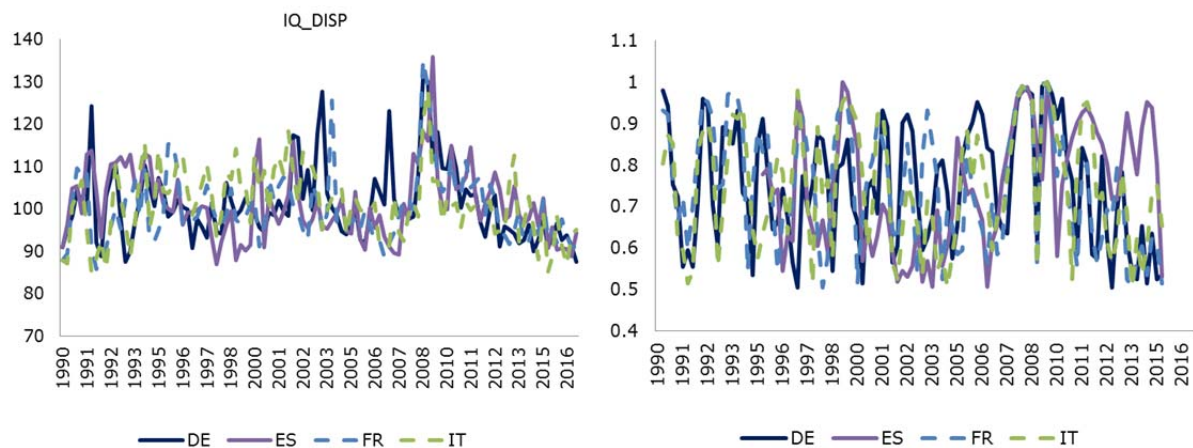
The second option for deriving country-level uncertainty indicators is to use the information contained in broad cross-country macroeconomic forecasts. Rossi and Sekhposyan (2016) calculate a forecast error-based uncertainty measure originally developed in Rossi and Sekhposyan (2015) from the Survey of Professional Forecasters (SPF) administered by the ECB. The indicators are therefore *limited 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 needs a point forecast and the actual realizations of macroeconomic variables. Given their aggregated and ex-post nature, this indicator does not suffer from the problem of heterogeneity. On the other hand, the SPF relies on the 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), namely the forecast errors in the quarterly forecasts of GDP (MU_GDP) and inflation (MU_INFL). The indicators are based on a comparison of the realized forecast error with the unconditional distribution of the 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, so the macroeconomic environment was very uncertain. Based on an inspection across euro area countries (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 following 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 reasonably be related to any known uncertainty-generating event. In any case, these indicators should be understood as proxies of uncertainty rather than as direct measures. Consequently, for robustness of empirical analysis it seems appropriate to use various available uncertainty indicators 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, which plots both selected indicators (IQ_DISP and MU_GDP) for the four largest euro area countries.

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

Figure 3: Uncertainty Indicators Constructed from BCS (IQ_DISP) and SPF (MU_GDP) for Four Largest EA Countries



Formal statistical factor analysis (Table 1) 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. For the euro area countries, the equivalent figure is 82%, and in the case of the MU_GDP indicator (available for the euro area countries only), only one factor is needed to explain 100% of 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. This is consistent with the economic priors about specific uncertainty-generating events in these countries⁶ and in non-EA countries such as Hungary and the UK.

Table 1: Factor Model Estimates

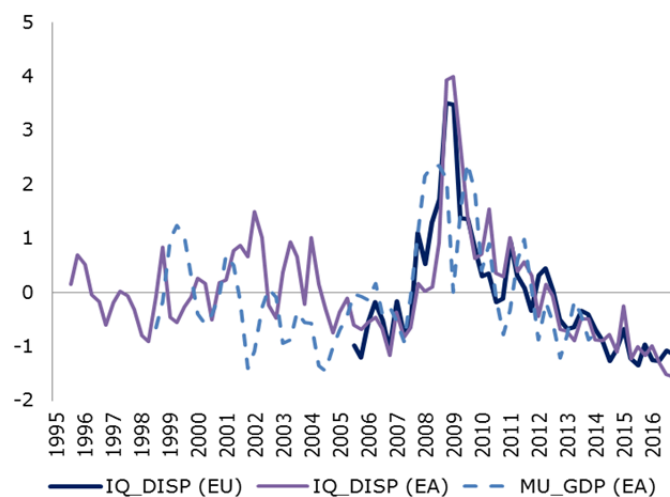
EU					
Factor	Variance	Cumulative	Difference	Proportion	Cumulative
Factor 1	20.44	20.44	11.66	0.70	0.70
Factor 2	8.78	29.22	---	0.30	1.00
Total	29.22	29.22		1.00	
EA					
Factor	Variance	Cumulative	Difference	Proportion	Cumulative
Factor 1	6.33	6.33	4.90	0.82	0.82
Factor 2	1.43	7.76	---	0.18	1.00
Total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

⁶ The decoupling of these countries is 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).

uncertainty as from 2008, peaking at the height of the global financial crisis in 2009, after which the uncertainty 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 also reflects 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 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 of other uncertainty proxies. They find that spells of uncertainty do not occur frequently but happen only at a few points in time when large economic shifts occur. Such shifts included 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 for different projections and for a broad set of countries. These data come from Consensus Economics (CE). CE conducts a survey – mainly based on OECD countries – among professional economists working for commercial or investment banks, government agencies, research centres and university departments. Most of the experts surveyed provide forecasts for their own country only. However, there are also a few experts working for international financial institutions or research institutes who provide forecasts for several countries simultaneously. The survey queries respondents in the first week of each month about current and future developments for a number

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

of macroeconomic and financial variables, including yields on 10-year benchmark government bonds. The forecasts are then published early in the second week of the same month.⁸

The evidence shows that CE forecasts are less biased and more accurate than the forecasts of some international institutions.⁹ The CE data are public, which helps prevent participants 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, so discrepancies between the survey and their private recommendations would be hard to justify (Keane and Runkle, 1990). Overall, we can reasonably argue that the CE survey data broadly reflect the spectrum of expectations of market experts.

We focus on forecasts of inflation, economic growth and unemployment in the U.S., Japan, Germany, France, the UK 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 who 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.

Table 2: Number of Forecasters in CE, January 1990–December 2015

Country	Total	Maximum	Selection
U.S.	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: The total number of forecasters in the 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 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 instead extract a few factors employing the method of principal factors (Stock and Watson, 2005). The Minimum Partial Average (MPA) method indicates that three factors (alternative statistical criteria point to

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.

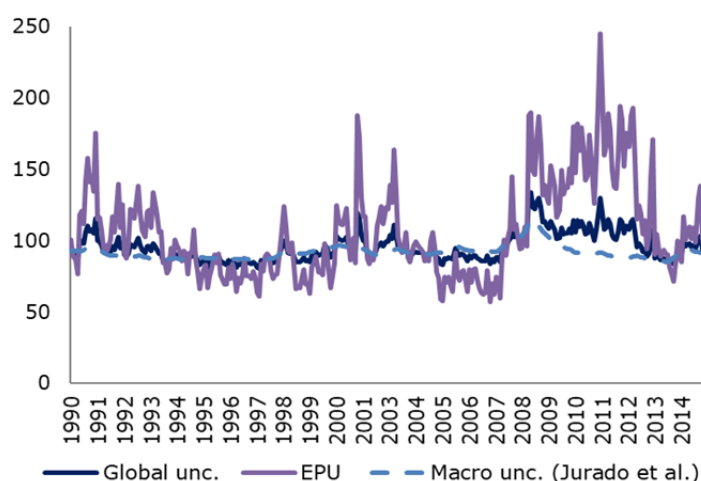
the same number of factors) are able to explain close to 90% of the original series' variability. Table 3 provides details on the factors' unrotated loadings. The first factor explains around 55% of the total variability. This factor is related to the business cycle, calculated as the average growth 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 the forecast errors.¹⁰ The second factor explains around 32% of the 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 the three episodes that they find to be important spells of uncertainty (2001, 2008). The reason is that by decomposing the forecast errors into a notable cyclical component, we clean the dispersion of forecast errors of any strong recessionary effect. We nevertheless find significant rises in the index in these episodes too. If we compare the factor-based measure with the news index of Baker et al. (2016), the opposite result holds. Their measure displays more variation over time than the factor-based uncertainty indicator.

Figure 5: Global Uncertainty Measure Comparison



Notes: EPU – economic policy uncertainty (source: www.policyuncertainty.com); Macro unc. is measure of Jurado et al. (2015) at 12 months (scaled by 100 to fit the EPU index) and Global unc is the factor-based measure based on CE forecasts (described above).

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

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 us to estimate a model with several endogenous variables in face of a limited data sample. The model includes six variables (next to a constant term and a linear trend to control for nonstationarity of some variables) in the following order: (the log of) stock prices, the Economic Sentiment Indicator (ESI), an uncertainty indicator (IQ_DISP, the common factor of the IQ_DISP country-level indicators, a global uncertainty indicator and, in country-specific VARs, also MU_GDP and EPU), the short-term interest rate, log HICP and log real GDP, consumption or investment. The ESI and the other indicators needed to construct IQ_DISP come from the Business and Consumer Surveys of the EC, while the macroeconomic data come from Eurostat, the ECB and the OECD. As we work with quarterly data, we include four lags of each variable.

The country-level estimates come from a 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 also be written as:

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

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

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

$$y_i = (Im \otimes X_i)\theta_i + e_i$$

where i stands for $i = 1, 2, \dots, N$ cross-sectional units. The dynamic equation for each variable in a cross-sectional unit i at time t contains $k = Nnp + m$ 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 four 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 properties and (if deemed reasonable) allow us to obtain additional degrees of freedom and in turn gain more accurate estimates. Given that we are mainly interested in the average responses for a certain subgroup of EU countries, we use the Bayesian pooled estimator,¹¹ which is the Bayesian counterpart of the classical mean-group estimator. With this approach, each cross-sectional unit (country) is independent of the other units and the dynamic coefficients are homogeneous across units. While this implies relaxing properties such as the static and dynamic linkages between cross-sectional units, we

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

deem it appropriate, 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 subsamples include countries that share especially strong linkages that need 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, not in the cross-country linkages.¹² The standard normal-Wishart prior is used for the estimation, and 5,000 iterations (with 1,000 as a burn-in) are used.

While we are mainly interested in the impact of uncertainty shocks on economic activity, the presence of other variables in the BVAR is needed to distinguish the impact of *uncertainty shocks* from other similar shocks likely to affect economic activity. This applies especially to *confidence shocks* and *financial shocks*.¹³ Firstly, confidence can affect consumer and investment decisions. Whereas confidence shocks are understood as changes in the *level* of confidence about future outcomes (first moment shocks), uncertainty shocks are rather changes in the *dispersion* 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 or the 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 the Cholesky factorization and generalized impulse-response analysis, which provide largely similar results. Therefore, for the panel BVAR, we rely on the Cholesky factorization only.¹⁵ For robustness, we also tested other orderings, which did not materially alter the impulse-response functions. On the contrary, the variance decomposition (not reported further) featured some discrepancies. Specifically, an alternative ordering of stock prices, the ESI and the uncertainty indicator changed the relative importance of financial, confidence and uncertainty shocks for explaining real economic developments. In this context, we need to order the uncertainty indicator after stock prices and the ESI as a conservative choice.

While the IQ_DISP uncertainty indicator can be calculated for most EU countries, the unavailability of other variables reduces the dataset used for the empirical analysis to 18 EU Member States, namely Austria (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), the Netherlands (NL), Portugal (PT), Sweden (SE), Slovenia (SI), Slovakia (SK) and the United Kingdom (UK).

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 shocks are another type of shock studied recently. However, unlike the other ones, these shocks are understood as news about future total factor productivity, which affects the real economy only in the longer term (e.g. Jaimovich and Rebelo, 2008, or Barsky and Sims, 2011)

¹⁴ There is also a 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 the Cholesky and triangular factorization, which in our case provide very similar results.

5. Empirical Results

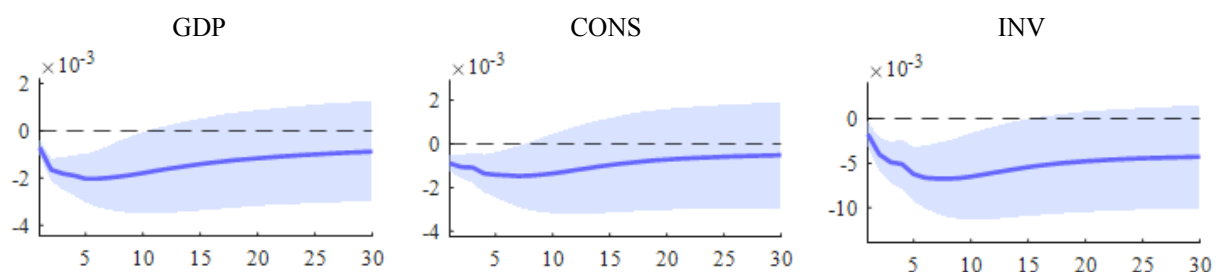
This section provides empirical evidence on the impact of uncertainty shocks across EU countries using (panel) BVAR models. In some cases, we refer only to the EU countries where additional uncertainty indicators are available. We usually report the impact of unexpected uncertainty shocks on GDP, but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

5.1 The EU-wide Evidence on the Impact of Uncertainty Shocks

The evidence on the overall impact of uncertainty shocks in EU countries is provided in Figure 6. Uncertainty is proxied by the country-level uncertainty indicator *IQ_DISP* derived from the BCS (see subsection 3.2 and Appendix A). 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 its baseline. The impact is especially pronounced for investment, which is the most volatile part of GDP. While the response of consumption is significant as well, the decline is substantially smaller and shorter-lived than for investment. Importantly, there is no evidence of overshooting when economies recover from the shocks, suggesting that the temporary decline in economic activity is not subsequently compensated for.

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

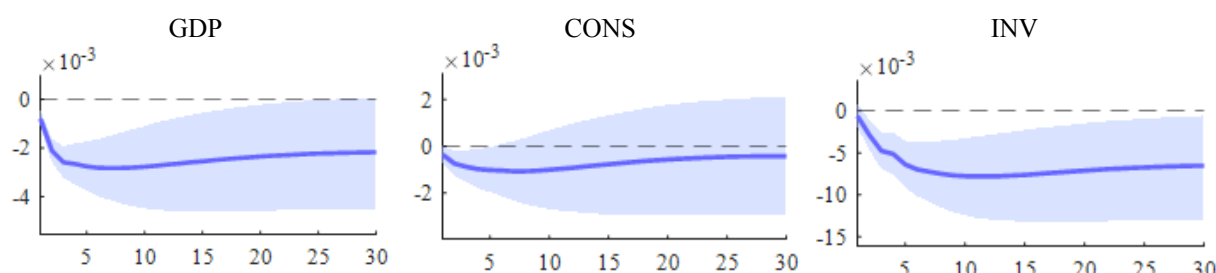
Figure 6: Impact of Domestic Uncertainty Shocks on GDP, Consumption and Investment – Panel of 18 EU Countries



Notes: The graph represents the estimated response of GDP following an unexpected (idiosyncratic) uncertainty shock (of one standard deviation) in the panel BVAR model containing 18 EU countries. Uncertainty is proxied by the *IQ_DISP* indicator. The figures on the x-axis represent quarters and those on the y-axis represent percentage points (when multiplied by 100). The shaded area shows the 90% confidence interval.

As the EU economies are tied by strong trade and financial linkages, they may also be 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 a common uncertainty shock, with uncertainty proxied by the first principal component of the country-level IQ_DISP measures. The estimated impact of such a synchronized uncertainty shock is even more pronounced, especially for investment, whose decline turns out to be very persistent.

Figure 7: Impact of Common EU Uncertainty Shock on GDP, Consumption and Investment – Panel of 18 EU Countries

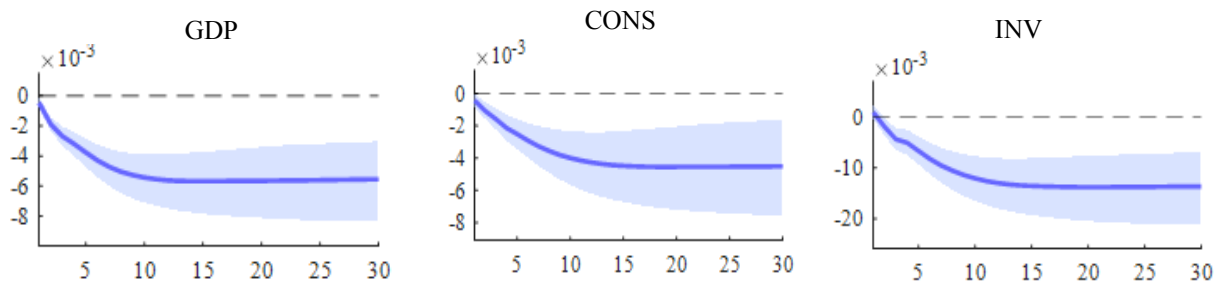


Notes: The graph represents the estimated response of GDP following an unexpected (common) uncertainty shock (of one standard deviation) in the panel BVAR model containing 18 EU countries. Uncertainty is proxied by the first principal factor derived from the country-level IQ_DISP indicators. The figures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

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 a 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 of even larger magnitude than that after the EU-wide uncertainty shock. Besides a 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 U.S. (Baker et al., 2016) and the original macroeconomic uncertainty indicators by Jurado et al. (2015).¹⁶ Spells of global uncertainty (as reported in Figure 5) occur only infrequently, during major events such as the global financial crisis. Therefore, the response of the real economy can also be seen as rather extraordinary.

¹⁶ To save space, these results are not reported here but are available from the authors.

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 containing 18 EU countries. Uncertainty is proxied by the first principal factor derived from the country-level IQ_DISP indicators. The figures on the x-axis represent quarters and those on the y-axis represent percentage points (when multiplied by 100). The shaded area shows the 90% confidence interval.

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

The global financial crisis of 2008/2009 is often seen as a period in which political and economic uncertainty contributed considerably to a financial meltdown and generalized economic collapse. However, from the point of view of individual EU Member States this was a case of global rather than idiosyncratic uncertainty.¹⁷ A historical decomposition (reported for three sample countries – Germany, Spain and the UK – in Appendix E) from a panel BVAR for 18 countries where uncertainty is proxied by the global uncertainty indicators shows that over that period, the uncertainty shock accounted for about a quarter to a third of the total variability in GDP. For example, GDP in Germany, Spain and the UK fell by almost 4%–5%, around 1.0%–1.5% of which can be attributed to uncertainty shocks. In addition, the negative impact of uncertainty dragged down the 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 stresses the role of other shocks closely related to uncertainty shocks, namely financial and confidence shocks.

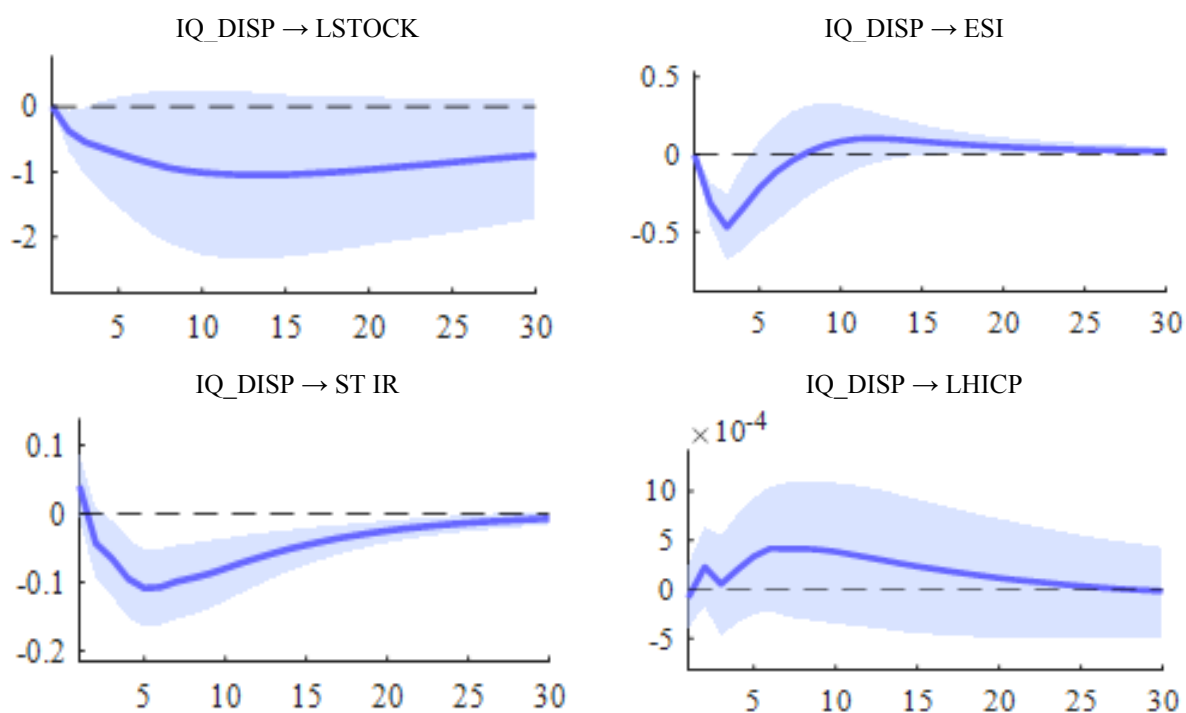
Beyond the analysis of the impact of uncertainty shocks on the real economy, it is interesting to evaluate their impact on other macroeconomic and financial variables. Given the significant diversity in model settings across empirical studies with regard to both the indicators used for uncertainty and 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 that were included in the panel BVAR model to an uncertainty shock. The results show that stock prices experience a

¹⁷ Appendix B reports the identified idiosyncratic uncertainty shocks (when the 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 C in turn reports the identified global uncertainty shocks (when the common global uncertainty measure described in section 3.3 is used) for three sample countries. As expected, given that the other endogenous variables differ across the countries, the identified uncertainty shock is not identical for all the countries, although the differences are very minor.

protracted decline, economic sentiment drops quickly but only for a short period, short-term interest rates decline, and prices display no significant response.

While the country-level IQ_DISP indicators were used for this estimation, the use of common or global uncertainty indicators does not change the picture very much. The only discrepancy is in the response of prices. Specifically, when our global measure of uncertainty is used, prices respond positively. This is confirmed when Baker's EPU indicator is used. Conversely, when the original macroeconomic uncertainty by Jurado et al. (2015) is employed, prices record a significant decline. The direction of the responses of the economy 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 contractionary aggregate demand shocks (as the shock induces a rise in unemployment and declines in inflation and the nominal interest rate), pointing to nominal price rigidity and search frictions in the labour market as representing the key link between the increase in uncertainty and economic activity.

Figure 9: Impact of Uncertainty Shock on Other Variables – Panel of 18 EU Countries

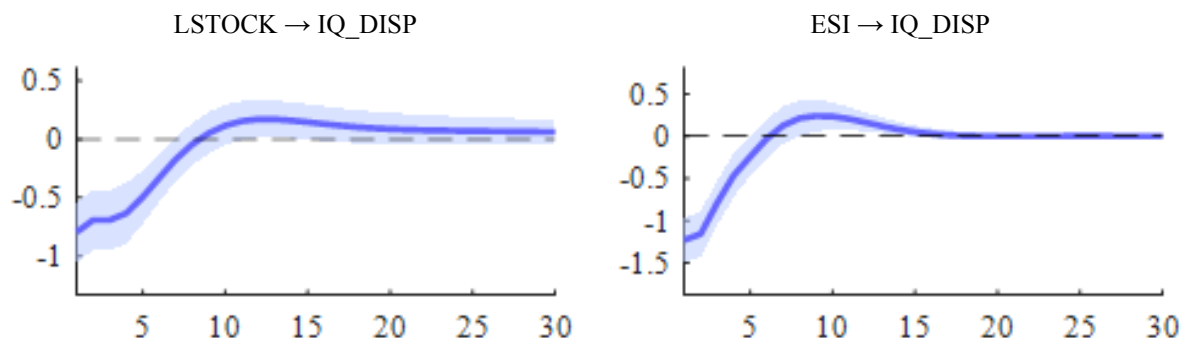


Notes: The graph represents the estimated response of stock prices, the ESI, the EONIA and the HICP following an unexpected uncertainty shock (of one standard deviation) in the panel BVAR models containing 13 EA countries (AT, BE, DE, EE, EL, ES, FI, FR, IT, NL, PT, SE, SK). Uncertainty is proxied by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

So far, we have looked at the 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 also increases following a drop in stock market prices (a proxy for financial shocks) and the Economic Sentiment Indicator (a proxy for

confidence shocks). These results 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 reduce economic confidence and hurt the financial sector today. This, in turn, can feed back into higher uncertainty.

Figure 10: Impact of Other Shocks on Uncertainty – Panel of 18 EU Countries



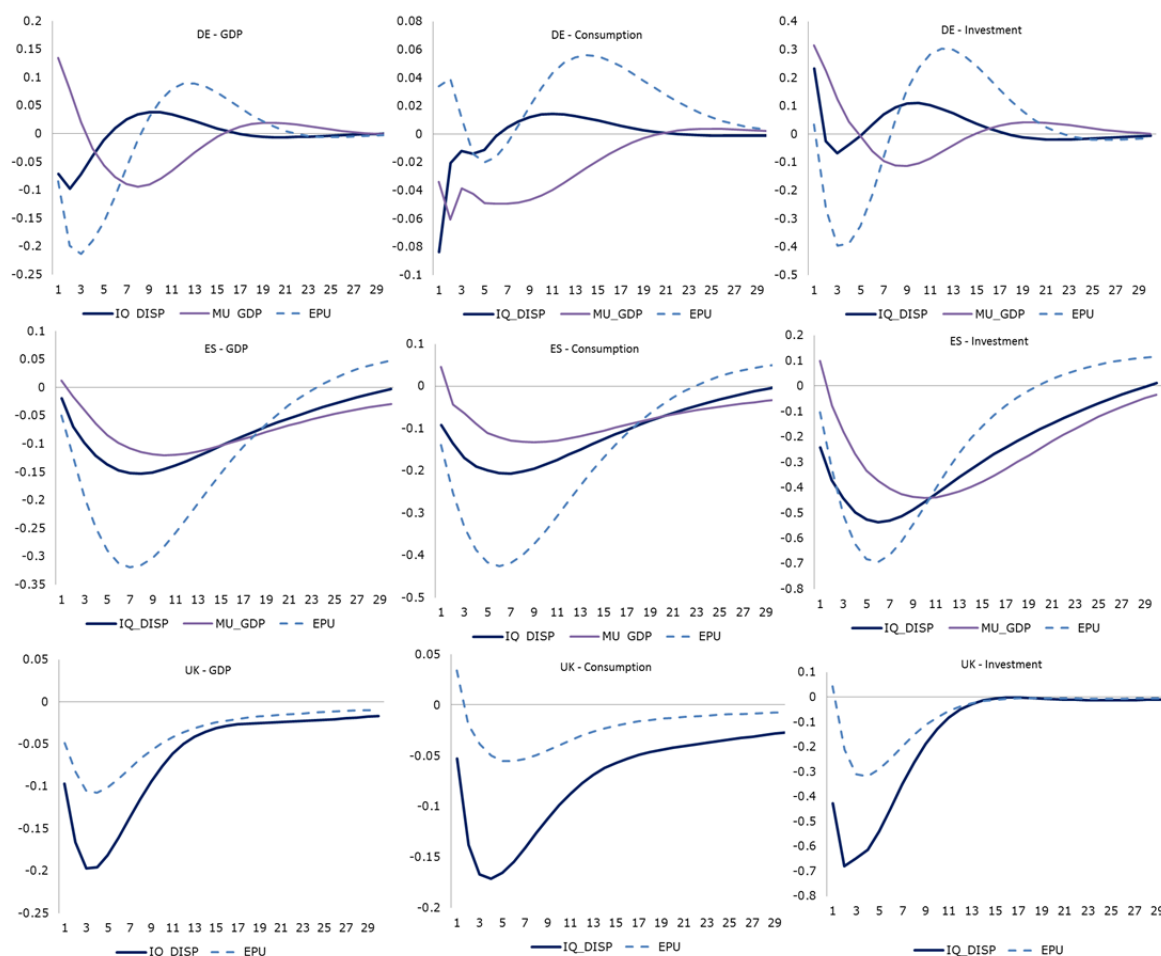
Notes: The graph represents the estimated response of the uncertainty indicator following an unexpected financial shock and sentiment shock (of one standard deviation) in the panel BVAR model containing 18 EU countries. The figures on the x-axis represent quarters and those on the y-axis represent the units of the uncertainty indicator IQ_DISP. The shaded area shows the 90% confidence interval.

5.2 The Heterogeneous Impact of Uncertainty Shocks across the EU Countries

Figure 11 provides a first glimpse of the heterogeneity of the 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 aforementioned 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 especially investment suffer 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 GDP and investment suffer a statistically significant decline (as does consumption when the IQ_DISP indicator is used), but unlike in Spain, where the impact of uncertainty on the real economy fades away only after several years, the UK economy recovers within two years.

¹⁸ To save space, the confidence intervals along the point estimates are not plotted.

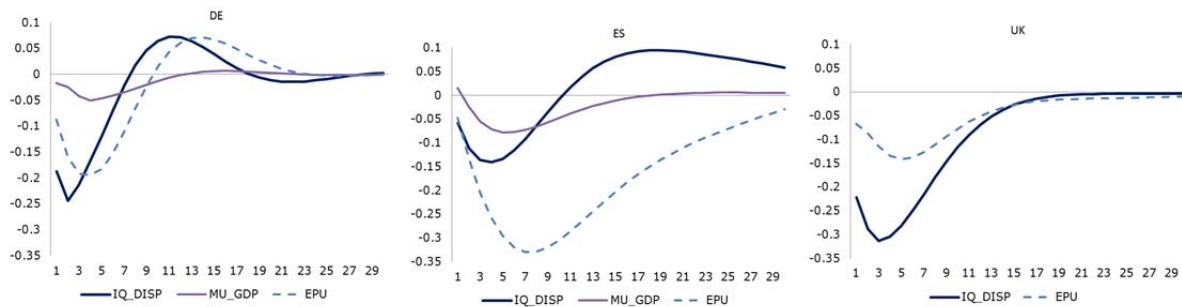
Figure 11: Impact of Domestic Uncertainty Shock on GDP, Consumption and Investment – Germany, Spain and UK



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

The differential impact of domestic uncertainty shocks on the economy, as is evident from the results presented above, may 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 common EU uncertainty is relevant in driving domestic uncertainty, it is interesting to assess how Member State economies respond to common uncertainty shocks. This allows 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 that on Spanish and UK GDP.

Figure 12: Impact of Common EU Uncertainty Shocks (Three Alternative Measures of Uncertainty) on GDP of Germany, Spain and UK



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

This preliminary evidence suggests that (i) the different indicators of uncertainty provide a largely similar picture at country level, (ii) the EU countries suffer from both idiosyncratic and common uncertainty shocks, reflecting the high degree of interconnectedness of their economies, and (iii) the response to uncertainty shocks differs across Member States, reflecting not only the different severity of uncertainty shocks, but also differences in economic resilience.

5.3 Uncertainty Shocks and Structural Characteristics of EU Countries

While it is impossible to prevent 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 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 the EU countries across some characteristics. These can be broadly assigned to three large categories: (i) economic flexibility, (ii) economic openness 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 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 also plays an important role in strengthening economic resilience in that it determines the flexibility of price adjustment. We proxy labour and product market flexibility with the corresponding measures from the *World Economic Forum Competitiveness Database*.¹⁹

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

(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. Economic openness makes an economy more vulnerable to external shocks but may also improve its shock-absorption capacity through cross-border risk sharing (via cross-border holdings of financial assets). We use trade as a percentage of 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 the 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 (the Herfindahl-Hirschman index) comes from UNCTAD.

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

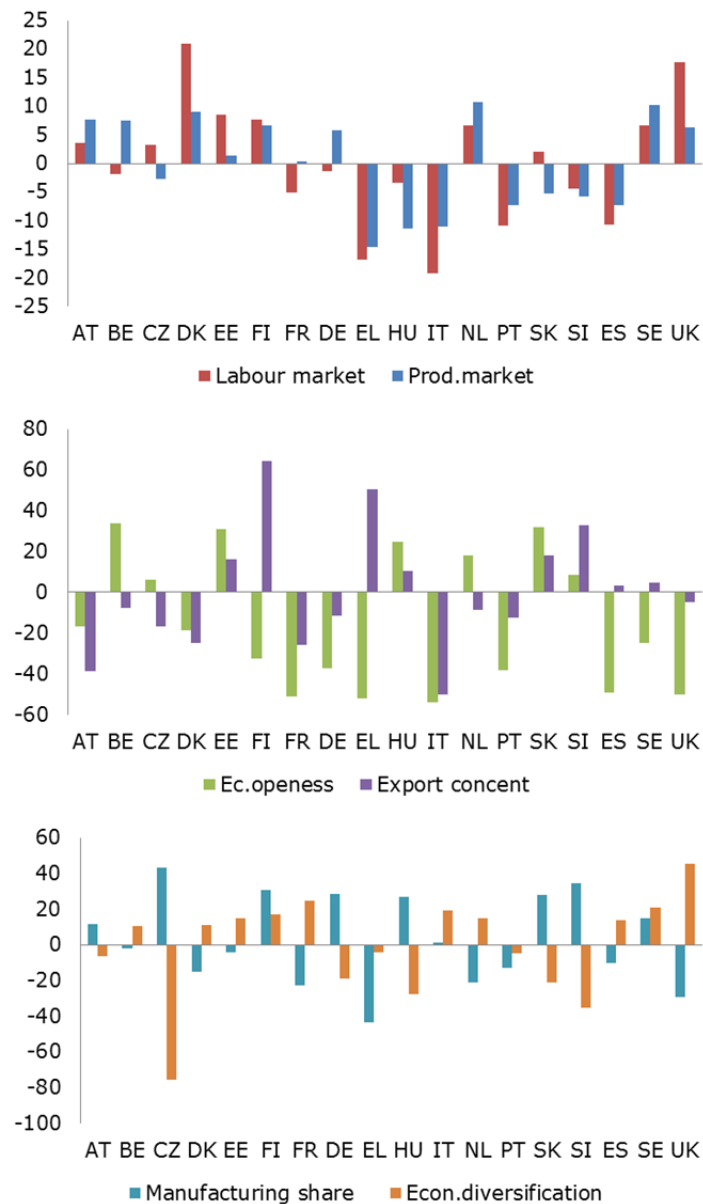
We use the time average of each indicator and country, including data from 1995 to 2016. Figure 13 plots these structural characteristics for the 18 EU countries. The indicators are normalized to have zero mean, and the bars in the graph represent the (positive or negative) deviation from the mean EU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

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

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

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

Figure 13: Six Structural Characteristics for EU Countries



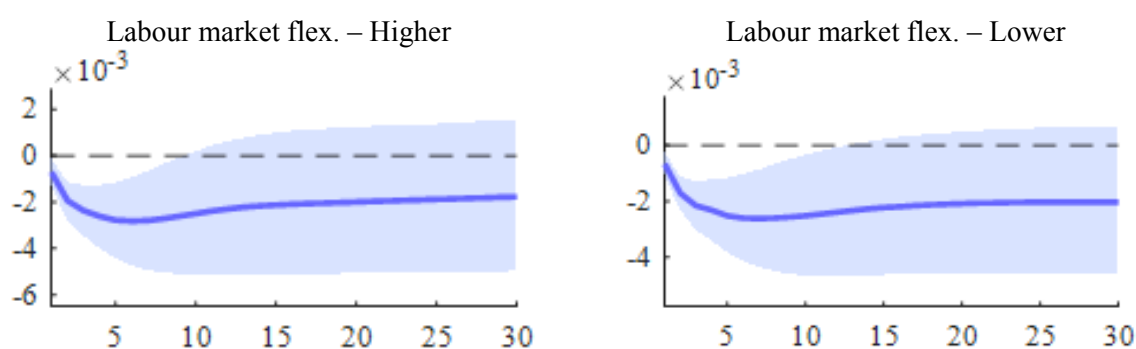
Notes: The graph represents the deviation of each structural characteristic from the sample (18 EU countries) mean value (normalized to zero).

²⁰ The very low diversification of the Czech economy (as measured by the standard deviation of the relative share of different sectors in gross value added) is a result of a very high share of manufacturing (26% vs. 17% on average for the EU-18) and 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) and arts, entertainment and recreation (2% vs. 3% for the EU-18).

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. We construct a subpanel of Member States having more flexible labour markets versus a subpanel 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, the results are driven 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 IQ_DISP, but very similar results are obtained when the common uncertainty indicator (a common factor from country-level IQ_DISP indicators; see subsection 3.2) or the global uncertainty indicator (a common factor from a 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 us to additionally employ the SPF forecast-error-based measure MU_GDP.

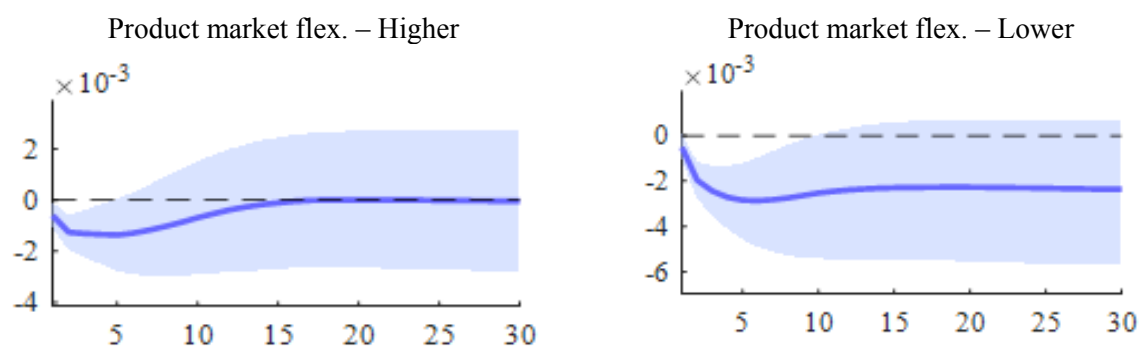
Figure 14 reports the impact of uncertainty shocks on GDP using impulse-response functions from the estimated panel BVAR for the EU according to labour and product market flexibility. While the 90% confidence interval around the mean estimate is rather wide (which may reflect further heterogeneity of responses within each subgroup), 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 flexible labour markets is statistically significant for around a year longer than that on countries with more flexible labour markets. Moreover, when the sample is reduced to the EA countries and the MU_GDP measure is used,²² the difference is much more pronounced.

Figure 14: Impact of Uncertainty Shock on GDP in EU Countries according to Economic Flexibility



²¹ The pooled estimator is used, and the reported impulse-response functions come from the Cholesky factorization.

²² These results are not reported here due to space constraints.



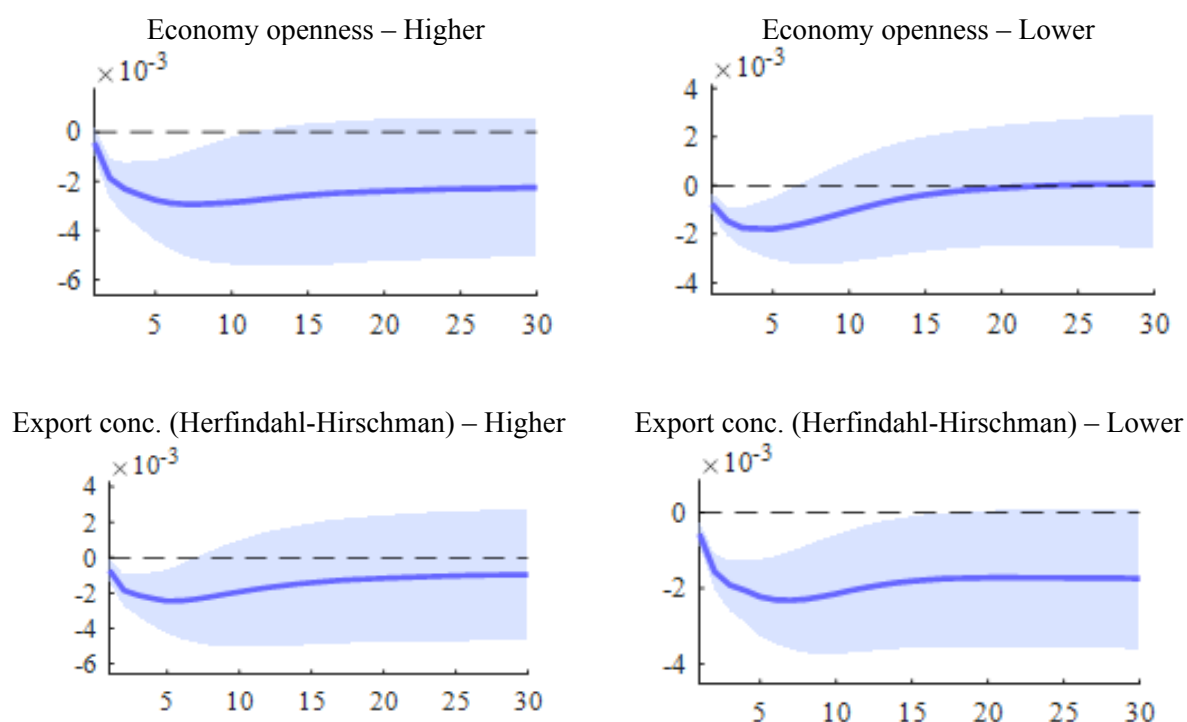
Notes: The graph represents the estimated response of GDP following an unexpected uncertainty shock (of one standard deviation) in the panel BVAR models. The EU countries are split into two subpanels according to labour and product market flexibility. Labour market flexibility, higher: AT, CZ, DK, EE, 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 figures on the x-axis represent quarters and those on the y-axis represent percentage points (when multiplied by 100). The shaded area shows the 90% confidence interval.

Product market flexibility seems to matter more, as the impact of the uncertainty shock is only marginally significant for the 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 also seems to be (at least temporarily) affected in countries with low labour market flexibility.²³ More flexible product markets allow, for example, for faster adjustment of prices, which may be needed when the economy is hit by adverse shocks.

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 contains all the large Member States (Germany, France, Italy and Spain). Figure 15 confirms that the impact of uncertainty shocks is slightly more persistent in countries that are more open than in it is more closed economies. Given that economic openness is closely related to economic size, it can also be claimed that larger economies cushion uncertainty shocks better. However, this result does not seem to be very robust, because when we limit the sample to the EA countries and also use the other uncertainty indicator (MU_GDP), the result is just the opposite (i.e. more open economies are less affected by uncertainty shocks). Therefore, while openness can on the one hand make countries more vulnerable to external shocks, international trade – specifically 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 depends on the relative strength of these two factors. However, there are more factors at play than just economic openness. The degree of export diversification, which in turn often reflects the domestic diversification of the economy, may be important. On the other hand, there is the argument of comparative advantage, which is more likely to hold for economies with specialized exports and for developed countries like the EU Member States, which, unlike many emerging countries, do not rely on exports of just a few raw materials (see Claeys, 2017).

²³ These results are not reported here due to space constraints.

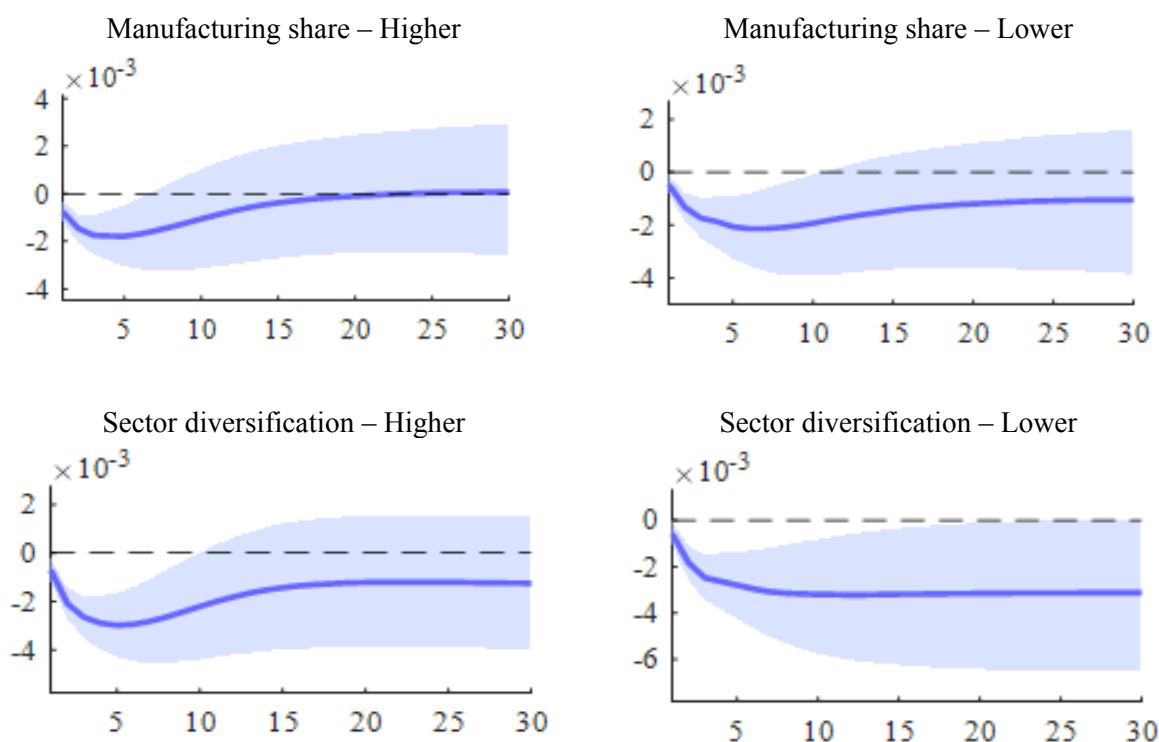
Figure 15: Impact of Uncertainty Shock on GDP in EU Countries according to Economic Openness and Trade Characteristics



Notes: The graph represents the estimated response of GDP following an unexpected uncertainty shock (of one standard deviation) in the panel BVAR models. The EU countries are split into two subpanels according to economic openness, trade differentiation and export concentration. Economic openness, 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 figures on the x-axis represent quarters and those on the y-axis represent percentage points (when multiplied by 100). The shaded area shows the 90% confidence interval.

Finally, Figure 16 reports the 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 relative to total GDP is understood mainly as a proxy for output tradability, but manufacturing is usually characterized by faster productivity growth. However, manufacturing represents only a minor part of total output, and the degree of diversification of overall production may also be important. When we split the countries according to diversification in terms of the shares of individual industries (NACE10) in overall output (a lower standard deviation means smaller differences in the shares of individual industries and a more diversified economy), it appears that more diversified economies also suffer from uncertainty shocks, 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 the estimated response of GDP following an 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 figures on the x-axis represent quarters and those on the y-axis represent percentage points (when multiplied by 100). The shaded area shows the 90% confidence interval.

6. Concluding Remarks

Spells of uncertainty are argued to drive rapid drops in economic activity. Wait-and-see behaviour 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 (in the labour market, the product market and the financial system) are particularly strong. However, other structural features (economic openness and product diversification) may mitigate how an economy responds to an uncertainty shock. Besides, the EU countries are small and open and hence probably feel the effects not just of domestic uncertainty, but also of uncertainty spilling over from the EU level or even from global economy.

This paper employs novel proxies of uncertainty at both the country and international level and uses them to test the differential impact of domestic, common European and global uncertainty shocks. Domestic uncertainty is derived from the dispersion in the Business and Consumer

Surveys administered by the European Commission, and EU-wide uncertainty is derived as the main common factor underlying the domestic measures. This common component is quite strong, suggesting 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) and Claeys (2017).

We then estimate a Bayesian (panel) VAR over the period 1996–2016 to test the impact of uncertainty shocks on real GDP, consumption and investment. The overall results suggest that real output in EU countries is negatively affected by spikes in uncertainty, which is driven mainly by investment. Unlike for the U.S., there is little evidence that after initially declining, economic activity temporarily 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 feed back and amplify each other.

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

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

Spikes in the 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 suffering 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 for strengthening resilience, therefore dampening the effects of adverse shocks.

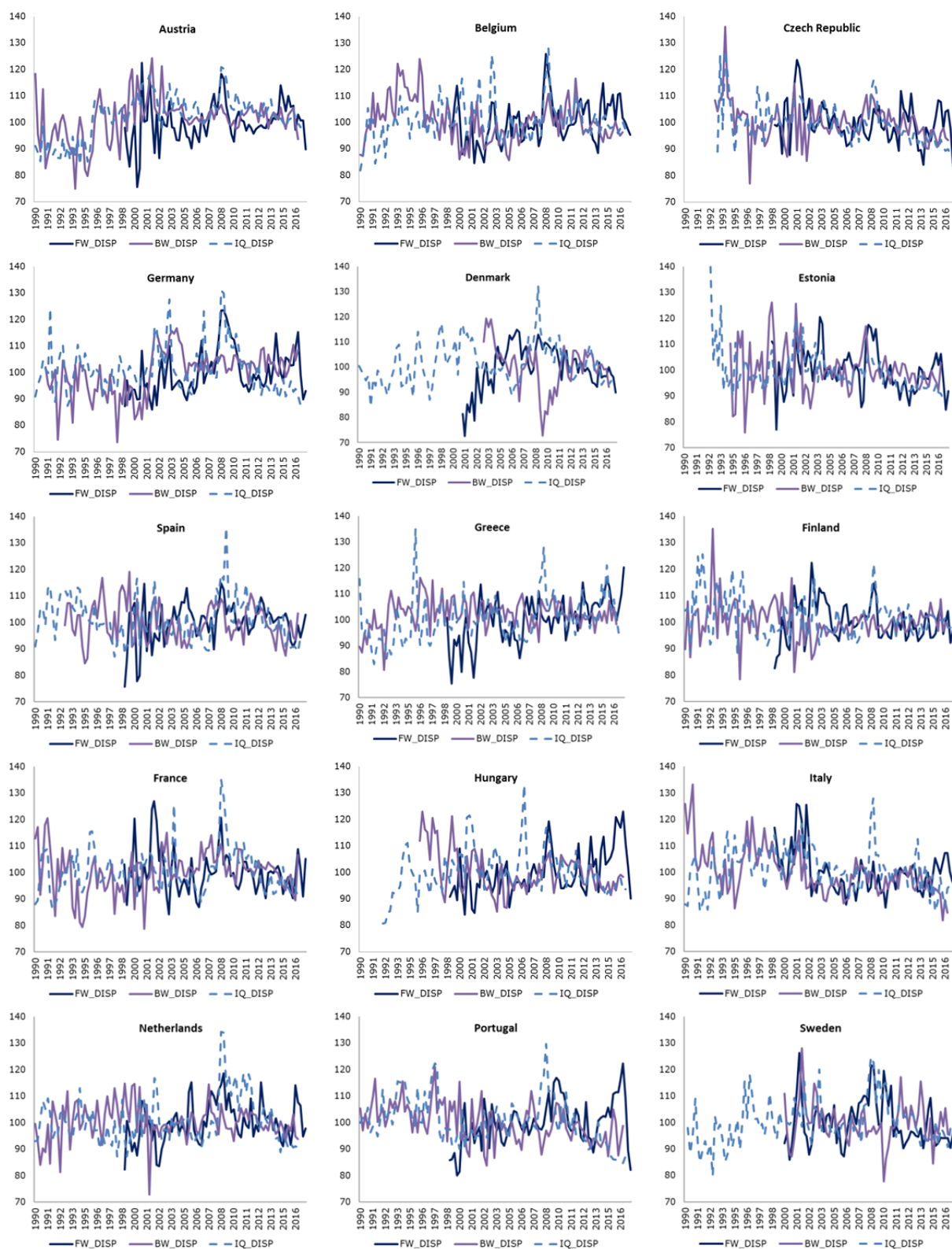
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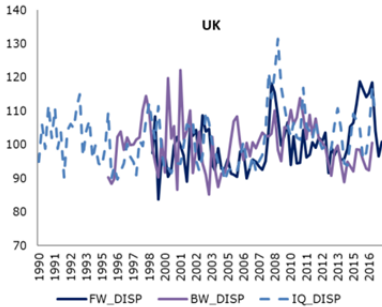
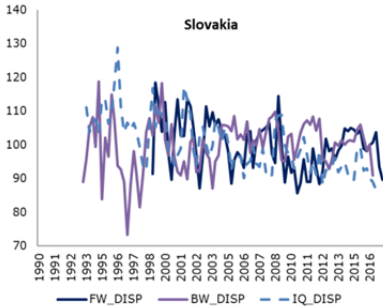
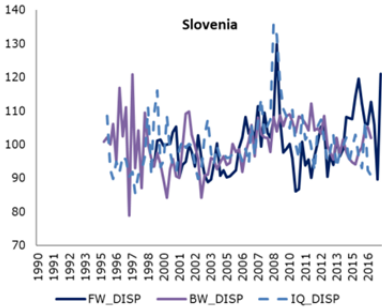
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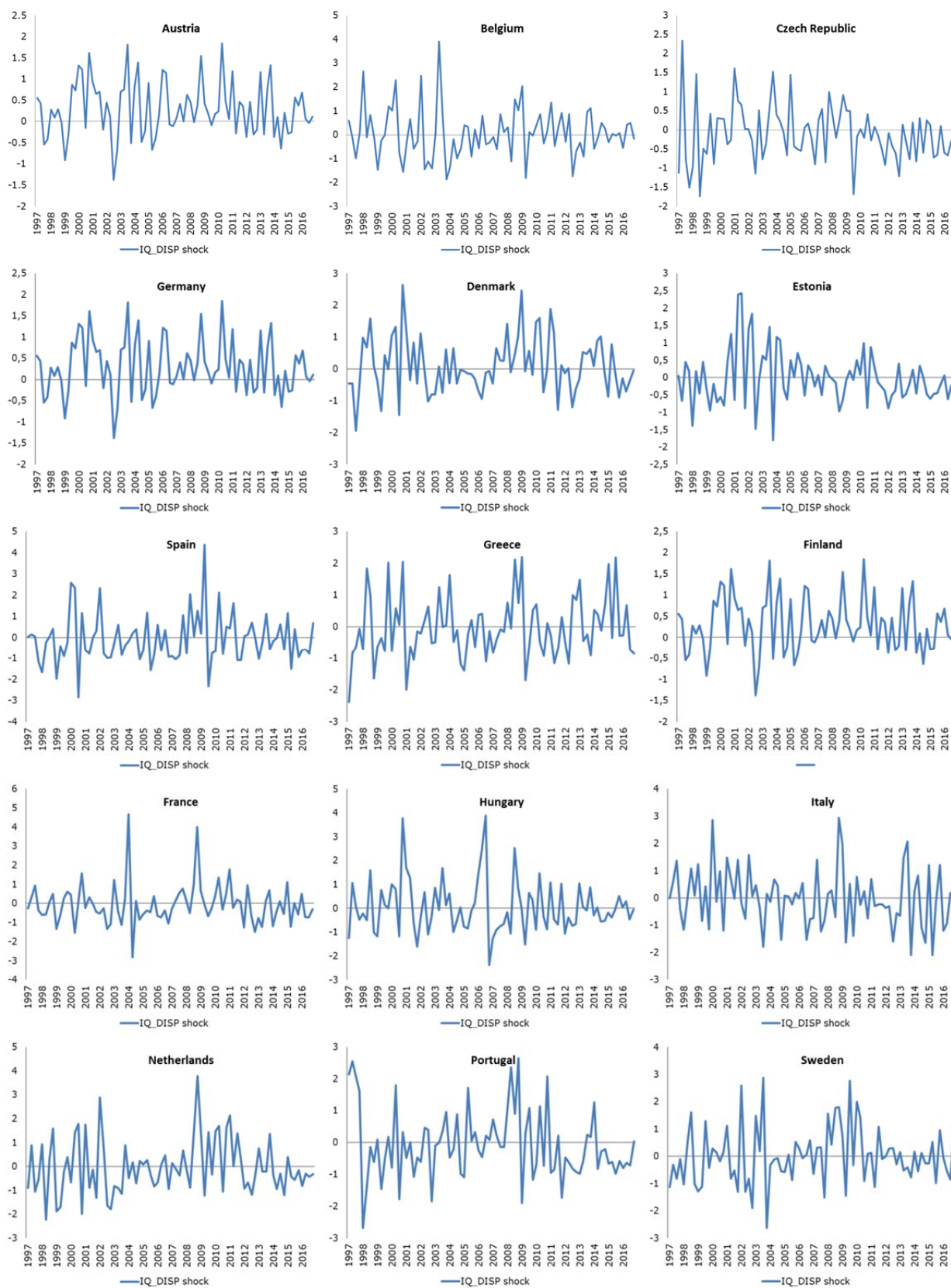
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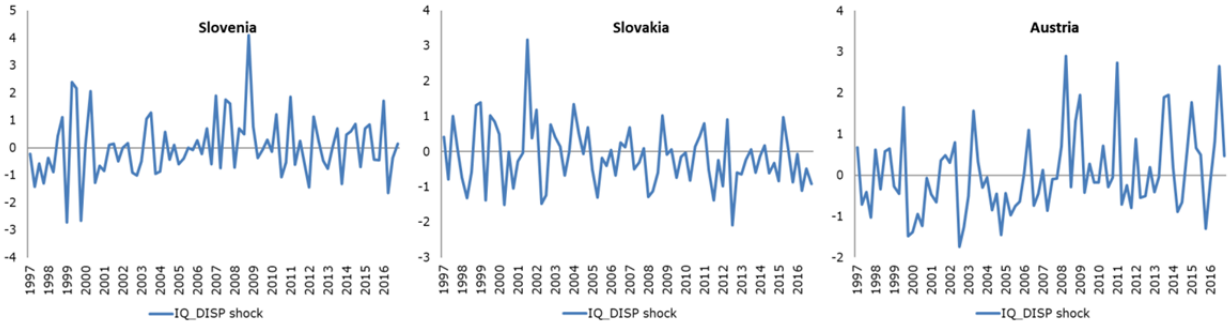
Appendix A: Uncertainty Measures Derived from BCS



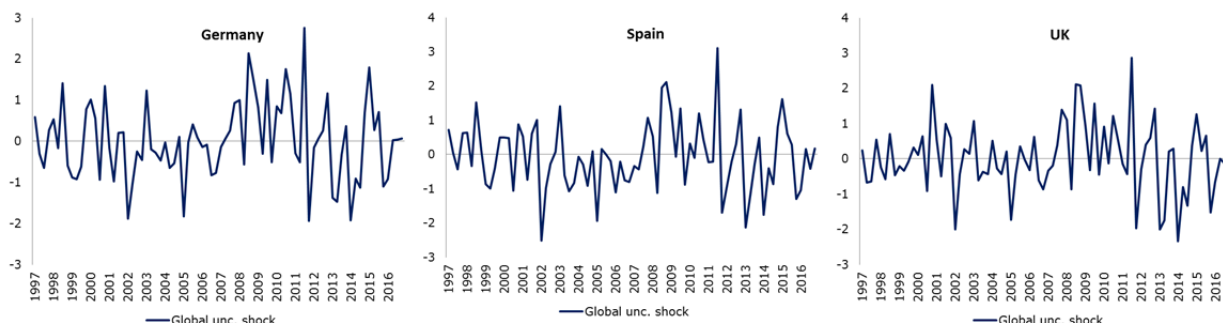


Appendix B: Uncertainty Shocks Identified in Panel VAR of 18 EU Countries (IQ_DISP Variable)

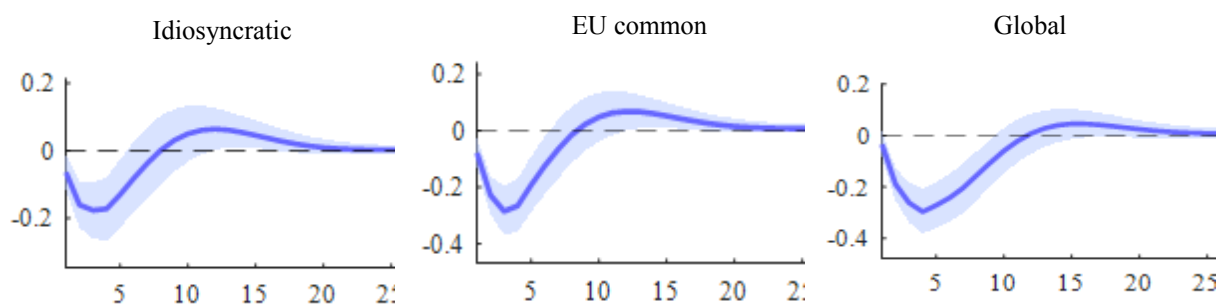




Appendix C: Global Shock Identified in Panel VAR of 18 EU Countries

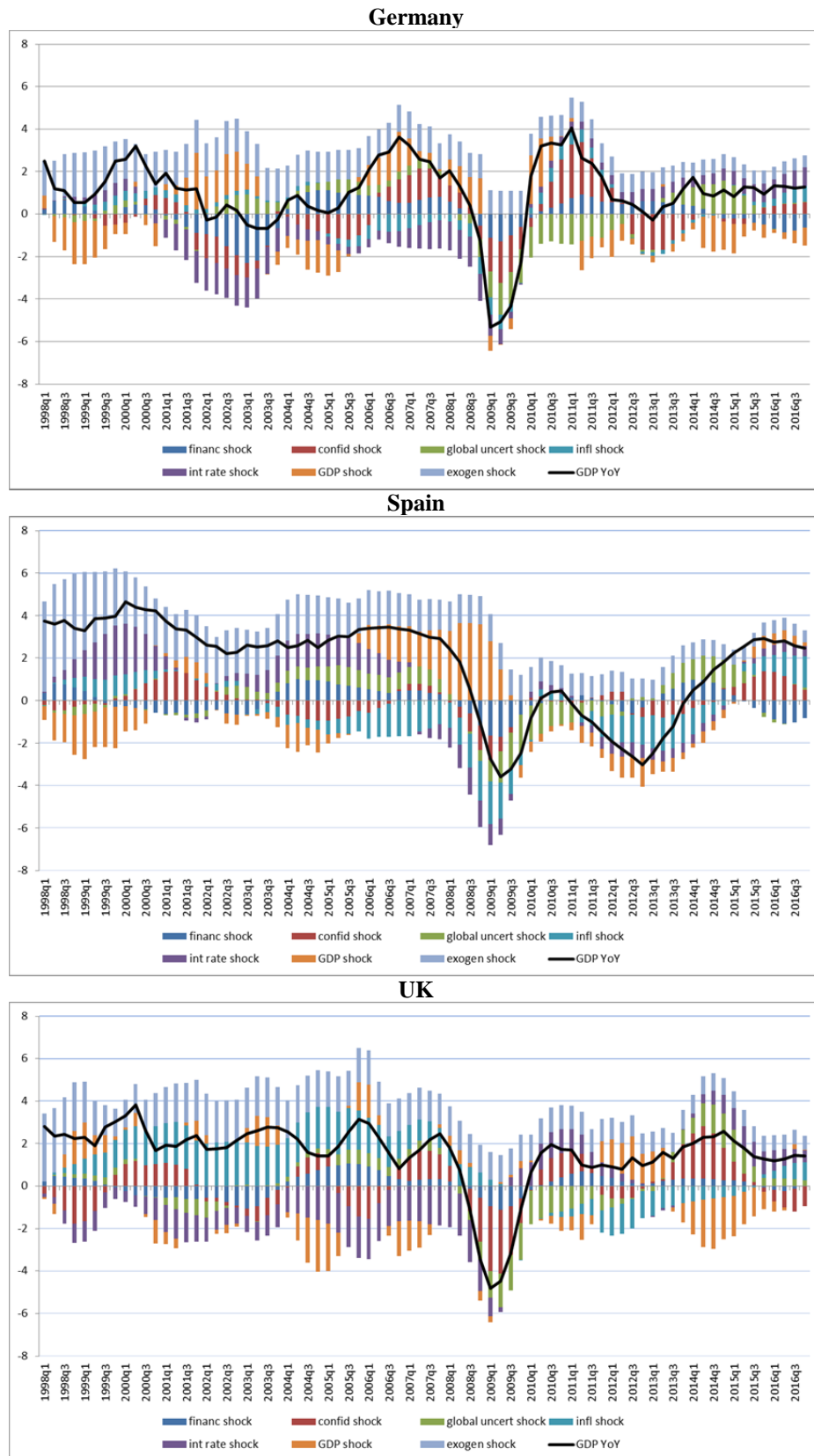


Appendix D: Impact of Uncertainty Shocks on GDP (YoY Growth Rates)



Notes: The graph represents the estimated response of GDP following an unexpected (idiosyncratic, EU common and global) uncertainty shock (of one standard deviation) in the panel BVAR model containing 18 EU countries. The figures on the x-axis represent quarters and those on the y-axis represent percentage points. The shaded area shows the 90% confidence interval.

Appendix E: Historical Decomposition of GDP (YoY Growth Rates)



Notes: The graph represents the estimated historical variance decomposition of GDP growth as attributed to shocks in the endogenous variables included in the BVAR model containing 18 EU countries and to exogenous shocks (of one standard deviation) in the panel BVAR model containing 18 EU countries.

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Czech National Bank
Economic Research Division
Na Příkopě 28, 115 03 Praha 1
Czech Republic

phone: +420 2 244 12 321

fax: +420 2 244 12 329

<http://www.cnb.cz>

e-mail: research@cnb.cz

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