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Economic Policy Uncertainty in Europe: Spillovers and Common Shocks

Jaromír Baxa and Tomáš Šestořád *

Abstract

This paper proposes a novel approach to decompose the Economic Policy Uncertainty indices of European countries into the common and country-specific components using the time-varying total connectedness. Then, by employing a Bayesian panel VAR model, we assess how common and country-specific uncertainty shocks influence economic activity, prices, and monetary policy, with the shocks identified using zero and sign restrictions. Our results reveal that only common shocks have significant effects on all macroeconomic variables. This result is robust across alternative samples and structural identifications. Therefore, our findings imply that policymakers should focus on uncertainty shocks that are synchronized across countries.

Abstrakt

Tento článek navrhuje postup pro dekompozici nejistoty v evropských zemích na společnou a na idiosynkratickou složku s pomocí časově proměnlivé celkové propojenosti. Poté pomocí bayesovského panelového VAR modelu odhadujeme dopady šoků do společné a idiosynkratické nejistoty na ekonomickou aktivitu, cenovou hladinu a měnovou politiku, přičemž šoky jsou identifikovány pomocí nulových a znaménkových restrikcí. Naše výsledky ukazují, že významné dopady na makroekonomické proměnné mají pouze společné šoky. Tento výsledek je robustní napříč alternativními vzorky a strukturálními identifikacemi. Naše zjištění tedy implikují, že tvůrci hospodářských politik by se měli zaměřit především na změny úrovně nejistoty, které jsou synchronizované napříč zeměmi.

JEL Codes: C32, F42, F45.
Keywords: Common uncertainty, economic policy uncertainty, panel VAR, spillovers.

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1. Introduction

There is increasing evidence that uncertainty developments are driven by a common factor (Ozturk and Sheng, 2018; Antonakakis et al., 2018; Mumtaz and Musso, 2021; Pfarrhofer, 2023). This international dimension of uncertainty shocks is particularly relevant for European countries, especially those integrated within the euro area where shocks originating at the level of individual member states often affect other countries and become common in their nature. These common shocks might have different effects on nominal and real variables than those shocks that do not spread to other countries, as suggested, particularly, by Berger et al. (2016). Therefore, distinguishing between common and purely domestic shocks is crucial from both an analytical perspective and for policymakers to formulate responses, as including an aggregate uncertainty indicator in an econometric model can conflate the minimal effects of domestic shocks with the larger effects of common shocks, leading to inaccurate estimates of the impact on the economy.

However, tracking and separating the common uncertainty components from any uncertainty index is not straightforward, because most such indices have been developed to approximate uncertainty at the level of individual countries regardless of whether it is of domestic origin or has arisen from spillovers from other countries. This is also the case of the Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016) that has become one of the most popular approximations of uncertainty in the empirical literature. We use the EPU index as our preferred measure of uncertainty because is is available monthly and for a wider set of countries than other uncertainty proxies. In addition, the EPU index was constructed to track broader dimensions of uncertainty than other indicators, derived from either the volatilities of the financial markets, the forecast errors of macroeconomic series (Jurado et al., 2015; Meinen and Roehe, 2017), or the disagreement between professional forecasters (for example, Bachmann et al. 2013).

In the literature, there appear a number of competing approaches to the decomposition of uncertainty into its common and individual components. The options include averaging across country-specific indices (Baker et al., 2016; Ozturk and Sheng, 2018), averaging across residuals in country-specific VAR models (Biljanovska et al., 2021), factor analysis (Berger et al., 2016; Mumtaz and Theodoridis, 2017), a factor model of the volatilities of groups of variables with multiple layers (Mumtaz and Musso, 2021), and a factor model with stochastic volatilities incorporated into a global time-varying parameter VAR model (Pfarrhofer, 2023). Alternatively, a related stream of literature approximates common uncertainty using a different uncertainty indicator with multinational or global coverage and studies the transmission of common uncertainty to national economies without decomposing any particular uncertainty index into its common and country-specific components. Those indices of global uncertainty include, for example, the global version of the EPU index, the GEPU (Davis, 2016), the Global Financial Uncertainty (Caggiano and Castelnuovo, 2023), the Trade Policy Uncertainty Index (Caldara et al., 2020), the geopolitical risk indicator by Caldara and Iacoviello (2022), and a global macroeconomic uncertainty index with shocks instrumented by changes in prices of gold around specific events (Bobasu et al., 2023).[1]

While all these alternatives have their pros and cons, this paper proposes a novel approach to decomposing the country-level EPU into its common and country-specific components. Our approach uses dynamic total connectedness, which is derived from the generalized forecast error

[1] Additionally, there is also a growing literature that provides estimates of common uncertainty shocks derived from common volatility patterns but without separating the common and domestic components. These applications usually confirm that common uncertainty has a significant effect on the macroeconomic variables of the countries under scrutiny; see Cross et al. (2018) and Carriero et al. (2020) for examples.

variance decompositions of a time-varying parameter VAR model and represents the ratio of the uncertainty explained by the spillovers from each country to the others. The connectedness methodology was developed by Diebold and Yilmaz (2009, 2012) and extended to the space of time-varying parameter models by Antonakakis et al. (2020). Previously, Antonakakis et al. (2018) used this framework to uncover time variation in uncertainty spillovers between the United States, the United Kingdom, the European Union, Japan, and Canada, and Baxa and Šestořád (2024) provided a detailed analysis of spillovers across European countries. Building on these results, we infer the common uncertainty as the cross product of the dynamic total connectedness and the average EPU and show on the example of European countries that this approach leads to a plausible representation of comovements in EPU indices.

Compared to alternative approaches to identify the common and country-specific components, the method proposed in this paper has several benefits, particularly when the effects of uncertainty approximated by the news-based Economic Policy Uncertainty index are of interest. First, it does not require the construction of alternative news-based indices to track country-specific uncertainty, such as in Baker et al. (2022) for state-level uncertainty in the United States.[2] Second, our approach allows the components of common and country-specific uncertainty to be correlated, because single-country events often affect both domestic and common uncertainty simultaneously. For example, the Brexit referendum was a large shock to the common European-wide uncertainty due to its potential effect on trade links with the United Kingdom and a fear that similar exits from the EU could happen in other countries as well. In addition to this common shock, the Brexit referendum led to the resignation of British Prime Minister David Cameron and sparked a large wave of economic policy uncertainty within the United Kingdom, since it was not clear how the proponents of *Leave* would manage the Brexit negotiations and what the outcome would mean for business. Therefore, the correlation between the domestic and common components should not be excluded, especially in applications aiming to evaluate the differences in the impacts of common and domestic uncertainty shocks on output and other variables.[3]

In addition, our estimates of the common uncertainty can be considered as an alternative to the European EPU developed by Baker et al. (2016), which is based on a simple average of uncertainty-related articles in two newspapers from Germany, France, Italy, Spain, and the United Kingdom. Unlike the European EPU, our approach distinguishes whether the articles refer to a country-specific or broader uncertainty by employing total connectedness in the calculation of the common component because it measures the intensity at which the EPU indices move together.

In the literature, the relative contributions of common and country-specific components remains subject to debate. Mumtaz and Theodoridis (2017), using a factor model with uncertainty represented by common volatility of macroeconomic and financial variables, find that since the early 1970s, the contribution of the common component to the dynamics of output growth in 11 OECD countries has been relatively minor, between 4.2 and 35.8 percent in the case of European countries. On the other hand, the results obtained by Berger et al. (2016) using a similar dynamic factor model with stochastic volatility on a larger set of countries but a more limited set of

[2] Baker et al. (2022) construct their state-level EPU by searching for articles related to economic policy uncertainty in 3500 local newspapers. They construct three types of subindices, one for purely state-level uncertainty (EPU-S), one for national and international uncertainty (EPU-N), and a composite index capturing both (EPU-C).

[3] For the United States, Baker et al. (2022) find that the state-level EPU indices and composite EPU indices comove, with the overlap between them caused by articles containing both sources of uncertainty being about 20%. Pfarrhofer (2023) likewise does not impose the orthogonality restriction on common and country-specific uncertainty, and finds a correlation between these two components of greater than 0.5 for Germany, France, and the United Kingdom.

variables suggest that global uncertainty is a major driver of macroeconomic fluctuations, whereas the impact of domestic uncertainty is small and often insignificant. Both levels of uncertainty are found to be relevant for real activity by Mumtaz and Musso (2021) with their multi-layered dynamic factor model, and by Biljanovska et al. (2021) with common uncertainty approximated by the average EPU. These papers, however, estimate the common uncertainty on panels of European and non-European countries where larger heterogeneity is expected. With the exception of Biljanovska et al. (2021), they do not employ the popular EPU index as an uncertainty proxy. To address this gap, we use a Bayesian panel VAR model to investigate the effects of common and country-specific uncertainty components on economic growth, represented by the industrial production index, on inflation and interest rate setting, with structural shocks identified using sign and zero restrictions. Our results show that the negative effects of uncertainty shocks on economic activity of European countries are driven primarily by common uncertainty. On the other hand, country-specific shocks without significant cross-border effects have only marginal impacts on European economies. Our results also suggest that policymakers already respond predominantly to the common part of uncertainty, and hence mitigate the adverse impact of uncertainty on their economies.

The prominent role of common shocks in the economy is robust to a number of sensitivity checks. First, we extended the panel VAR model for industrial production in the United States to control for fluctuations in global economic activity. We found that the inclusion of U.S. industrial production led to smaller contributions of demand and supply shocks to fluctuations in economic activity, but the importance of uncertainty shocks remained robust to our baseline specification. Next, we expanded our sample to cover six additional countries, for which the EPU index was calculated, and we also employed two different structural identifications, an alternative set of zero and sign restrictions, and the traditional Cholesky decomposition. In all cases, the results were largely robust and confirmed the primary role of common uncertainty shocks for the macroeconomic variables considered.

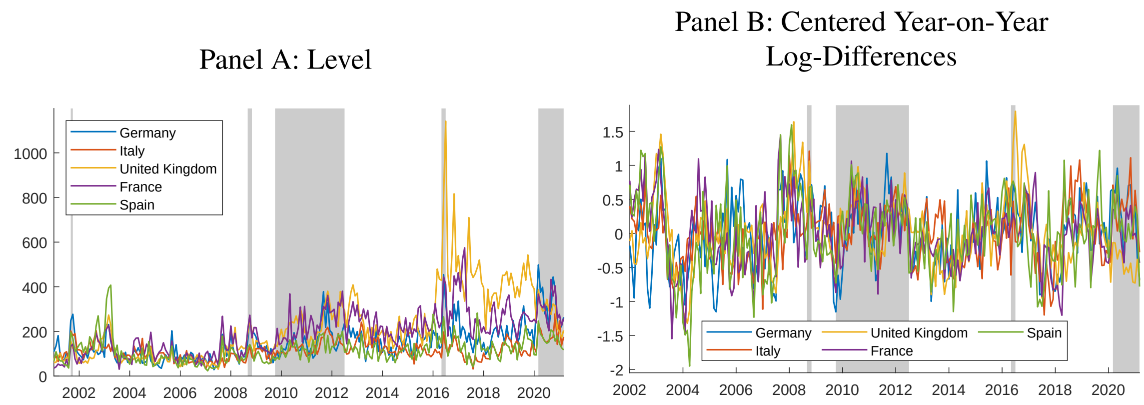
The remainder of this paper is organized as follows. Section 2 presents the concept of total connectedness and its application to uncertainty. Section 3 provides the decomposition of uncertainty into its country-specific and common components. The subsequent analysis of the impact of both factors of uncertainty on the economy is presented in Section 4. Section 5 provides a sensitivity analysis of our results with respect to an extended sample of data and an alternative structural identification of the panel VAR model. Our conclusions are summarized in section 6.

2. Dynamic Connectedness of Uncertainty Across European Countries

2.1 Data

Our primary specification uses the EPU indices for the five largest European economies, France, Germany, Italy, Spain, and the United Kingdom, constructed by Baker et al. (2016) (Panel A in Figure 1) from January 2001, when the EPU is available for all the five countries, to March 2021. The EPU indices move closely together until the European debt crisis but then their dispersion increases. Nonetheless, the peaks in the EPU indices align around major uncertainty events such as the Brexit referendum and the COVID-19 pandemic. Furthermore, the findings by Baxa et al. (2023) suggest that EPU trends do not inherently reflect the trends in the underlying uncertainty, but are influenced by fluctuations in the count of all newspaper articles, which act as a scaling factor for the count of articles related to uncertainty in creating the EPU index. Moreover, the ADF test does not reject unit roots in the EPU indices of Germany, France, and the United Kingdom. Therefore, we estimate the model in year-on-year log differences, centered and

Figure 1: Economic Policy Uncertainty Index



Note: Shaded areas depict major uncertainty events worldwide. 2001M09–2001M10: 9-11 terrorist attack; 2008M09–2008M11: bankruptcy of Lehman Brothers; 2009M10–2012M07: EU debt crisis; 2016M05–2016M07: Brexit referendum; 2020M03–2021M03: Covid-19.

Table 1: Correlation Coefficients of EPU Index among Countries

Levels						*Centered year-on-year log-differences*				
Germany	Italy	UK	France	Spain		Germany	Italy	UK	France	Spain
1.00	0.56	0.62	0.72	0.56	Germany	1.00	0.39	0.45	0.53	0.52
0.56	1.00	0.31	0.50	0.47	Italy	0.39	1.00	0.25	0.47	0.43
0.62	0.31	1.00	0.74	0.42	UK	0.45	0.25	1.00	0.46	0.52
0.72	0.50	0.74	1.00	0.50	France	0.53	0.47	0.46	1.00	0.54
0.56	0.47	0.42	0.50	1.00	Spain	0.52	0.43	0.52	0.54	1.00

standardized (Panel B in Figure 1). These transformed series exhibit notable synchronization over the entire period.

The similarity of the dynamics of the EPU indices is further corroborated by the correlation coefficients (Table 1), which reach 54 % for the data in levels and 46 % for the centered year-on-year log differences. These correlations indicate that spillovers and the common factor play an important role in the EPU indices of European countries. Note that the common factor accounts for broader international uncertainty, which could originate either in one of the countries in the sample or in other countries, such as the United States, China, Russia, or any other country.[4]

For the sensitivity analysis, we extended the sample by including EPU for other European countries for which EPU indices are available. These include Greece (Hardouvelis et al., 2018),[5] Ireland

[4] The uncertainty in the United States, China, Russia, and other important trade partners no doubt has an impact on the uncertainty in European countries. This is apparent from a comparison of the common uncertainty component with the index of global economic policy uncertainty, GEPU (Davis, 2016), provided in the next section. We decided not to include non-European countries in our baseline samples since our primary goal is to estimate the total connectedness and the effects of common uncertainty on the economy. This total connectedness encompasses all the uncertainty that the countries in the sample have in common, and the role of the countries not included in the sample enters through the impact on individual European countries.

[5] We opted for the index by Hardouvelis et al. (2018) since it is based on text mining in four newspapers, while the alternative index by Fountas et al. (2018) uses just one newspaper to derive the uncertainty index.

(Rice, 2020), Belgium (Borms et al., 2020), the Netherlands (Kok et al., 2015), Denmark (Bergman and Worm, 2021) and Sweden (Armelius and Hull, 2017).[6]

2.2 Concept of Total Connectedness

As a starting point for the decomposition of the common and country-specific uncertainty, we utilize the concept of dynamic connectedness. The calculation of dynamic connectedness proceeds as follows. First, we estimate a VAR model with time-varying parameters and stochastic volatility (Koop and Korobilis, 2014), with selected EPU indices as endogenous variables:

$$y_t = c_t + B_{t,1}y_{t-1} + \ldots + B_{t,p}y_{t-p} + \varepsilon_t \qquad \varepsilon_t \sim \mathcal{N}(0, Q_t) \tag{1}$$

where y is a vector of m endogenous variables, c_t is time-varying constant, and $Bt, 1 \ldots B_{t,p}$ denote time-varying regression coefficients. Disturbances ε_t follow a normal distribution with zero mean and covariance Q_t, which ensures stochastic volatility in the system. The optimal number of lags p is selected according to the Akaike information criterion, which suggests four lags.

All parameters are stacked to vector β_t such that

$$\beta_t = (c_t^{'}, vec(B_{t,1})^{'}, \ldots, vec(B_{t,p})^{'}) \tag{2}$$

$$\beta_t = \beta_{t-1} + \eta_t \qquad \eta_t \sim \mathcal{N}(0, R_t) \tag{3}$$

where β_t evolves as a random walk over time with a normally distributed error term η_t.[7]

To estimate the time-varying parameters, we rely on a two-step algorithm developed by Koop and Korobilis (2014), with error covariance matrices R_t and Q_t estimated dynamically using exponentially weighted moving averages (EWMA). The priors on the time variation in volatility and coefficients are set by the forgetting factors κ_1 and κ_2. Their values are between 0 and 1, with higher values implying lower time variation. Hence, time variation is absent if the forgetting parameters are set to one. Following Koop and Korobilis (2014), we set $\kappa_1 = 0.96$ and $\kappa_2 = 0.99$.

After estimating the TVP-VAR model, we infer the generalized forecast error variance decompositions of the variable i from the generalized impulse response functions ψ_{ij}^g at the horizon n (Pesaran and Shin, 1998) as:

$$GFEVD_x = \phi_{ij,t}^g(n) = \frac{\sum_{t=1}^{n-1}(\psi_{ij,t}^g)^2}{\sum_{j=1}^{m}\sum_{t=1}^{n-1}(\psi_{ij,t}^g)^2} \tag{4}$$

with m being the dimension of the vector of endogenous variables, i being the i-th variable from a vector x, and j being the variable associated with a particular shock δ_j. In our case, shock δ_j is equivalent to the standard deviation of the residuals.

The estimates of the generalized forecast error variance decompositions show the relative share of the variance of the uncertainty in each country explained by shocks originating in the domestic economy and the contribution of other countries to the overall economic policy uncertainty index.

[6] The uncertainty indices of those countries are regularly updated and the updates are available at `www.policyuncertainty.com/europe_monthly.html`.

[7] Note that the time-varying parameter VAR reduces to a linear VAR if covariance matrix $R_t = 0$. Stochastic volatility reduces to homoskedasticity if $Q_t = Q$.

Because the time-varying parameter VAR model was used for the estimation, the variance decompositions are allowed to vary over time as well, to account for potentially changing contributions of different countries to the common uncertainty.

Then, following Antonakakis et al. (2020), we obtain the *total connectedness*, $TC_t(n)$, among the uncertainty indices of individual countries as follows:

$$TC_t(n) = \frac{\sum_{ij=1,i\neq j}^{m} \phi_{ij,t}^{g}(n)}{\sum_{ij=1}^{m} \phi_{ij,t}^{g}(n)} = \frac{\sum_{ij=1,i\neq j}^{m} \phi_{ij,t}^{g}(n)}{m}. \tag{5}$$

The $TC_t(n)$ expresses how a shock to the variable i transmits to all other variables j for a given horizon n at time t. The horizon of the generalized impulse responses and forecast error variance decompositions n is set to 24 months, at which the relative contributions of the different countries to the generalized forecast error variance decompositions are stable.

2.3 Estimated Dynamic Connectedness

The estimates of dynamic connectedness are presented in Figure 2. Our benchmark specification with the five largest European economies and the EPU indices by Baker et al. (2016) yields an average connectedness of 45.9, implying that 45.9 % of the EPU fluctuations across these countries are driven by uncertainty spillovers. When considering the extended sample with 11 countries, the connectedness increases, to a range between 50 and 70, with an average connectedness of 62.8.[8]

Furthermore, we see a decrease in connectedness during the European debt crisis between 2009 and 2012 in both variants, linked to the divergence of the core and periphery economies of the EU. Similar results were obtained by Śmiech et al. (2020) for spillovers in financial, consumer and industrial uncertainty, and by Fernandez-Perez et al. (2024) for consumer confidence.[9]

3. Disentangling Common and Country-Specific Uncertainty

Since dynamic connectedness shows the intensity with which the EPU indices of individual countries comove, it is appealing to use dynamic connectedness to disentangle the common and country-specific components of the overall EPU. Therefore, we define the common component for country i as the uncertainty of country i shared with other countries as the product of the dynamic connectedness $TC_t(n)$ and the average EPU:

$$\Delta EPU_t^{common}(n) = \frac{TC_t(n)}{100} * \frac{\sum_{i=1}^{m} \Delta EPU_{i,t}}{m} \tag{6}$$

where $TC_t(n)$ is *total connectedness* as defined above and $\Delta EPU_{i,t}$ is the centered year-on-year log difference of the EPU index for each country in the model.[10]

Finally, the country-specific component of the EPU of country i is the difference between the EPU index $EPU_{i,t}$ and the common component EPU_t^{common}

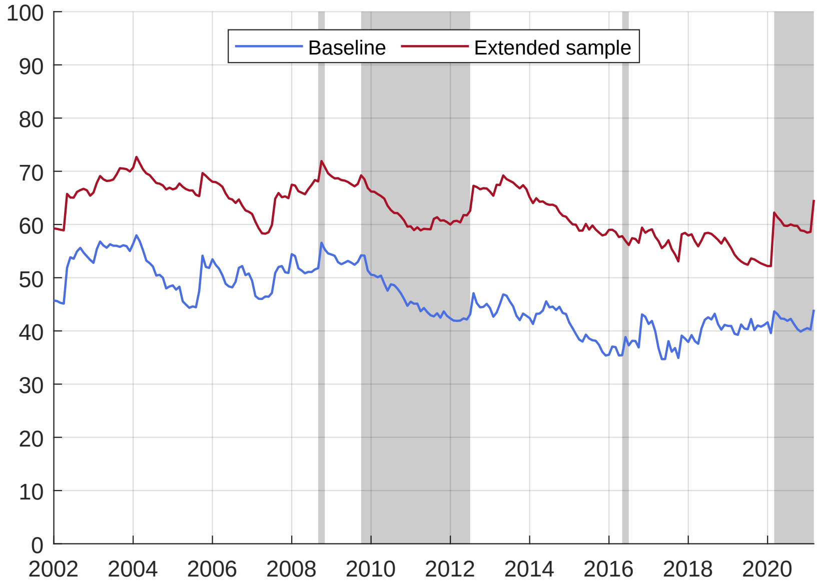
$$\Delta EPU_i^{local}(n) = \Delta EPU_{i,t} - \Delta EPU_t^{common}(n). \tag{7}$$

[8] Four lags were used for the estimation of the time-varying parameter VAR model with stochastic volatility in the case of the extended sample of countries, too.

[9] The contributions of the individual countries and their differences across alternative samples are broadly discussed in Baxa and Šestořád (2024).

[10] As a variant, we also considered the common component defined as the uncertainty imported into country i from other countries, that is

Figure 2: Total Connectedness in European Uncertainty



Note: Shaded areas depict major events around the world. 2008M09–2008M11: bankruptcy of Lehman Brothers; 2009M10–2012M07: EU debt crisis; 2016M05–2016M07: Brexit referendum; 2020M03–2021M03: Covid-19.

This method for separating the common and domestic components allows us to derive both components from one index while maintaining some correlation between both components. This is a desirable property given that many uncertainty events originate from events within a particular country but then have the power to influence the uncertainty of others, such as the unexpected result of the Brexit referendum and the fiscal announcements during the European debt crisis. In our case, the correlation between the common and country-specific components ranges between 0.47 and 0.66, with the exception of Italy, where the correlation reaches modest 0.23. This is comparable to Pfarrhofer (2023), who also does not impose the orthogonality restriction on the common and country-specific uncertainty, finds a correlation between these two components above 0.5 in the case of the three largest European economies, Germany, France and the United Kingdom.

Figure 3 presents the common components in the year-on-year changes of the EPU indices. Despite the difference in the level of total connectedness between the two samples and some minor differences in their dynamics, the trajectories of the estimated common components for both the baseline and extended sample are remarkably similar. Most importantly, the common component is

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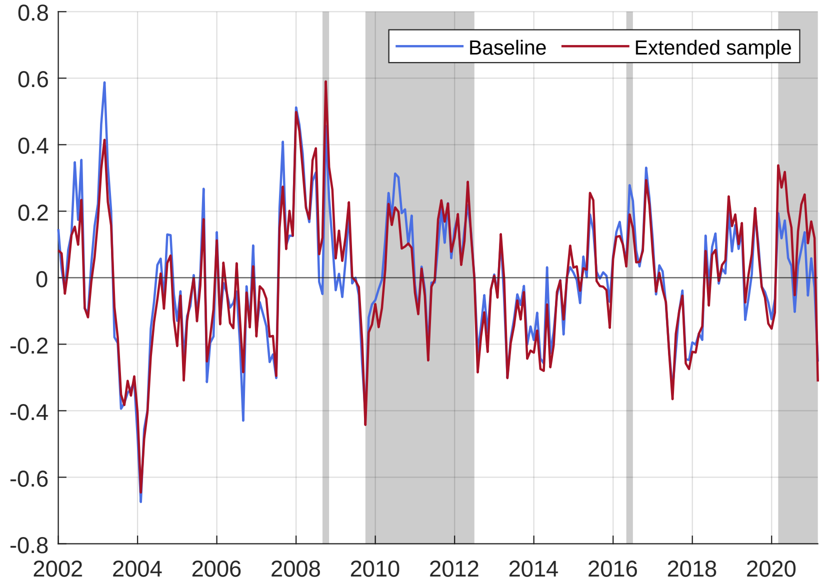
$$EPU_{i,t}^{common} = TC_{i\leftarrow j,t}(n) * \frac{\sum_{j=1,j\neq i}^{m} EPU_{j,t}}{m-1}$$

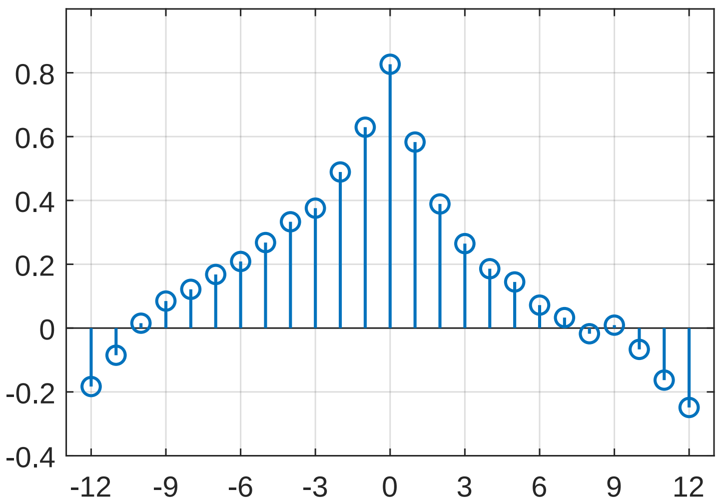
with $TC_{i\leftarrow j,t}(n)$ being *the total directional connectedness from others*. This alternative specification implies that the common component of the uncertainty of country i is equal to the share of the uncertainty of other countries that explains the uncertainty of country i. However, the cost of this specification is that the resulting common components are not the same across countries, as some countries might be more exposed to uncertainty from other countries than others. Nevertheless, the main result of the next section about the dominant effect of common uncertainty on economic activity and monetary policy setting was robust to the switch from one specification of common uncertainty to another. These results are available upon request.

Figure 3: Common Component of Uncertainty



Note: Shaded areas depict major events around the world. 2008M09–2008M11: bankruptcy of Lehman Brothers; 2009M10–2012M07: EU debt crisis; 2016M05–2016M07: Brexit referendum; 2020M03–2021M03: Covid-19.

Figure 4: Cross-Correlation of Common EPU and GEPU



Note: Negative (positive) values show how common uncertainty is correlated with a lagged (leading) GEPU. The x-axis denotes months.

most pronounced during the most significant uncertainty episodes, such as in 2003 around the war in Iraq, during the 2007/2008 financial crisis, and during the subsequent European debt crisis. After a temporary decrease, the common uncertainty rose again in 2016, mainly because of political instability in the United Kingdom due to Brexit, in Spain with repeated elections due to the impossibility of forming a majority in a fragmented parliament, and in Italy around time of the constitutional referendum.

What drives the uncertainty component? Figure 4 shows that the common uncertainty obtained as a product of dynamic connectedness and the average EPU is largely correlated with the global EPU index (Davis, 2016), which tracks the uncertainty of 21 economies accounting for 80 % of the global GDP.[11] Therefore, the common component estimated from the EPU indices of individual countries also accounts for the uncertainty coming from other countries that are not included in the sample but have an impact on those that are included. However, in contrast to the GEPU Index, the common component derived using total connectedness disregards those fluctuations of uncertainty that are not directly relevant for the countries of interest and therefore provides a more tailored representation of the cross-border dimension of uncertainty than indices averaging uncertainty indices across countries, such as the GEPU. The ability of the common component to track the uncertainty stemming also from other countries is partly caused by the construction of the EPU index, which is based on the count of newspaper articles that contain words related to uncertainty, economy, and economic policy within a given month. Thus, events happening in the United States with a possible impact on, for example, Germany appear as a part of the German EPU directly, because German newspapers report on events happening in the United States, which often have implications for the economic growth and economic policy of other countries as well.[12]

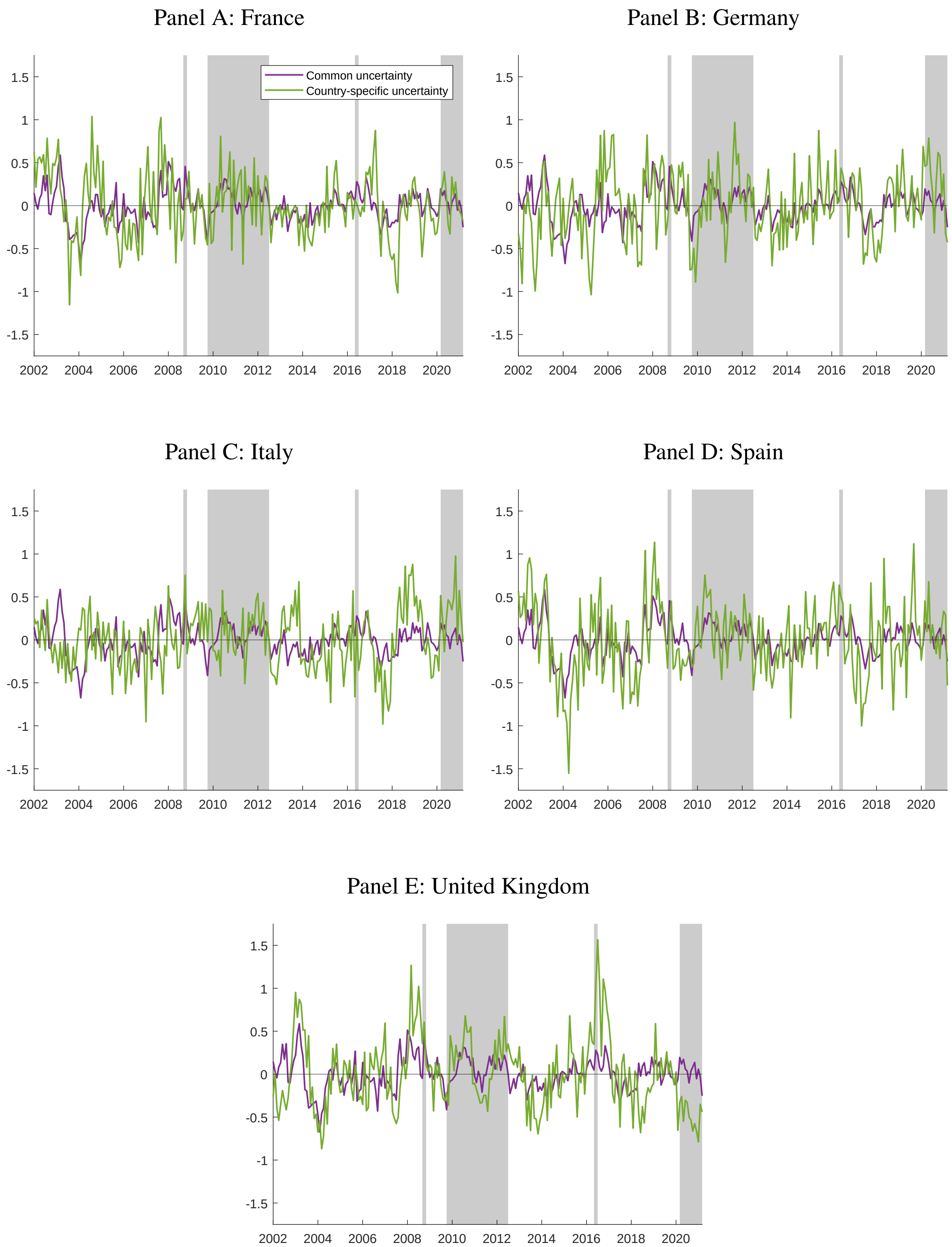
Then, Figure 5 provides a plot of common and country-specific uncertainty components at the level of individual countries. This comparison shows that the country-specific uncertainty component is more volatile and much less persistent compared to the common component. Several events are worth highlighting. In the early 2000s, more persistent increases in domestic components appeared first in France during the growing discontent with Jacques Chirac's second presidency, marked by the loss of his UMP party in regional elections in 2004 and rejections of the European constitution in the referendum in 2005. A similar increase in the domestic component in Germany in late 2005 coincides with the aftermath of snap elections followed by the resignation of that time chancellor Gerhard Schöder and the formation of the Grand coalition led by Angela Merkel. The uncertainty associated with the financial crisis of late 2007 is visible mainly in the increase of the common component, further amplified by the country-specific components, particularly in the United Kingdom and Spain, but shortly also in France after BNP Paribas froze its three funds in the United States and became one of the first major banks admitting problems due to its exposure to the subprime mortgage market crisis.

After the drama of the European debt crisis, the domestic components peaked most dramatically in the United Kingdom following the Brexit referendum and then in Italy after the 2018 elections, which led to a minority government formed by two populist parties, the Five Star Movement and Lega. However, the increased unpredictability of Italian economic policy had limited effects on common uncertainty. Finally, the Covid-19 pandemic is reflected mainly in the country-specific components, probably due to different timings of the main waves of infections across countries and different degrees of disagreement about the appropriate policy responses.

[11] The GEPU Index is a GDP-weighted average of the national EPU indices for 21 countries: Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States. We present results for the GEPU Index with GDP weights based on market exchange rates; however, the results for the PPP-weighted index were nearly identical.

[12] Another implication of the ability of the common component to encompass the effects of uncertainty coming from other countries is that the estimates of the common component are robust to the inclusion of the EPU of the United States in the set of countries used to calculate the total connectedness. These results are available upon request.

Figure 5: Decomposition of EPU Index to Common and Country-Specific Component



Note: Shaded areas depict major events around the world. 2008M09–2008M11: bankruptcy of Lehman Brothers; 2009M10–2012M07: EU debt crisis; 2016M05–2016M07: Brexit referendum; 2020M03–2021M03: Covid-19.

4. Effects of Common and Country-Specific Uncertainty: Panel VAR Evidence

4.1 Identification Strategy

We employ panel vector autoregression to analyze the economic implications of the common and country-specific uncertainty inferred in the previous section. Our panel VAR includes the industrial production index to track economic activity at monthly frequency, the HICP to represent the price level, and the shadow interest rate by Krippner (2013), along with the common and country-specific uncertainty components. We use monthly data from January 2002 to March 2021, with the macroeconomic data obtained from the Eurostat database. In line with the transformation of the EPU indices for the analysis of connectedness and the decomposition into common and country-specific components, the industrial production index and the price level are transformed into year-on-year log differences. All data are demeaned to ensure a more appropriate and robust historical decomposition (Bergholt et al., 2024). The model is estimated using the Bayesian framework, with the normal-Wishart prior, and three lags using the pooled estimator implemented in the BEAR toolbox (Dieppe et al., 2016).[13] For the estimation, we use 2000 iterations, with the first 1000 iterations discarded as a burn-in. As an alternative, we employed the random effects model with a hierarchical prior to account for potential cross-country heterogeneity. The results for our baseline model were consistent across countries and similar to the more parsimonious pooled model.

To achieve the structural identification, we rely on the zero and sign restrictions of Arias et al. (2018) rather than on the Cholesky decomposition used by Baker et al. (2016), Leduc and Liu (2016), Caggiano et al. (2020), and Biljanovska et al. (2021) because of the endogeneity of uncertainty and the business cycle. This endogeneity makes the quantification of the impact of uncertainty shocks on economic activity prone to the choice of ordering uncertainty before or after the variables representing economic activity, as shown by Kilian et al. (2022) and highlighted in the survey by Castelnuovo (2023).

The restrictions for the aggregate demand, aggregate supply, and monetary policy shocks follow the characteristics of standard New Keynesian DSGE models. Therefore, it is assumed that (i) the adverse demand shock reduces economic activity, prices, and the policy rate; (ii) the supply shock increases prices and the interest rate but dampens economic activity; and (iii) the monetary policy tightening is characterized by an increase in the interest rate and a decrease in both economic activity and prices. The contemporaneous responses of both uncertainty components to the demand, supply, and monetary shocks are constrained by zero restrictions at impact to differentiate particularly the demand shock from the uncertainty shocks.

Both uncertainty components are then assumed to have a contemporaneous negative impact on industrial production, in line with the empirical literature documenting the countercyclical nature of the dynamics of uncertainty—see the survey by Castelnuovo (2023)—and with DSGE models

[13] The results are robust to the choice of a lag length of between two and five lags, as can be seen from Figure D1 in the Appendix. The identification of structural shocks is robust in the period from January 2002 to December 2019 regardless of whether the subsequent pandemic period is included. The correlation coefficients of the structural shocks are provided in Table D1 in the Appendix.

Table 2: Structural Identification of Shocks

Variable\Shock	Demand	Supply	Monetary policy	Country-specific uncertainty	Common uncertainty
Production	-	–	-	-	-
Prices	-	+	-		
Interest rate	-	+	+		
Country-specific EPU	0	0	0	+	+
Common EPU	0	0	0	0	+

Note: A "0" ensures that this variable cannot move contemporaneously in response to the particular shock. A "+"("−") indicates that this variable must respond positively (negatively) to the particular shock.

linking uncertainty shocks to aggregate demand shocks (Leduc and Liu, 2016; Basu and Bundick, 2017). No other restrictions are placed on interest rates and prices.[14]

The restrictions used to identify the common and country-specific uncertainty shocks reflect the comovement of EPU across European countries during significant political events. Therefore, a shock to common uncertainty is characterized by simultaneous increases in the common and country-specific uncertainty components. On the other hand, the country-specific shock to uncertainty is defined as an increase in country-specific uncertainty, while the response of the common component is set to zero at impact. All restrictions are summarized in Table 2.

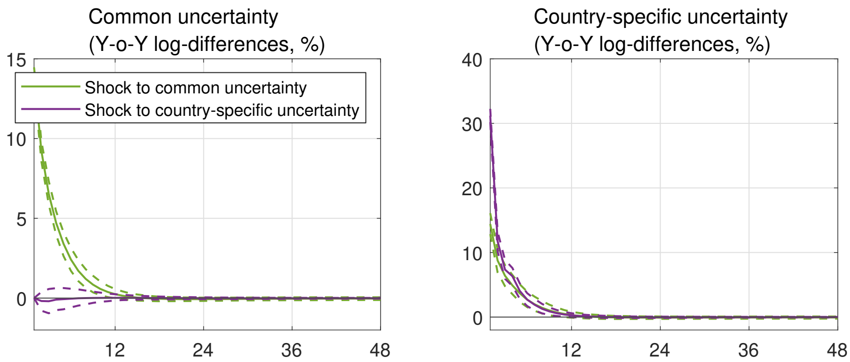
We also estimated the panel VAR model with the EPU index instead of its common and country-specific components taken separately to compare the quantitative effects of common and country-specific uncertainty shocks with the quantitative effects of shocks to the aggregate EPU index. The structural identification is equivalent, with the uncertainty shock defined as a simultaneous decrease in industrial production and increase in EPU (Table C1 in the Appendix). This knowledge is particularly relevant for policymakers, who are increasingly following uncertainty developments but face the problem of many false signals due to the frequent ups and downs of country-specific uncertainty indices, which do not provide a clear-cut distinction between increases in uncertainty due to common causes and those due to domestic causes.

4.2 Estimated Effects of Uncertainty Shocks

The estimated effects of the shocks to the common and country-specific components are presented in Figure 6 and Figure 7, which show the median impulse responses to one-standard deviation shocks along with the 90% credible intervals. In line with the sign restrictions, we observe comovement of the two uncertainty components in response to the common uncertainty shocks. In terms of year-on-year growth, both components initially increase by 15 %. However, the country-specific uncertainty

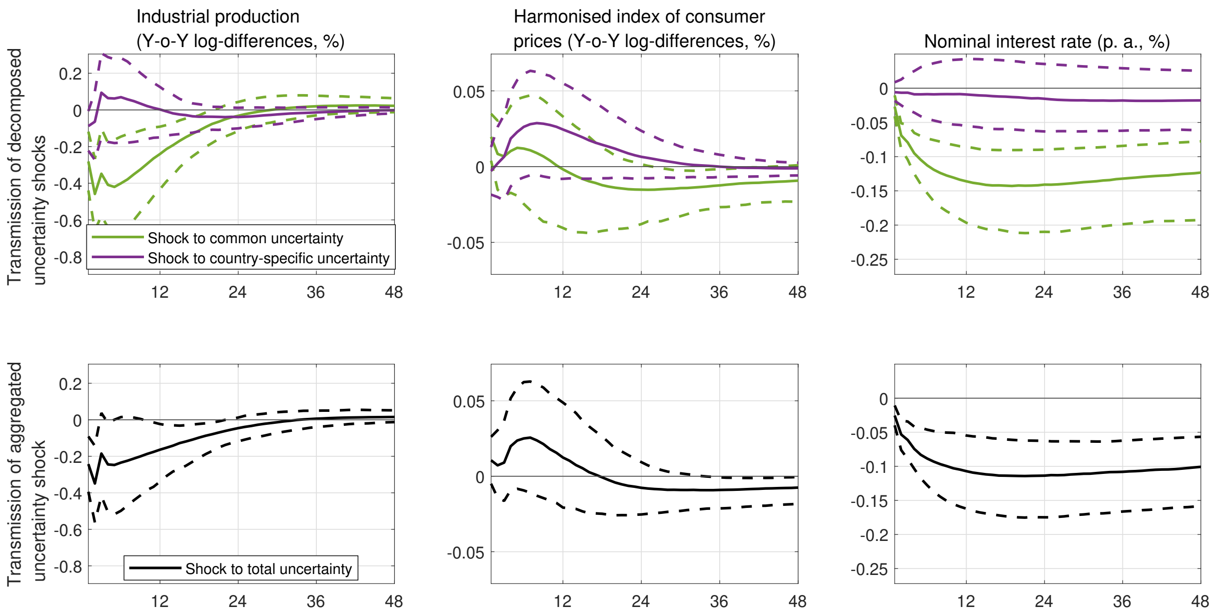
[14] Meinen and Roehe (2018) argue that the responses of prices to uncertainty shocks are ambiguous and restricting them to be negative attenuates the impact of prices on economic activity. Therefore, we leave the responses of prices unrestricted.

Figure 6: Spillovers in Common and Country-Specific Uncertainty



Note: Median responses with 90% credible intervals. The responses correspond to one standard deviation shocks and cover the 48 months after the initial shock.

Figure 7: Implications of Common and Country-Specific Uncertainty Shocks



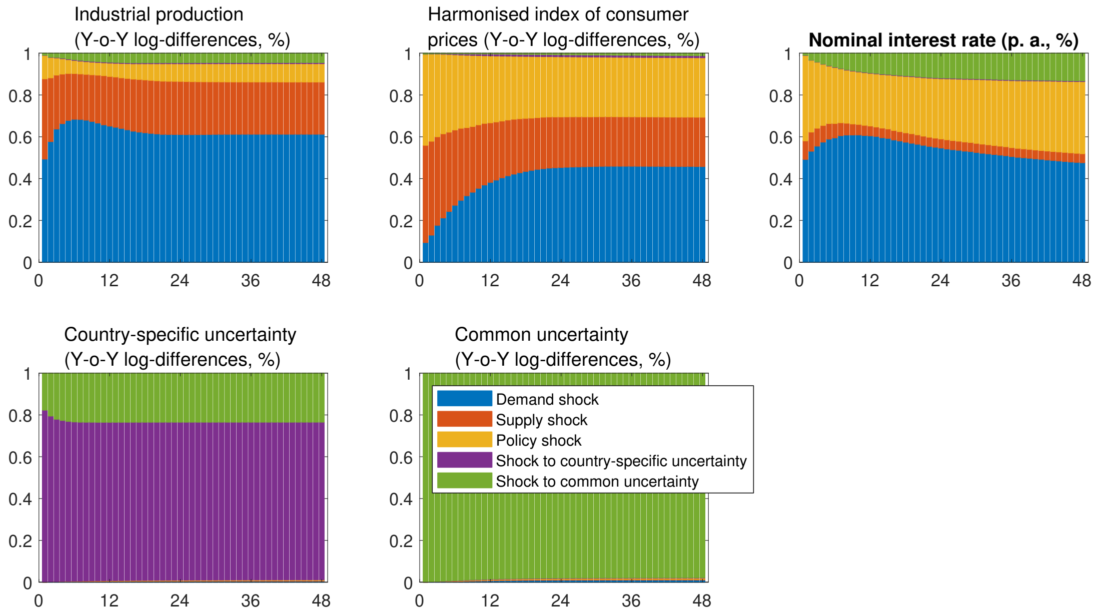
Note: Median responses with 90% credible intervals. The responses correspond to one standard deviation shocks and cover the 48 months after the initial shock.

shock does not lead to an increase in common uncertainty, despite the response being constrained to zero only at impact. The results confirm rapid transmission of the common uncertainty shock to the country-specific uncertainty (Figure 6).[15]

The impulse responses of industrial production reveal that the adverse effects of uncertainty shocks commonly found in the literature (e.g., Castelnuovo 2023) are driven predominantly by the common

[15] As an alternative, we considered an identification relying on the immediate response of common uncertainty to a country-specific shock, while country-specific uncertainty is contemporaneously restricted to a common shock by the zero restrictions. In this case, the country-specific uncertainty still increases markedly in response to the shock to common uncertainty, although the magnitude of this response is less pronounced than in the baseline. The response of common uncertainty to a country-specific shock remains muted even when a sign restriction is applied at impact.

Figure 8: Forecast Error Variance Decomposition



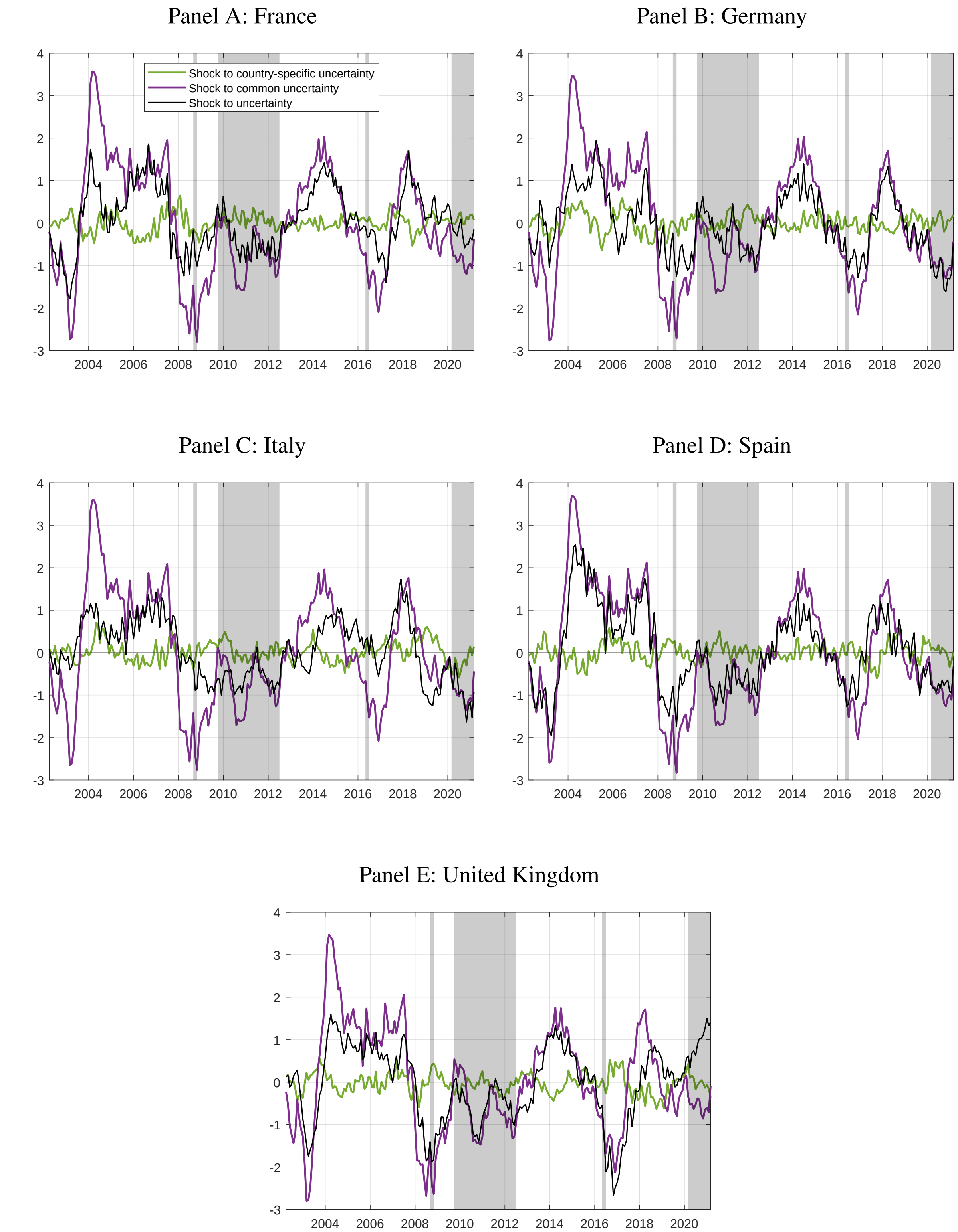
Note: The x-axis denotes months; the y-axis represents the share of the shocks in the variability.

uncertainty, as suggested notably by Berger et al. (2016) with uncertainty defined as a common component in the unexplained volatility of macroeconomic variables. Nevertheless, the response of industrial production to the country-specific uncertainty shock is small and statistically insignificant (Figure 7). The direct comparison of these impulse responses with the responses to the shock to the aggregate EPU shown in the second line of this figure proves that the negative responses of industrial production to EPU shocks commonly found in the literature are driven primarily by common uncertainty shocks, because the effects of aggregate EPU shocks are less pronounced than the responses to common uncertainty. Similarly, the positive response of prices to the EPU shock resembles the path of the impulse response of prices to the shock to the common component of uncertainty.

The responses of monetary policy to the common uncertainty shock corroborate the primary role of common uncertainty in the effects of uncertainty on the economy, as the interest rate decreases in response to the shock to the common component, as if the central bank uses the interest rate cut to offset the expected fall in economic activity due to increased uncertainty. However, the impact of an increase in country-specific uncertainty on interest rate setting seems to be negligible.

Figure 8 presents the forecast error variance decompositions. The dynamics of industrial production, inflation, and interest rates are driven predominantly by the demand, supply, and monetary policy shocks, in line with the findings by Carriero et al. (2020) and others suggesting that uncertainty shocks are not the primary driver of business cycles. Nevertheless, the common uncertainty component explains 4.49% of the variance of industrial production and 13% of that of the interest rate. However, the role of country-specific uncertainty is negligible. Quantitatively, our estimate of the contribution of uncertainty to the variance of industrial production matches that by Alessandri et al. (2023), who show that when uncertainty shocks are estimated using daily data and aggregated to monthly frequency, their adverse impact on industrial production is statistically significant but small, thus pointing to a possible misspecification of models that suggest that uncertainty shocks play a large role in economic activity. In addition, a quantitatively smaller

Figure 9: Comparison of Contribution of Aggregate and Decomposed Uncertainty to Industrial Production



Note: Contribution of uncertainty shocks to centered year-on-year log-differences in industrial production index, in percentage points. Shaded areas depict major events around the world. 2008M09–2008M11: bankruptcy of Lehman Brothers; 2009M10–2012M07: EU debt crisis; 2016M05–2016M07: Brexit referendum; 2020M03–2021M03: Covid-19.

contribution of uncertainty to the dynamics of economic activity is consistent with the recent DSGE model with varying mark-ups due to uncertainty by Born and Pfeifer (2021).

Although the forecast error decompositions indicate that uncertainty shocks make a limited contribution to the variability of other variables, the historical decompositions (Figure 9) reveal that the common uncertainty component caused an additional two percent decline in industrial production during periods associated with higher uncertainty, including at the time of the Iraq war in 2003, during the Great Recession and the European debt crisis, and after the Brexit referendum. This effect is stronger than the effect of the aggregate EPU, which does not distinguish whether the changes in EPU are common or idiosyncratic.

5. Robustness

5.1 The Role of Foreign Economic Activity

We have shown that the common uncertainty component is closely related to the global EPU. However, it needs to be investigated to what extent the common uncertainty component represents shifts in uncertainty and to what extent it tracks fluctuations in foreign demand and supply. To approximate the impact of foreign economic activity, we extend the model for U.S. industrial production, and the adverse foreign shock is defined as a simultaneous decrease in European and U.S. industrial production. The responses of the other variables are left unrestricted. On the other hand, the response of U.S. industrial production to the other shocks in the model is restricted to zero at impact. All zero and sign restrictions are summarized in Table 3.

Table 3: Structural Identification Controlled for Global Shock

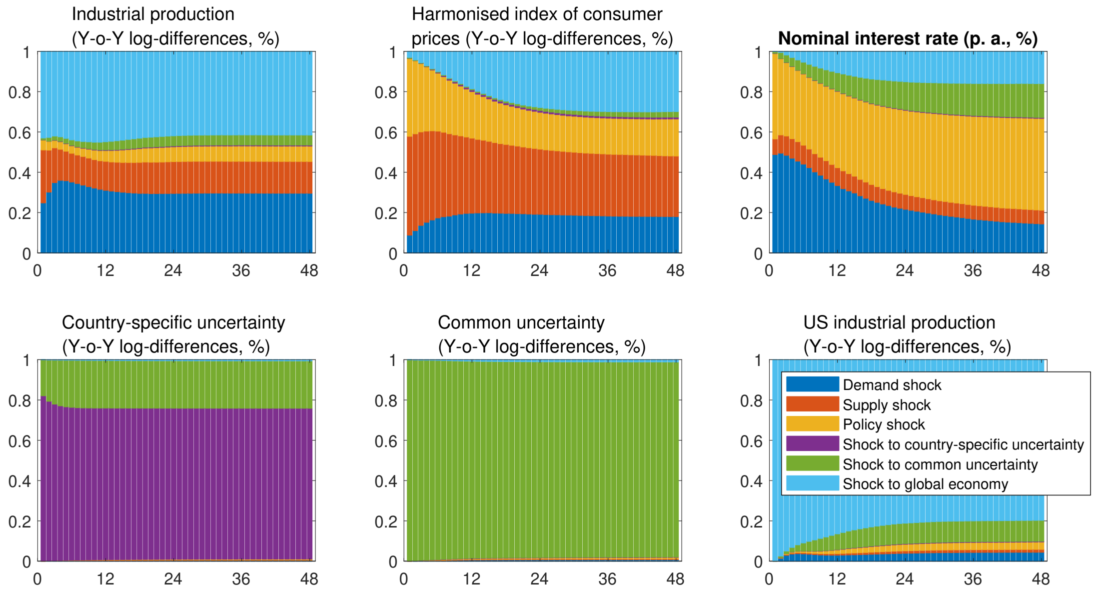
Variable\Shock	Demand	Supply	Monetary policy	Country-specific uncertainty	Common uncertainty	Global
Production	-	–	-	-	-	-
Prices	-	+	-			
Interest rate	-	+	+			
Country-specific EPU	0	0	0	+	+	
Common EPU	0	0	0	0	+	
Foreign production	0	0	0	0	0	-

Note: A “0” ensures that this variable cannot move contemporaneously in response to the particular shock. A “$+$”(“$-$”) indicates that this variable must respond positively (negatively) to the particular shock.

The implications of the extension for the industrial production of the United States are best illustrated by the forecast error variance decompositions (Figure 10). They show that the inclusion of the global shock reduces the role of domestic demand and supply shocks in the dynamics of industrial production, inflation, and the interest rate, but the relative contribution of the common uncertainty component remains robust to our benchmark.[16]

[16] The historical decompositions (Figure B1 in the Appendix) corroborate the conclusion that the common uncertainty component appears to be related to uncertainty and not to foreign demand or supply shocks.

Figure 10: Forecast Error Variance Decomposition (Controlled for U.S. Industrial Production)

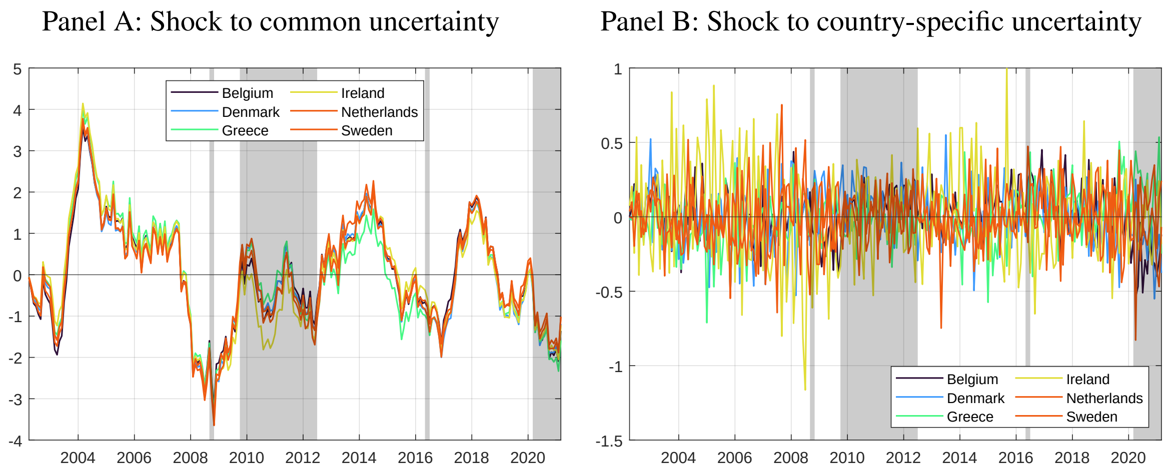


Note: The x-axis denotes months; the y-axis represents the share of the shocks in the variability.

5.2 Extended Sample of Countries

We estimate the panel VAR on an extended sample including Belgium, Denmark, Greece, Ireland, the Netherlands, and Sweden. Given that the estimated common component is already similar to our baseline, the resulting contributions to the historical decompositions are also close to our baseline specification (Figures 12). The relevance of shocks only to common uncertainty for the additional

Figure 11: Contribution of Decomposed Uncertainty to Industrial Production in Additional Countries



Note: Contribution of uncertainty shocks to centered year-on-year log-differences in industrial production index, in percentage points. Shaded areas depict major events around the world. 2008M09–2008M11: bankruptcy of Lehman Brothers; 2009M10–2012M07: EU debt crisis; 2016M05–2016M07: Brexit referendum; 2020M03–2021M03: Covid-19.

countries confirms the contribution to industrial production in the historical decomposition depicted in Figure 11. Moreover, the credible intervals of the impulse responses are narrower than in the baseline (Figure 13). Consequently, the differences in the impacts of shocks to country-specific and common uncertainty on industrial production are clearly statistically significant when considering 90% credible intervals.

5.3 Alternative Identifications

As an alternative to the identification presented in Table 2, we considered a set of zero and sign restrictions with the responses of the uncertainty components to the demand, supply, and monetary shocks left unrestricted, in line with Meinen and Roehe (2018). On the other hand, zero restrictions are imposed on the responses of industrial production, inflation, and the interest rate to the shocks to both uncertainty components to let the data speak about the signs and magnitudes of the responses to the two distinct uncertainty shocks. This way, we also ensure that the uncertainty shocks are distinct from the aggregate demand shocks. Table 4 provides the list of sign restrictions.

The resulting impulse responses of this alternative specification are broadly similar to our baseline specification. However, the difference between the response of industrial production to the common and country-specific uncertainty shocks is less pronounced than in our baseline (compare the last row of plots with the first row in Figure 13). Also, the interest rate now decreases after the country-specific uncertainty shock, although not as much as in response to the common uncertainty shock.

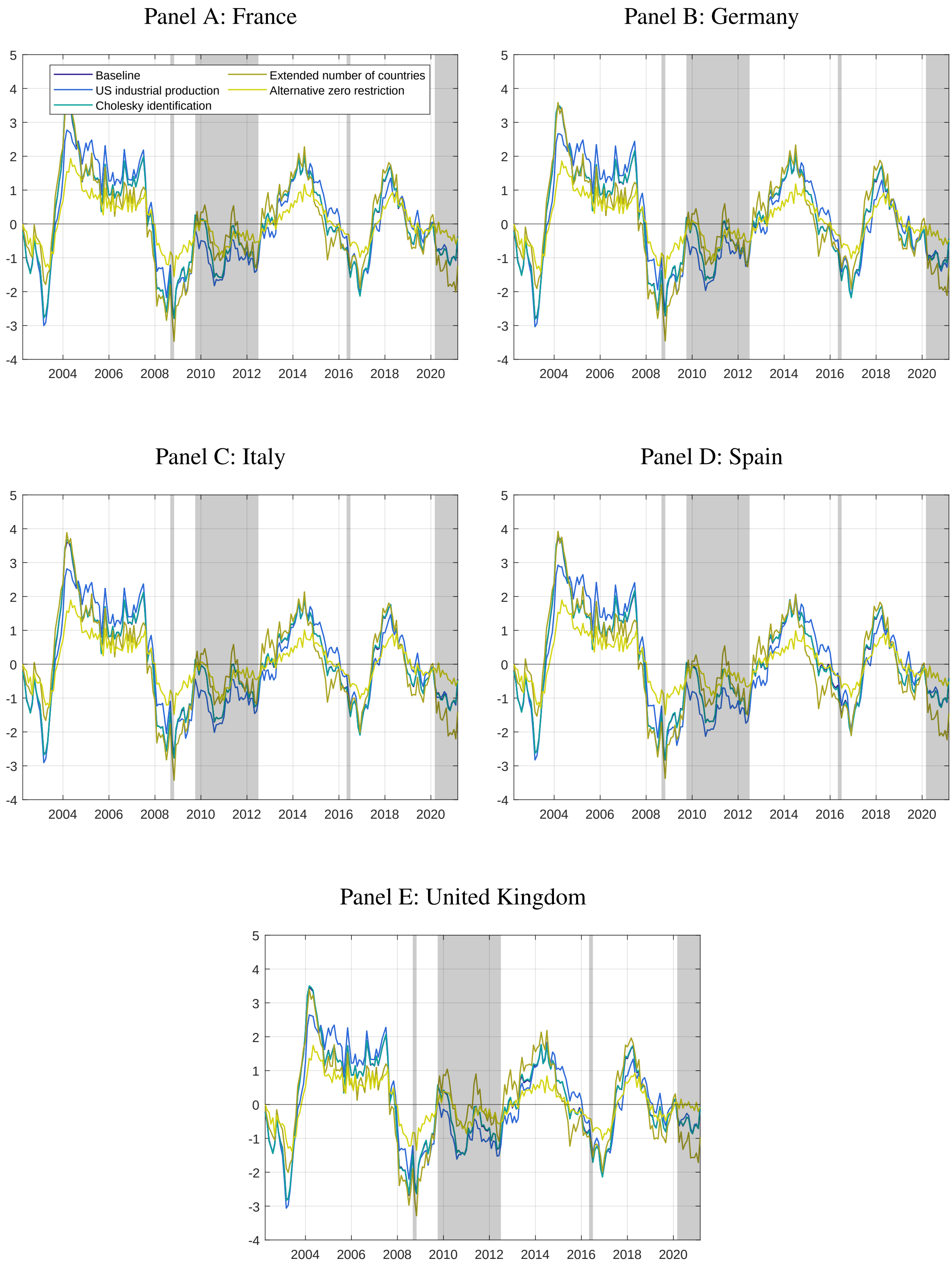
In addition, we estimate the impulse responses identified through Cholesky decomposition. First, we order the uncertainty before economic activity, prices, and the interest rate, assuming that uncertainty shocks are predetermined for other macroeconomic variables, in line with Baker et al. (2016), Caggiano et al. (2020), Biljanovska et al. (2021), and others. Furthermore, because international shocks spread almost instantaneously across European countries, with the respective EPU peaks synchronized across countries at monthly frequency, we order the common uncertainty before the country-specific component so that the common uncertainty reacts to purely country-specific shocks with a lag. The results are broadly consistent with the previous estimates,

Table 4: Alternative Structural Identification of Shocks

Variable\Shock	Demand	Supply	Monetary policy	Country-specific uncertainty	Common uncertainty
Production	-	–	-	0	0
Prices	-	+	-	0	0
Interest rate	-	+	+	0	0
Country-specific EPU				+	+
Common EPU				0	+

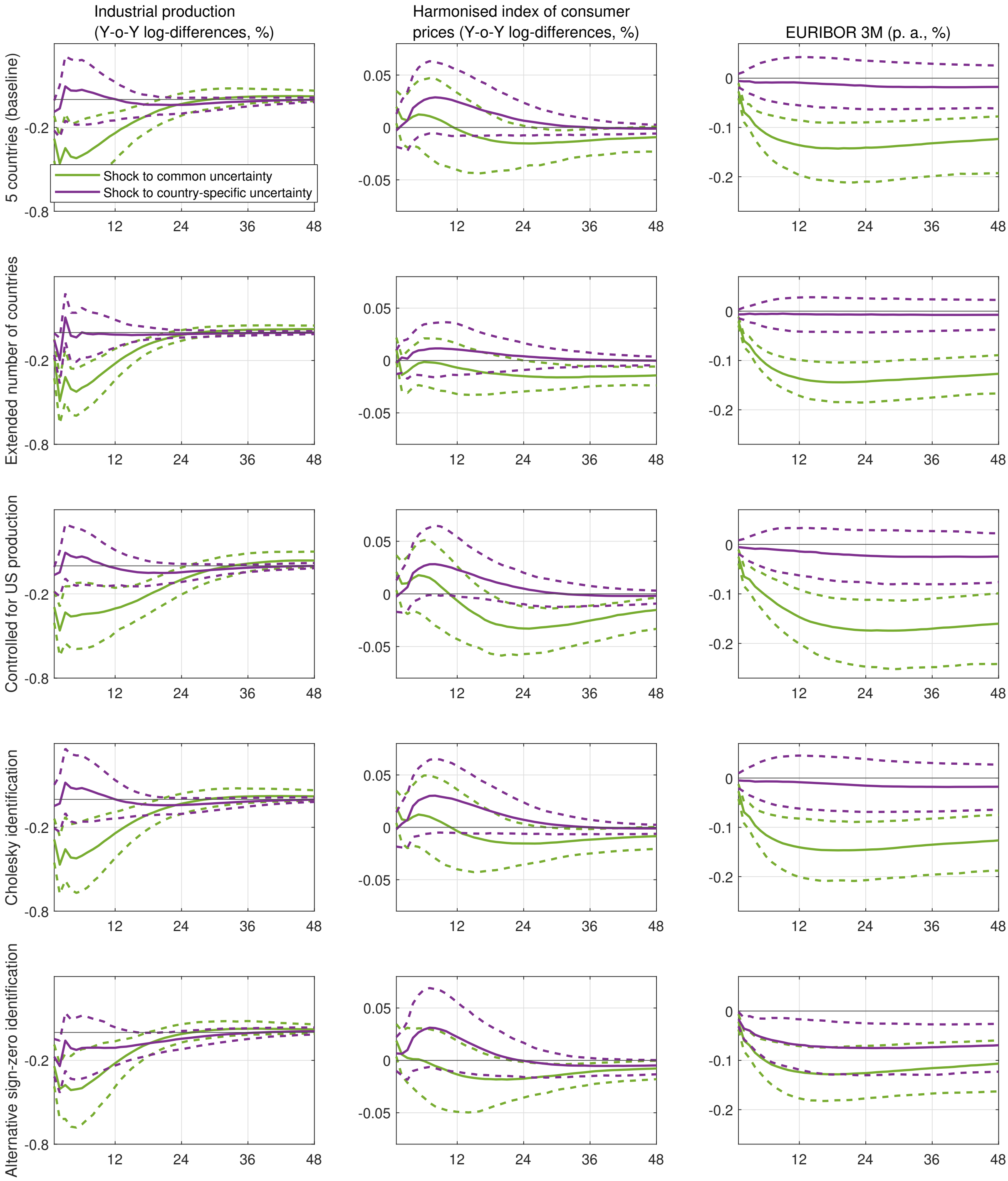
Note: A “0” ensures that this variable cannot move contemporaneously in response to the particular shock. A “ + ”(“ – ”) indicates that this variable must respond positively (negatively) to the particular shock.

Figure 12: Sensitivity Analysis: Contribution of Common Uncertainty to Industrial Production



Note: Contribution of common uncertainty shock to centered year-on-year log-differences in industrial production index, in percentage points. Shaded areas depict major events around the world. 2008M09–2008M11: bankruptcy of Lehman Brothers; 2009M10–2012M07: EU debt crisis; 2016M05–2016M07: Brexit referendum; 2020M03–2021M03: Covid-19.

Figure 13: Sensitivity Analysis: Impulse Response Functions for Alternative Panel VAR Models



Note: Median responses with 90% credible intervals. The responses correspond to one standard deviation shocks and cover the 48 months after the initial shock.

confirming our finding that the adverse effects of uncertainty on industrial production are driven by common uncertainty. This finding is also robust to re-ordering the common uncertainty below the country-specific uncertainty (Figure 12). Finally, the results are also robust to ordering the uncertainty components last, with quantitative implications close to our baseline specification.

6. Conclusion

This paper investigated the impact of uncertainty on economic activity, prices, and monetary policy setting, while focusing on the difference between the effects of uncertainty shocks shared with other countries—common uncertainty—and the effects of country-specific uncertainty. To separate these two components, we proposed a procedure that first infers the spillovers of uncertainty across countries using dynamic total connectedness and, second, defines common uncertainty as the cross product of the total connectedness and the average uncertainty. We showed that the common uncertainty defined this way helps to identify periods of more intense uncertainty across countries. Moreover, this procedure preserves a positive correlation between the common and country-specific components, therefore permitting single historical events such as Brexit and the fall of Lehmann Brothers to cause an increase in the common component as well as a country-specific reaction complementing the common shock.

After decomposing the uncertainty into its two components, we estimated their effects on macroeconomic variables using a Bayesian panel VAR model, with the shocks identified using zero and sign restrictions. Most importantly, we showed that only the common shock has significantly negative effects on economic growth, despite being partially offset by monetary policy easing. However, the impact of the country-specific uncertainty components on macroeconomic variables was negligible. These results were robust across alternative samples and structural identifications.

Our results imply that only common uncertainty shocks drive the adverse effects of uncertainty on European economies. Therefore, policymakers should pay attention to uncertainty developments particularly when large and synchronized increases are observed, no matter which country is the source of uncertainty.

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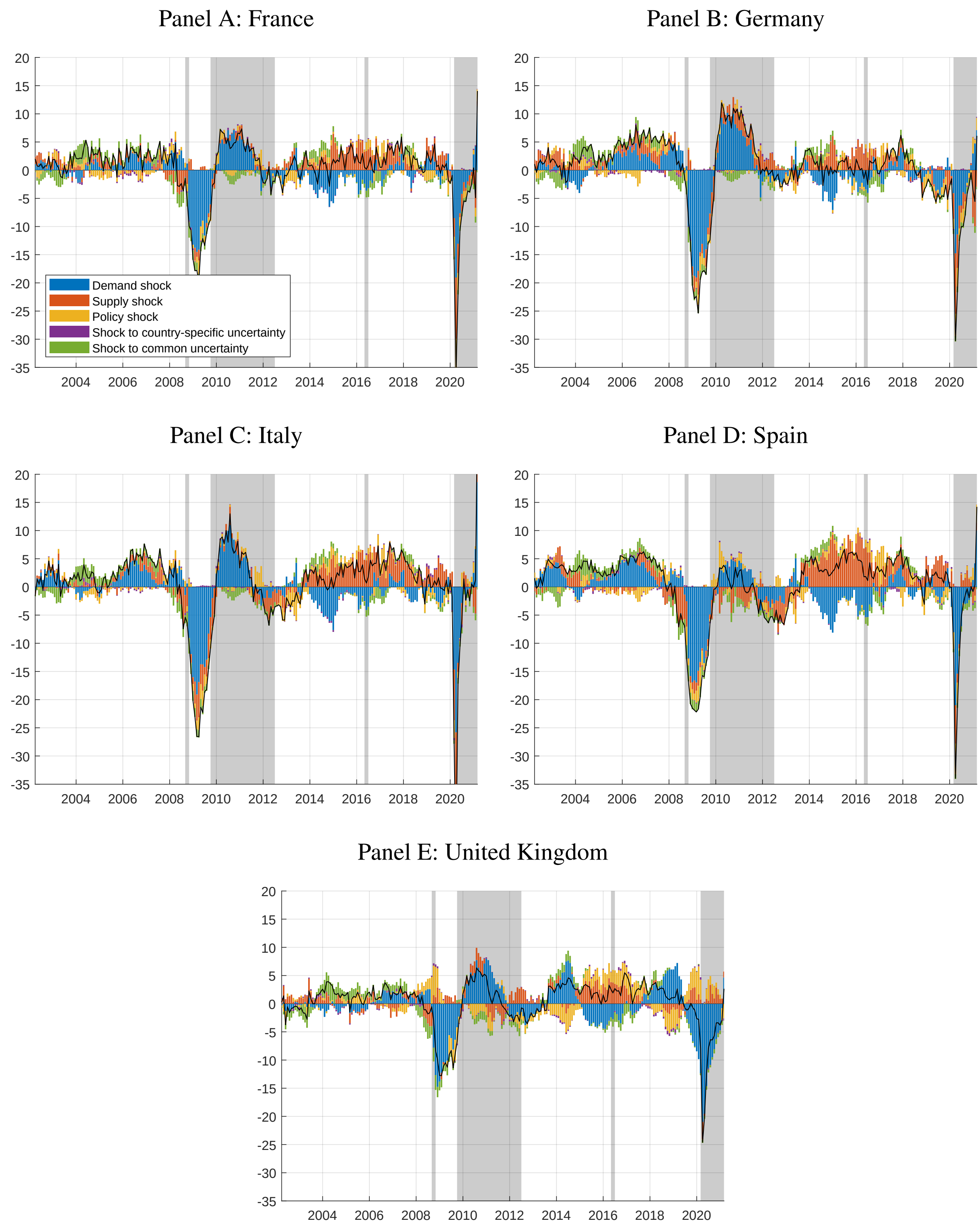
Appendix A: Complementary Results for Baseline PVAR

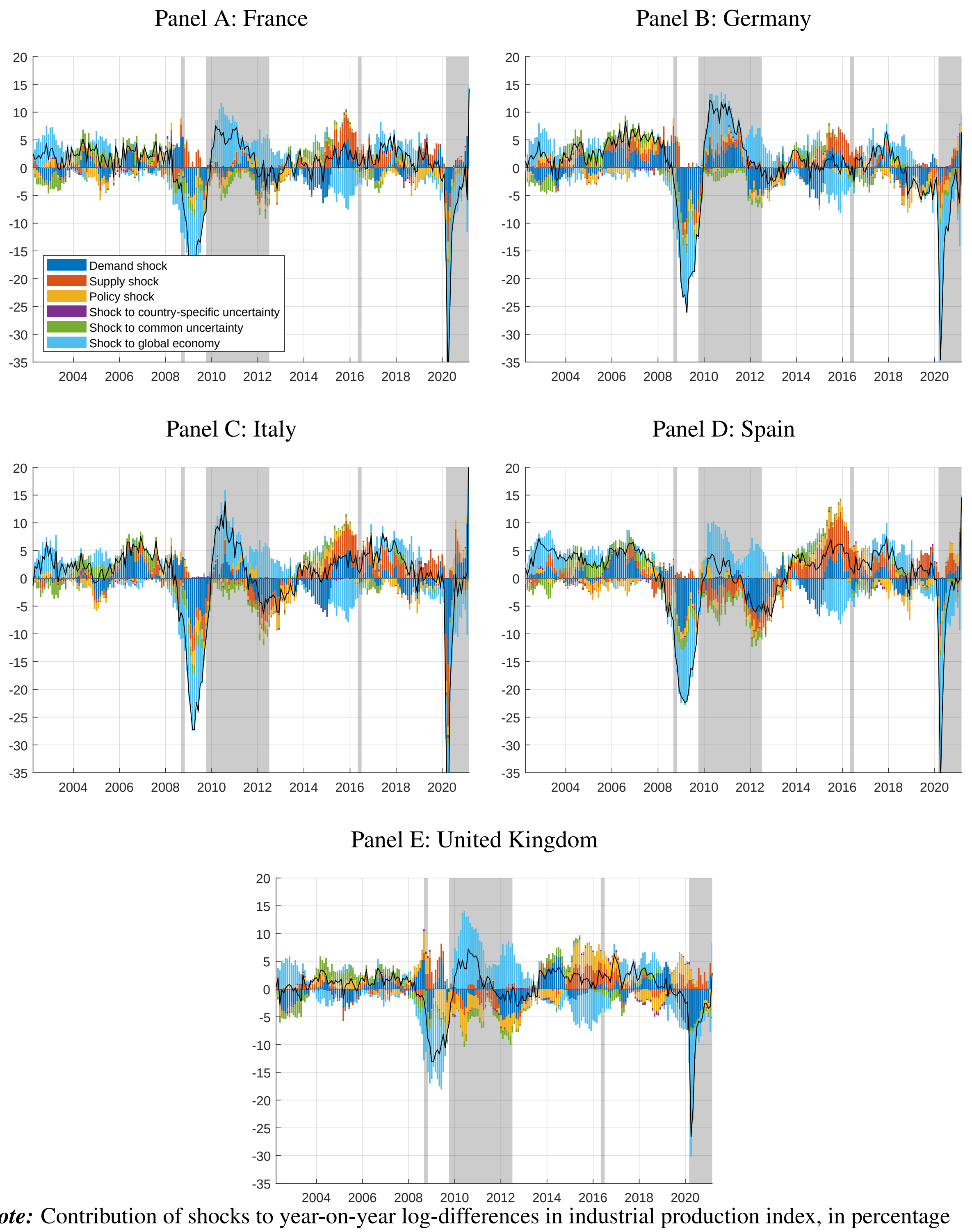
Figure A1: Historical Decomposition of Industrial Production



Note: Contribution of shocks to year-on-year log-differences in industrial production index, in percentage points. Deviations from mean and from contribution of initial conditions. Shaded areas depict major events around the world. 2008M09–2008M11: bankruptcy of Lehman Brothers; 2009M10–2012M07: EU debt crisis; 2016M05–2016M07: Brexit referendum; 2020M03–2021M03: Covid-19.

Appendix B: Complementary Results for PVAR Controlled for U.S. Industrial Production

Figure B1: Historical Decomposition of Industrial Production



Note: Contribution of shocks to year-on-year log-differences in industrial production index, in percentage points. Deviations from mean and from contribution of initial conditions. Shaded areas depict major events around the world. 2008M09–2008M11: bankruptcy of Lehman Brothers; 2009M10–2012M07: EU debt crisis; 2016M05–2016M07: Brexit referendum; 2020M03–2021M03: Covid-19.

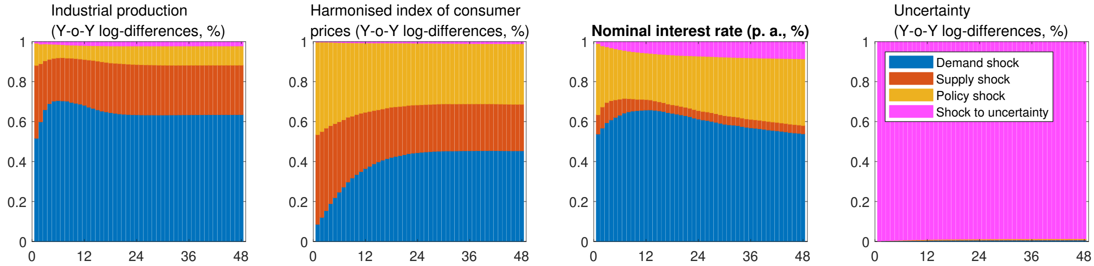
Appendix C: Complementary Results for PVAR Without Decomposition of Uncertainty

Table C1: Structural Identification of Shocks for Aggregate Uncertainty

Variable\Shock	Demand	Supply	Monetary policy	Uncertainty
Production	-	–	-	-
Prices	-	+	-	
Interest rate	-	+	+	
EPU	0	0	0	+

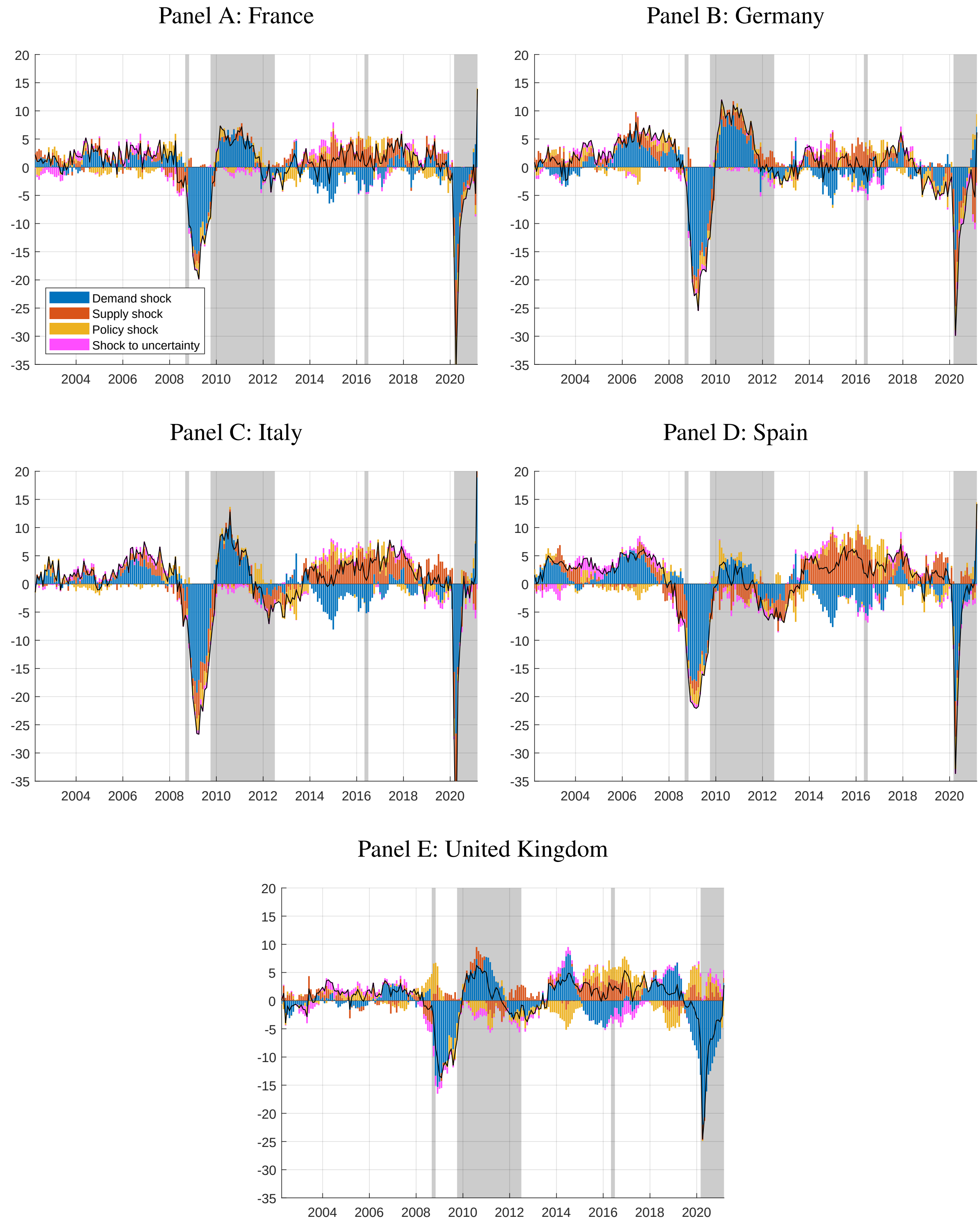
Note: A "0" ensures that this variable cannot move contemporaneously in response to the particular shock. A "+"("−") indicates that this variable must respond positively (negatively) to the particular shock.

Figure C1: Forecast Error Variance Decomposition



Note: The x-axis denotes months; the y-axis represents the share of the shocks in the variability.

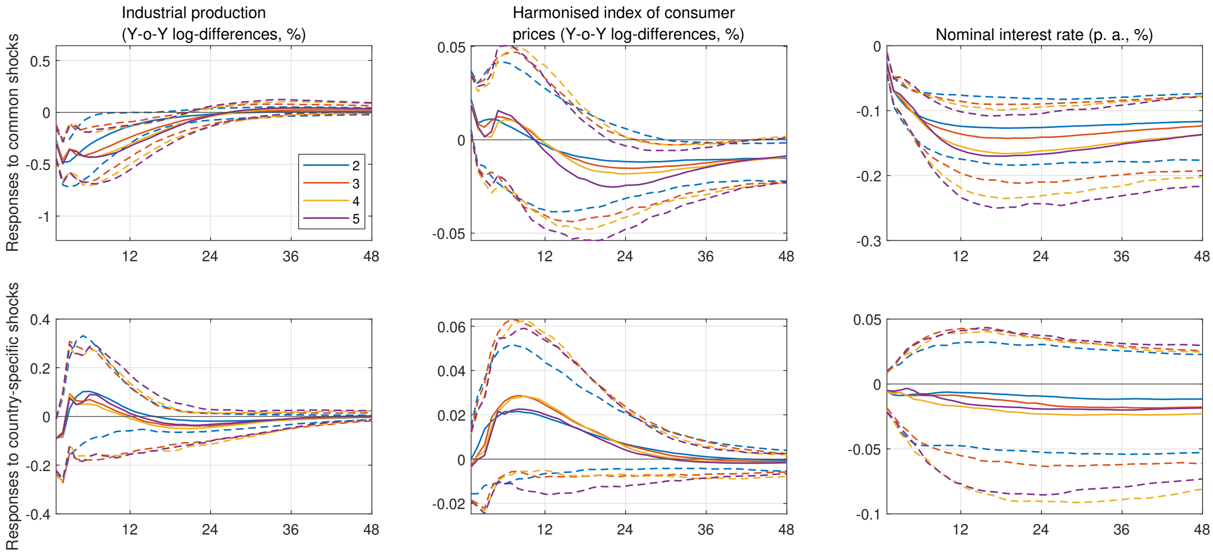
Figure C2: Historical Decomposition of Industrial Production



Note: Contribution of shocks to year-on-year log-differences in industrial production index, in percentage points. Deviations from mean and from contribution of initial conditions. Shaded areas depict major events around the world. 2008M09–2008M11: bankruptcy of Lehman Brothers; 2009M10–2012M07: EU debt crisis; 2016M05–2016M07: Brexit referendum; 2020M03–2021M03: Covid-19.

Appendix D: Additional Sensitivity Checks

Figure D1: Effects of Uncertainty Shocks for Different Numbers of Lags



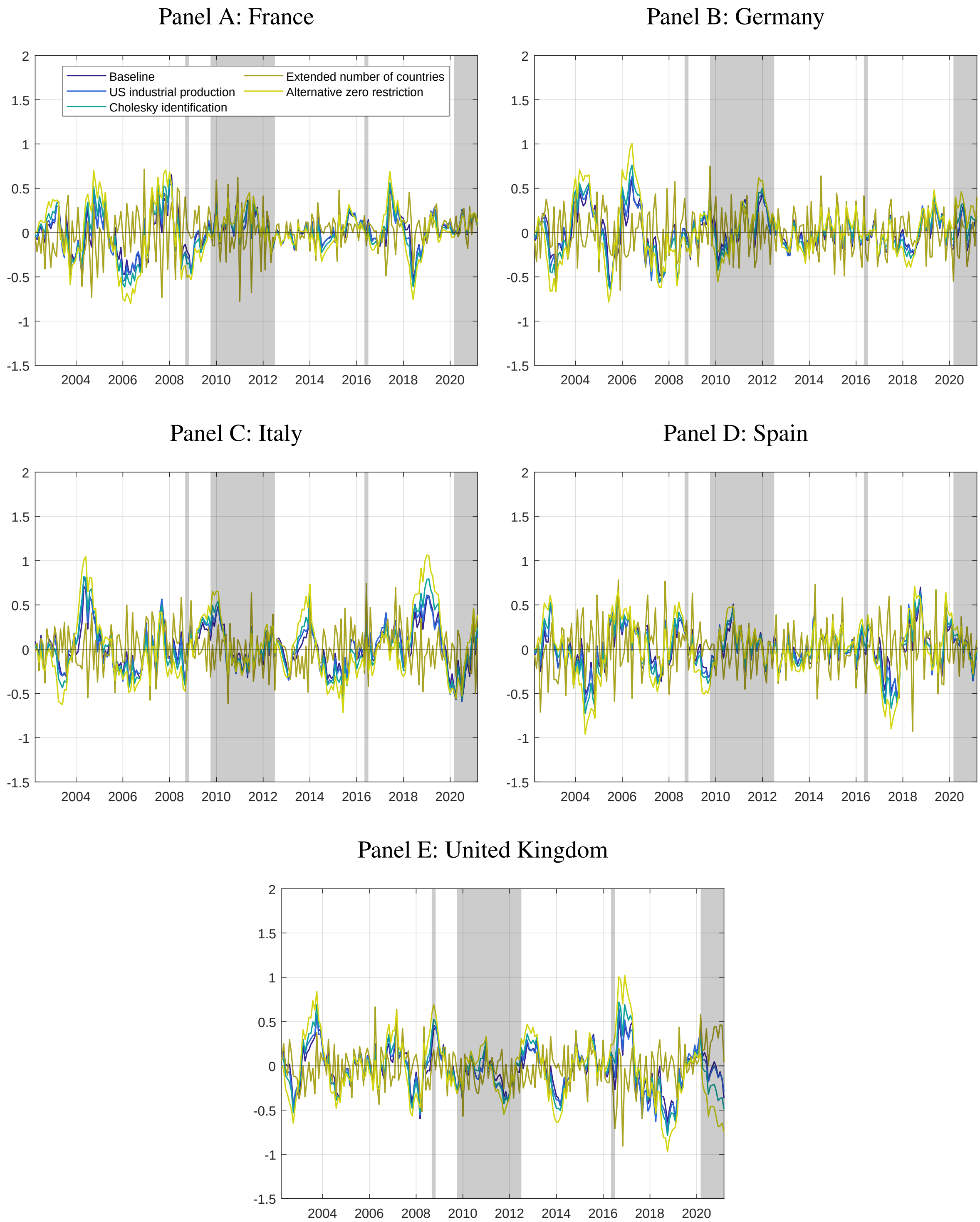
Note: Median responses with 90% credible intervals. The responses correspond to one standard deviation shocks and cover the 48 months after the initial shock.

Table D1: Correlation of Structural Shocks Across Samples

Shock\Country	France	Germany	Italy	Spain	United Kingdom
Demand	0.96	0.96	0.96	0.96	0.97
Supply	0.97	0.97	0.97	0.96	0.97
Monetary policy	0.97	0.98	0.98	0.98	0.98
Country-specific uncertainty	0.99	0.99	0.99	0.99	0.99
Common uncertainty	0.99	0.99	0.99	0.99	0.99

Note: The structural shocks for the baseline estimation and the pre-Covid sensitivity check are compared in the period 2002M01–2019M12. The correlations are based on the median of the shock's posterior distribution.

Figure D2: Sensitivity Analysis: Contribution of Country-Specific Uncertainty to Industrial Production



Note: Contribution of country-specific uncertainty shock to centered year-on-year log-differences in industrial production index, in percentage points. Shaded areas depict major events around the world. 2008M09–2008M11: bankruptcy of Lehman Brothers; 2009M10–2012M07: EU debt crisis; 2016M05–2016M07: Brexit referendum; 2020M03–2021M03: Covid-19.

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