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Emanuele Bacchiocchi
Catalin Dragomirescu-Gaina

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Emanuele Bacchiocchi

University of Bologna, Department of Economics, Bologna, Italy

Catalin Dragomirescu-Gaina

Università Cattolica del Sacro Cuore, Department of Economics and Finance, Milano, Italy

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Abstract

No matter its source, financial- or policy-related, uncertainty can feed onto itself, concealing its true origin and leading to identification challenges in empirical applications. We add to the existing stock of analytical methods able to disentangle among various types of uncertainty shocks, by generalising an identification approach based on magnitude restrictions to a multi-country setting. Within the Euro Area, we find evidence of sizable spill-overs arising from country-specific uncertainty shocks, with financial realm being a more important source than the policy realm. By leveraging on the flexibility of our identification strategy, we quantify the valuation 'mistakes' that arise from the inability to separate uncertainty shock types within a given country; we then show that the implicit under/over-valuations can be related to some simple cross-sectional indicators of financial and political stability, especially before the 2008/2009 crisis. A comparison between the responses of sovereign yields within and outside the Euro Area suggests strong within institutional arrangements and risk-sharing mechanisms that can blur the thin separation line between uncertainty shock types. In this context, we find that ECB reacted to those identified uncertainty shocks with the highest potential to spill over abroad, thus filling a leadership vacuum within the Euro Area.

JEL: C3, E58, E60, F36, F40

Keywords: policy uncertainty, financial integration, global VAR, unconventional monetary policy

Non-Technical Summary

No matter its source, financial- or policy-related, uncertainty can feed onto itself, concealing its true origin and leading to identification challenges in empirical applications. Given the deep and complex intertwining between policy and financial realms in Europe, and in Euro Area in particular, identification in such a context would be not only interesting as an exercise, but also a policy relevant one. For the ECB, the distinction is important because it can help in calibrating its monetary policy reactions. For financial investors, being able to separate between various types of uncertainty is important because their hedging strategies need to be adjusted accordingly.

We add to the existing stock of analytical methods able to disentangle among various types of uncertainty shocks, by generalising an identification approach based on magnitude restrictions to a multi-country setting. By leveraging on the flexibility of our identification strategy, we quantify the valuation 'mistakes' that arise from the inability to separate uncertainty shock types within a given country; we then show that the implicit under/over-valuations can be related to some simple cross-sectional indicators of financial and political stability, especially before the 2008/2009 crisis. This helps us see why, in the aftermath of crises triggering large changes in the information set, investors become better at disentangling among uncertainty types.

Based on impulse responses derived from our identification, we find that within the Euro Area there are sizable spill-overs arising from country-specific uncertainty shocks, with financial realm being a more important source than the policy realm. Depending on the origin country, one type of uncertainty shock might generate more substantial domestic effects and spill-overs than the other, the difference being relevant mainly in terms of policy responses. Our results suggest that ECB deployed its tools with respect to those uncertainty shocks having the highest potential to spill over abroad. Such policy actions might further blur the thin separation line between uncertainty shock types, as long as ECB only has a mandate for price and financial stability. However, a simple comparison between the responses of sovereign yields within and outside the EA reveals strong institutional arrangements and risk-sharing mechanisms existing within the EA; given the lack of institutional leadership in dealing with various types of shocks within the Euro Area, we believe ECB has managed to fill the leadership vacuum.

1. INTRODUCTION

For a few days every year, in Davos, an exclusive alpine resort in Switzerland, global financial elite can mingle with political elite, central bankers and policymakers. And yet, the World Economic Forum is a hallmark event that exposes only in part the interesting overlaps existing between financial and policy realms. From an analytical perspective, these overlaps and cross-influences can cancel or amplify each other, especially during uncertain times. Financial stress and market uncertainties can bring changes in policies or political considerations, as much as uncertainty stemming from policy changes creates anxieties for financial markets and investors. No matter its source, financial or policy-related, uncertainty will feed onto itself, contaminating the real economy, and leading to identification challenges in empirical applications. We try to add to the existing stock of analytical methods able to disentangle among various sources or types of uncertainty but in a multi-country context, where spill-overs and overlaps are expected to pose additional identification challenges.

From this perspective, the European Union (EU), and the Euro Area (EA) in particular – with its rather incomplete institutional architecture –, make for an interesting case due to a high potential for uncertainty spill-overs and overlaps. On the one hand, domestic policy uncertainty can reverberate at European and global levels with serious financial consequences measured in terms of sovereign yields, as well as stock prices and currency moves. In June 2015 the Greek government called a snap referendum over its bailout terms, triggering chaos in European policy circles, but also among financial investors who feared a Euro Area (EA) breakdown; as market sentiment turned sour, Greek sovereign yields reached unprecedented levels, while the country was effectively cut off global financial markets and forced to impose strict capital controls. On the other hand, banking sector turmoil can echo in the policy domain, as risks get transferred from the private to the public sector due to bank-rescue packages that increase sovereign risks (see Acharya et al., 2014; Attinasi et al., 2010; Bicu and Candelon, 2013; Stanga, 2014). Ireland perfectly illustrates this latter case, when the government introduced guarantees to address the weakness of the domestic banking sector in September 2008, after the Lehman shock; as a result, banks' credit default swaps (CDS) came down, but the Irish sovereign CDS spiked abruptly (Stanga, 2014; Leonello, 2018).

The current paper aims at exploring the deep and complex intertwining, that is so prevalent in Europe, between the policy and financial realms, whose interactions might create amplification mechanisms for country-specific uncertainty shocks. As sovereign yields set the risk-free benchmark for financing costs in a given country, financial markets play a fundamental role in the transmission of both financial and policy uncertainty shocks to the real economy (see Christiano et al., 2014; Gilchrist et al., 2014). Concentrating on the very first stage of this process, we ask, firstly, whether such mechanisms work to amplify financial uncertainty, policy uncertainty, none, or both; and secondly, to what extent uncertainty shocks transmit to sovereign yields, both domestically and abroad. Moreover, what types of uncertainty arise most often in different EA countries and what drives the heterogeneity seen in results? Financial investors do care if they face a sovereign or a banking crisis because their hedging strategies would be different in each case. But if they err on their initial evaluations, confusing one crisis type with the other, what helps them correct such 'mistakes'? We seek therefore to contribute to a new and rapidly expanding literature strand that deals with various uncertainty measures, their sources, effects, and cross-border spill-overs (see among many others Bekaert et al., 2013; Caldara et al., 2016; Bacchiocchi, 2017; Cascaldi-Garcia and Galvão, 2021; Cesa-Bianchi and Fernandez-Corugedo, 2018; Shin and Zhong, 2018; Ludvigson et al., 2019; Angelini et al., 2019, and the excellent recent survey by Castelnuovo, 2022).

We are also interested in examining ECB's reactions, given the lack of EA institutional leadership in dealing with various uncertainty sources, to which one can recently add geopolitical anxieties. The existing literature on (monetary and fiscal) policy interactions within a common currency area does not provide sufficient clarifications in this regard (for a recent survey, see Foresti, 2018). ECB faces numerous and delicate policy trade-offs in pursuing its price stability mandate, set according to the EU Treaties. A clearer distinction between policy and financial uncertainty shocks could improve ECB policy effectiveness, narrow the spread in sovereign yields to reduce asymmetries in the transmission of its monetary policy, and even shield it from possible legal actions.[1] There have been many controversies surrounding ECB monetary policy conduct, especially with respect to its unconventional measures. In August 2011, for example, the Securities Markets Programme (SMP) made some sizeable bond purchases from the EA periphery, especially Italian and Spanish sovereigns, with some positive effects on yield spreads in unsettled market conditions. However, the program was soon suspended for Italian bonds as it became clear that the Berlusconi government was not delivering on its promised reforms; fast forward in November 2011, market confidence in the Italian government collapsed and a new prime minister was appointed.

We approach all these questions from an empirical perspective that can efficiently address the inherent identification challenges. Dealing with multi-country models requires a different framework for conceptualizing the nature of shocks that one wishes to identify, particularly because of the strong cross-sectional dimension of these models (see Dees et al 2014; Dungey and Osborn, 2014). As a first contribution to the literature, we apply absolute magnitude restrictions in a global vector autoregressive (GVAR) model by adapting and generalising De Santis and Zimic (2018) approach such as to allow for the implementation of a *fuzzy* identification strategy. This helps us to quantify the valuation 'mistakes' that arise when financial markets and investors have imperfect knowledge about the type of the crisis they are facing, but know exactly the origin country. The implicit under/over-valuations in country risk profiles can then be related to some simple cross-sectional indicators of financial and political stability;

[1] See the decision of the Court of Justice of the European Union in favour of the ECB's Public-Sector Purchase Programme (PSPP) at https://www.reuters.com/article/us-ecb-policy-court/ecb-wins-courts-backing-for-buying-government-debt-idUSKBN1OA0Q0. This decision stands in contrast to a more recent decision of the German Constitutional Court, thus raising unprecedented legal challenges for the EU governance system.

while this relation was strong before the 2008/2009 crisis, it has weakened recently suggesting that large changes in the information set can help in correcting (at least partially) these valuation 'mistakes'. Our second contribution is to reveal the sizeable spill-overs generated by the identified uncertainty shocks, mainly within the EA, for which we find that financial realm is more important than the policy realm as a source of systemic risk.[2] A comparison between the responses of sovereign yields within and outside the EA suggests there are strong institutional arrangements and/or risk-sharing mechanisms at play within the EA that can blur the thin separation line between uncertainty shock types. In this context, we show that ECB deployed its conventional as well as unconventional tools to counteract particularly those uncertainty shocks with the highest *potential* (given that real-time identification is difficult) to generate significant uncertainty spill-overs abroad; in a robustness check, we see these same uncertainty shocks raising the dispersion in EA sovereign yields – an objective to which ECB seems to assign a growing importance.

There are few other distinct but comparable approaches in a rapidly expanding empirical literature that aims at identifying (different types of) uncertainty shocks (e.g. Bacchiocchi, 2017; Shin and Zhong, 2018; Ludvigson et al., 2019; Angelini et al., 2019). As each methodological approach has its own merits, we regard them as largely complementary to ours. Our identification strategy is performed within a GVAR model estimated with a small number of country-specific endogenous variables that capture the main interactions between financial and uncertainty proxies, whose first-order real economic effects are reflected at the EA level where ECB policies are most effective. To capture financial uncertainty, we use the Composite Indicator for Systemic Stress (CISS), a highly relevant, weekly policy indicator for ECB, that is available for all EU Member States (see Hollo et al., 2012).[3] Broader (or Knightian) uncertainty, instead, encompassing changes in the political landscape, in rhetoric, opinions and national policies is harder to measure (see discussion in Bekaert et al., 2013; Jurado et al., 2015; Baker et al., 2016; Ludvigson et al., 2019). In a highly influential paper, Baker et al., (2016) propose an *economic policy uncertainty* (EPU) measure based on the frequency of some relevant keywords in major newspapers; they further show their indicator is orthogonal to other common measures of risk and uncertainty, such as forecasts dispersion or financial volatility etc. Because of its wide availability for different EU and EA countries, and its robustness in empirical applications, we rely on EPU as a measure of policy uncertainty.[4] In spite of a high correlation seen

[2] Angelini et al., (2018) also deal with uncertainty spill-overs in some Eurozone countries, although they only focus on macroeconomic uncertainty shocks. Other contributions on uncertainty spill-overs, although not related to EU countries, are Klößner and Sekkel (2014), Caggiano et al., (2020), Mumtaz and Theodoridis (2015).
[3] Fratzscher et al., (2016), Burriel and Galesi (2018), Boeckx et al., (2017) use the CISS index proposed in Hollo et al., (2012) to uncover transmission channels and consequences of financial stress across European markets.
[4] Ludvigson et al., (2019) employ EPU, along with other measures of uncertainty, to identify the consequences of uncertainty shocks on output; Ioannidis and Ka (2021) use EPU to forecast term premia; Stock and Watson (2012), Caldara et al., (2016), Choi and Furceri (2019) use EPU for robustness checks.

during specific periods of time, note that CISS and EPU draw on different data sources and construction methodologies.[5]

The remaining of the paper is organised as follows. Section 2 discusses the theoretical background we consider relevant for our empirical analysis. Section 3 presents the data and the modelling approach. Section 4 provides a detailed overview of the main results and their policy implications. Finally, section 5 concludes. More detailed results from our analysis are presented in the Appendixes.

2. THEORETICAL BACKGROUND

This section briefly summarises the literature strands that most closely relate to our empirical model. An important thread refers to the sovereign-bank nexus, which can capture the most relevant interactions between financial and policy realms, although from a single-country perspective. What we are most interested in understanding here is the very first stage of this interaction process, where policy and financial uncertainty usually combine and amplify each other, leading to identification challenges in empirical works. Once uncertainty arises, it propagates to inflict the real sector, affecting investment dynamics, asset prices, firms' balance sheets, etc., amplified mainly by financial frictions (see among many others, Arellano et al., 2010; Christiano et al., 2014; Bloom, 2014; Gilchrist et al., 2014; Bloom et al., 2018).[6] To keep our model's estimation tractable, we choose to strip these mechanisms to the bare bone by reducing the set of financial variables used and letting sovereign yields, which set the risk-free benchmark for financing costs in any country, play the key role in the model's dynamics. However, we track the first-order economic effects of uncertainty shocks by including real economic activity proxies (inflation and industrial production volume) at the EA level, allowing us to better expose and understand ECB responses.

The theoretical mechanism underpinning the main feedback loops that arise between banks and sovereigns are best described in Farhi and Tirole (2017), Faia (2017), Leonello (2018), Allen et al., (2018), Cooper and Nikolov (2018).[7] For brevity, we only summarize the two key ingredients featuring in these models. On the one hand, since banks hold sovereign bonds in their books for liquidity and regulatory reasons, sovereign distress can contaminate the banking sector. On the other hand, the

[5] A related literature strand employs sovereign and banking risk measures derived directly from market dynamics and prices, like CDSs for example (see Bicu and Candelon 2013; Stanga 2014; Acharya et al., 2014; Greenwood-Nimmo et al., 2019). One can easily substitute our uncertainty proxies with CDSs, for example, with no material consequences on the feasibility of our empirical approach and identification method. However, the number of confounding factors and common components that need to be removed before identifying country-specific shocks would increase, given the stronger statistical overlaps; also, the high level of integration across EA banking sector would make it difficult to pick up bank-specific CDSs to be paired with a particular country's CDS.

[6] For empirical evidence on these transmission mechanisms see Stock and Watson (2012); Caldara et al., (2016).

[7] There is a substantial literature strand discussing other compelling mechanisms that can amplify the feedback loops between financial and policy realms; however, these alternative explanations usually involve political factors, as for example in Funke et al., (2016), exposing thus slower transmission mechanisms that focus on voters' choices and behaviours.

(implicit or explicit) guarantees provided by the government allow banking sector distress to inflict the public sector. Empirical evidence on these theoretical transmission mechanisms is provided, among many others, in Bicu and Candelon (2013) and Stanga (2014). While the evidence is clear, there are some nuances one needs to consider. A government's commitment to bailing out the banking sector depends on its fiscal capacity and debt dynamics, but even these constraints can fail. Moral suasion for example explains why EA periphery banks had higher levels of domestic sovereign bonds in their books (Acharya et al., 2014; Koijen et al., 2017; Greenwood-Nimmo et al., 2019). Besides the fiscal costs of a bailout, the central bank can be involved along with the government, in which case there will be inflation and devaluation costs (Farhi and Tirole, 2017).

Yet, without a fully operational Banking Union and a complete political integration within Europe, the theoretical mechanisms describing these sovereign-bank feedback loops do not directly apply at the EA level. Therefore, focusing on domestic bond holdings and government guarantees is no longer sufficient; instead, the focus must fall on the mechanisms that explain the rebalancing of international portfolios across financially integrated markets. The literature distinguishes between two main potential mechanisms that rely either on (i) cross-border information frictions as in Freixas and Holthausen, (2004) or on (ii) information acquisition choices made by investors facing complex information cost structures as in Van Nieuwerburgh and Veldkamp (2010), Garleanu et al. (2015). In general, risk in these models is seen as an aggregation of a common component and an idiosyncratic one, whose interactions with the available information depend on learning opportunities and costs.

European cross-border banking has dramatically increased financial integration as a direct result of the two banking directives adopted in 1977 and 1989 that aimed at eliminating restrictions, harmonizing regulation, and achieving better coordination in prudential supervision. Freixas and Holthausen (2004) show that integration of the EA interbank market can magnify the asymmetry of information in cross-border banking, creating a contagion channel and financial fragility. Depending on the amount of information frictions, their model allows for multiple equilibria. In particular, the model differentiates between financial *segmentation* and *integration*, where the former relates to a case where all interbank transactions occur within the national borders, liquidity distribution is inefficient and interest rates are higher, while the latter refers to the opposite case. Their main theoretical insights are that a segmented market equilibrium is always possible, but an integrated market equilibrium is not necessarily feasible at all times.[8] Asymmetries leading to market segmentation in their model arise when information remains locally bounded for reasons unrelated to investors' choices, like in the case of substantial differences in cultures and accounting practices (e.g. policy decisions to restrict risk modelling options for banks), or in local policy preferences with respect to prudential supervision (e.g. commitment to

[8] Freixas and Holthausen (2004) find that the integrated market equilibrium is not welfare improving due to increased financial fragility. More recently, Passari and Rey (2015) conclude that large welfare gains from financial integration, in general, are rather hard to find (in contrast to earlier findings from Allen et al., 2011).

bail out a bank in distress). These few examples seem to be pointing at uncertainty sources that originate in the policy realm.

In more recent models, financial outcomes and information acquisition choices are all inter-related. In Van Nieuwerburgh and Veldkamp (2010) investors might not want to hold a fully diversified portfolio (e.g. *home bias*) if they can systematically collect information, preferring thus to deepen rather than broaden their knowledge. Garleanu et al. (2015) present a theoretical model where access to (foreign and domestic) financial markets is subject to information costs that lead to limited market integration in equilibrium. Because portfolio diversification (i.e. participation in distant markets) and leverage are complements in their model, a symmetric equilibrium might fail to exist, just as in Freixas and Holthausen (2004). In reality, the potential for diversification benefits within the EA depends on a delicate balance between common and idiosyncratic factors, as well as on the information acquisition choices made by investors. Holding EA-periphery versus EA-core sovereign bonds has brought substantial profits for European banks – an investment strategy that Acharya and Steffen (2015) have labelled as "the 'greatest' carry trade ever". These examples referring to *home bias* and diversification point instead to the financial realm as a main source of uncertainty.

3. DATA AND METHODOLOGY

3.1 The GVAR model

The global vector autoregressive model, or GVAR, was designed to model both cross-sectional dependence and time-series behaviour in macroeconomic data. This very flexible empirical framework was originally proposed by Pesaran et al. (2004) and extended by Dees et al. (2007). In essence, the GVAR is a collection of country-specific vector autoregressive models (or VARs), conveniently linked via a weighting matrix that makes the estimation feasible by reducing the parameter space.

The GVAR model generally embeds three channels of cross-country interactions through: (i) foreign-specific (denoted by an *) variables, (ii) common factors, proxied here mainly by ECB monetary policy proxies, and (iii) contemporaneous dependence of shocks. As long as the pairwise cross-country correlations left in the model residuals are low, most GVARs in the literature capture the cross-country interactions only through the first two channels, restricting[9] the variance-covariance matrix to be block-diagonal (e.g. Cesa-Bianchi, 2013; Eickmeier and Ng, 2015; Feldkircher and Huber, 2016). However, since our focus is specifically on uncertainty spill-overs, we mainly want to capture the second-order moments in the data, and therefore leave the variance-covariance matrix unrestricted.

[9] In technical terms, this restriction would amount to a lack of contemporaneous volatility spill-overs between the countries included in the sample, though it would still allow for *indirect* volatility spill-overs that work through the complex lag structure of the model.

In the basic GVAR specification, each country i is represented by a country-specific VAR model denoted as VARX (p_i, q_i), with p_i and q_i lags, and $Y_{i,t}$ a vector of endogenous variables. Each country-specific model is specified as:

$$Y_{i,t} = a_i + \sum_{j=1}^{p_i} B_{i,j} Y_{i,t-j} + \sum_{j=0}^{q_i} C_{i,j} Y_{i,t-j}^{*} + v_{i,t} \qquad (1)$$

where a_i is a vector of intercepts; $B_{i,j}$ and $C_{i,j}$ are coefficient matrixes; and $v_{i,t}$ is a vector of idiosyncratic shocks, serially uncorrelated and with full variance-covariance matrix. The vector of endogenous variables $Y_{i,t}$ includes domestic variables that are specific to country i, while foreign variables are denoted by $Y_{i,t}^{*} = \sum_{i \neq h} w_{i,h} Y_{h,t}$, which are constructed as weighted averages of country-specific endogenous variables using a matrix of weights, W, where for each i we have $\sum_{i \neq h} w_{i,h} = 1$.

In order to solve the GVAR, we can exploit the fact that foreign variables are linear combinations of the complete set of domestic variables Y_t, , i.e. $Y_{i,t}^{*} = W_i Y_t$, being W_i the appropriate country-specific link matrix based in our case on IMF CPIS data. Starting from eq. (1), if we define $G_{i,0} = [I\ , -C_{i,0}]$ and $G_{i,j} = [B_{i,j}\ ,\ C_{i,j}\ ]$, for $j = 1, \ldots, p = max(p_i, q_i)$, for each country i we can obtain the alternative notation of the country-specific model:

$$G_{i,0} W_i Y_t = a_i + \textstyle\sum_{j=1}^{p} G_{i,j} W_i Y_{t-j} + v_{i,t}.$$

By staking all countries together, and denoting by $p = \max_i\left(\max(p_i, q_i)\right)$ we obtain:

$$G_0 Y_t = g_0 + \sum_{j=1}^{p} G_j Y_{t-j} + v_t \qquad (2)$$

where $G_0 = \begin{pmatrix} G_{1,0} W_1 \\ \vdots \\ G_{N,0} W_N \end{pmatrix}$, $G_j = \begin{pmatrix} G_{1,j} W_1 \\ \vdots \\ G_{N,j} W_N \end{pmatrix}$, $g_0 = \begin{pmatrix} a_1 \\ \vdots \\ a_N \end{pmatrix}$ and $v_t = \begin{pmatrix} v_{1,t} \\ \vdots \\ v_{N,t} \end{pmatrix}$, with N representing the number of countries. Provided that G_0 is invertible, we can write the GVAR in its reduced form as:

$$Y_t = h_0 + \sum_{j=1} H_j Y_{t-j} + u_t \qquad (3)$$

where $h_0 = G_0^{-1} g_0$, $H_j = G_0^{-1} G_j$ are coefficients, and $u_t = G_0^{-1} v_t$ are reduced form residuals with unrestricted covariance matrix given by Ω_u. This specification of the model allows us to understand the dynamic properties of the data, as well as the response of each variable in each country to a particular shock. The next step, discussed in Section 3.3, is the strategy used for the identification of the structural shocks, starting from the obtained residuals u_t, and, specifically, from the information contained in the covariance matrix Ω_u.

3.2 Data and specification of the model

Our dataset focuses on the European region that is represented here by 24 individual countries and one aggregate, to which we also add US, as summarised in Table 1. Given the limitations of our dataset, the EA region comprises 14 individual Member States and one aggregate, i.e. the Baltics.[10] Similarly, the EU includes 20 individual countries, and the Baltics group.[11] Outside EU, we consider Russia, Turkey, Norway and Switzerland due to their strategic importance (e.g. for economic, financial, geopolitical reasons). Finally, we add US as a key global financial centre and an important source of macroeconomic fluctuations relevant for Europe, and for EA in particular.

Table 1: Countries included in the empirical analysis

Euro Area, EA	**Other Europe**	**Others**
Austria, AT	Czech Republic, CZ	United States, US
Belgium, BE	Denmark, DK	
Finland, FI	Hungary, HU	
France, FR	Norway, NO	
Germany, DE	Poland, PL	
Greece, EL	Russia, RU	
Ireland, IE	Sweden, SE	
Italy, IT	Switzerland, CH	
Luxemburg, LU	Turkey, TR	
the Netherlands, NL	United Kingdom, UK	
Portugal, PT		
Slovakia, SK		
Slovenia, SI		
Spain, ES		
Baltics, BA		

Note: Due to data limitations for specific indicators, we aggregate Latvia, Lithuania and Estonia into a single group, denoted as "Baltics"; all indicators pertaining to Baltics are simple averages of the available indicators.

Our dataset consists in monthly time-series running from January 2003 to December 2018 (all data description and definitions are provided in Appendix A). The endogenous vector includes, besides the two uncertainty proxies, the 10-year sovereign yields such that: $Y_t = [yields_t, EPU_t, CISS_t]'$. In this

[10] Slovenia and Slovakia joined EA in 2007 and 2009 respectively, therefore, very early in the sample and before the European sovereign debt crisis. The Baltics joined the EA between 2011 and 2015, but we consider them part of the EA given their small relative size, highly open economies, and their participation in the European Exchange Rate Mechanism (ERM II) since mid-2000s – underlining the importance of ECB monetary policy for their economies.

[11] Romania, Bulgaria, Croatia, Malta and Cyprus suffer from limitations on data availability; aggregating these countries is not feasible either due to their larger heterogeneity than in the case of Baltics.

way, the model captures the inherent risk–return trade-off that is relevant for financial market investors. In the benchmark specification[12] we consider sovereign yields that represent the risk-free benchmark for financing costs in any given country, encompassing the first stage of the transmission mechanism of uncertainty to the real economy.

Concerning our uncertainty proxies, CISS is available with a weekly frequency from the ECB data warehouse, but EPU indicators are available only with a monthly frequency. We believe that such a frequency is sufficient to uncover the most relevant spill-overs and cross-influences between the financial and policy uncertainty, due to the latter concept and measurement methodology. All country-specific EPU indexes have been calculated based on the same approach, detailed in Baker et al. (2016), who perform text searches on major media outlets in order to gauge the frequency of some relevant keywords pertaining to the *economic, policy* and *uncertainty* domains. Obviously, rumours and speculations about (un-announced) policy changes, intentions or political declarations can be read almost daily in economic and business publications, but time is of essence in order to observe sufficient political tensions that eventually feature prominently in the news (and get captured in the EPU). Considering our sample, EPU time-series are available for the following 13 countries: BE, DK, FR, DE, NL, ES, IT, EL, IE, SE, UK, RU and US. More importantly, both EPU and CISS are available in some countries that have taken the centre stage in various EU policy debates over the last two decades (e.g. BE, EL, IT, ES, FR, IE).

This rich GVAR specification allows us to clean our data from aggregate dynamics that dominates most of the EA datasets. This 'cleaning' occurs through the inclusion of foreign variables $Y_{i,t}^{*}$ and common global factors, such as the VIX index – which is a proxy for global risk appetite in the literature on global financial cycles (see Rey, 2015; Bruno and Shin, 2014; Miranda-Agrippino and Rey, 2015) as well as in the literature on global financial spill-overs (Chudik and Fratzscher, 2011).

The original idea behind a GVAR model is the complex re-weighting of country-specific VARs that reduces the parameters space and makes its estimation feasible (see Pesaran et al., 2004; Dees et al., 2007). To this end, we use a weighting scheme derived from data on bilateral portfolio exposures taken from the IMF's Coordinated Portfolio Investment Survey (CPIS), which describes cross-border investments in bonds and equities.[13] Due to data limitations and in order to streamline the interpretation

[12] As a robustness check, we use 10-year yield spreads against Germany or against US; see section 4.5.

[13] Data source is http://data.imf.org/cpis (see Appendix A). A similar weighting scheme based on CPIS data is employed, for example, in Hebous and Zimmermann (2013) and Greenwood-Nimmo et al. (2019). Most GVARs instead use weighting schemes based on bilateral trade flows. Eickmeier and Ng (2015) investigate several weighting schemes (e.g. based on bilateral trade, portfolio investment, foreign direct investment, banking exposures) and find that a combination between trade and financial weights works best to expose credit supply shocks in a GVAR model including real and financial variables. See also Feldkircher and Huber (2016) for an analysis of different weighting schemes in GVARs.

of results, we use a fixed rather than a time-varying weighting matrix,[14] although the latter would probably only amplify the effects we uncover, particularly because higher capital outflows are associated with spikes in contagion risk (and uncertainty spill-overs).

Capital flows, in general, echo the risk-return trade-offs arising across limitedly integrated markets (see discussion in Garleanu et al., 2015; Rey, 2015; Bruno and Shin, 2014). Our modelling approach also reflects the link between international capital flows and changes in sovereign yields through the international portfolios rebalancing channel. According to this literature strand (see Rey, 2015; Bruno and Shin, 2014; Cerutti et al., 2017; Choi and Furceri, 2019), global capital flows co-move with global risk factors and monetary policy changes in centre countries like US and EA. By amplifying the effects of foreign shocks on the domestic economy, capital flows can limit the policy options available to governments (Dragomirescu-Gaina and Philippas, 2015) and/or financial supervisory authorities (Allen et al., 2011), further increasing policy uncertainty. The main ingredients of these mechanisms are mirrored in our empirical specification, which includes aggregate uncertainty (i.e. weighted averages of EPU and CISS), global risk proxies (i.e. VIX), sovereign yields, (weights based on) capital flows, and ECB policy proxies.

To account for ECB monetary policies, we can extend the specification given in equation (1) such that ECB can be considered as a synthetic country in the GVAR. To highlight the ECB role in the model, we can re-specify the GVAR equation (1) as:

$$Y_{i,t} = a_i + \sum_{j=1}^{pi} B_{i,j} Y_{i,t-j} + \sum_{j=0}^{qi} C_{i,j} Y^*{}_{i,t-j} + \sum_{j=0}^{qi} D_{i,j} X_{t-j} + v_{i,t} \tag{4}$$

where $Y_{i,t}$ and $Y^*{}_{i,t}$ are country-specific endogenous variables as before, but X_t denotes the common variables summarising the ECB policy proxies (and policy objectives), while $D_{i,j}$ are the associated coefficient matrices. Accordingly, the VARX associated with ECB will specify X_t as an autoregressive process with lag orders given by (px, qx) as:

$$X_t = m_x + \sum_{j=1}^{px} N_j X_{t-j} + \sum_{j=0}^{qx} P_j \tilde{Y}_{t-j} + v_{x,t} \tag{5}$$

where m_x, N_j and M_j are (matrix) coefficients, $v_{x,t}$ is a noise term, and $\tilde{Y}_t$ is a vector of feedbacks from the GVAR main endogenous variables, as in Burriel and Galesi (2018). Equation (5) balances persistence with feedback effects, and thus can be seen as a reaction function where ECB responds to

[14] Large part of the GVAR literature simply employs fixed rather than time-varying weighting matrixes, thus focusing more on the interactions between the model variables, rather than on weights.

developments in the EA region with respect to aggregate inflation, economic activity, sovereign yields, as well as uncertainty dynamics.[15]

We follow Boeckx et al. (2017) and Burriel and Galesi (2018) and define X_t above such as to capture the main aspects of the ECB policy toolbox. More specifically, we include: (i) a proxy for conventional monetary policy, denoted as CMP, (ii) a liquidity proxy, denoted as $Liquidity$, and (iii) an unconventional monetary policy proxy, denoted as UMP (see data description in Appendix A). In particular, we proxy CMP using the Main Refinancing Operations (MRO) interest rate, which is the ECB main policy rate. As a liquidity proxy we use the spread between EONIA (i.e. the Euro Overnight Index Average) and the MRO rate. As UMP proxy we use the annual change in the (log of) ECB balance sheet, which has become the standard indicator in the literature on unconventional monetary policy. In addition, X_t includes the EA aggregate CPI inflation and (annual change in) industrial production, which help control for the first-order economic effects of uncertainty.

Regarding the specification of the country-specific VARs, only those variables for which data is available are included. As an example, for Italy, the endogenous vector includes all the three variables mentioned above, but for Portugal only $yields$ and CISS are included because EPU is missing; for US, the vector of endogenous variables includes $yields$, EPU and VIX instead, which (in the absence of CISS) also serves as a global proxy for financial risk.

The foreign vector $Y_{i,t}^*$ includes the foreign counterparts of the domestic variables, but also VIX and ECB proxies, which feature only in EA countries' models. Moreover, for all EU countries, we capture the common European policy-making framework through the inclusion of EPU^*, and the common financial regulatory framework through the inclusions of $CISS^*$. Given its dominant global financial position, there is no $Y_{i,t}^*$ specified for the US model.

Following Pesaran et al. (2004) and Dees et al. (2007), we estimate the parameters of the reduced-form GVAR, with ECB treated as a synthetic country, and use the information contained in the covariance matrix Ω_u to identify the structural shocks as described in the following section.

3.3 Identification through absolute magnitude restrictions

As noted in Dees et al., (2014) and in Dungey and Osborn (2014), dealing with multi-country models is challenging because it requires a different framework for conceptualizing the nature of shocks that one wishes to identify, particularly due to the strong cross-sectional dimension of these models. Here

[15] Goldstein et al., (2011) highlight the key role of uncertainty in driving policy responses of a central bank that has imperfect information about the economic fundamentals but can learn from market data. In our setting, even if ECB has significantly extended its regulatory and prudential oversight, the heterogeneous dynamics and fragmentation of the EA financial system implies substantial information gains if uncertainty is reduced.

lies one of the main contributions we bring to the uncertainty-related empirical literature, which deals largely with shock identification in single country models. Our GVAR specification can elegantly solve such challenges by effectively removing the common (or aggregate) component, which then reduces the cross-sectional correlation of residuals. To wit: the largest cross-sectional correlation in our GVAR residuals is 0.083, and the corresponding median correlation across all model equations is 0.0001.[16]

In terms of identification, we extend De Santis and Zimic (2018) and implement a structural identification through absolute magnitude restrictions in a multi-country modelling framework. To better reveal the value of identifying two types of uncertainty shocks, besides the *main* identification we also propose a *fuzzy* identification. The *main* identification strategy pins down both the origin country and type of the (uncertainty) shock, while the *fuzzy* identification only pins down the origin country, allowing for significant overlaps (i.e. measured in terms of covariance) between the two uncertainty shocks; more technical details are provided in Appendix C. Unless otherwise stated, the results and the discussion refer to the *main* identification strategy.

Any structural identification requires a mapping from reduced-form residuals, u_t, into structural ones, ε_t, say in the form: $u_t = S\varepsilon_t$, where S is a matrix that is the focus of any identification strategy. If we normalize the structural shocks to have unit variance $E(\varepsilon_t \varepsilon_t') = I$, then we have that $\Omega_u = SS'$. A candidate for S can be obtained by orthogonalizing the reduced form residuals through a rotation of the Cholesky factor of Ω_u as in Uhlig (2005) or Bacchiocchi and Kitagawa (2020), where $S = \Omega_{tr}Q$, for an orthogonal matrix Q. Focusing on this latter, unfortunately the rotation matrix Q is not unique, unless further (e.g. zero or sign) restrictions are imposed.

Our identifying constraints are in the form of absolute magnitude restrictions as in De Santis and Zimic (2018). These restrictions work by conveniently constraining the space where specific columns of S must lie. The required inequalities are such that the relative size of the contemporaneous response of variable i to a shock j, with $i \neq j$, must be smaller (in absolute terms)[17] than the contemporaneous response of variable j to the shock j. In other words, when both variables i, j are scaled by their standard deviations, the indirect effect of a structural shock ε_j on variable $i,\ i \neq j$, is lower than the direct effect of ε_j on variable j. The intuition behind applying absolute magnitude restrictions to our case is that any of our two uncertainty measures should be better than the other one in capturing structural shocks that stems from its own data/policy domain – a plausible assumption, given the obvious methodological differences between the two measures. Indeed, CISS is a composite indicator designed, and empirically

[16] Such small correlations, however, cannot be completely neglected, particularly in a study dealing with uncertainty spill-overs for which second moments are most relevant; therefore, we do not restrict the variance-covariance matrix of the reduced-form model. Not including the country-specific foreign vector $Y_{i.t}^*$ would rise all these cross-sectional correlations to within the 0.2 – 0.4 range.

[17] This means that the two uncertainty variables are allowed to move contemporaneously in any direction in response to a structural shock, as along as the relative (measured in terms of standard deviations) impact fulfils the respective inequality.

tested (see Hollo et al., 2012), to quantify financial market stress rather than Knightian uncertainty; similarly, EPU is a news-based proxy designed to quantify policy uncertainty reflected in the media and related to government's initiatives, public proposals, or changes in rhetoric and public opinions rather than to measure financial stress.

For each shock and for each country in our GVAR, the object of restrictions concerns an entire column of S. Our idea is to apply these restrictions in two different ways, to maximize the insights we can derive and take advantage of the flexibility of this identification approach. When performing the *main* identification, the restrictions are applied separately on the two columns of S that correspond to the two country-specific uncertainty variables; this is the original approach in De Santis and Zimic (2018). In the case of a *fuzzy* identification, instead, the restrictions are applied jointly on the same two columns of S, but this time the identification can only pin down the origin country. In other words, under the *fuzzy* identification, the on-impact reactions seen in EPU and CISS are likely to be contaminated such that it gets observationally difficult to disentangle the origin of the shock.

Denote the absolute value of the (i, j) element of S by $S_{a(i,j)}$ and let EPU and CISS be ordered in the system as the first and the second variable respectively. Since we are checking restrictions by column, under the *main* identification strategy we must have that $S_{a(1,1)} > S_{a(1,j)}$ for all $j \neq 1$ and $S_{a(2,2)} > S_{a(2,j)}$ for all $j \neq 2$. Under the *fuzzy* identification, instead, it is sufficient that $max(S_{a(1,1)}, S_{a(1,2)}, S_{a(2,1)}, S_{a(2,2)}) > max(S_{a(1,j)}, S_{a(2,j)})$ for all $j > 2$; these latter restrictions practically allow for any uncertainty shock to spread fast enough such as to contaminate (within one observational period) both EPU and CISS, thus hampering a precise separation (on a monthly basis) between the two shocks within a given country. Shocks that do not create quick ripple effects across realms would be picked up by both identifications above, but noisy and/or fast shocks would be only picked up by the *fuzzy* identification in the special case that $max(S_{a(1,2)}, S_{a(2,1)})$ is larger than $max(S_{a(1,1)}, S_{a(2,2)})$. The feasible set of rotation matrixes is also larger under the *fuzzy* identification compared to the *main* identification strategy. Note also that the time aggregation bias is not an issue in our case, since our two identification strategies automatically deal with differences in transmission speed for shocks. We return to the importance of using two identification strategies in the next section.

At this point, it is important to discuss some of the advantages of our approach in relation to other structural identification methods available in the broader (G)VAR literature. Firstly, our identification through magnitude restrictions does not impose any time precedence on the two uncertainty variables, like would be the case when applying a standard Cholesky identification (which is just a special case of the identification based on magnitude restrictions as it imposes a zero contemporaneous response of some variables to some shocks).[18] In our case, imposing a time precedence between two uncertainty

[18] Bekaert et al. (2013) estimate a VAR specified in business cycle, monetary policy, risk aversion and expected market volatility, using a Cholesky decomposition (with variables ordered as listed), and a combination of

proxies would be a too strong assumption, given the complex, dynamic, double causality influences between policy and financial uncertainty. For example, in the cases of Greece and Ireland, the precedence of the shocks is obviously different (see Farhi and Tirole, 2017); however, for most other situations that are relevant for empirical analyses, it is not that clear which of the two uncertainty shocks would come first.

Secondly, an alternative identification method based on sign restrictions would require strong theoretical predictions about the transmission mechanisms underlying the two types of uncertainty shocks. This might be hard to achieve when conceptual overlaps are present, particularly in the case of uncertainty where a perfect match between the theoretical notion and its empirical counterpart remains challenging (see discussion in Jurado et al., 2015). Moreover, as noted in Caldara et al. (2016), different uncertainty shocks, despite differences in measurement, can have similar effects on other macroeconomic variables, complicating identification.[19] Thirdly, Bacchiocchi (2017) and Angelini et al. (2019) build on the original "identification through heteroskedasticity" idea proposed in Rigobon (2003) to identify uncertainty shocks in a VAR model. While their method is successful in dealing with endogeneity challenges that arise between uncertainty and real or financial variables, it requires that (at least some) structural parameters remain constant over time and across volatility regimes – a restriction we find difficult to satisfy in periods of major policy innovations (e.g. Q.E.) by major central banks. Fourthly, Caldara et al. (2016) identify the effects of economic uncertainty and financial shocks by employing a penalty function approach, which shares some similarities with our identification approach. In their case, the structural shock should maximize the impulse response of its respective target variable over a pre-defined period. However, although they can identify the two structural shocks, they still use a sequential identification due to reverse causality fears. Fifthly, Piffer and Podstawski (2018) use external instruments (e.g. the price of gold) to identify uncertainty shocks. While effective in other applications, applying their approach to our setting would face big challenges because it requires finding not just one, but two distinct instruments, i.e. one for each uncertainty proxy, and in each country.

4. RESULTS

4.1. Preliminary analysis

As a preliminary data analysis, we look at the substantial empirical overlaps between the two (policy and financial) uncertainty proxies. Tables A1 and A2 from Appendix A display the correlations between

contemporaneous with long-run restrictions. They find that risk aversion decreases more strongly than volatility to a lax monetary shock, with both expected volatility and risk aversion extracted from VIX. Others, like Baker et al. (2016) and Jurado et al. (2015), also employ Choleski decompositions, but use a single uncertainty proxy, not two different ones.

[19] As the required inequality restrictions must be fulfilled only in absolute terms in our case, EPU and CISS are free to either co-move or move in opposite directions, and they might have similar effects on bond yields.

country-specific EPU and CISS indexes, in log terms, computed over the entire sample 2003 – 2018 (for countries where EPU is available), at a monthly frequency. The main challenge to our identification of country-specific shocks rests specifically on these substantial correlations, measured both across as well as within countries. Most of the within-country correlations between EPU and CISS in Table A1 are positive and statistically significant. In Table A2, we see that the cross-border contemporaneous correlations among similar types are even higher than the pair-wise correlations displayed in Table A1. This observation highlights the challenge we face in identifying *country-specific* uncertainty shocks within the EU (or the EA), where the common components might contribute more to driving observed uncertainty dynamics than the country-specific components. This is a challenge we directly address through the estimation of a multi-country GVAR model, which is best suited to tackle the dynamics of the common components.

We caution readers not to make any causality inference from these pair-wise correlations, which lack sufficient robustness and sometimes change with the sample size and period. This lack of robustness, instead, should be interpreted as an illustration of the dynamic nature of the existing interactions between policy (EPU) and financial (CISS) uncertainties, which might amplify or cancel each other, depending on the period, or the nature of the triggering event (or crisis) in a particular country. Once we identify the shocks from the reduced-form residuals, we can investigate the overlapping of the structural shocks' time-series with some well-known episodes that marked the recent history of some of the countries under consideration.

4.2. Estimation of the GVAR model under the *main* identification strategy

With most model variables expressed in log terms, we estimate the model directly in levels, allowing an easy interpretation of its impulse responses, which provide us with the main insights.[20] Sims et al., (1990) recommend against differencing even in the presence of unit roots, arguing that the goal of the analysis should be to determine the interactions between variables. They show that the VAR specified in levels delivers consistent estimates, even in the presence of stochastic trends and cointegration. Elliot (1998) further shows theoretically that imposing cointegration for near unit root variables can lead to large distortions. We do not estimate cointegrating relations, nor include time trends and error correction terms, also because our short sample and small set of variables would preclude a robust identification of these long-term relationships.[21]

Our sample includes 16 years of monthly observations, spanning a period over which EA has been shaken by many different crises. The main trade-off we are facing in the estimation of our GVAR is

[20] ECB balance sheet, EA inflation and EA industrial production enter the ECB model in (log) annual changes.
[21] Both theory and empirical studies (e.g. De Santis, 2020) provide evidence that European sovereign yields (and spreads therefore) are cointegrated with fundamentals (e.g. fiscal proxies, economic and financial proxies), which are omitted from our estimated GVAR because we focus on the identification problem.

between model parsimony and its statistical properties (e.g. stability, residual tests). Kapetanios et al. (2007) notice that the quality of a VAR approximation to the true model depends on both the number of variables and the lag order; as the GVAR includes more variables than a normal VAR (i.e. both domestic and foreign variables in each country-specific model), small lag orders are regularly employed. To eliminate residual autocorrelation (or serial dependence) and preserve a parsimonious specification, we set $pi = 1$ for all EA countries and $pi = 2$ for all others. To maintain model stability and parsimony we let $qi = 1$ for all countries. In most cases, the inclusion of country-specific foreign variables is supported by F-tests, where the null restricts the $C_{i,j}$ coefficients in equation (1) to zero.[22] Model's parsimony and statistical properties justify our choice for the specification of Eq. (5), where we increase the lag length of the endogenous vector, setting $px = 3$ and $qx = 1$. As a first evidence to support our identification, we compute the within-country correlations between the identified shock time-series and find these are small and statistically insignificant. Some specification checks for our GVAR are presented in Appendix B.

To derive our main insights, we rely on the models' impulse response functions (IRFs) to the two uncertainty shocks identified through absolute magnitude restrictions. In a first step we discuss the *main* identification strategy and its results; in a second step, in order to stress the importance of distinguishing between the two kinds of uncertainty shocks, we will apply the less restrictive *fuzzy* identification strategy. To gauge statistical significance of IRFs, we use bootstrapped 68% confidence intervals[23] based on 500 replications, allowing for a maximum of 100 draws of the orthogonal matrix Q at each replication; the success rate is around 40%. The details of the algorithm used for obtaining the impulse response functions and the related confidence intervals are reported in Appendix C. Table 2 conveniently summarises the model results under the *main* identification strategy for uncertainty shocks originating in IT, ES, EL, IE, and FR – a relevant group of countries that allows us to draw interesting insights. The first four countries in this list were seen (at specific moments) as the most vulnerable EA members, while France makes for an interesting case as it had to weather a series of recent uncertainty shocks, mostly originating in the policy realm. More detailed plots for these five countries are given in Appendix D.

[22] Results of the F-tests are available upon request from the authors.
[23] 68% confidence intervals are common in GVAR specifications, which are known to deliver wider confidence bands due to over-parameterization (e.g., see Burriel and Galesi 2018).

Table 2: Summary of IRFs to uncertainty shocks under the *main* identification strategy

Shock origin	Observed responses	CISS responses to a CISS shock	EPU responses to a CISS shock	CISS responses to a EPU shock	EPU responses to a EPU shock
Italy	**domestic**	Significant up to 24 months	Significant starting with the 6th month	Insignificant	Significant up to 12 months
	cross-border	Significant up to 9-24 months	Significant up to 12-36 months	Mostly insignificant	Significant up to 3 months for some EA countries
Spain	**domestic**	Significant up to 18 months	Significant starting with the 3rd month	Insignificant	Significant up to 6 months
	cross-border	Significant up to 12-24 months	Significant up to 12-36 months	Mostly insignificant	Significant up to 3-36 months
Greece	**domestic**	Significant, up to 18 months	Significant up to 9 months	Insignificant	Significant up to 36 months
	cross-border	Significant up to 3-18 months	Significant up to 3-18 months	Significant up to 12 months in some EA countries	Significant up to 36 months
Ireland	**domestic**	Significant up to 12 months	Significant up to 18 months	Insignificant	Significant only on impact
	cross-border	Significant up to 9-24 months	Significant up to 6-36 months	Insignificant	Insignificant, except on impact in UK
France	**domestic**	Significant up to 16 months	Significant between 3rd - 36th month	Significant between 3rd -12th month	Significant up to 36 months
	cross-border	Significant up to 12-24 months	Significant up to 6-24 months	Significant in few EA countries	Significant up to 9-36 months

Note: The table displays a summary description of the IRFs to the two identified uncertainty shocks. Statistical significance is assessed based on the bootstrapped 68% confidence intervals derived from 200 replications, with a maximum of 100 maximum draws of the orthogonal matrix $\tilde{Q}$ at each bootstrap replication.

Two main findings emerge from Table 2. Firstly, there are substantial and persistent cross-border effects generated by domestic EPU and CISS shocks. In general, domestic CISS shocks are more important than EPU shocks in generating significant and persistent spill-overs (i.e. cross-border effects). Spanish CISS shocks, for example, generate more persistent CISS responses in Portugal and Greece rather than in Spain; similarly, French CISS shocks generate more persistent foreign responses in the Italian, Portuguese and Greek financial systems compared to France. Greek and Spanish EPU shocks also have substantial consequences abroad, but these are not more persistent than at home. The potential for domestic EPU shocks to spill over and generate more persistent responses abroad appears to be rather limited, suggesting that shocks spawning from the domestic policy/political arena carry a more significant idiosyncratic component. Therefore, our results suggest that CISS is more likely to reflect common dynamics, while EPU is more likely to reflect idiosyncratic dynamics, in line with the theoretical predictions and the associated empirical literature (e.g. Acharya and Steffen, 2015).

Secondly, there are important overlaps between policy and financial realms as revealed by the substantial but asymmetric interactions observed between the two uncertainty proxies. From Table 2 we see it is more likely that EPU responds to CISS shocks (both within as well as across countries) but less likely that CISS reacts to EPU shocks. This asymmetry in responses is remarkable given the symmetric treatment of the two uncertainty proxies in the 5 countries above. This asymmetry is also reflected in the $yields$ responses, as any move in risk has a counterpart in returns; as changes in sovereign yields are propagated through financial markets, this asymmetry can lead to larger real effects. Yet, it reveals the importance of financial frictions for real (macro)economic dynamics, and therefore for policy stability. In fact, exploiting the ECB block of the model, reported in equation (5), we can highlight negative responses of EA inflation and industrial production to a majority but not all of country-specific uncertainty shocks, with some clear asymmetries highlighted. To wit: we find statistically significant declines in industrial activity in response to Italian CISS but not EPU shocks, and to Greek EPU but not CISS shocks – identifying therefore a narrow list of shocks with high *potential* to spill over across the entire EA (see figure D.6 in Appendix D). Moreover, it is more likely in our results that EA industrial activity declines are statistically significant, while EA inflation responses are not, in line with large swaths of literature discussing the economic effects of uncertainty shocks (for a recent survey, see Castelnuovo, 2022).

We see these asymmetries and overlaps across uncertainty responses as being in line with the inner mechanisms underpinning the functioning of the EA, which features a deeply integrated financial market, but still lags in terms of institutional and political integration. Responses in EA sovereign yields would therefore be expected to reflect these same functional and institutional asymmetries. In the cross-section, however, we see that yields' responses (on-impact) to a CISS shock in a given origin country are highly correlated with yields' responses (on-impact) to an EPU shock arising in the same country, suggesting that financial investors do not differentiate much between the two types of uncertainty sources. Unsurprisingly, these correlations are much higher when we consider only the EA countries as a subgroup (see Table 4 below). Overall, this suggests that the sovereign yields of non-EA countries respond differently to EA uncertainty shocks, while the EA sovereign yields are more similar due to the many risk-sharing mechanisms that blur the thin separation line between uncertainty types. Table 4 presents a summary of these correlations, which beg further analysis that we perform in the next subsection.

Table 4: Yield responses to uncertainty shocks

Cross-sectional correlations between *yield* responses to uncertainty shocks	**All countries**	**All countries, except the origin country of the shock**	**EA countries subsample**	**EA countries, except the origin country of the shock**
Origin country of the shock				
Italy	0.516	0.508	0.606	0.619
Spain	0.585	0.576	0.757	0.748
Greece	0.909	0.683	0.938	0.329
Ireland	0.537	0.550	0.687	0.723
France	0.593	0.589	0.917	0.915

Note: Cross-sectional correlations are calculated based on the on-impact *yields* responses in all countries to a country-specific uncertainty shock, whose origin country is indicated on the first column of the table above. See Appendix D for detailed plots of the *yields* responses to each identified shock.

4.3. Separating uncertainty shock types

The IRFs discussed so far provide a summary of the estimated effects of the two uncertainty shocks, but do not reveal the importance of separating between shock types. Yet, whether investors face a sovereign or a financial crisis stemming from within the EA is an important question worth answering; international portfolio reallocations and hedging strategies would have to be updated in different ways, because different countries have different vulnerabilities and risks that can escalate, and even lead to contagion abroad. To answer, we decompose the on-impact responses into two components: (i) responses derived from applying the *fuzzy* identification (i.e. only the origin country is identified, but not the exact type of the shock), and (ii) *revaluations* that are calculated as the difference between the *fuzzy* and the *main* identification strategy. All figures from Appendix D include in their panels (d) a decomposition of the median IRFs, computed on impact. What can be easily revealed in these plots is the heterogenous contribution of revaluations in determining the (domestic and foreign) responses to uncertainty shocks. Since these *revaluations* are our model's approximations of valuation 'mistakes' in countries' risk profiles, we concentrate on understanding what drives the cross-country heterogeneity seen in these revaluations.

French CISS shocks, for example, determine positive revaluations in CISSs everywhere, but mostly negative revaluations in EPUs, and mixed revaluations in *yields* (see Figure D5, in Appendix D). In other words, once we recognize the type of the uncertainty shock hitting France, this helps reduce policy uncertainty (e.g. political risk) but instead increases financial risk everywhere (and hence contagion risk). We can presume that French financial vulnerability should have been high enough such as to raise contagion risk within the EA after a French shock. Indeed, several available data, rankings and anecdotal evidence (e.g. French banks' capital ratios that lay below EA average; Dexia's financial troubles and the coordinated bailout that followed) point to this being the case. News, announcements and even rumours trigger changes in investors' risk valuation profiles all the time; Attinasi et al. (2010), for example, find that the simple announcement of bank rescue packages led to a re-assessment of risks by investors during the global financial crisis.

Can we find some general patterns to explain the heterogeneity seen in revaluations after a country-specific uncertainty shock? To answer, we draw on two simple indicators that can be easily connected with our two uncertainty sources. In the case of CISS we use available data for TIER 1 bank capital ratios – a proxy for financial stability, while for EPU we use country-specific rankings for *Political Stability and Absence of Violence/Terrorism* (data source World Bank) – more details are in Appendix A. Because the global financial crisis and the subsequent European sovereign debt crisis have significantly changed the information set of global financial markets and investors, for a clearer separation we use data for both pre-2008 and post-2009 periods.[24] Table 5 provides an interesting summary of some simple cross-sectional correlations with on-impact revaluations. Firstly, notice that correlations are generally negative because more financially or politically vulnerable countries (i.e. low TIER1 or low *Political Stability* rankings) would see more significant upward revaluations in uncertainty once the type of the shock is known. Secondly, uncertainty revaluations are more strongly correlated with the relevant indicator before rather than after[25], suggesting that crises generally bring new useful pieces of information that can help in reducing valuation 'mistakes'; this underscores the key role of information revelation and learning for the identification of uncertainty shocks.

[24] In principle, one can set the cut-off date differently for each country, depending on when and what is considered as the most relevant crisis event altering the information set.

[25] The only exceptions are Greece for EPU shocks (because 2008/2009 does not represent a relevant cut-off date in this case) and Ireland for EPU shocks (because Ireland suffered from financial woes after bailing out its banks but had no particular political crisis); if our cut-off date is not relevant, investors are not expected to 'learn' anything new after the event passes.

Table 5: *Revaluations* explained by cross-sectional indicators of financial and political stability

Cross-sectional correlations between indicators and revaluations:	Indicator: TIER 1 capital ratios (year 2008)	Indicator: TIER 1 capital ratios (year 2018)	Indicator: Political Stability rankings (pre-2008)	Indicator: Political Stability rankings (post-2009)
	Revaluations in CISS after a CISS shock	**Revaluations in CISS after a CISS shock**	**Revaluations in EPU after a EPU shock**	**Revaluations in EPU after a EPU shock**
Origin country of the shock				
Italy	-0.516	-0.369	-0.327	-0.176
Spain	-0.595	-0.142	-0.729	-0.580
Greece	-0.568	-0.135	-0.511	-0.730
Ireland	-0.494	-0.053	0.456	0.323
France	-0.339	-0.122	-0.471	-0.363

Note: Cross-sectional correlations between country-specific indicators and on-impact revaluations (calculated based on the difference between the *fuzzy* IRFs and the IRFs of the *main* identification strategy). For TIER 1 ratios, ECB data before 2008 is incomplete, for which reason we use 2008 and 2018 as the two refence points. Pre-2008 refers to the average ranking for 2003-2008, while post-2009 denote the average ranking for 2009-2018.

4.4. ECB policy reactions to uncertainty shocks

One of the questions we raised in the introduction relates to the ECB role in filling the leadership gap within the EU institutional and governance structure. From an empirical perspective, as long as the ECB proxies are included in EA country models, their relevance can be validated statistically. In this respect, we perform a battery of F tests where, for each country, equation by equation, the coefficients in $D_{i,j}$ in Eq. (4) are jointly equal to zero or not. For each country of the EA, we can have evidence whether the ECB, through its proxies, has an impact on the three variables of interest. The results of all tests are reported in Table E1, in Appendix E. Such simple F-tests show that ECB had varying degrees of influence (from a statistical perspective) on EA countries; in synthesis, for Belgium, Italy, Spain and Greece the impact falls mostly on EPU, while for Austria, Finland, Netherlands, Spain and Baltics this impact falls on sovereign yields.

An analysis of the IRFs associated with ECB policy responses to uncertainty shocks provides a complementary perspective; detailed plots are to be found in Figure E1 from Appendix E. Concentrating on the same subset of 5 countries as in the previous section, we see that ECB would adjust its CMP in line with expectations, by reducing its MRO in response to (at least one) uncertainty shock. Except for Greece, ECB always reduces its MRO swiftly in response to CISS shocks; its responses to EPU shocks are similar, except for Italy and Ireland. ECB is also quick in increasing its liquidity provision in response to CISS shocks from all vulnerable countries; meanwhile, its liquidity responses to EPU shocks are more sluggish, and in the case of Italy and Ireland even statistically insignificant. Regarding its UMP reactions, the IRFs show that the ECB balance sheet increases in a statistically significant way in response to all uncertainty shocks stemming from the five countries considered, except again to EPU shocks from Italy and Ireland.

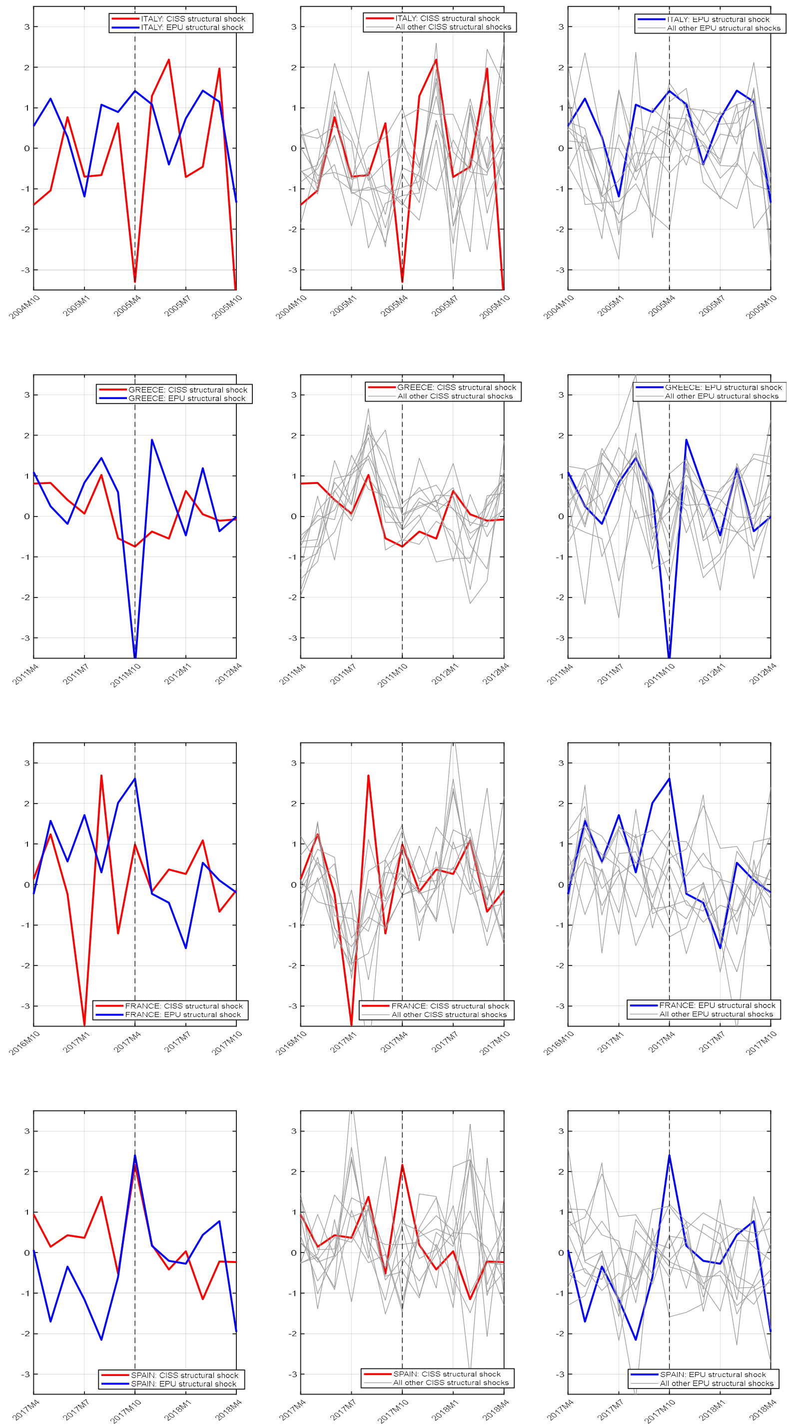
More interesting observations emerge when contrasting these findings with the ones from Table 2. Looking back at our previous discussion, we see that ECB has reacted to precisely those shocks that have more significant effects abroad, i.e. shocks that are most likely to spill over beyond the origin country; within our five countries sample, these are: Italian and Irish CISS shocks, Greek EPU shocks, French EPU and CISS shocks, Spanish EPU and CISS shocks. Some of these shocks also generate negative asymmetric responses in our economic activity proxies, highlighting their spill-over potential at the EA level. De Grauwe and Ji (2013) advocate for a more active ECB role in counteracting self-fulfilling crises driven by investors' fears rather than fundamentals, claiming that EA fragility (as perceived by investors) stems from the lack of a "lender of last resort" for both banks and sovereigns. In a similar vein, we posit here that ECB has tried to dampen those uncertainty shocks with the highest potential to spill over beyond the domestic country. In other words, ECB has done "whatever it takes" to prevent segmentation within the EA financial market.

4.5. Back-testing

De Santis and Zimic (2018) admit that their magnitude restrictions are inspired by event study techniques, which require a good understanding of the historical patterns present in the time-series being modelled. As already mentioned, magnitude restrictions can provide a mathematical approach to identification in a VAR including some highly correlated time-series. While this approach guarantees that, on a particular time moment, the identified shock has the largest magnitude among all the other shocks, there is no guarantee that the shock has any real, meaningful interpretation. This section addresses this issue and provides evidence on the suitability of using magnitude restrictions in our case.

We draw on multiple media sources to categorise a set of unique country-specific events that stand as outliers in the time-series of the identified uncertainty shocks (Appendix F provides an overview on the complete distribution of these shocks in different countries). Figure 1 below illustrates some major events that shaped the recent history of some European countries. To facilitate interpretation, for each event we plot the two uncertainty shocks (in the leftmost panel for each event), as well as a comparison of the time profile for the same-type uncertainty shocks in all remaining countries for which we perform the identification (see the remaining two panels associated with each event).

Figure 1: Overlap of identified uncertainty shocks and historical major (country-specific) events



<u>Apr. 2005: Consolidation of the Italian banking sector</u>

Mar. 29, Spanish BBVA launches bid to become majority owner of Italian BNL.

Mar. 30, ABN AMRO launched a bid for Antonveneta. (https://en.wikipedia.org/wiki/Bancopoli)

Apr. 29, Banca Popolare di Lodi proposed a merger with Antonveneta, thus challenging ABN AMRO bid. (https://en.wikipedia.org/wiki/Bancopoli)

<u>Oct. 2011: Greece avoids default</u>

Oct. 19, In Greece new austerity measures won initial parliamentary approval (SFC, 10/20/11)

Oct. 21, Finance ministers from 17 eurozone countries agreed to pay Greece $11 billion in its next batch of bailout loans (SFC, 10/22/11)

Oct. 26, Europe sealed a last-ditch deal to fix its festering debt crisis. Greece was provided with a second bailout package worth €130 billion to stave off bankruptcy. (AFP, 10/27/11; AP, 10/28/11)

<u>Apr. 2017: French presidential elections</u>

Apr 23, First round of a highly unpredictable presidential election seen vital for the future of the European Union. Centrist Emmanuel Macron won 23.7 percent of votes while far-right leader Marine Le Pen won 21.5. (AFP, 4/23/17; Reuters, 4/24/17)

<u>Oct. 2017: Catalonia's independence referendum</u>

Oct 11, Spanish PM Mariano Rajoy threatened to impose direct rule on Catalonia following its disputed independence referendum. (AFP, 10/11/17; AP, 10/11/17)

Oct 17, Spain's top court officially ruled that Catalonia's disputed independence referendum was illegal. (AP, 10/17/17; Reuters, 10/17/17)

Note: The date of the main historical event indicated in text on the right side is also highlighted with a vertical dash line in the associated graphs. Uncertainty shocks are identified in the following countries: BE, DE, DK, IT, ES, FR, EL, SE, IE, NL, and UK. News and headlines are borrowed from the following online repositories: www.timelines.ws, https://en.wikipedia.org and https://en.wikipedia.org/wiki/Portal:Current_events, although the original source might be different, as indicated in the text.

4.6. Robustness checks

Different robustness checks are performed in order to validate our findings. Since our main results remain qualitatively unchanged, here we only provide a short discussion for each robustness check.

As a first robustness check, we replace sovereign yields with the spreads computed against both Germany (which is the European benchmark) and US (which is the global benchmark). Spreads are a more standard measure of risk and have been used in various empirical applications (see among many others Bacchiocchi, 2017; De Santis and Zimic, 2018).

Secondly, we add a measure of global liquidity risk, i.e. the TED spread, which is the spread between the 3-Month LIBOR based on US dollars and the 3-Month Treasury Bills (see Brunnermeier, 2009). Although our GVAR already includes a liquidity proxy relevant for EA markets (i.e. the spread between EONIA and the main ECB policy rate), the US dollar-denominated funding costs of European banks play a key role within the literature on global financial cycles[26] (see Rey, 2015; Bruno and Shin, 2014). When uncertainty raises, banks charge themselves higher interest rates for uncollateralised loans (i.e. LIBOR rate is the reference rate for interbank lending) compared to the yield of risk-free US Treasuries, and therefore the TED spread is actually a global liquidity proxy. The cost of US dollar funding has been a central element of the policy reactions during the peaks of the financial crisis of 2007/2008. All major central banks, including ECB, set up direct currency swap lines with the US Federal Reserve System, precisely to alleviate pressures from the US dollar funding.[27] By adding the TED spread as an endogenous variable to the US model, we account for changes in global liquidity and US dollar funding, providing a consistency check to our main findings from the previous sections.

In a third robustness check, we re-estimate the GVAR with a different weighting matrix based on BIS Locational Banking Statistics (LBS) data; see Appendix A for more details. Weights based on BIS LBS data are also employed in Bicu and Candelon, (2013), Feldkircher and Huber (2016), Eickmeier and Ng (2015). Yet, capital flows driving bank cross-border exposures are generally more volatile than flows driving portfolio exposures according to balance of payments statistics. Despite some differences in weighting between IMF CPIS data and BIS LBS data[28], estimating the GVAR with weights based on the latter dataset delivers qualitatively similar findings.

Fourth, to account for ECB focus on yield divergences within the EA, we append the ECB model given in Eq. (5) with a dispersion proxy. This proxy is computed as the cross-sectional absolute

[26] This is because the US dollar is the world's main reserve currency. Similar to the global financial cycle literature, the international bank lending channel, exposed in Schmidt, Caccavaio, Carpinelli and Marinelli (2018), highlights the importance of US dollar funding costs on lending in Europe.
[27] See https://www.federalreserve.gov/monetarypolicy/bst_liquidityswaps.htm.
[28] The IMF CPIS data show that most countries in our sample have over-weighted exposures towards US, UK and LU. Instead, according to BIS LBS data, most countries have over-weighted exposures towards UK and LU.

dispersion (CSAD) of all EA sovereign yields (according to out sample shown in Table 1). The additional insight we get from this exercise is that dispersion raises mostly in reaction to CISS shocks, while its reactions to EPU (apart from Greek) shocks are rather insignificant; this result further highlights the systemic importance and prevalence of CISS shocks over EPU shocks in terms of their impact on EA financial fragmentation and the efficiency of ECB monetary policy transmission. It also reinforces our previous result regarding the narrow list of uncertainty shocks having the highest potential to spill over abroad, shocks to which ECB reacted with all its policy instruments.

Fifth, we compare our results with those derived by using the most common identification strategy in GVARs models, that is the generalised IFRs or GIRFs (see Pesaran et al., 2004). Compared to our IRFs, the GIRFs generate substantial (on-impact) underestimations precisely for those uncertainty (CISS or EPU) shocks that have the highest potential to spread across borders and raise contagion risk (see Appendix G for more details).

5. CONCLUSIONS

Given the deep and complex intertwining between policy and financial realms in Europe, and in Euro Area in particular, separating between these two overlapping sources of uncertainty can be empirically challenging. For the ECB, this distinction is particularly important because it can help in calibrating its monetary policy reactions. For financial investors, being able to separate various types of uncertainty is important because their hedging strategies need to be adjusted accordingly. Large strands of the literature portray the sovereign-bank nexus as a key mechanism blurring a clearer identification, but in a multi-country setting this could be of limited use due to the incomplete nature of the European integration and institutional governance. We draw on theoretical models featuring information acquisition costs and frictions to interpret the dynamics and the spill-over effects of the identified country-specific uncertainty shocks. Our estimated GVAR model can efficiently summarise the cross-sectional and time-series properties of a large multi-country dataset, for which reason we believe its results can provide novel relevant insights. We complement our identification with a back-testing exercise in which we find that the identified shocks can match the dates of some remarkable events that marked the recent history of the European project.

The identification of country-specific financial and policy uncertainty shocks here is obtained by generalizing the absolute magnitude restrictions, originally proposed by De Santis and Zimic (2018), to a multi-country framework. This generalization allows us to adapt and implement the magnitude restrictions approach more flexibly, in order to perform a *fuzzy* identification from which we quantify the under/over-valuations arising when the origin country is known, but not the type of the uncertainty shock; in other words, we reveal the strength of the existing overlaps between policy and financial realms that could preclude identification. This helps us see why, in the aftermath of crises triggering large changes in the information set, investors become better at disentangling among uncertainty types.

Within the Euro Area, our impulse responses reveal statistically significant and persistent spill-overs from financial- but also policy-driven uncertainty shocks. Depending on the origin country, one type of uncertainty shock might generate more substantial domestic effects and spill-overs than the other, the difference being relevant mainly in terms of policy responses. Our results suggest that ECB deployed its conventional as well as unconventional tools with respect to those particular uncertainty shocks having the highest *potential* (because identification in real-time is difficult) to spill over abroad. While such actions can blur the thin separation line between uncertainty shock types, a simple comparison between the responses of sovereign yields within and outside the EA hints at strong institutional arrangements and risk-sharing mechanisms existing within the EA. As the European financial markets gyrated towards either more integration or more fragmentation with each passing crisis, we believe the ECB managed to fill the leadership vacuum when reacting to country-specific uncertainty shocks, no matter the type and the realm they originated from.

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DECLARATIONS OF INTEREST

None.

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ONLINE APPENDIXES

Appendix A: Data description and sources

CISS – Composite Indicator for Systemic Risk. Frequency: monthly averages. Transformation: natural logarithm. Adjustment: seasonally adjusted using X-12 procedure. Source: ECB warehouse (https://sdw.ecb.europa.eu/browse.do?node=9689686). See Hollo et al. (2012) for the construction methodology. For Baltics, we compute the average of CISS indexes for all three countries.

EPU – economic policy uncertainty index, computed based on the methodology proposed by Baker et al. (2016). Transformation: natural logarithm. Adjustment: seasonally adjusted using X-12 procedure. Source: data and methodology available from www.policyuncertainty.com.

EONIA – is the Euro Overnight Index average or the Euro Interbank Offered Rate defined as the weighted rate for the overnight maturity, calculated by collecting data on unsecured overnight lending in the EA provided by banks belonging to the EONIA panel.[29] Frequency: monthly averages. Transformation: $yield^{adjusted} = \frac{1}{12} * \ln\left(1 + \frac{yield}{100}\right)$. Source: ECB warehouse. The liquidity proxy used in the GVAR is the difference between EONIA and the Main Refinancing Operations rate.

ECB assets – defined as central bank assets for Euro Area (11-19 countries). Frequency: monthly, end of month. Transformation: natural logarithm. Source: Federal Reserve Bank of St. Louis database. The UMP proxy used in the GVAR is the annual growth rate of the natural logarithm of ECB assets.

Main Refinancing Operations (MRO) rate – is the short-term interest rate at which ECB provides the bulk of liquidity to the banking system of the Euro Area.[30] Source: ECB warehouse.

Political Stability and Absence of Violence/Terrorism – an aggregate indicator from the Worldwide Governance Indicators, a dataset compiled by the World Bank; the data used is the percentile ranking based on this indicator. Frequency: annual. Source: http://info.worldbank.org/governance/wgi/

TIER 1 capital ratio – defined as the average ratio of banks' core capital to total risk-weighted assets. Frequency: annual. Transformation: none. Source: ECB warehouse.

TED spreads – defined as the spread between the 3-Month LIBOR based on US dollars and the 3-Month US Treasury Bills. Frequency: monthly averages. Transformation: none. Source: Federal Reserve Bank of St. Louis database.

YIELDS – the 10-year sovereign bond yields for each country, adjusted according to formula below; data is not available for Turkey, for which we use its 5-year sovereign bond yields instead; for the Baltics, only data for Lithuania and Latvia are available, so the average is used in the model. Transformation: $yield^{adjusted} = \frac{1}{12} * \ln\left(1 + \frac{yield}{100}\right)$ to smooth spikes in the time-series. Source: Eurostat and ECB warehouse.

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[29] See also the conclusions of the public consultation on euro risk-free rates at https://www.ecb.europa.eu/paym/pdf/cons/euro_risk-free_rates/ecb.consultation_details_201905.en.pdf.
[30] See https://www.ecb.europa.eu/stats/policy_and_exchange_rates/key_ecb_interest_rates/html/index.en.html

VIX – the Chicago Board Options Exchange (CBOE) Volatility Index. Frequency: monthly averages. Transformation: natural logarithm. Source: Federal Reserve Bank of St. Louis database.

Table A1: Within-country pair-wise correlations between EPU and CISS indexes

Country	EPU(T) x CISS(T-2)	EPU(T) x CISS(T-1)	EPU(T) x CISS(T)	EPU(T-1) x CISS(T)	EPU(T-2) x CISS(T)
BE	0.608***	0.630***	0.658***	0.626***	0.599***
	(10.496)	(11.145)	(12.041)	(11.046)	(10.248)
FR	0.088	0.140*	0.190***	0.186***	0.141*
	(1.214)	(1.940)	(2.668)	(2.602)	(1.952)
DE	0.117	0.172**	0.245***	0.217***	0.162**
	(1.615)	(2.399)	(3.476)	(3.053)	(2.252)
DK	0.182**	0.192***	0.244***	0.253***	0.215***
	(2.533)	(2.688)	(3.671)	(3.595)	(3.026)
EL	0.328***	0.317***	0.311***	0.309***	0.283***
	(4.753)	(4.589)	(4.504)	(4.461)	(4.041)
IT	0.462***	0.426***	0.454***	0.399***	0.357***
	(7.138)	(6.482)	(7.031)	(5.985)	(5.239)
IE	0.120*	0.109	0.131*	0.148**	0.143**
	(1.663)	(1.504)	(1.818)	(2.053)	(1.983)
NL	0.238***	0.234***	0.284***	0.260***	0.261***
	(3.363)	(3.312)	(4.079)	(3.704)	(3.711)
ES	0.263***	0.311***	0.397***	0.367***	0.317***
	(3.733)	(4.504)	(5.960)	(5.432)	(4.581)
SE	-0.255***	-0.216***	-0.170**	-0.169**	-0.168**
	(-3.621)	(-3.048)	(-2.374)	(-2.362)	(-2.331)
UK	0.040	0.039	0.029	-0.015	-0.041
	(0.543)	(0.536)	(0.397)	(-0.212)	(-0.569)

Note: The effective sample is: 2003:M01 – 2018:M12. The first rows display the lag/lead structure of the two time-series for which we compute the correlations, with T-1, T-2 and T+1, T+2 denoting 1 and 2 period lags, and leads respectively. Both EPU and CISS time series are in log terms. The t-statistics are provided in parentheses. The *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

Table A2: Cross-country contemporaneous correlations for EPU and CISS indexes

Country	BE	FR	DE	DK	EL	IT	IE	NL	ES	SE	PT
						CISS(T) x CISS(T)					
FR	0.75**										
DE	0.64**	0.73**									
DK	0.58**	0.69**	0.59**								
EL	0.55**	0.48**	0.42**	0.48**							
IT	0.66**	0.66**	0.51**	0.58**	0.77**						
IE	0.78**	0.72**	0.56**	0.67**	0.42**	0.60**					
NL	0.69**	0.73**	0.73**	0.62**	0.40**	0.49**	0.74**				
ES	0.77**	0.76**	0.58**	0.62**	0.70**	0.81**	0.70**	0.60**			
SE	0.65**	0.61**	0.67**	0.54**	0.25**	0.40**	0.69**	0.62**	0.50**		
PT	0.62**	0.67**	0.41**	0.63**	0.71**	0.85**	0.62**	0.47**	0.85**	0.33**	
UK	0.63**	0.58**	0.58**	0.72**	0.39**	0.52**	0.71**	0.58**	0.54**	0.68**	0.48**

Country	BE	FR	DE	DK	EL	IT	IE	NL	ES	SE
						EPU(T) x EPU(T)				
FR	0.41**									
DE	0.43**	0.78**								
DK	0.48**	0.68**	0.69**							
EL	0.23**	0.66**	0.61**	0.42**						
IT	0.50**	0.54**	0.48**	0.42**	0.45**					
IE	0.41**	0.57**	0.52**	0.49**	0.39**	0.40**				
NL	0.51**	0.25**	0.27**	0.17**	0.19**	0.48**	0.15*			
ES	0.34**	0.63**	0.67**	0.64**	0.64**	0.56**	0.48**	0.32**		
SE	0.39**	0.69**	0.68**	0.63**	0.56**	0.48**	0.46**	0.26**	0.58**	
UK	0.37**	0.83**	0.76**	0.64**	0.64**	0.44**	0.65**	0.16*	0.64**	0.69**

Note: The effective sample is: 2003:M01 – 2018:M12. Both EPU and CISS time series are in log terms. The * and ** denote statistical significance at 5% and 1% respectively. The T in parentheses denotes that we are taking contemporaneous correlations.

Figure A1 below displays the GVAR weighting matrix, W, computed based on IMF CPIS data for the 2000-2015 period; some countries like the Baltics have much shorter samples. Weights reflect portfolio allocations from countries mentioned on rows towards countries mentioned on columns (country labels are according to Table 1 in the main text). The colour of each cell indicates the share of country's portfolio allocation towards other countries, based on the scale displayed on the right of the figure. Each row sums to 1, as countries on the column represent the entire investable universe for the country specified at the start of each row.

Figure A1: IMF CPIS weights

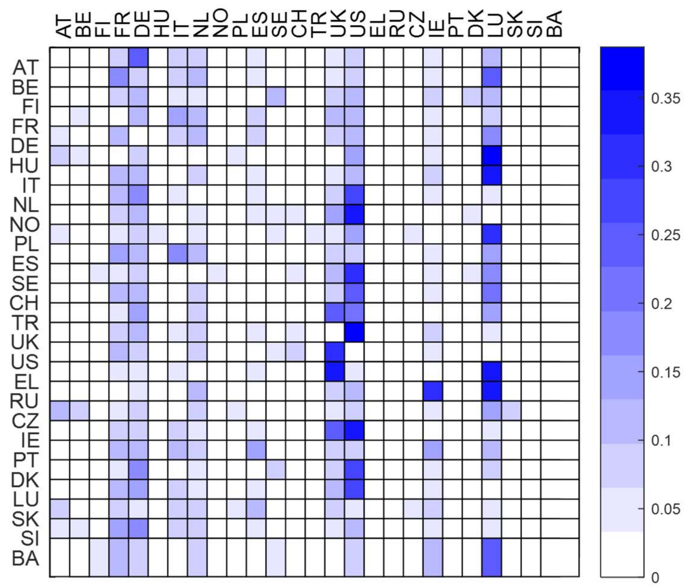
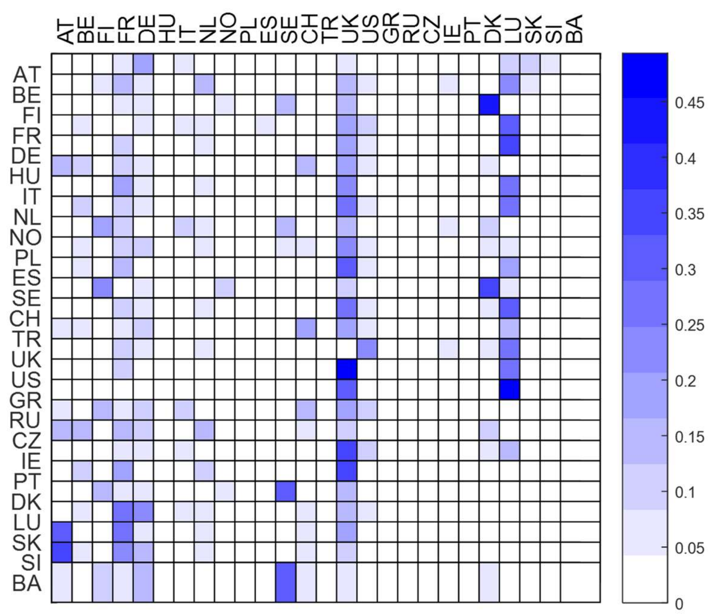


Figure A2 below displays the weighting matrix used as a robustness check in section 4.5, based on data from BIS Locational Banking Statistics, tables A6.2.[31] These tables contain data on cross-border positions in mil. USD, by counterparty's country of residency, and by location of the reporting bank. Since not all 28 countries (i.e. 25 individual countries and the 3 Baltics) are reporting to BIS, cross-border positions for banks located in other countries are only indirectly available as the reverse balance sheet positions of banks located in BIS reporting countries; for example, outward claims of banks located in Poland can be inferred as inward liabilities of banks located in BIS reporting countries with Polish resident banks as their counterparties. Moreover, for banks located in BIS reporting countries, there might be some differences between what banks from country X reports as outward claims in country Y, and what banks from country Y reports as inward liabilities from country X. To mitigate the

[31] See https://stats.bis.org/statx/toc/LBS.html.

impact of such inconsistencies, we average between (outward) claims and (inward) liabilities for all country pairs and use bank-to-all sectors rather than just bank-to-bank positions. Further to reduce the impact of time-variation, we average the end of year (4th quarter) exposures over a 7-year period from 2010 to 2016. The colour of each cell indicates the share of country's outward exposures (i.e. claims) towards other countries, based on the scale displayed on the right of the figure. Each row sums to 1, as countries on the column represent the entire investable universe for the country specified at the start of each row.

Figure A2: BIS LBS weights



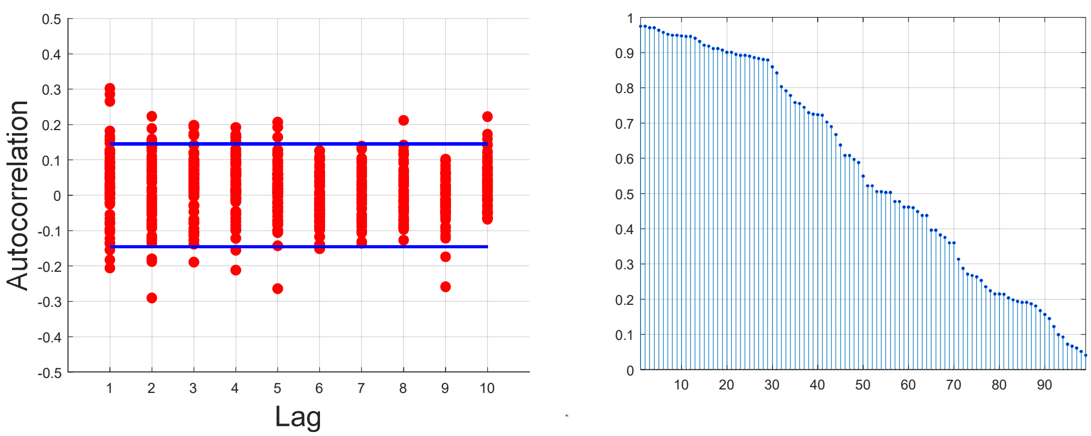
Appendix B: GVAR specification and identification checks

Figure B1 depicts the estimated residual autocorrelation and the eigenvalues of the estimated GVAR. Residual autocorrelations lie very close to, or within, the confidence bands set at ± 2 standard deviations; given the large number of variables and the inherent over-parameterization of the GVAR, a small number of larger autocorrelations are to be expected. Despite some inherent persistency, all model eigenvalues are strictly less than one, the maximum eigenvalue being 0.97.

Figure B1: GVAR specification checks

Panel (a): Residual autocorrelation

Panel (b): Eigenvalues of GVAR



Note: Panel (a) plots the residual autocorrelations for all GVAR variables and all country-specific models, as a function of the serial lag. Panel (b) plots the GVAR eigenvalues.

Appendix C: The algorithm used for structural identification

In the empirical analysis presented in the main text we have used the De Santis and Zimic's algorithm. The algorithm is implemented after the estimation of the reduced-form model given in equation (3). To facilitate notation, each country for which we perform the identification is ordered first (i.e. model solution matrixes are reshuffled accordingly). The algorithm consists in the following steps:

1. Bootstrap the reduced-form GVAR model given in equation (3) to obtain the variance-covariance matrix of reduced-form errors, $\Omega_u^{(b)}$, where the superscript (b) is the bootstrap index that runs from 1 to 500. The Choleski decomposition of $\Omega_u^{(b)}$ is denoted as $\Omega_{tr}^{(b)} = chol(\ \Omega_u^{(b)})$.

2. Aim at obtaining a candidate matrix $S^{(b,i)}$ whose first 2 columns satisfy the magnitude restrictions. The superscript (i) would index the draw that runs from 1 to 100.

   (2a) Draw a 2x2 matrix from a standard normal distribution and obtain its QR decomposition, where the orthogonal matrix in the decomposition is denoted as $\mathrm{Q}^{(b,i)}$, i.e. $\mathrm{Q}^{(b,i)}\mathrm{Q}^{(b,i)'} = \mathrm{I}$.

   (2b) Construct the block diagonal matrix $Q_{diag}^{(b,i)} = diag(\mathrm{Q}^{(b,i)}, I)$, with a size that corresponds to the size of $\Omega_u^{(b)}$.

   (2c) Check whether the matrix $S^{(b,i)} = \Omega_{tr}{}^{(b)} Q_{diag}^{(b,i)}$ satisfies the magnitude restrictions (see section 3.3. for the exact definition of these restrictions). If it does, we keep this (i) draw for $S^{(b,i)}$. If not, we go back to step (2a). We repeat this process for 100 times to obtain a sufficient number of successful draws.

4. Repeat step 1 and 2 for 500 times; compute the 68% confidence bands of the IFRs after considering all successful candidate matrices $S^{(b,i)}$ from step 2c).

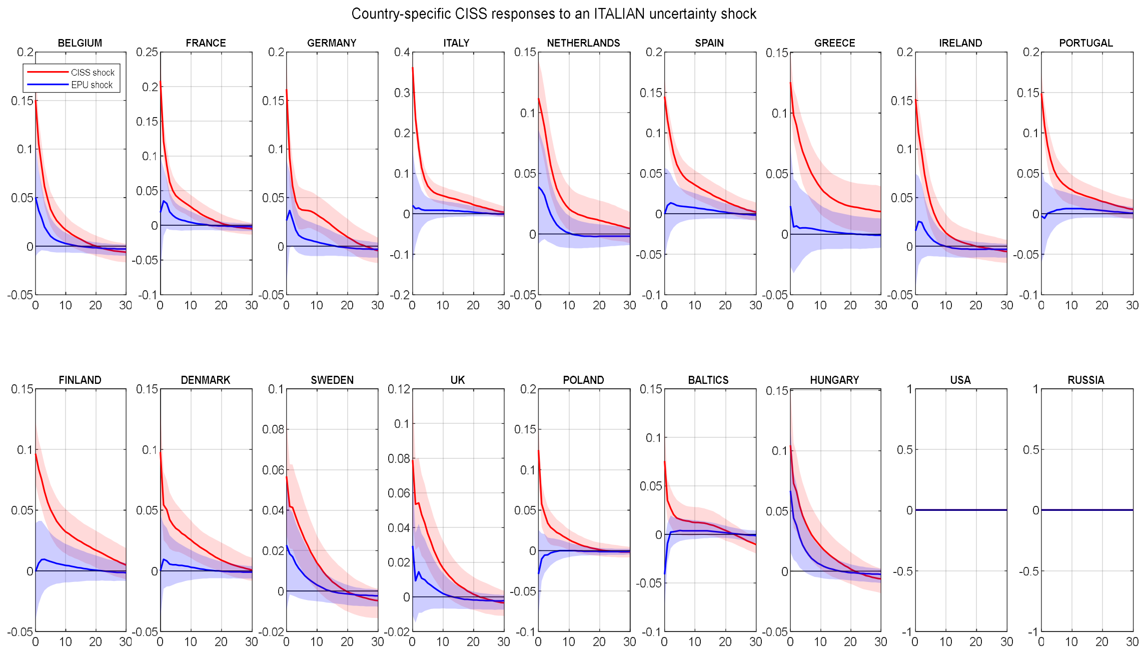
Given the reduced number of variables in each single VARX, De Santis and Zimic's algorithm works well for the results that we discussed in this paper. However, we have cross-checked these results using an extension of their algorithm, as we are proposing here, an extension that works well even for larger systems. The challenging point, in fact, is that the whole set of imposed magnitude restrictions enormously reduces the number of admissible Q matrices among those randomly generated in standard algorithms used in the literature. Our proposal here is based on block-diagonal Q matrices with perturbations. We solve the identification issue within each country by generating N admissible orthogonal matrixes $Q_1, \dots, Q_N$, one for each of the N countries, and form the admissible block-diagonal orthogonal matrix $Q = diag(Q_1, \dots, Q_N)$. We rotate Q by a *small rotation* matrix $(I - H)(I + H)^{-1}$, with H hemisymmetric, i.e. $\tilde{Q} = Q(I - H)(I + H)^{-1}$, and then check for the magnitude restrictions on the columns of interest of the obtained matrix $S = \Omega_{tr}\tilde{Q}$. This strategy allows to increase the success rate in large systems. In practical terms, for our case it implies adding a new step into the original algorithm above, between steps (2b) and (2c), denoted by say (2b$'$), a step that reads as follows:

> (2b$'$) After having obtained the orthogonal matrix $Q_{diag}^{(b,i)}$ in step (2b), rotate this by a small rotation matrix constructed as $(I - H^{(b,i)})(I + H^{(b,i)})^{-1}$, where $H^{(b,i)}$ is hemisymmetric, i.e. $H^{(b,i)} = -H^{(b,i)\prime}$, and its elements are drawn from a random normal distribution. The new matrix $Q_{diag}^{(b,i)}(I - H^{(b,i)})(I + H^{(b,i)})^{-1}$ will be orthogonal as well and can be used to construct $S^{(b,i)}$ in the next step (2c).

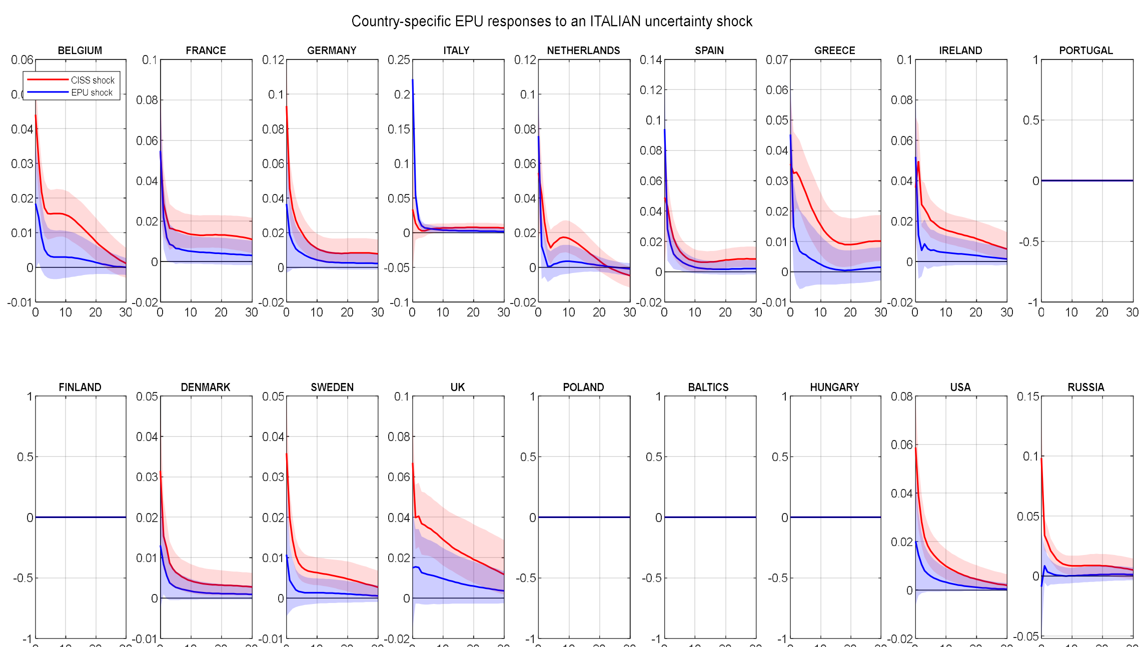
Appendix D: IRFs to uncertainty shocks identified through magnitude restrictions

Figure D1: IRFs to Italian uncertainty shocks

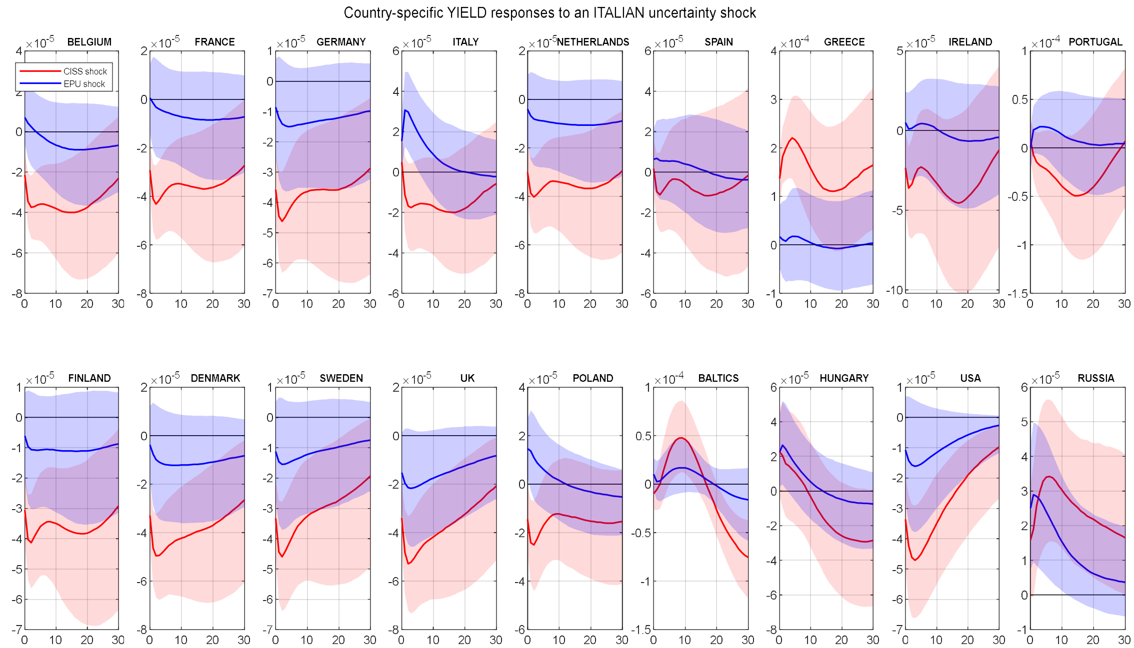
Panel (a)



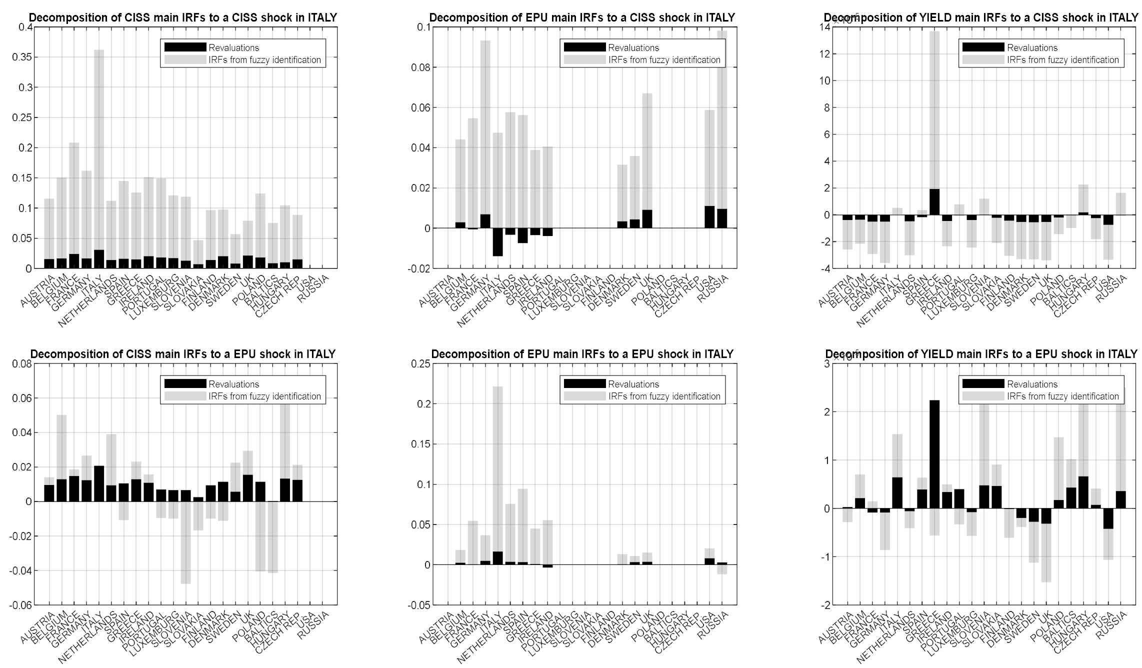
Panel (b)



Panel (c)



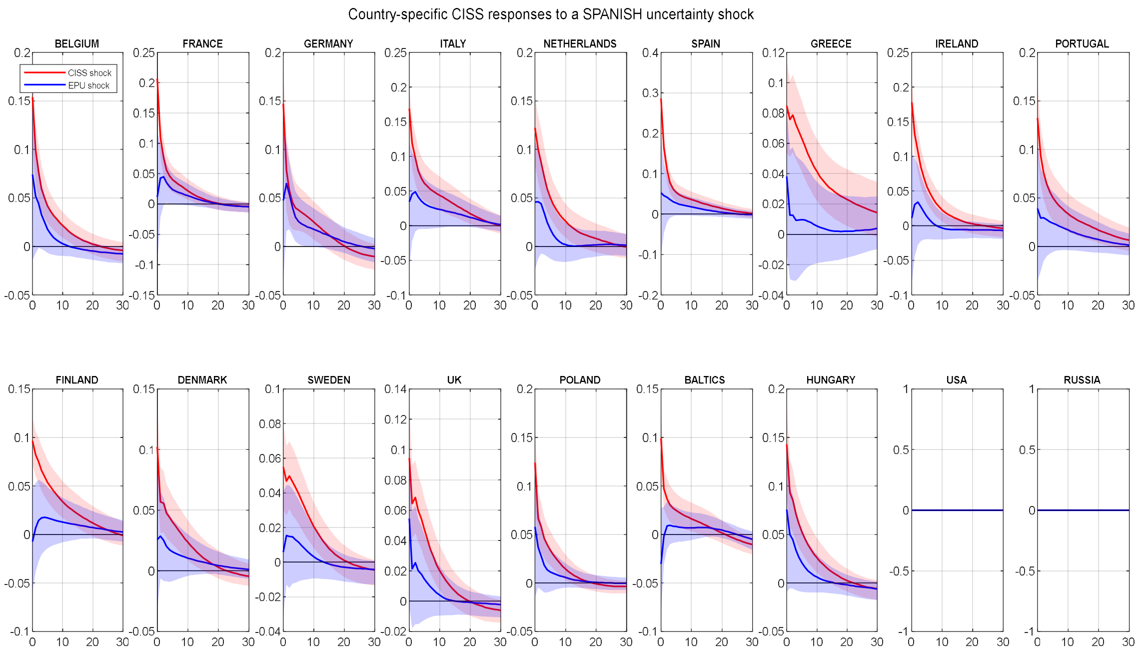
Panel (d)



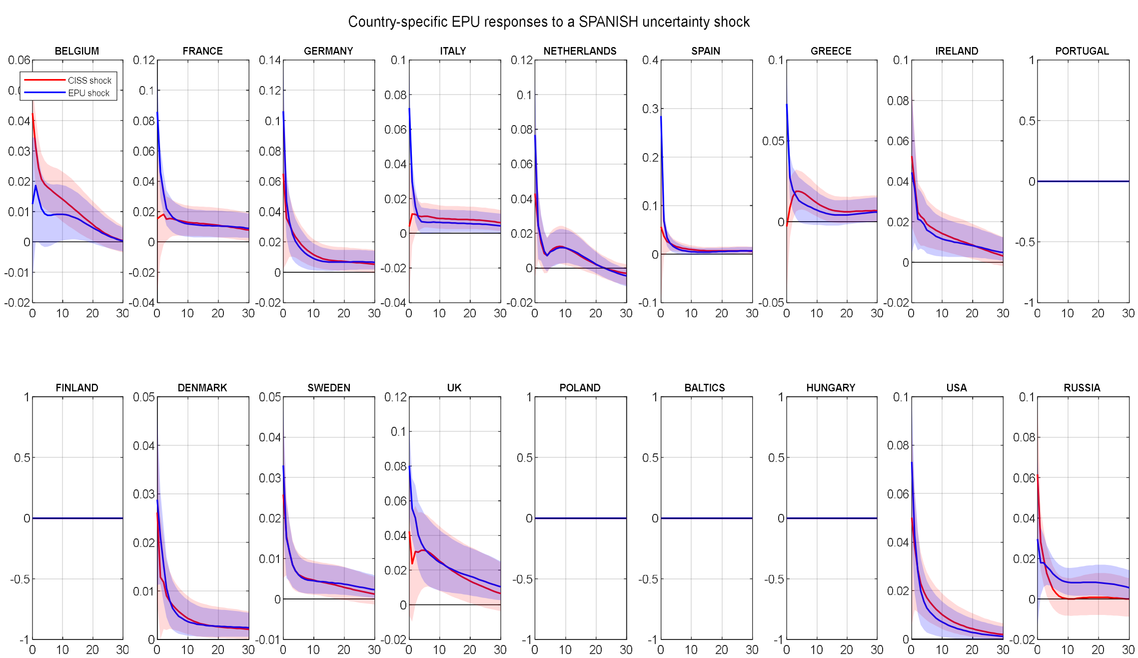
Note: Panels (a), (b) and (c) plot the IRFs to both EPU and CISS positive uncertainty shocks (of 1 standard deviation). The median and the 68% confidence bands are constructed from 500 bootstrapped replications of the GVAR, each with 100 maximum draws for the orthogonal matrix. Panel (d) displays the contribution from initial responses and revaluations evaluated at impact. Revaluations are calculated as the difference between the IRFS of the fuzzy and straight identifications.

Figure D2: IRFs to Spanish uncertainty shocks

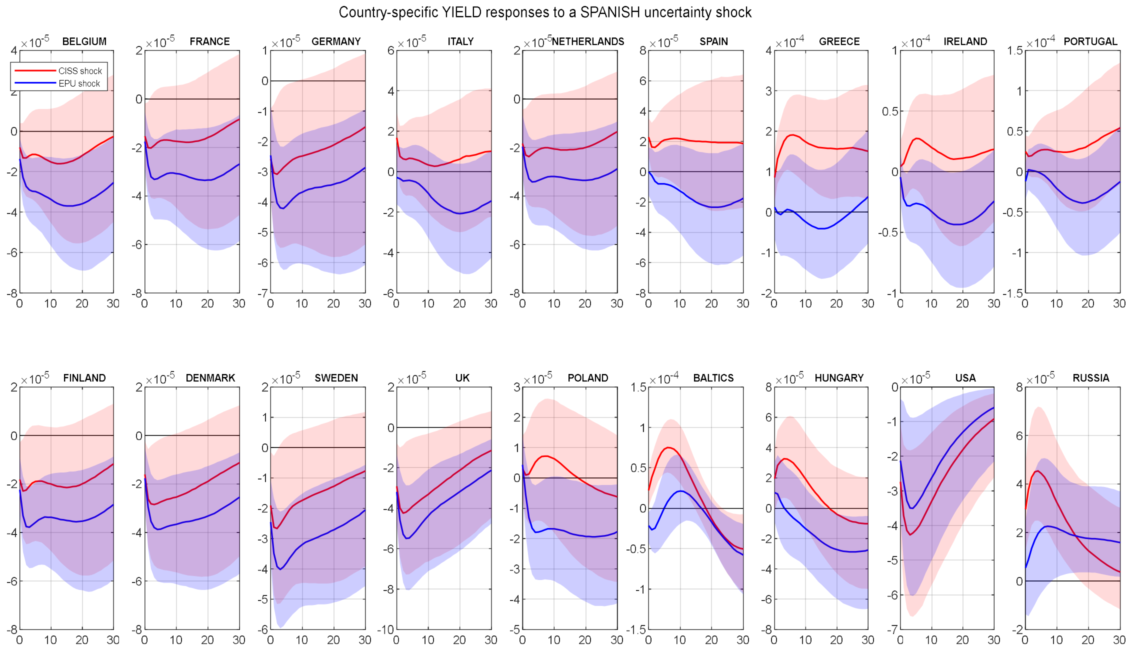
Panel (a)



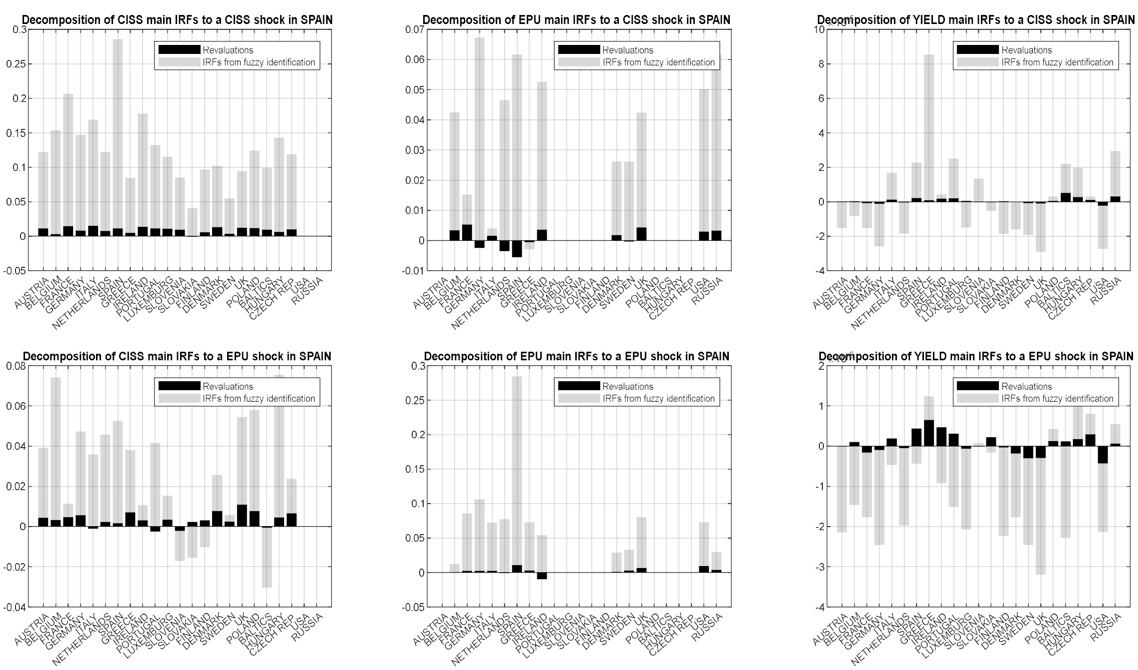
Panel (b)



Panel (c)



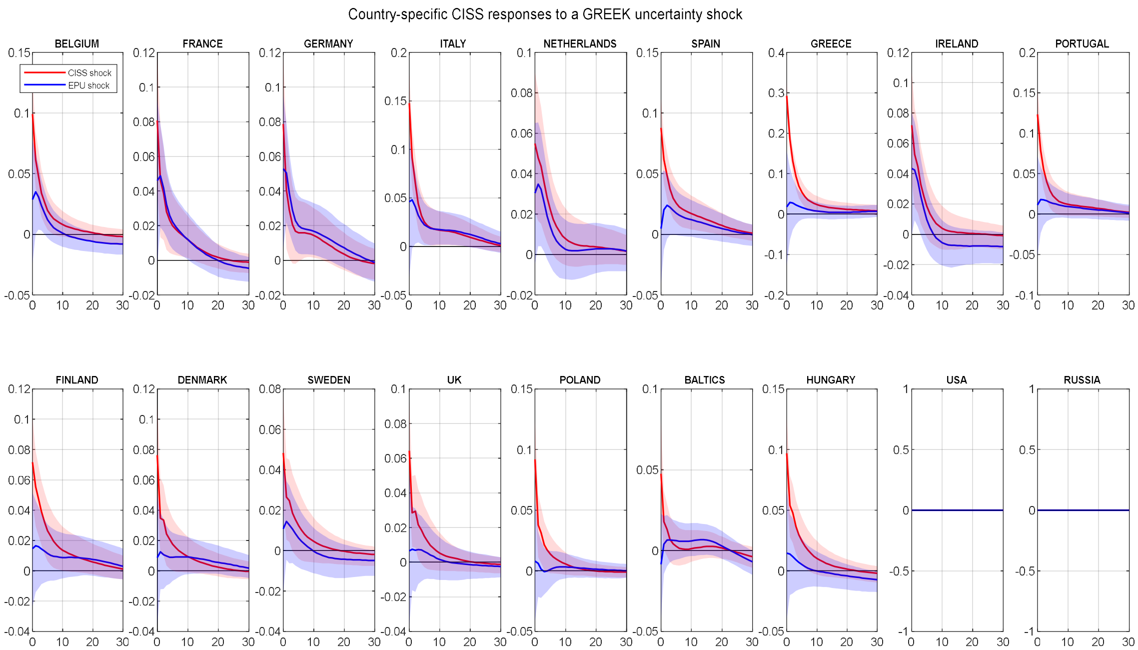
Panel (d)



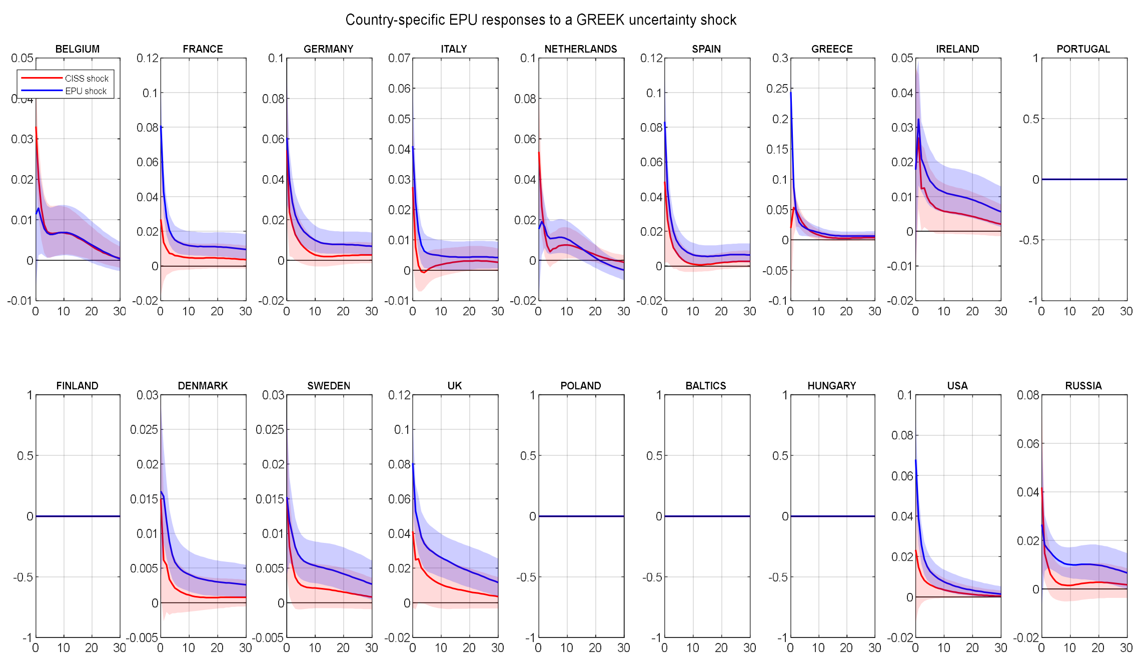
Note: Panels (a), (b) and (c) plot the IRFs to both EPU and CISS positive uncertainty shocks (of 1 standard deviation). The median and the 68% confidence bands are constructed from 500 bootstrapped replications of the GVAR, each with 100 maximum draws for the orthogonal matrix. Panel (d) displays the contribution from initial responses and revaluations evaluated at impact. Revaluations are calculated as the difference between the IRFS of the fuzzy and straight identifications.

Figure D.3: IRFs to Greek uncertainty shocks

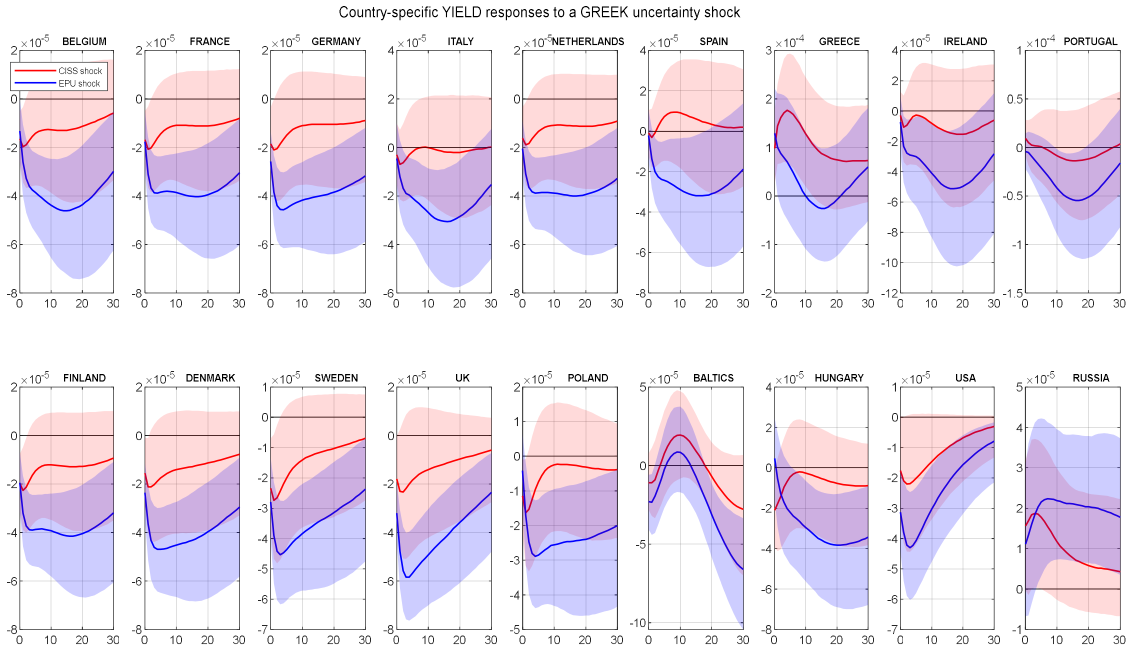
Panel (a)



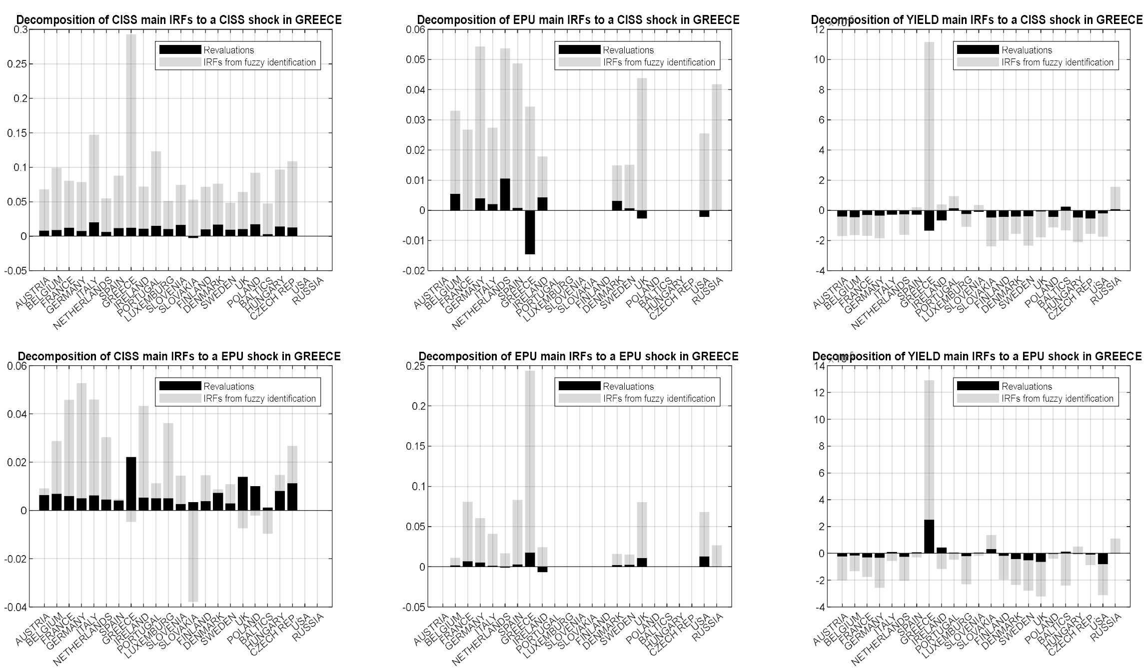
Panel (b)



Panel (c)



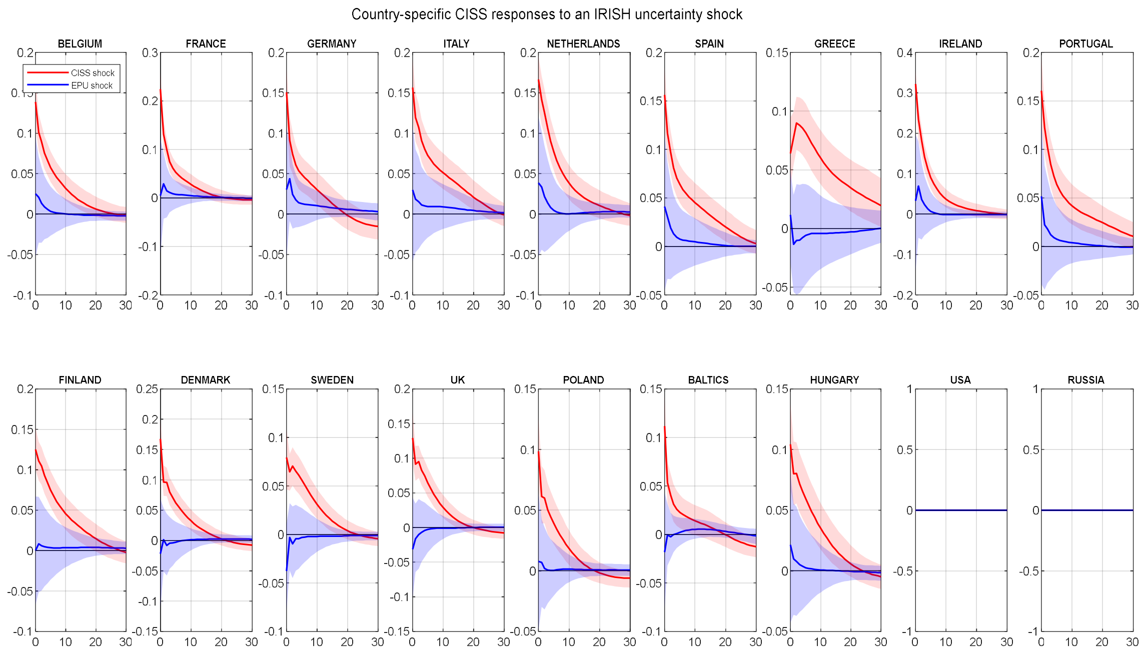
Panel (d)



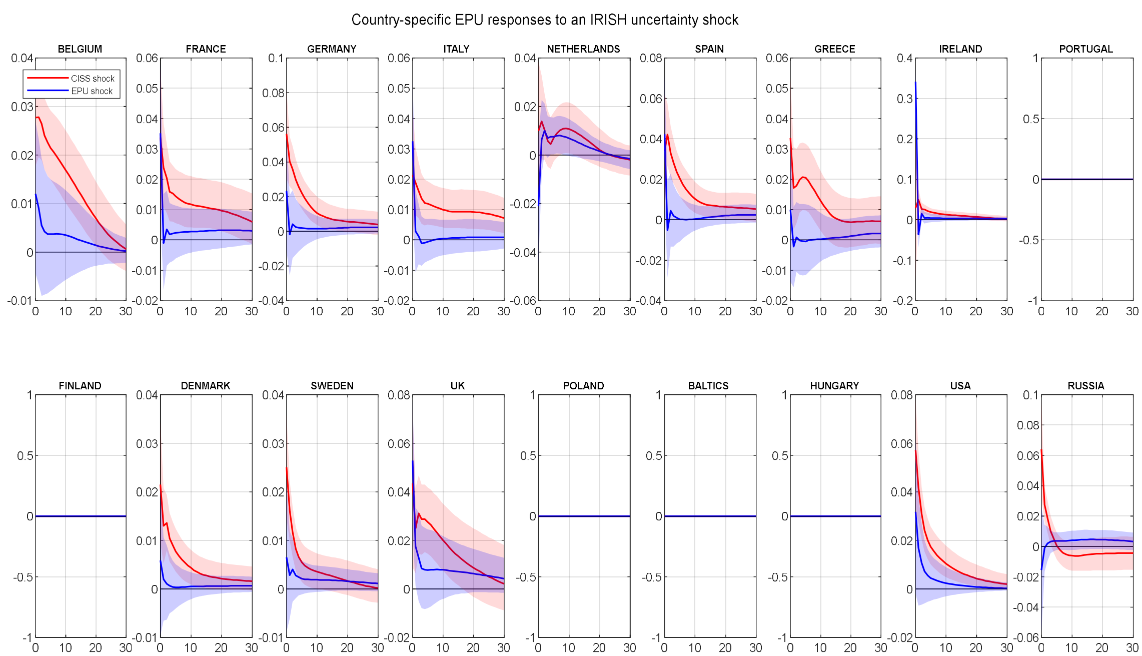
Note: Panels (a), (b) and (c) plot the IRFs to both EPU and CISS positive uncertainty shocks (of 1 standard deviation). The median and the 68% confidence bands are constructed from 500 bootstrapped replications of the GVAR, each with 100 maximum draws for the orthogonal matrix. Panel (d) displays the contribution from initial responses and revaluations evaluated at impact. Revaluations are calculated as the difference between the IRFS of the fuzzy and straight identifications.

Figure D.4: IRFs to Irish uncertainty shocks

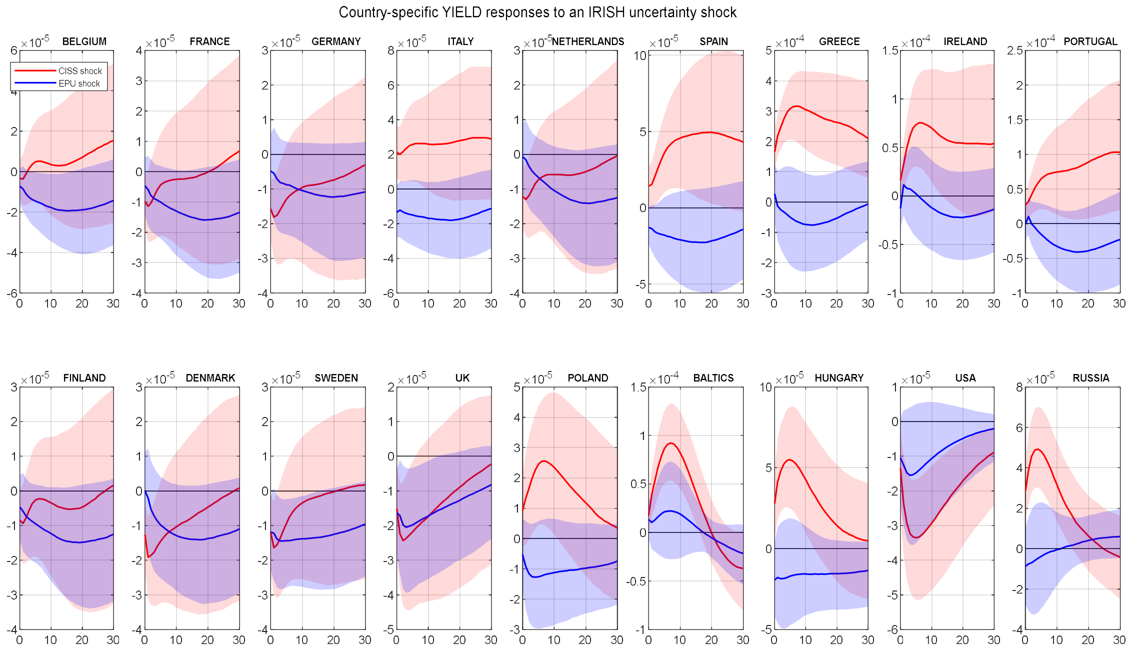
Panel (a)



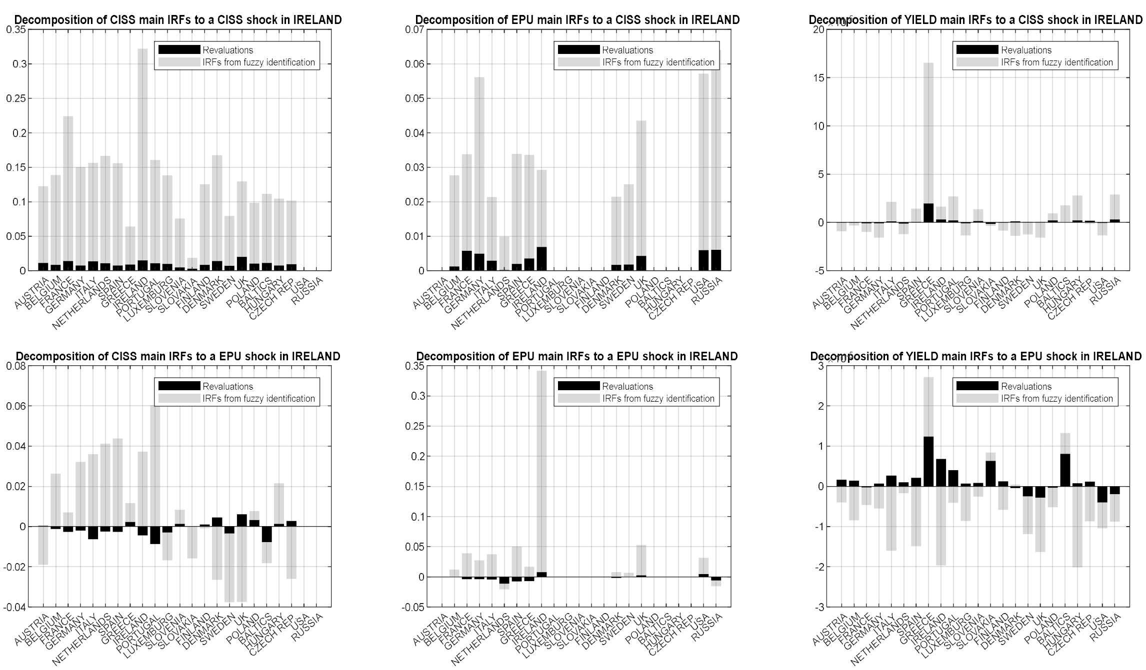
Panel (b)



Panel (c)



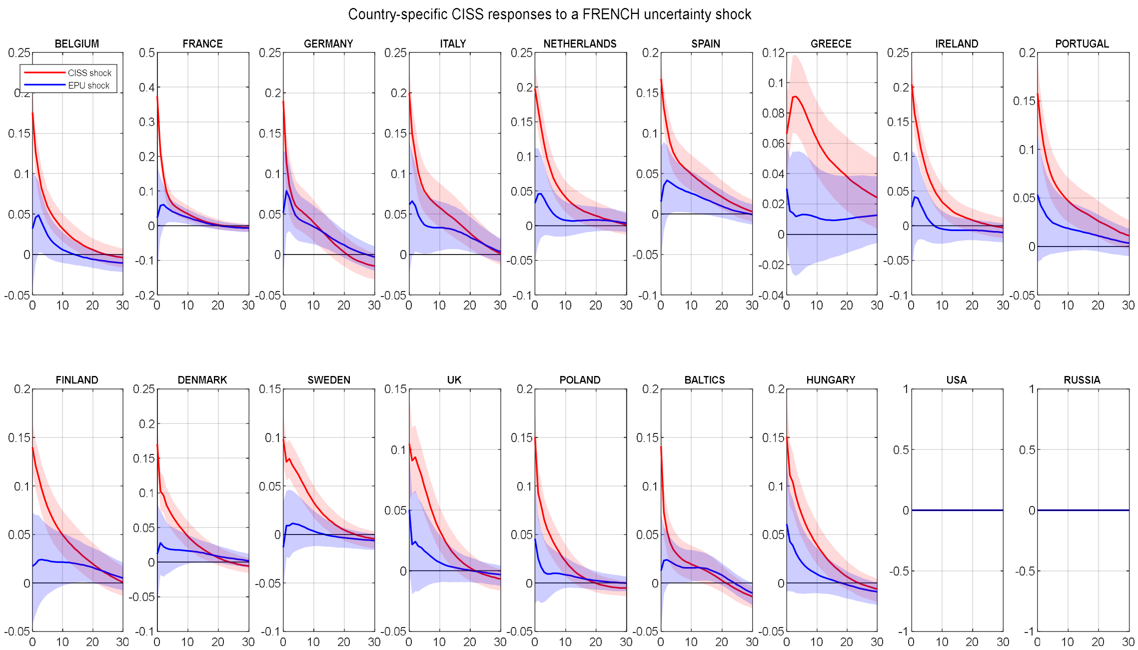
Panel (d)



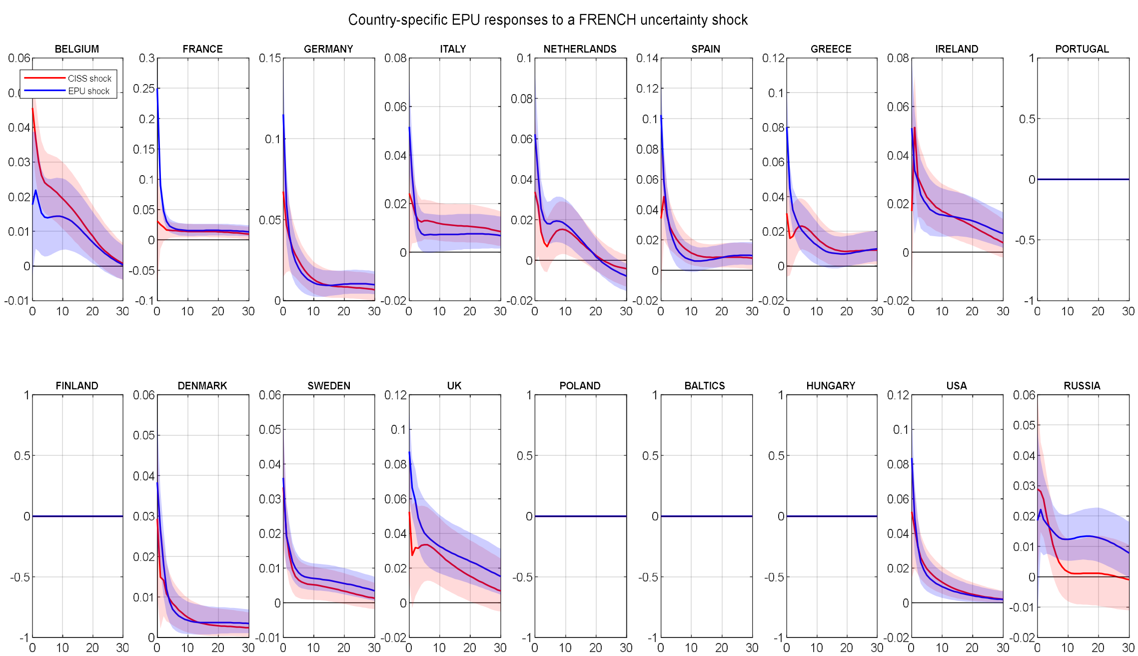
Note: Panels (a), (b) and (c) plot the IRFs to both EPU and CISS positive uncertainty shocks (of 1 standard deviation). The median and the 68% confidence bands are constructed from 500 bootstrapped replications of the GVAR, each with 100 maximum draws for the orthogonal matrix. Panel (d) displays the contribution from initial responses and revaluations evaluated at impact. Revaluations are calculated as the difference between the IRFS of the fuzzy and straight identifications.

Figure D.5: IRFs to French uncertainty shocks

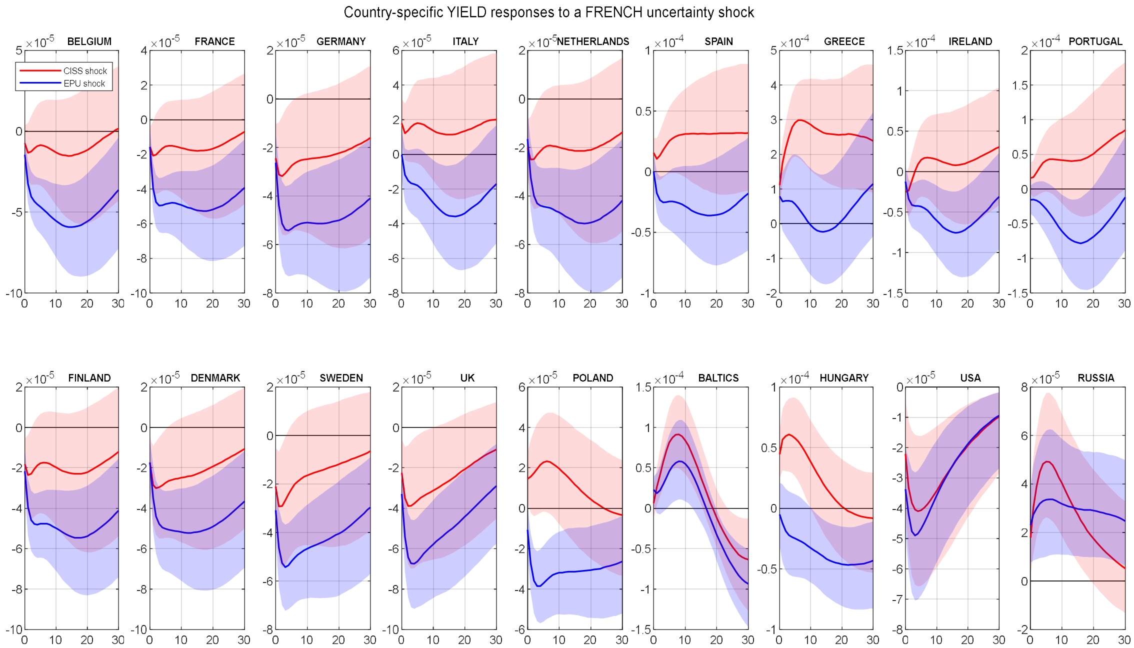
Panel (a)



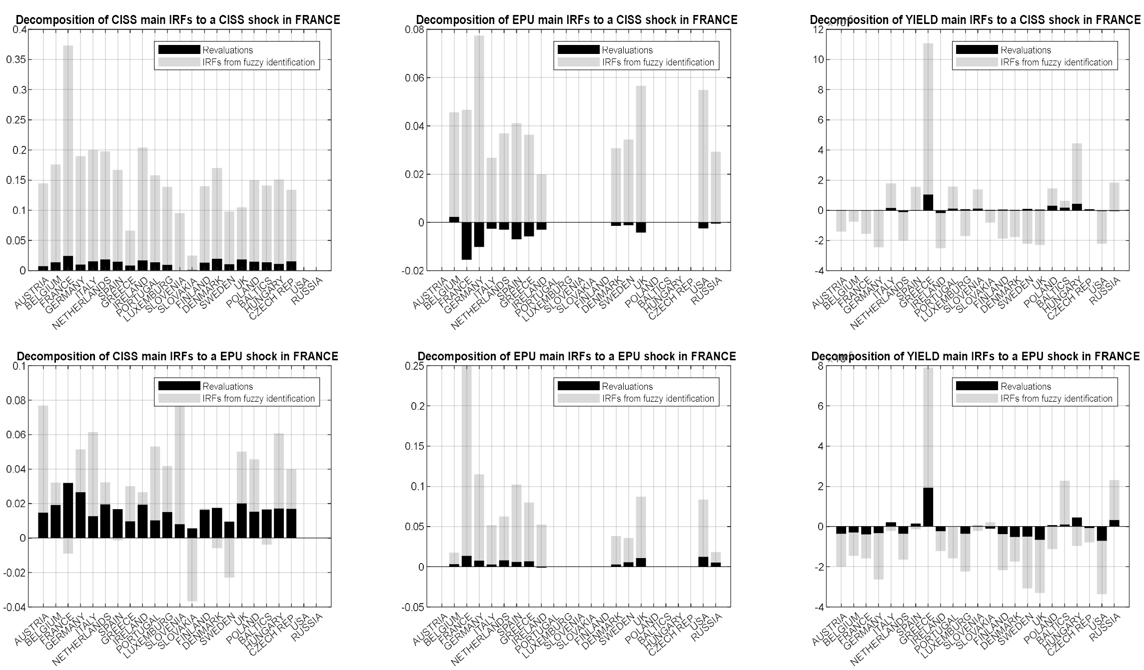
Panel (b)



Panel (c)



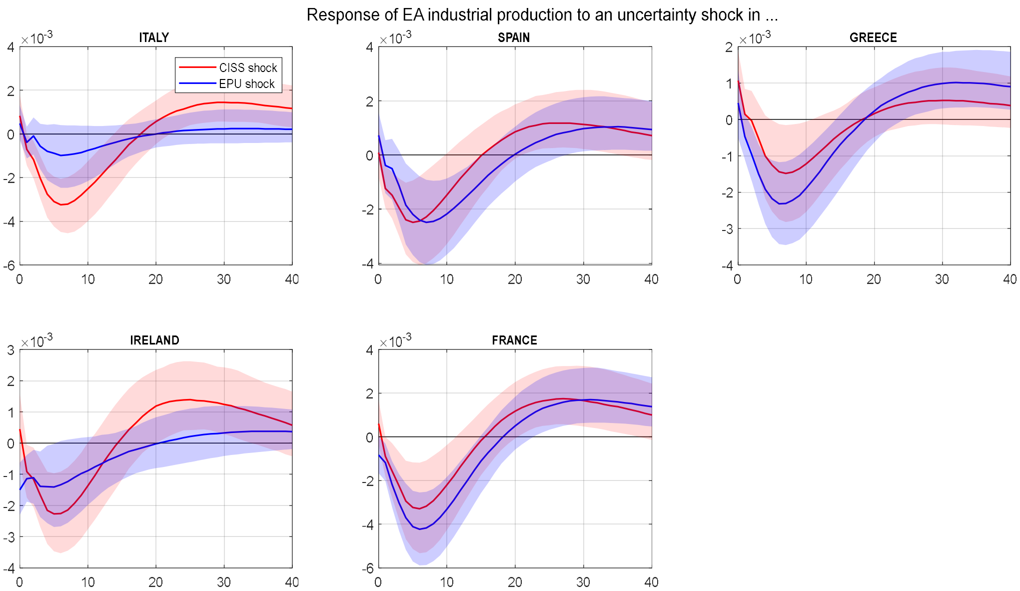
Panel (d)



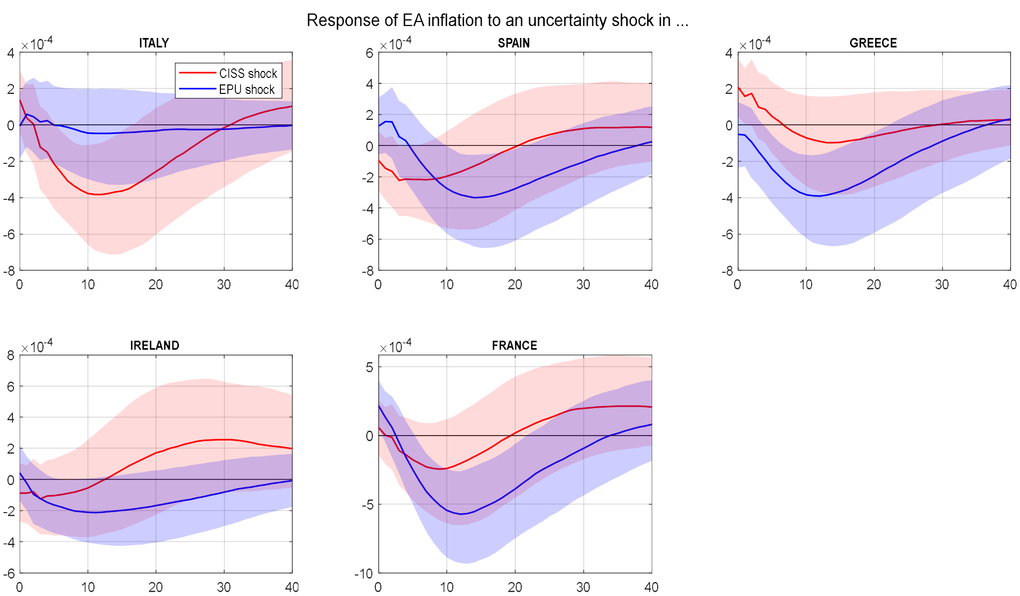
Note: Panels (a), (b) and (c) plot the IRFs to both EPU and CISS positive uncertainty shocks (of 1 standard deviation). The median and the 68% confidence bands are constructed from 500 bootstrapped replications of the GVAR, each with 100 maximum draws for the orthogonal matrix. Panel (d) displays the contribution from initial responses and revaluations evaluated at impact. Revaluations are calculated as the difference between the IRFS of the fuzzy and straight identifications.

Figure D.6: IRFs for EA industrial production and inflation

Panel (a)



Panel (b)



Note: The title of the plots in each panel displays the origin country of the uncertainty shock. The legend displays the corresponding uncertainty shock that is being simulated. The 68% confidence bands are constructed from 500 bootstrapped replications of the GVAR, each with 100 maximum draws for the orthogonal matrix (see algorithm in Appendix C).

Appendix E. ECB influence and policy reactions

Table E1 below presents, by country i and by equation (or variable), the F-statistics of the null hypothesis that in equation (4) we have $D_{i,j} = 0$, jointly for all $j = [0,1]$ in country i.

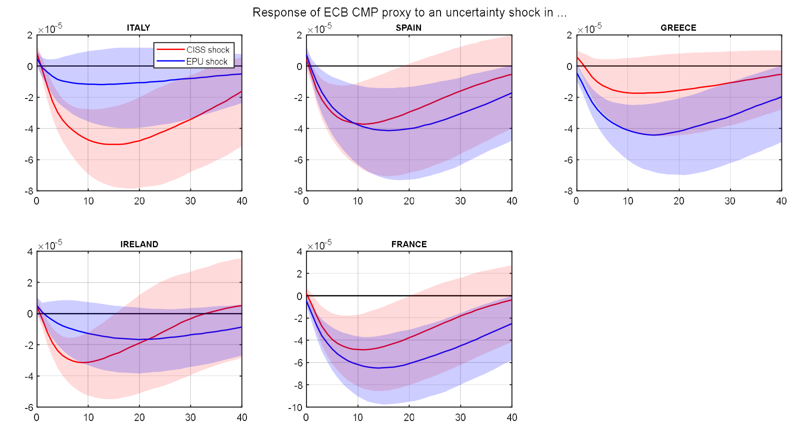
Table E1: F-tests of the joint null that ECB policies had no influence on each EA country/equation

Country:	Equation: Yields	Equation: CISS	Equation: EPU
Austria	3.16*	1.25	
Belgium	0.91	1.05	3.32*
Finland	2.29*	0.37	
France	1.89	1.01	1.20
Germany	0.56	1.91	0.73
Italy	0.93	1.54	2.30*
Netherlands	3.40*	0.41	1.29
Spain	2.32*	1.01	2.76*
Greece	1.22	0.81	3.31*
Ireland	1.02	0.66	0.96
Portugal	1.69	1.57	
Luxemburg	1.48	0.54	
Slovakia	1.41	1.63	
Slovenia	1.21	2.07	
Baltics	3.47*	1.05	

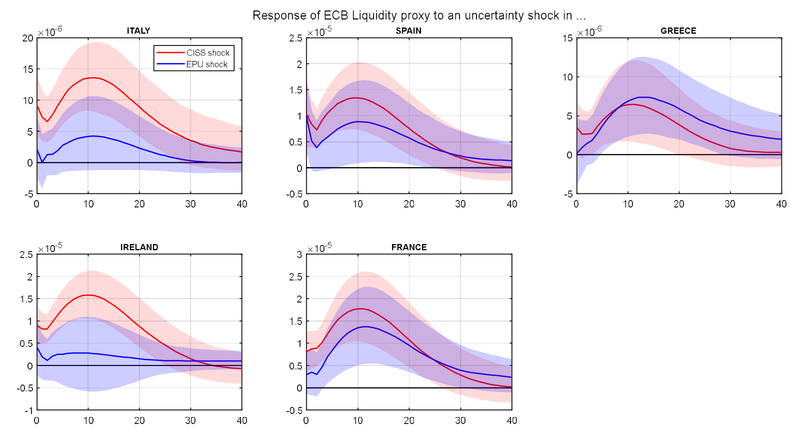
Note: The table displays the F-statistics computed by restricting the coefficients of the three ECB policy proxies to be exactly zero in the country/equation indicated on the first column/row of the table. The * denotes cases where the F-statistics is higher than the critical value of 2.15, and therefore the null can be rejected at a 5% significance level.

Figure E1: IFRs for ECB monetary policy proxies to uncertainty shocks

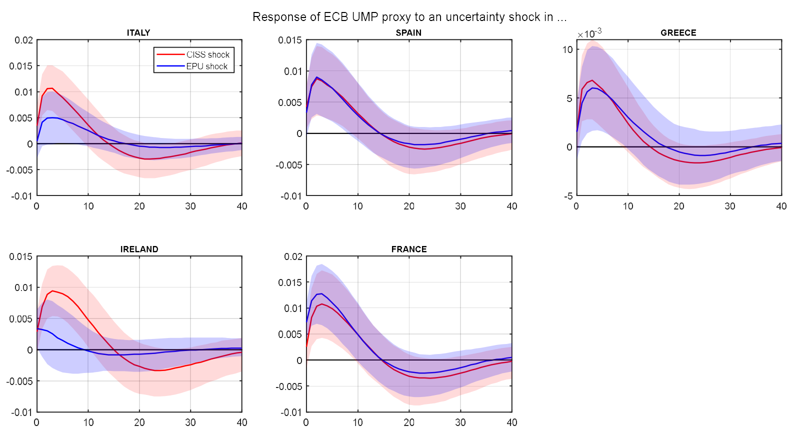
Panel (a)



Panel (b)



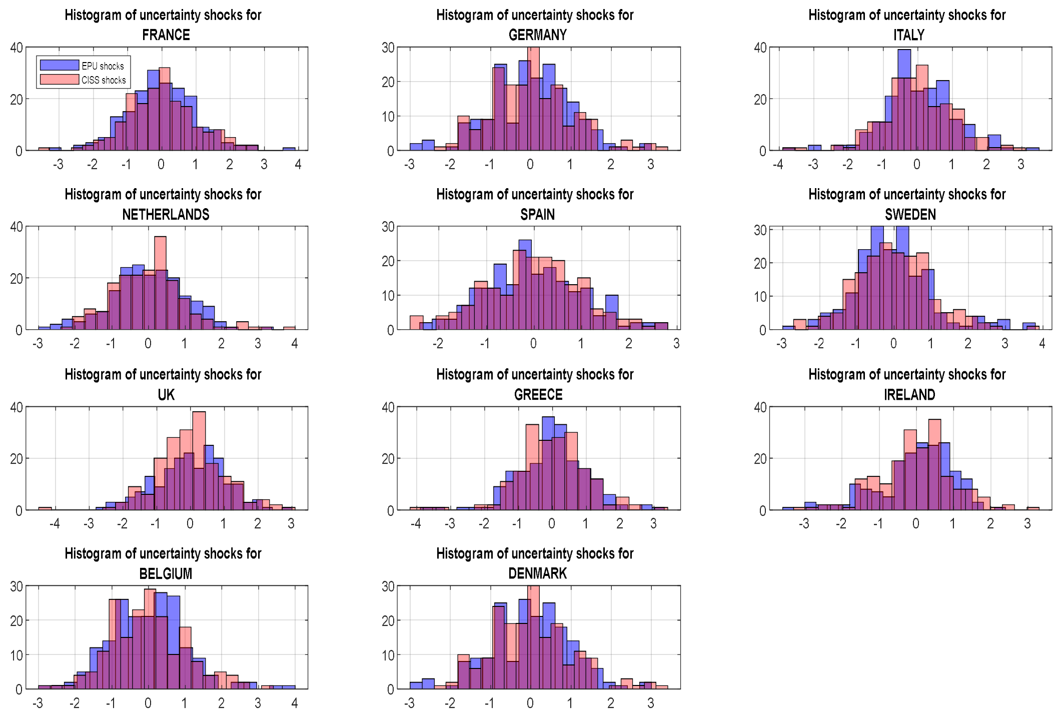
Panel (c)



Note: The title of the plots in each panel displays the origin country of the uncertainty shock. The legend displays the corresponding uncertainty shock that is being simulated. The 68% confidence bands are constructed from 500 bootstrapped replications of the GVAR, each with 100 maximum draws for the orthogonal matrix (see algorithm in Appendix C).

Appendix F

Figure F1: Histograms of the uncertainty shocks in countries where identification is performed

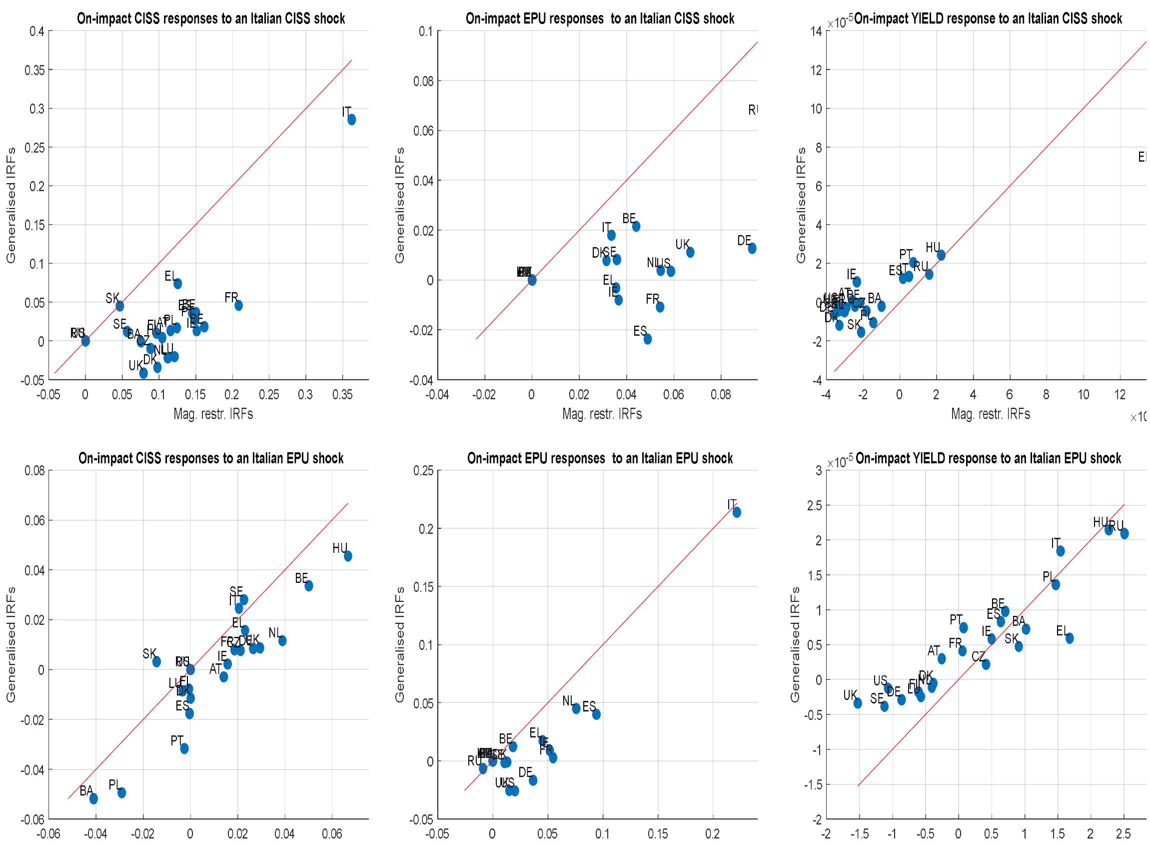


Note: Median values (for each time period) of the identified shocks are used to generate the histograms above.

Appendix G. Generalised Impulse Responses (GIRFs)

Figure G1 below compares on-impact GIRFs with on-impact IRFs derived from our magnitude restrictions, for the case of Italy. As revealed in the first row of the figure below, there is a substantial underestimation in the case of GIRFs for the impact of Italian CISS shocks, which are exactly those with the highest potential to spill over abroad according to our discussion in the main text. For Italian EPU shocks, whose responses are displayed on the second row of the figure G1, the differences are smaller. Moreover, according to these GIRFs' confidence bands, there are fewer and much shorter (2 months on average) statistically significant foreign responses to Italian CISS shocks, compared to those derived from magnitude restrictions (see Appendix D). These results are in opposition with the ones we uncover from our magnitude restrictions.

Figure G1. Comparison between magnitude restrictions IRFs and GIRFs



Note: On-impact responses for GIRFs are computed based on 5000 bootstraps, while for magnitude restrictions, on-impact responses are computed based on 500 bootstraps replications of the GVAR, each replication with 100 maximum draws for the orthogonal matrix; success rate are around 40%.

Alma Mater Studiorum - Università di Bologna
DEPARTMENT OF ECONOMICS

Strada Maggiore 45
40125 Bologna - Italy
Tel. +39 051 2092604
Fax +39 051 2092664
http://www.dse.unibo.it