Heterogeneity and cross-country spillovers in macroeconomic-financial linkages

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Abstract

We investigate heterogeneity and spillovers in euro area macro-financial linkages, with a particular emphasis in the most recent recession. A panel Bayesian VAR model including aggregate real and financial variables for most of the euro area economies as well as other relevant European and world economies identifies a statistically significant common component in the recent recession. Country-specific factors are also found to be very important, which explains the heterogeneous behaviour observed at times. Spillovers are found to matter: A negative shock to a financial variable in a given country affects all other euro area countries, more so if the shock originates in Germany or the US.

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1 Introduction

The recent crisis has been a worldwide phenomenon in which shocks to one area of the financial system of one country or group of countries have spread rapidly to the real economy not only in the originating country or group of countries, but also to other economic areas. Thus, this recent crisis has shown once again how deeply intertwined financial and real developments are, not only within a country but also across countries. In this paper, we explore whether the interaction between financial and real variables is different across countries or whether they follow a common pattern. In particular, we are interested in whether there is a common or rather a heterogenous pattern of macroeconomic-financial linkages and whether this pattern has changed over time.

Furthermore, we want to investigate the cross-country transmission of shocks in the following dimensions: How important are spillovers across countries? What causes larger spillovers: real or financial shocks? Have spillovers changed during the recent crisis? We investigate these issues for a wide set of countries but take a particular emphasis in the euro area and in Europe in general. Although tight institutional and economic interdependencies may have made euro area countries more alike, the recent recession has shown that together with some common behaviour there may still be a substantial degree of heterogeneity in the macroeoconomic-financial linkages across countries within the euro area and within the european union, and that those linkages may have changed over time.

To address these issues, we build an empirical model where real and financial variables are jointly modelled for several countries. A time-varying Panel BVAR (of the type developed in Canova and Ciccarelli, 2009, and Canova, Ciccarelli and Ortega, 2007) is used to study simultaneously interdependence and time variation across a panel of time series and countries. The aim is to measure whether there are common patterns in the interactions between financial and real variables over the last three decades (and the recent crisis in particular), considering the euro area economies and also other EU and non-EU economies. Moreover, those possible commonalities can be analyzed jointly for all variables and countries, or alternatively by variable-type (e.g. real variables versus financial variables) or by country groupings (e.g. euro area versus others).

With such an econometric tool we can explore further issues like (i) what is the role of country-specific vs. common factors, (ii) does the lead-lag relationship between financial and real variables found in previous studies hold once international spillovers are taken into account, (iii) how much does the transmission of shocks across countries matter, and (iv) did commonalities prevail more in the recent crisis than in previous ones? To our knowledge, this is the first attempt in the literature to address the issues of heterogeneity and spillovers simultaneously in such a rich methodological environment.

The evidence found confirms the need to allow for cross-country and cross-variable interdependence when studying real-financial linkages. An empirical model including real and financial variables for most of the euro area economies, as well as other relevant European and world economies, identifies a statistically significant common component in the recent recession. However, country-specific factors remain very important, which explains the presence of a heterogeneous pattern. Finally, we find evidence of significant spillovers: a negative shock to a financial variable in a given country also affects all other euro area countries, especially if this shock originates in Germany or the US.

The fact that heterogeneity across countries matters, despite the common evolution of the business cycles around the world regularly found in the data, is consistent with the recent literature on international business cycle which recognizes the importance of both group-specific and global factors in driving world cyclical fluctuations. This phenomenon seems to be a robust feature of the data, i.e. it is not limited to countries in any particular geographic region and is not a mechanical effect of crisis episodes (Kose et al. 2008).

Moreover, financial shocks matter explaining real developments and, perhaps more importantly, they spill over in a heterogeneous way across countries. This is consistent with evidence from more standard VAR studies (Guarda and Jenfils, 2011). However, by jointly estimating a system including many countries we may find stronger linkages than those in country-by-country VAR analyses, given amplification through interdependence.

The analysis has important implications for theoretical models of the international business cycles. The results suggest that data is more consistent with models which provide a prominent international dimension, with countries endogenously reacting to impulses occurring abroad.

The facts illustrated in this paper also have important implications from a policy perspective. First, despite important heterogeneity, countries share common financial shocks, suggesting that international financial markets are important to understand co-movements in economic activity. Therefore, policymakers should monitor foreign financial developments. Second, since national policy affects the national component more than the common component, policies designed to counteract world conditions may be ineffective. Third, time variations suggest important asymmetries in the shape and the dynamics of international cycles, so linear models may miss policy-relevant features of the data.

The paper is structured as follows: section 2 describes the model; section 3 illustrates the data; section 4 highlights the main findings regarding commonalities vs. heterogeneity in macroeconomic-financial linkages; section 5 discusses the cross-country transmission of shocks; section 6 summarizes the results and concludes.

2 The empirical model

We use the panel VAR model developed by Canova and Ciccarelli (2009) and Canova et al. (2007). The model has the form:

$$y_{it} = D_{it}(L)Y_{t-1} + F_{it}(L)W_{it} + e_{it} \tag{1}$$

where $i = 1, ..., N$ indicates countries, $t = 1, ..., T$ time, and L is the lag operator; y_{it} is a $G \times 1$ vector of variables for each i and $Y_t = (y'_{1t}, y'_{2t}, \ldots y'_{Nt})'$; $D_{it,j}$ are $G \times NG$ matrices for each lag $j = 1, \ldots, p$, W_{it} is a $M \times 1$ vector of exogenous variables, $F_{it,j}$ are $G \times M$ matrices each lag $j = 1, \ldots, q$; e_{it} is a $G \times 1$ vector of random disturbances.

This model (1) displays three important features which makes it ideal for our study. First, the coefficients of the specification are allowed to vary over time. Without this feature, it would be difficult to study the evolution of cyclical fluctuations and one may attribute smooth changes in business cycle characteristics to once-and-for-all breaks which would be hard to justify given the historical experience. Second, the dynamic relationships are allowed to be country specific. Without such a feature, heterogeneity biases may be present, and economic conclusions could be easily distorted. Third, whenever the $NG \times NG$ matrix $D_t(L) = [D_{1t}(L), \ldots, D_{Nt}(L)]'$, is not block diagonal for some L, cross-unit lagged interdependencies matter. Thus, dynamic feedback across countries are possible and this greatly expands the type of interactions our empirical model can account for. We do not allow the variance of e_{it} to be time varying but, as will be evident below, the model we estimate permits changes in the volatility of reduced form disturbances.

Model (1) can be re-written in a simultaneous-equation form:

$$Y_t = Z_t \delta_t + E_t \qquad E_t \sim N(0, \Omega) \tag{2}$$

where $Z_t = I_{NG} \otimes X_t'$; $X_t' = (Y_{t-1}', \; Y_{t-2}', \ldots, Y_{t-p}', W_t', W_{t-1}', \ldots, W_{t-q}')$, $\delta_t = (\delta_{1t}', \ldots, \delta_{Nt}')'$ and δ_{it} are $Gk \times 1$ vectors containing, stacked, the G rows of the matrix D_{it} and F_{it}, while Y_t and E_t are $NG \times 1$ vectors of endogenous variables and of random disturbances. Since δ_t varies in different time periods for each country-variable pair, it would be difficult to estimate it using unrestricted classical methods. And even if δ_t were time invariant, its sheer dimension (there are $k = NGp + Mq$ parameters in each equation) could prevent any meaningful unconstrained estimation.

To cope with the curse of dimensionality we adapt the framework in Canova and Ciccarelli (2009) and assume δ_t has a factor structure:

$$\delta_t = \Xi \theta_t + u_t \qquad\qquad u_t \sim N(0, \Sigma \otimes V) \tag{3}$$

where Ξ is a matrix, $dim(\theta_t) << dim(\delta_t)$, and u_t is a vector of disturbances, capturing unmodelled features of the coefficient vector δ_t. We consider the following specification:

$$\Xi \theta_t = \Xi_1 \theta_{1t} + \Xi_2 \theta_{2t} + \Xi_3 \theta_{3t}$$

where $\Xi_1, \; \Xi_2, \; \Xi_3$ are matrices of dimensions $NGk \times s$, $NGk \times N$, $NGk \times G_1$, respectively; $G_1 \leq G$ denotes the number of variables or variable groups; and $\theta_{1t}, \theta_{2t}, \theta_{3t}$ are mutually orthogonal factors capturing, respectively, movements in the coefficient vector which are common across s groups of countries and variables; movements in the coefficient vector which are country specific; and movements in the coefficient vector which are variable (or group-variable) specific.

Factoring δ_t as in (3) reduces the problem of estimating NGk coefficients into the one of estimating. for example, $s+N+G_1$ factors characterizing their dynamics. Factorization (3) transforms an overparameterized panel VAR into a parsimonious SUR model, where the regressors are averages of certain right-hand side VAR variables. In fact, using (3) in (2) we have

$$Y_t = \mathcal{Z}_t \theta_t + v_t \tag{4}$$

where $\mathcal{Z}_t = Z_t \Xi$ and $v_t = E_t + Z_t u_t$.

Economically, the decomposition in (4) is convenient since it allows us to measure the relative importance of common and country-specific influences in explaining fluctuations in Y_t and provides their evolution over time. In fact, $\mathcal{Z}_{1t}\theta_{1t}$ is a common indicator for Y_t, while $\mathcal{Z}_{2t}\theta_{2t}$ is a vector of country specific indicators, $\mathcal{Z}_{3t}\theta_{3t}$ is a vector of variable specific indicators. Note that $\mathcal{Z}_{1t}\theta_{1t}$, $\mathcal{Z}_{2t}\theta_{2t}$ and $\mathcal{Z}_{3t}\theta_{3t}$ are correlated by construction – the same variables enter in all $\mathcal{Z}_{it}$ – but become uncorrelated as the number of countries and variables in the panel becomes large.

To complete the specification we need to assume that θ_t evolves over time as a random walk

$$\theta_t = \theta_{t-1} + \eta_t \qquad\qquad \eta_t \sim N\left(0, \bar{B}\right). \tag{5}$$

and specify $\bar{B}$ as a block diagonal matrix. We also set $\Sigma = \Omega$, $V = \sigma^2 I_k$; and assume E_t, u_t and η_t are mutually independent. The random-walk assumption is very common in the time-varying VAR literature and has the advantage of focusing on permanent shifts and reducing the number of parameters in the estimation procedure.[1]

The spherical assumption on V reflects the fact that the factors have similar units, while setting $\Sigma = \Omega$ is standard (see e.g. Kadiyala and Karlsson, 1997). The variance of η_t could in principle also be time varying to account for ARCH-M type effects and other generic volatility clustering in Y_t.[2] The block diagonality of $\bar{B}$

[1] On this, see Primiceri (2005), also for a discussion on alternative specifications.
[2] See e.g. Canova and Ciccarelli (2009) for a specific example.

guarantees orthogonality of the factors, which is preserved a-posteriori, and hence their identifiability. Finally, independence among the errors is standard.

To summarize, our estimable empirical model has the state space structure:

$$\begin{aligned} Y_t &= (Z_t\Xi)\theta_t + v_t \\ \theta_t &= \theta_{t-1} + \eta_t \end{aligned} \tag{6}$$

While model (6) can be estimated both with classical and Bayesian methods, the latter approach is preferable since the exact small sample distribution of the objects of interest can be obtained even with relatively small T and N.

2.1 Prior information

To compute posterior distributions for the parameters of (6), we assume prior densities for $\phi_0 = (\Omega^{-1}, \bar{B}, \theta_0)$ and let σ^2 be known. We set $\bar{B}_i = b_i * I,\ i = 1, \ldots, r$, where b_i controls the tightness of factor i in the coefficients, and make $p(\Omega^{-1}, b_i, \theta_0) = p(\Omega^{-1}) \prod_i p(b_i) p(\theta_0)$ with $p(\Omega^{-1}) = W(z_1, Q_1),\ \ p(b_i) = IG\left(\frac{\varpi_0}{2}, \frac{S_0}{2}\right)$ and $p(\theta_0 \mid \mathcal{F}_{-1}) = N\left(\bar{\theta}_0, \bar{\mathsf{R}}_0\right)$ where N stands for Normal, W for Wishart and IG for Inverse Gamma distributions, and $\mathcal{F}_{-1}$ denotes the information available at time -1. The prior for θ_0 and the law of motion for the factors imply that $p(\theta_t \mid \mathcal{F}_{t-1}) = N\left(\bar{\theta}_{t-1|t-1}, \bar{\mathsf{R}}_{t-1|t-1} + B_t\right)$.

We collect the hyperparameters of the prior in the following vector

$$\mu = (\sigma^2, z_1, Q_1, \varpi_0, S_0, \bar{\theta}_0, \bar{\mathsf{R}}_0).$$

Values for the elements of μ are either obtained from the data (this is the case for $\bar{\theta}_0, Q_1$) to tune the prior to the specific application, selected a-priori to produce relatively loose priors (this is the case for $z_1, \varpi_0, S_0, \bar{\mathsf{R}}_0$) or initialized with simple OLS techniques on a training sample (this is the case of σ^2). The values used are: $z_1 = N \cdot G + 5, Q_1 = \hat{Q}_1, \varpi_0 = 10^5,\ S_0 = 1.0, \bar{\theta}_0 = \hat{\theta}_0$ and $\bar{\mathsf{R}}_0 = \mathrm{I}_r$. Here $\hat{Q}_1$ is a block diagonal matrix $\hat{Q}_1 = diag\,(Q_{11}, ..., Q_{1N})$ and Q_{1i} is the estimated covariance matrix of the time invariant version for each country VAR; $\hat{\theta}_0$ is obtained with OLS on a time invariant version of (1), over the entire sample, and r is the dimension of θ_t. Since the fit improves when $\sigma^2 \to 0$, we present results assuming an exact factorization of δ_t.

2.2 Posterior distributions

To calculate the posterior distribution for $\phi = (\Omega^{-1}, b_i, \{\theta_t\}_{t=1}^{T})$, we combine the prior with the likelihood of the data, which is proportional to

$$L \propto |\Omega|^{-T/2} \exp\left[-\frac{1}{2}\sum_t (Y_t - Z_t \Xi \theta_t)' \, \Omega^{-1} (Y_t - Z_t \Xi \theta_t)\right] \tag{7}$$

where $Y^T = (Y_1, ..., Y_T)$ denotes the data. Using the Bayes rule, $p\left(\phi \mid Y^T\right) = \frac{p(\phi)L\left(Y^T|\phi\right)}{p(Y^T)} \propto p(\phi)\, L\left(Y^T \mid \phi\right)$. Given $p\left(\phi \mid Y^T\right)$, the posterior distribution for the elements of ϕ, can be obtained by integrating out nuisance parameters from $p\left(\phi \mid Y^T\right)$. Once these distributions are found, location and dispersion measures can be obtained for ϕ or for any interesting continuous function of these parameters.

For the model we use, it is impossible to compute $p\left(\phi \mid Y^T\right)$ analytically. A Monte Carlo technique which is useful in our context is the Gibbs sampler, since it only requires knowledge of the conditional posterior distribution of ϕ. Denoting $\phi_{-\kappa}$ the vector ϕ excluding the parameter κ, these conditional distributions are

$$\begin{aligned}
\theta_t \mid Y^T, \phi_{-\theta_t} &\sim N\left(\bar{\theta}_{t|T}, \bar{\mathsf{R}}_{t|T}\right) \quad t \leq T, \\
\Omega^{-1} \mid Y^T, \phi_{-\Omega} &\sim Wi\left(z_1 + T, \left[, \sum_t (Y_t - Z_t \Xi \theta_t)(Y_t - Z_t \Xi \theta_t)' + Q_1^{-1}\right]^{-1}\right) \\
b_i \mid Y^T, \phi_{-b_i} &\sim IG\left(\frac{\varpi^i}{2}, \frac{\sum_t \left(\theta_t^i - \theta_{t-1}^i\right)' \left(\theta_t^i - \theta_{t-1}^i\right) + S_0}{2}\right)
\end{aligned} \tag{8}$$

where $\bar{\theta}_{t|T}$ and $\bar{\mathsf{R}}_{t|T}$ are the smoothed one-period-ahead forecasts of θ_t and of the variance-covariance matrix of the forecast error, respectively, calculated as in Chib and Greenberg (1995), $\varpi^i = K + \varpi_0$, and $K = T$, if $i = 1$, $K = Tg$, if $i = 2$, $K = TN$, if $i = 3$, etc.

Under regularity conditions (see Geweke, 2000), cycling through the conditional distributions in (8) in the limit produces draws from the joint posterior of interest. From these, the marginal distributions of θ_t can be computed averaging over draws in the nuisance dimensions and, as a by-product, the posterior distributions of our indicators can be obtained. For example, a credible 90% interval for the common indicator is obtained ordering the draws of WLI_t^h for each t and taking the 5th and the 95th percentile of the distribution. The results we present are based on chains with 150000 draws: we made 3000 blocks of 50 draws and retained the last draw for each block. Finally 2000 draws were used to conduct posterior inference at each t.

3 The data

The model is estimated first for as many euro area countries as possible, and then for some other key economies around the world, using core variables of the real business cycle and a set of financial series.

The sample period is 1980q1-2010q4. This span of data includes several business cycles and in particular a large number of quarters before and after the introduction of the single currency. Thus, with this model we are able to capture not only possible time variation around business cycle phases but also time variation caused by (possibly lengthy) structural changes (Canova et al, 2012).

Real variables included are GDP, private consumption and gross fixed capital formation, which are best suited to capture the real business cycle. We include two types of financial variables representing both financial prices (of bonds –country risk–, of stocks and of real estate) and the situation of the lending market: the supply side (loans to deposit ratio) and the flow of credit into the economy. In particular, as financial prices we include the term spread (difference between 10-year government bond rates and 3-month interbank rates), real stock prices and real house prices. To capture the loan market we include a measure of banking leverage (total loans to deposits ratio) and bank credit growth. The latter is measured as the y-o-y growth of nominal credit divided by the GDP deflator.[3]

Most data come from the OECD and IMF databases; detailed sources for each variable can be found in the data appendix. We use annual growth rates, which are further standardized in order to obtain meaningful aggregations of these heterogeneous series.

The sample covers the biggest economies in the euro area as well as some of the

[3] In an attempt to improve the leverage measure by comparing flows with flows, we have also used the credit impulse instead of credit growth. The credit impulse is measured as the y-o-y difference of credit growth in any given quarter as a percentage of nominal GDP. The term credit impulse was coined by Biggs et al. (2009). All results remained essentially unchanged.

smaller ones, including some that suffered most during the financial crisis, as well as other relevant European and world economies. The nine euro countries included are Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands and Spain. Beyond the euro area, three other EU countries (Denmark, Sweden and the UK) are included, as well as three non-EU countries (US, Canada and Japan). In order to keep the estimation tractable we have split the sample into two different country sets and estimated the same statistical model on each group of countries. The first "euro area" set includes all nine euro area economies for which data were available for the whole sample period plus the US. The second "international" set restricts the euro area to its four largest economies, i.e. Germany, France, Italy and Spain, so that it is computationally feasible to include three non-euro European economies (Denmark, Sweden and the UK) and three non-EU economies (US, Canada and Japan). The choice of the non-euro countries is again determined by data availability, as well as by the intention to represent as much as possible the more relevant economies in the EU and the rest of the world.

3.1 Selected features of the data

Before proceeding to the empirical analysis, it is useful to present some facts about the data.

Despite including only highly developed countries in the sample we find large differences not only across countries but also over time. To illustrate this, we have calculated average y-o-y growth rates of GDP for the period before 1999 and after 1999. By splitting the sample along the introduction of the euro, we can check for any significant changes due to the creation of the European Monetary Union (EMU) in 1999. Although we also include non-member countries, it is fair to say that the EMU could have potentially influenced other parts of the world, in particular through financial markets.

In Table 1, we see that average GDP growth ranges from 1.91% to 3.87% in the pre-EMU period and between 0.66% and 4.01% in the post EMU-period. Out of the 15 countries only 5 show similar or slightly higher growth rates in the post-EMU period, for all the rest, growth rates in the pre-EMU period were higher. Despite the great moderation, the opposite is true for average standard deviations, possibly due to the effect of the recent recession. Standard deviations are higher for all countries (except Canada) in the post-EMU period and also the range across countries is wider. Thus, we see that despite concentrating on industrialized countries and on countries that should be converging (in particular within the euro area), there are remarkable differences in their growth patterns.

More interesting differences appear when we look at financial prices and financial ratios. Here we see also a large degree of heterogeneity. Again, only for illustrative purposes, we report the average levels of bank leverage measured as the percentage of total loans to deposits. This ratio ranges from around 40% for Luxembourg to around 200% for Germany and Italy. We also see that for most countries (except Japan and the United Kingdom) this ratio has increased in the post- EMU era, in particular for countries such as Italy and Spain.

4 Commonality vs. heterogeneity

After estimating different specifications, the highest marginal likelihood was found for the model including one common component for all series, one country-specific component for each economy and three variable-type components: one shared by all real variables across countries, another shared by loan ratios across countries, and a third shared by asset prices and term spreads across countries.[4] These common, country-specific and variable-type components quantify the relative contributions of common and heterogeneous factors in macro-financial linkages and help to address the following questions: Is there a significant common component in the macro-financial interactions across the euro area economies or do country-specific heterogeneities matter more? How does heterogeneity within the euro area compare to other economic areas?

Results show that there is indeed a significant common component, especially in the last recession. As found elsewhere in the literature on financial cycles we confirm

[4] An alternative specification with only two variable-type factors (one for the real variables and another for the financial ones) delivered a lower marginal likelihood for both sets. Another specification with no variable-type factors, that is, only a common component and a set of country-specific factors, had an even lower marginal likelihood. In all cases, including our benchmark specification, a Schwarz Bayesian Information Criterion favours a single lag for the VAR dynamics.

the existence of a statistically significant common factor linking all real and financial series across all countries. Figure 1 displays the evolution of this common factor for the two sets of countries considered, expressed as standard deviations from the historical average of annual growth rates. The common component estimated captures appropriately the recession during the EMS crisis of 92-94, obviously more visible in the estimation for the euro area set, and it identifies also the mild recession of 2001-02. It is noteworthy that the recent crisis appears by far as the largest common fluctuation in both sets of countries, and is even more intense in the international set. Moreover, the posterior uncertainty is remarkably low towards the end of the sample.

However, the country-specific element in fluctuations of real and financial variables remains significant, and this explains some heterogeneous behavior observed through time across countries. Figure 2 shows the country-specific components for both sets of countries. These indicators are very precisely estimated and posterior uncertainty seems to vary with the state of the economy. The charts also show that countries differ substantially in the intensity and duration of the cycle and, in some cases, also in the timing of the phases. While there are countries in which the fluctuations common to their real and financial series, as shown by the 68% confidence intervals, lie well above zero, in other countries they may be zero or even negative. The differences in the joint evolution of real and financial series across countries could be an indication of episodes of non-synchronized business cycles across countries. The origin of such heterogeneity could be, for example, the presence of a financial bubble in one country that may be absent in another, while in other countries only real economic developments drive the business cycle.

It is interesting to note the different behaviour of national factors relative to the common factor. For instance, as would be expected, the intensity of the crisis during the early 90's is much stronger in Finland (also in France and Spain), and in the two non-euro Nordic countries in the international set (Denmark and, especially, Sweden). On the other hand, the recession around 2002 was strongest in Germany and the Netherlands, and weaker in the US, France and Belgium.

Also of interest is the long period of almost uninterrupted growth (financial and real) in Ireland and, especially, Spain prior to the sharp fall in both economies during the last recession. This contrasts with the relatively weak performance of the Italian economy during most of that same period, and with the clear underperformance of the Japanese economy throughout the last two decades. The most common fluctuation across countries, albeit with different intensities, remains the last recession.

Three distinct variable-type components are identified for the two sets of countries: one common to all financial prices (real stock and house prices, and the term spread), one common to all real variables (GDP, private consumption and gross fixed capital formation), and one common to the loan market (ratio of total loans to deposits and credit growth). The panels in Figure 3 show that they are statistically significant for most of the sample period, i.e. the whole 68% posterior confidence interval is above or below zero, which means that each type of variable features a significant common movement across countries. We see, however, that prior to 1992 the common factors in the euro area (upper panel in fig.3) were not significantly different from zero, implying that the commonalities across euro area member states have increased since the mid 1990's. Looking at the international set (lower panel in fig.3), we see that while real variables seem to have a significant common pattern also in the period before 1992, this was not true for financial prices or for the lending market. Moreover, as would be expected, we see that the in the international set the significance of co-movements in financial prices is higher in the last decade than in the 1990's.

The analysis by variable groupings confirms that for the real economy the last recession was particularly unique from a historical perspective.[5] Figure 3 illustrates that the latest crisis produced larger fluctuations than those observed in the preceding three decades for all three variable types, but especially for real variables. Loan market variables fell as early as 2007, coinciding with the credit supply tightening documented by e.g. the Bank Lending Survey (BLS) indicators, then rose

[5] A historical decomposition exercise (not reported) comparing the last crisis to the two previous recessions shows that all three variable-type components played a significant role in the latest crisis, especially the drop in real variables (much less present in previous recessions) and the fall in financial prices. The role of the latter in explaining GDP movements during the latest crisis is much more pronounced in the international country set than in the euro area set. This suggests that the last recession saw stronger financial-real cross-country interdependencies around the world than within the euro area.

temporarily in 2008 coinciding with the initial fall in activity and income in National Accounts data. Lending market indicators dropped even more again after 2009 when the Bank Lending Survey (for the euro area) reported both credit demand and supply reductions. Ciccarelli, Maddaloni and Peydró (2010) performed a Panel VAR analysis using similar macro data as well as BLS indicators of credit supply and demand of credit over 2007-2010 and found similar results. The two country sets show remarkably similar patterns for the three variable components, except that loan market fluctuations in the more international set were somewhat milder in the last recession and the real variables recovered by 2010q4, which was not the case for the euro area set.

This analysis by variable type confirms previous findings on the leading nature of financial prices: across countries and periods, financial prices lead fluctuations in real variables, while loan ratios are lagging.[6] Comparing the evolution of these three variable-type components, in most recessions financial prices are usually the first to fall and to recover, followed by real variables and then by the loan market. An interpretation of the latter could be that lower activity shrinks credit demand but also credit supply, partly because of the increase in non-performing loans. Simple lead-lag cross-correlations among the three estimated factors suggest that financial prices lead real activity (with a maximum correlation coefficient of 0.75 at a 3-quarter lead for the euro area set and 0.8 at a 2-quarter lead for the international one). In turn, real variables appear to lead loan ratios (correlation peaks at 0.56 with a lead of 6 quarters in the euro area set, 0.6 at 4-quarter lead in the international set). This lead-lag pattern across variables was also observed in the last recession.

Among these three variable-type components, the more highly correlated with the component that is common to all series and countries is the real variable component, and in a synchronized manner: the maximum correlation coefficient between these two series is at lag zero with values as high as 0.7 in the case of the euro area set and 0.8 for the international set. In a sense, this suggests that real variables dominate the common business cycle that emerges across countries. Indeed, the international business cycle literature often finds stronger co-movement among real aggregates both within and across countries. On this issue see, among others,

[6] Giannone, Lenza, and Reichlin (2010) find the same result with a different methodology.

Crucini et al. (2011).

5 Cross-country transmission of shocks

Considering both real and financial series for several countries in the same empirical model makes it possible to assess the role of cross-country spillovers in the interdependencies between financial and real variables. The panel BVAR can determine how changes in a financial variable in a given country affect real variables in other countries. Spillovers across countries and between financial and real variables were especially relevant in the last recession. Consequently, we focus on the most recent recession, using generalized impulse response functions for the euro area set.

With this methodology we not only assess whether a negative financial shock in one country affects the real economy across the euro area, but also how much of the shock is transmitted to other countries. As expected, we find that spillovers matter and also that the transmission of the shock depends on the originating country. We find that real variables across the whole euro area were affected by shocks to financial variables in specific countries, in particular when the financial shocks originated in Germany or outside the euro area, in the US.

To measure these spillovers, we focus on the growth in the variable-type component common to real variables across countries. The generalized impulse response is computed as the difference between the forecast of this component conditional on the observed fluctuation in a given financial variable and its unconditional forecast during the recent recession. By construction, the shock to the financial series is the difference between its observed evolution and the model forecast at that point. The shock starts at the observed peak of the financial series and lasts until its observed trough. The choice is somewhat arbitrary and can differ across variables shocked and country of origin. However, it provides a measure of the shock based on what actually occurred, and is a convenient tool that does not require the identification of "structural shocks" as typically done in the VAR literature (Pesaran and Shin, 1998).

To assess interdependencies between the rest of the world and euro area countries, Figure 4 shows the generalized impulse response functions (IRFs) of the common component of real variables across the euro area to a financial shock in the US. The financial shock is defined as the unexpected part of the drop in US real stock prices in the period 2007q3 (peak) to 2008q4 (trough). For illustration, the responses to a real US shock are shown as well in the lower panel, where the shock is the unexpected part of the fall in US GDP growth between 2007q3 (peak) and 2009q2 (trough).

The extent of cross-country interdependence is clear from the chart, as the fall in US variables beyond the unconditional forecast (units are standard deviations of the demeaned series) causes a fall in the real variable component in every other country, sometimes by almost as much as in the US. For both financial and real shocks, the countries that show the largest response to events in the US are the same (Ireland, France, Netherlands and Spain). For all countries, the decline in the real components at about 7 quarters is larger for a real shock than for a financial shock.

The following figures report the response of the real variable component in different countries to a shock to a particular financial series in a given euro area country. First we focus on the impact of the unexpected drops in real house prices in Spain and in Ireland. Figure 5 shows that most economies suffered a drop in real activity following the Irish shock – defined over the period 2007Q3-2009Q4 – and the Spanish shock –defined over the period 2008Q3-2010Q4.

In terms of size, as would be expected, the fall in the real variable components outside the originating country is much smaller than the one triggered by a fall in the US. The responses are somewhat less than a fourth of the response observed in the country of origin of the shock. However, although the drop in house prices was 12% for Spain and 28% for Ireland, the impact of Spanish house prices on some economies was much larger, possibly reflecting the larger size of the Spanish economy and its stronger links to other euro area economies. Indeed, the largest responses are observed in France, and also in Ireland. The latter is possibly due to similarities in the boom-bust patterns of their respective housing sectors.

Turning to the impact on real variables of shocks to the loan market variables in the largest euro area economies, Figure 6 shows that a shock in France – defined over the sample 2008Q3-2009Q4 – has similar dynamics as the real house price shocks previously shown. However, when this shock occurs in Germany – over the same period – the responses in other economies are as large as that in Germany itself, although the unexpected fall in Germany was smaller. This suggests that when the shocks originate in Germany or the US, their transmission may be amplified.

6 Summary of results and discussion

Summing up, the evidence we found confirms the need to allow for cross-country and cross-variable interdependence when studying real-financial linkages. An empirical model including real and financial variables for most of the euro area economies as well as other relevant European and world economies identifies a statistically significant common component, especially large in the recent recession. However, country-specific factors remain very important, which explains the heterogeneous behavior observed at times. In addition, there are common components to real variables across countries, as there are for loan market variables and for financial prices such as housing, stocks and interest rate spreads. As in other recessions, financial prices seem to have entered the recent crisis somewhat earlier, while real variables suffered a greater fall. Finally, spillovers are found to matter: a negative shock to a financial variable in a given country also affects all other euro area countries, more so if the shock originates in Germany or the US.

These results cast a new perspective on the findings of the previous literature. First, although heterogeneity across countries matters, a common evolution of business cycles around the world remains a prominent feature of the data. This is also in line with the recent literature on international business cycles which finds significant effects of both group-specific and global factors in driving world cyclical fluctuations. This phenomenon seems to be a robust feature of the data, i.e. it is not limited to countries in any particular geographic region and is not a mechanical effect of episodes of crises (see Kose et al. 2008).

Second, financial shocks matter in the explanation of real developments and, perhaps more importantly, they spill over in a heterogeneous way across countries. This is consistent with previous studies, although the joint estimation performed in this paper including many countries might yield stronger linkages than those obtained in a country-by-country VAR analysis, given the amplification of the interdependencies allowed here.

The results carry important implications for theoretical models of the international business cycles as well as for policy making. From a modelling perspective, the data appears to favour models that assign a prominent role to the international dimension, with countries endogenously reacting to foreign impulses. Also, time variations suggest important asymmetries in the shape and the dynamics of international cycles, so linear models may miss policy-relevant features of the data.

From a policy perspective, some considerations are in order. First, despite important heterogeneity, countries share common financial shocks, suggesting that international financial markets are important to understand co-movements in economic activity. Therefore, policymakers should monitor foreign financial developments. Second, since national policy affects the national component more than the common component and these may evolve differently at times, policies designed to counteract world conditions may be ineffective or, worse, counter-productive for the domestic economy.

Clearly, these considerations immediately raise interesting questions that this paper has left unanswered. Despite its complexity, the empirical model used in this paper is as non-structural as a simple VAR, and as such it can provide useful information, but face limitations in identifying (i) the reasons behind the different reactions across countries to a common shock, (ii) the transmission channels which allow shocks to spill over, (iii) the causality between macro and finance and, (iv) the importance of economic and institutional factors in driving the transmission of a shock. All these issues could be addressed in future research.

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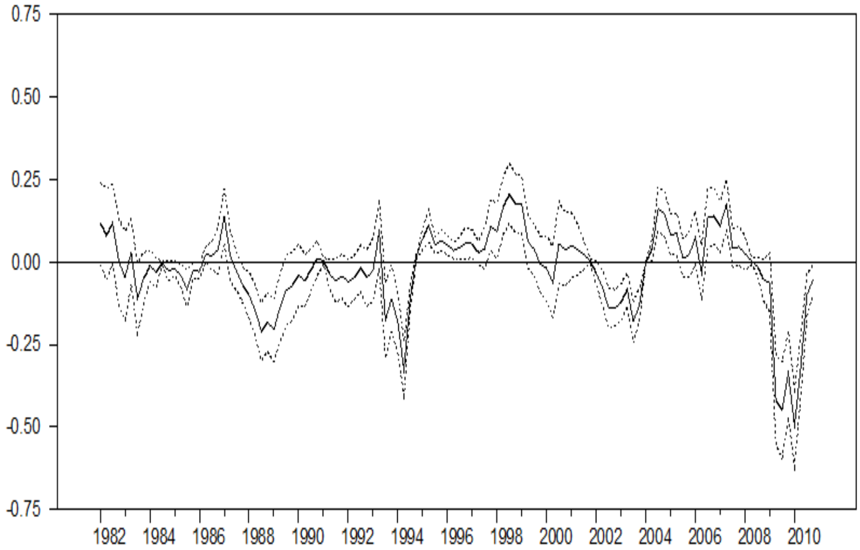
7 Tables and Figures

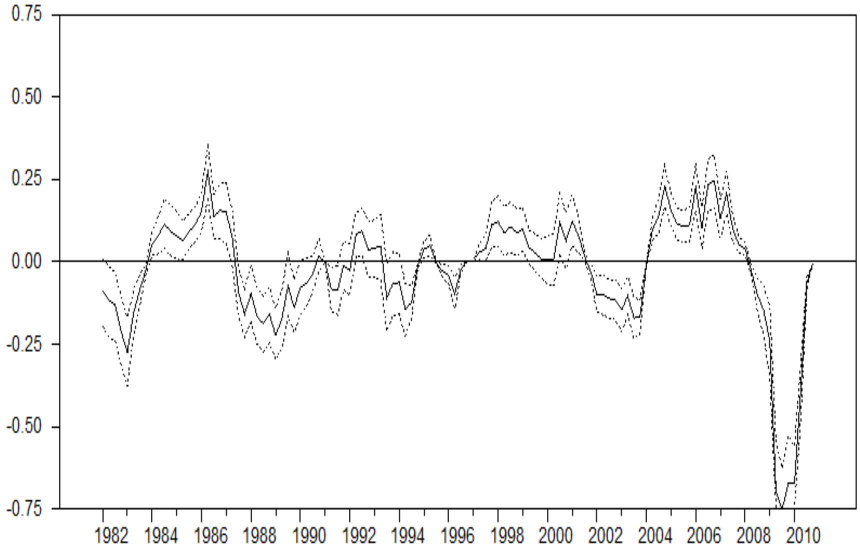
Table 1: Selected descriptive statistics

	GDP growth rates				Loans to deposit ratio			
	pre-EMU		post-EMU		pre-EMU		post-EMU	
	mean	std dev	mean	std dev	mean	std dev	mean	std dev
Belgium	2,02	1,63	1,75	1,89	87%	12%	81%	6%
Germany	2,13	1,77	1,17	2,41	171%	14%	197%	14%
Spain	2,51	1,66	2,56	2,46	127%	14%	188%	13%
Finland	2,32	3,35	2,33	3,68	142%	22%	162%	21%
France	2,05	1,37	1,6	1,74	135%	21%	145%	10%
Ireland	3,87	4,25	3,91	5,54	94%	8%	143%	22%
Italy	1,95	1,54	0,66	2,31	104%	19%	196%	16%
Luxembourg	3,64	2,57	4,01	3,67	42%	18%	38%	5%
Netherlands	2,54	1,85	1,86	2,35	101%	9%	142%	6%
Denmark	2,28	2,21	1,1	2,61	83%	10%	97%	8%
United Kingdo	2,55	1,97	1,81	2,38	95%	9%	78%	2%
Sweden	1,91	2,1	2,45	3,08	93%	18%	99%	5%
Canada	2,62	2,55	2,47	2,13	108%	4%	114%	5%
US	3,21	2,09	2,16	2,12	77%	3%	72%	3%
Japan	3,11	2,56	0,86	2,92	89%	4%	66%	6%
Average	2,58	2,23	2,05	2,75	103%	12%	121%	9%

Figure 1. Evolution of the common component over time



Euro area set: EMU9 (BE, DE, ES, FI, FR, IE, IT, LU, NL) and US.



International set: EMU4 (DE, ES, FR, IT) + DK, SE, UK, US, JP and CA.

Figure 2. Evolution of country components

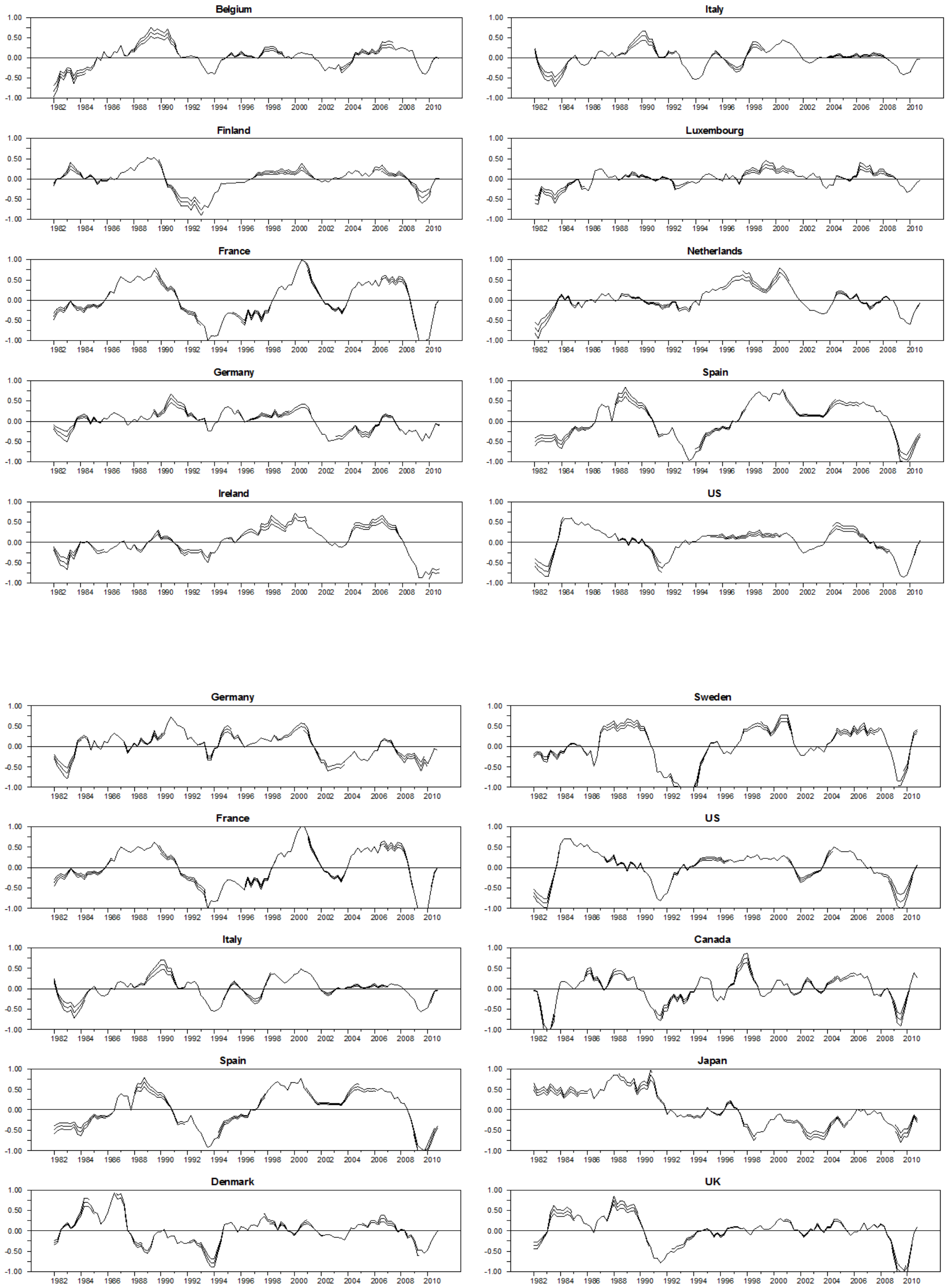
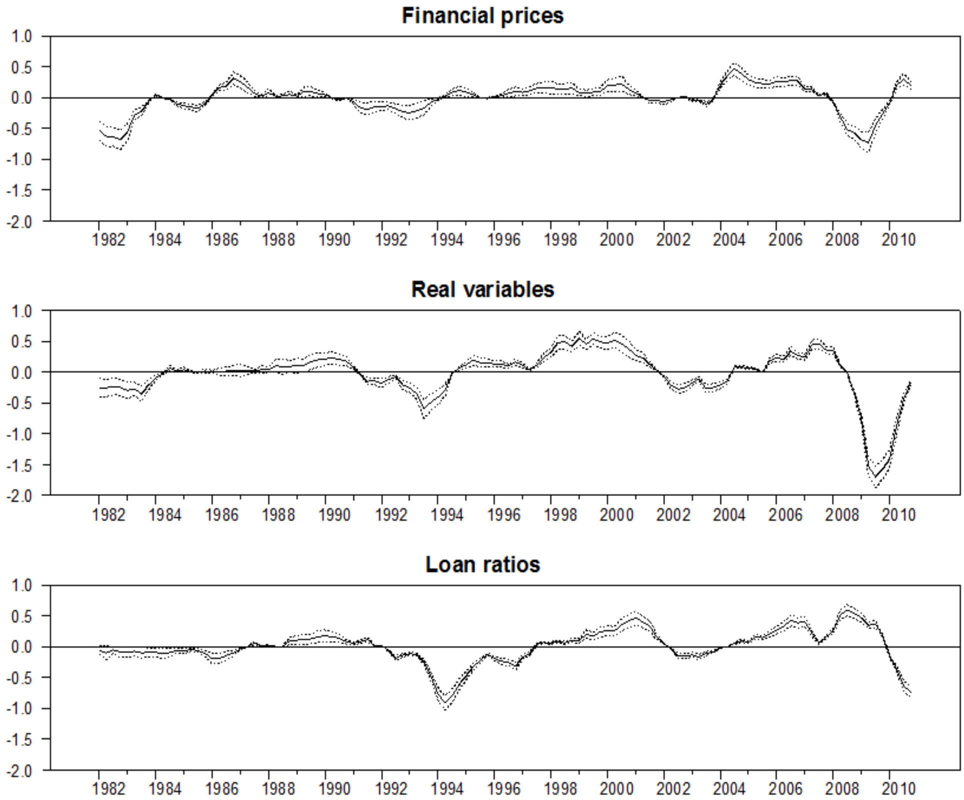
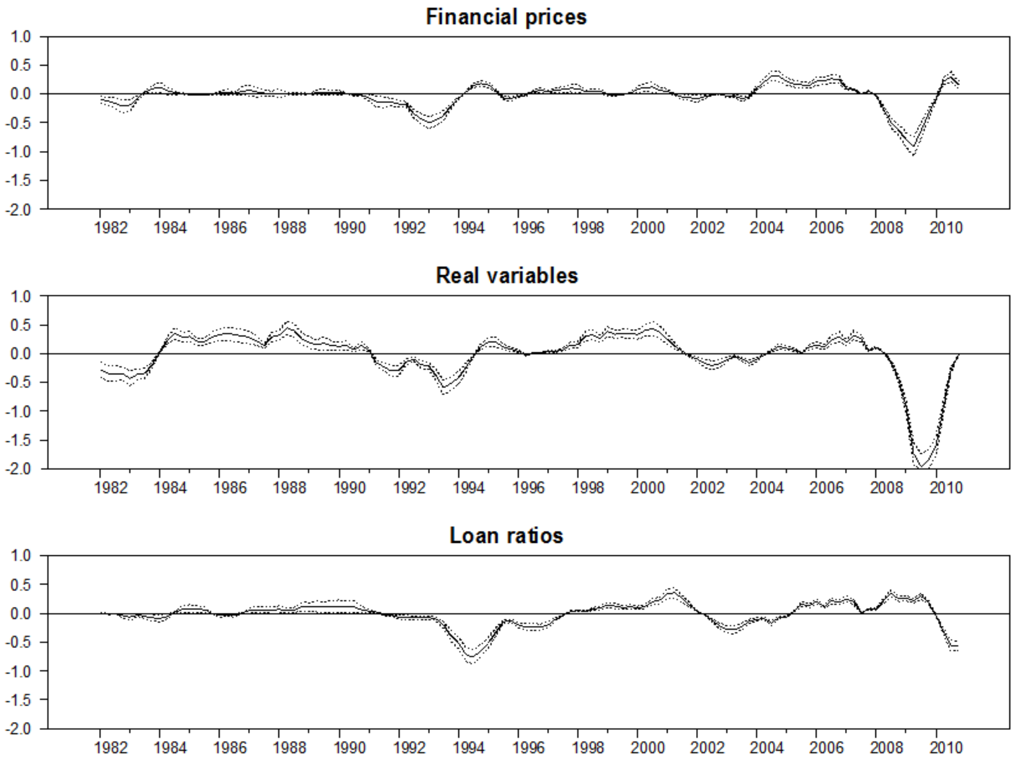


Figure 3. Evolution of variable-type component



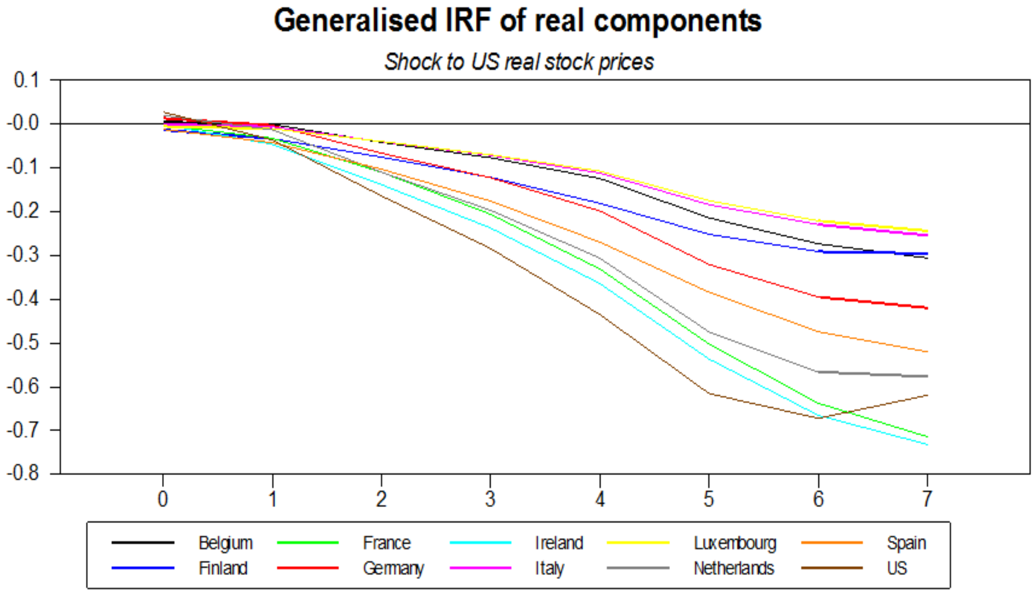
Euro area set: EMU9 (BE, DE, ES, FI, FR, IE, IT, LU, NL) and US.

Figure 3. Evolution of variable-type component (continued)



International set: EMU4 (DE, ES, FR, IT) + DK, SE, UK, US, JP and CA.

Figure 4. Generalised IRFs of real variable component to US shock (EMU9 and US)



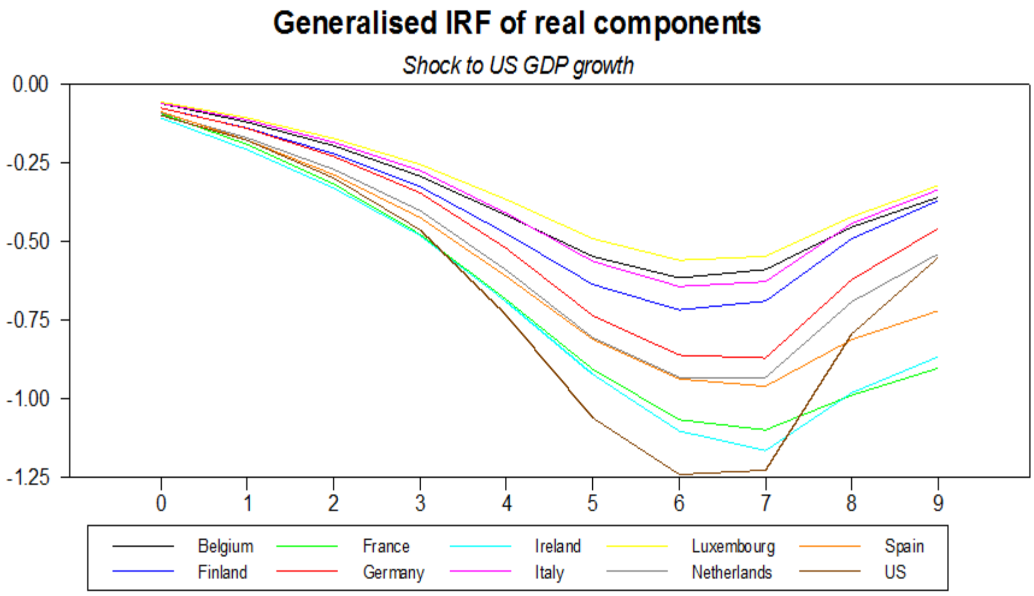
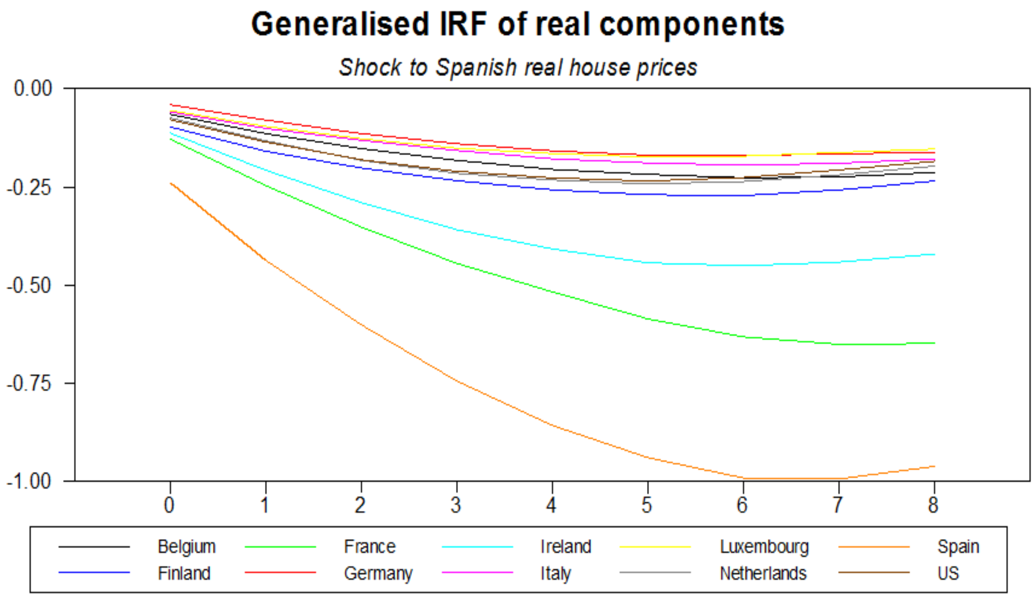


Figure 5. Generalised IRFs of real variable component to real house price shock (EMU9 and US)



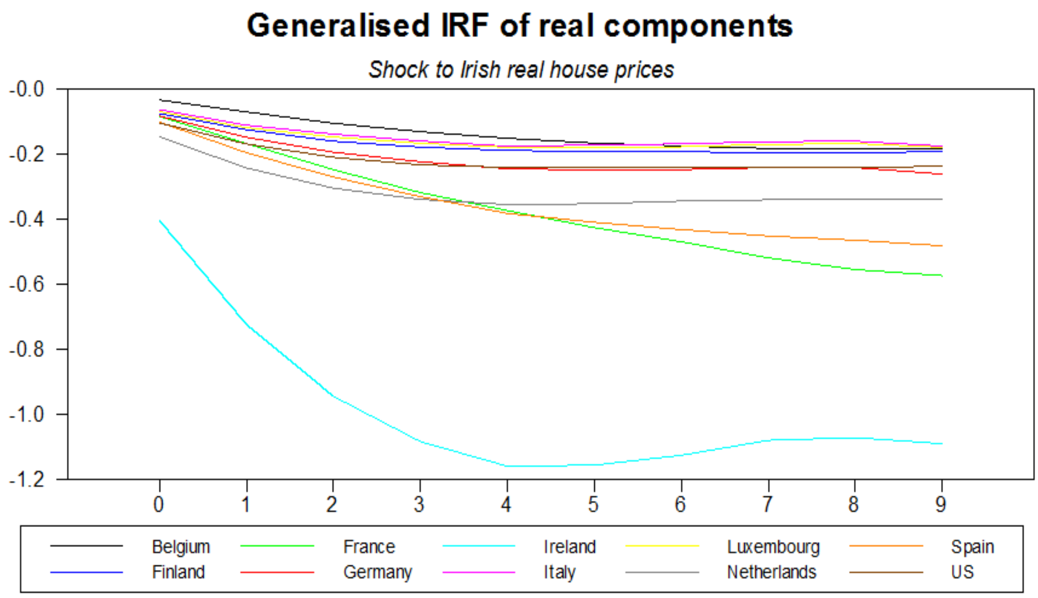
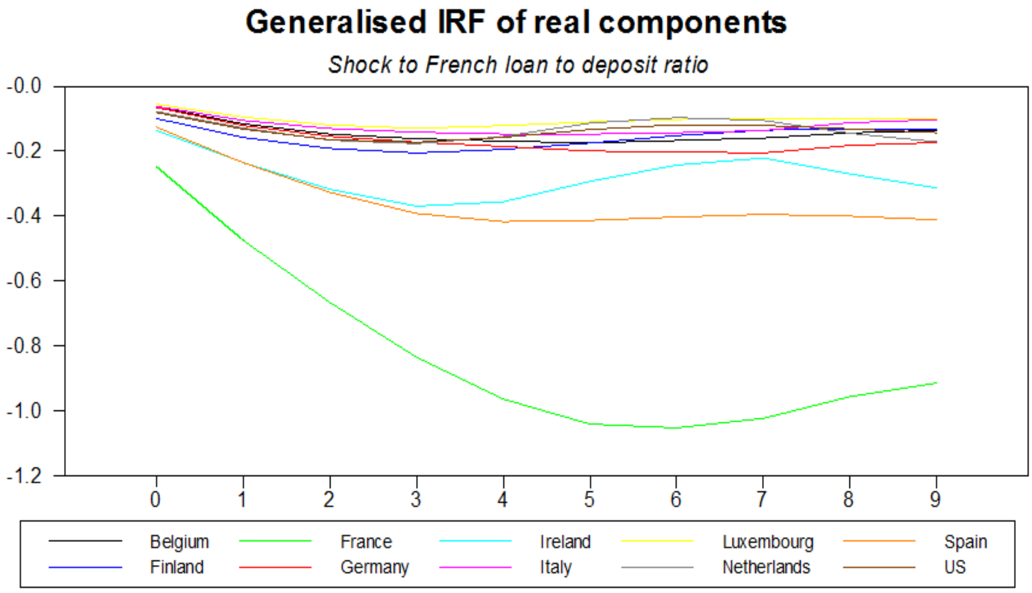
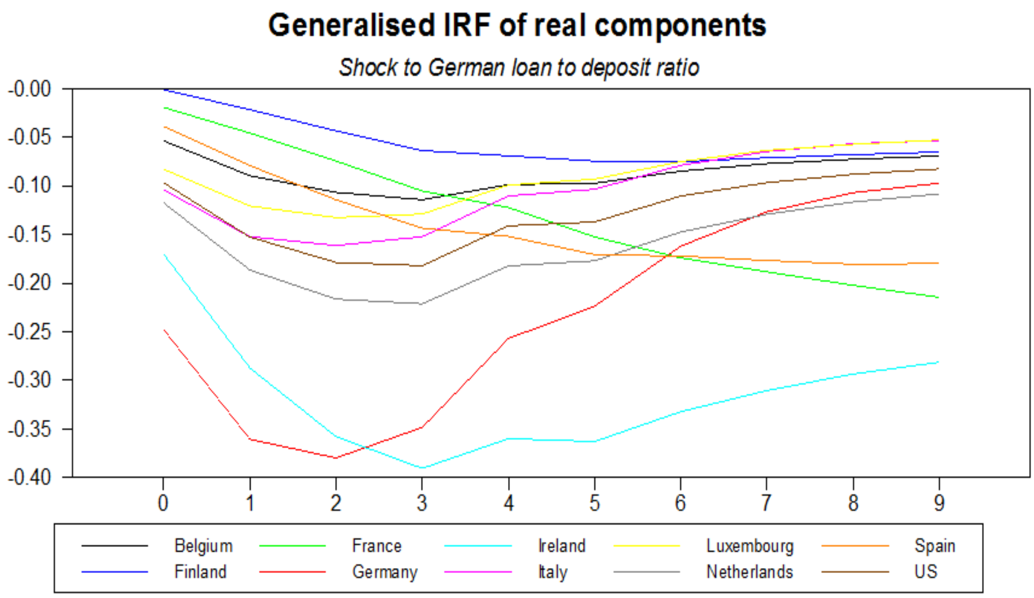


Figure 6. Generalised IRFs of real components to a shock to loan-to-deposit ratio (EMU9 and US)





8 Data appendix

Variable	Description	Sources
CPI	Consumer prices	OECD, Eurostat, IMF, ECB
YER	Gross Domestic Product (real)	OECD, Eurostat, NCB data
YEN	Gross Domestic Product (nominal)	OECD, Eurostat, NCB data
PCR	Private Final Consumption (real)	OECD, Eurostat, NCB data
ITR	Gross Capital Formation (real)	OECD, Eurostat, NCB data
STN	3-month (interbank) interest rate	OECD, IMF, ECB
LTN	10-year government bond rate	OECD, IMF, ECB
SP	Stock prices	OECD, IMF, ECB, NCB calculations
HP	House prices	OECD, ECB, NCB
Fin1	Term spread (10 year - 3 month rates)	own calculations
Fin2	Loan/Deposit ratio	own calculations
CG	Credit growth (see below)	own calculations
Loans	Total loans to private sector	IFS, ECB
Deposits	Total deposits of private sector	IFS, ECB

Note that all nominal variables (other than interest rates) were deflated by CPI prior to the calculation of year-on-year growth rates.

The loan-to-deposit ratio is used in year-on-year growth rates. The credit growth variable is defined as:

$$CG = 100 * \left[\frac{D_t/P_t - D_{t-4}/P_{t-4}}{D_{t-4}/P_{t-4}}\right]$$

where D_t is nominal loans and P_t is the GDP deflator.