Contributions

Matteo Ciccarelli*, Eva Ortega and Maria Teresa Valderrama Commonalities and cross-country spillovers in macroeconomic-financial linkages

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Abstract: In this paper, we investigate commonalities and spillovers in macro-financial linkages across developed economies. A Bayesian panel vector autoregression (VAR) model with real and financial variables identifies significant common components, especially during the Great Recession. Nevertheless, country-specific factors remain important, which is consistent with the heterogeneous behavior observed across countries over time. We also find that spillovers across countries and between real and financial variables are key to explain economic fluctuations. A shock to a variable in a given country affects all other countries, and the transmission seems to be faster and deeper between financial variables than between real variables. For a shock to a financial variable to have a noticeable effect on the real economy elsewhere, it needs to be either common to all countries or to have originated in a systemic country.

Keywords: financial crisis; macro-financial linkages; panel VAR models.

JEL classification: C11; C33; E32; F44.

1 Introduction

The Great Recession was a worldwide phenomenon in which shocks to the financial system spread rapidly, not only to the real economy but also across borders, highlighting the deep level of interdependence between the financial and real sectors.

There are several channels by which macroeconomic and financial linkages can arise. For instance, on the one hand, a deterioration of financial conditions may affect the economy through a negative wealth effect on consumption and

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investment decisions, or through credit rationing, as it becomes harder to identify solvent borrowers when liquidity is scarce. On the other hand, an economic downturn will affect the valuation of financial assets, as the present value of future cash flows decreases, which in turn will have an impact on financial conditions. The final effect on the economy depends not only on the response of economic agents, but also on the institutional framework, both of which vary across countries and over time (see, e.g. Hubrich et al. 2013, for references about macro-financial linkages).

There is a vast body of literature on the intensification of macro-financial linkages in the last few decades. As noted in Hirata, Kose, and Otrok (2013), the process of economic unification has gained momentum across regions. This has been accompanied by a marked increase in the number of regional trade agreements and rapid growth of intra-industry trade through international vertical specialization, especially in North America, Europe and Asia. As a result, global trade flows over the last 25 years have been growing at a much faster rate than world output. Furthermore, the growth in volume of global financial flows has outstripped that of global trade. Lane and Milesi-Ferretti (2007) show that this has been mainly due to the increase of financial flows among advanced economies. While intensive trade and financial flows have undoubtedly increased the magnitude of international spillovers, the relative importance of the real sector compared to the financial sector may also have changed over time.

In this paper, we analyze macro-financial linkages and international spillovers over the last three decades. We use an empirical model where real and financial variables are jointly modeled for a set of industrialized countries in a unified framework. The model allows for (i) country-specific dynamic relationships, (ii) dynamic feedback across countries and (iii) time variation in the coefficients.

Out of a total of ten industrialized countries, seven are Member States of the European Union, of which five are euro area countries. Ever-closer institutional and economic interdependencies may have made euro area countries more alike. However, the Great Recession and the sovereign debt crisis have demonstrated that, alongside some shared behavior, there is still a substantial degree of heterogeneity in macro-financial linkages across countries within the euro area and the European Union, and that over time those linkages may have changed.

We build a time-varying Bayesian panel vector autoregression (VAR) model of the type developed in Canova and Ciccarelli (2009) and Canova, Ciccarelli, and Ortega (2007). This allows us to carry out a simultaneous study of interdependence and time variation across a panel of countries. The aim is to identify possible stylised facts in the interactions between financial and real variables over the last three decades.

More specifically, this paper addresses the following three sets of questions: (1) Do macro-financial linkages differ across countries and over time? In

particular, what role do common and country-specific factors play, respectively in explaining economic fluctuations? (2) To what extent can economic fluctuations be explained by cross-country spillovers arising from real and financial shocks? Do shocks matter more if they are of real or financial origin? (3) How different was the 2008–2009 recession from previous recessions? Did commonalities prevail more in the last crisis than in previous ones?

The evidence found here confirms the need to allow for cross-country and cross-variable interdependence when modeling real-financial linkages. Regarding the first set of questions, the empirical model identifies statistically significant common components, which turned out to be most pronounced during the 2008–2009 recession. However, heterogeneity is still a robust feature of the data regardless of the level of commonality in the various economies. Country-specific factors also remain very important. This is consistent with the presence of a heterogeneous pattern in macro-financial linkages. Moreover, the fact that there is still some heterogeneity across countries, despite the fact that the data regularly points to the common evolution of business cycles around the world, is consistent with recent literature on international business cycles, 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. In other words, it is not limited to countries in any particular geographical region and is not a mechanical effect of crisis episodes (Kose, Otrok, and Prasad 2008). This paper does not attempt to focus on the origins of such heterogeneity, which would otherwise require a structural model to address this properly. We can only assume that the origins of such heterogeneity are related to financial and business cycles diverging within and between countries and are reinforced by the heterogeneous transmission of shocks.

As to the second set of questions, we find convincing evidence that spillovers across countries are important drivers of macro-financial linkages and that there are significant cross-border spillovers of shocks, from both real and financial variables. A shock to a real or financial variable in a given country is transmitted to all other countries (in our sample), albeit only partially and heterogeneously. These international spillovers seem to be faster and further-reaching between financial variables than between real variables. On the other hand, it seems that for a shock to a financial variable to affect significantly the real economy elsewhere, that shock needs to be either common to all countries or to have originated in a systemic country (e.g. the US).

Finally, as to whether the transmission of shocks changed during the great recession, we find that that is not the case: while the great recession features the largest real and financial shocks in our sample, their transmission across countries is similar to those observed during previous recessions. By jointly estimating

a system that covers many countries, we are able to identify linkages that are stronger than those identified in country-by-country VAR analyses. This finding can be attributed to the amplification effect that results from allowing for interdependence. Moreover, we document that all recessions since 1980 have had a common and an idiosyncratic (country-specific) component; however, in the most recent crisis the common factor was more evident in both its financial (i.e. asset prices and loan markets) and its real dimension.

The paper contributes to the more recent empirical macro-financial literature to have emerged following the financial crisis. To our knowledge, this has been one of the first attempts to address the issues of heterogeneity and spillovers simultaneously in a rich methodological environment. Other papers have focused on the international spillover of credit shocks (e.g. Eickmeier and Ng 2011) or on the role of financial and trade linkages in the transmission to GDP growth of idiosyncratic and common shocks (e.g. IMF 2013, and references therein).

Our paper differs from the existing literature in at least two respects. First, part of the focus of this paper lies in the importance of heterogeneity across countries. By understanding the interaction and balance between commonality and heterogeneity – and therefore seeing how shocks are propagated across countries –, policy makers will be better placed to take appropriate measures. In fact, our findings help qualify the existing academic literature alluding to the predominance of common or regional factors over country factors in international business cycles (see, e.g. Kose, Otrok, and Whiteman 2003; Canova, Ciccarelli, and Ortega 2007; Hirata, Kose, and Otrok 2013).

Second, this paper avoids focusing only on the Great Recession. It tries to establish important empirical facts using a comparative approach. The result is that new light is shed on whether and how macro-financial linkages have evolved over time and whether they have shared common characteristics across countries and over different types of economic crises. For instance, our comparative approach allows us to show that the Great Recession is characterized by larger shocks. However, our approach also reveals that the most recent crisis was not necessarily characterized by higher country responses than were observed during previous crises.

Both aspects of our contribution carry considerable implications for the theoretical modeling of international business cycles: the international dimension needs to be brought to the fore by adopting global, possibly non-linear, models. Our findings could have a bearing on policy-making: more emphasis should be placed on monitoring foreign financial developments than on devising domestic policies designed to counteract the effects of world conditions.

This paper is structured into four sections. Section 2 describes the data used and the empirical model. Section 3 reports on the results, organized according to

the three sets of questions asked above, regarding the relationship between commonalities and heterogeneity in macro-financial linkages (Section 3.1); the cross-country transmission of shocks (Section 3.2); and the relative role of financial and real factors as well as global and country-specific factors in the 2008–2009 crisis (Section 3.3). Finally, Section 4 summarizes and concludes.

2 Data and methodology

2.1 The data

The empirical model is estimated for the G7 economies and for some non-G7 European countries, using core variables of the real business cycle as well as a set of financial variables.

The sample period is the first quarter of 1980 to the fourth quarter of 2011. This span of data includes several business cycles and, notably, a high number of quarters both before and after the introduction of the euro. Thus, with this model we are not only able to capture any possible time variation around business cycle phases, but also time variation caused by (possibly lengthy) structural changes (see Canova, Ciccarelli, and Ortega 2012).

The real variables included are the growth rates of (i) GDP, (ii) private consumption, (iii) gross fixed capital formation, (iv) the real effective exchange rate and (v) trade – defined as the average of export and import growth – which best capture the real business cycle and competitiveness. We include two types of financial variables: one representing financial prices, the other reflecting the situation in the lending market. More specifically, as regards financial prices we use: (vi) the term spreads in order to account for country risk, and the growth rates of (vii) real stock prices and (viii) real house prices. Finally, for loans we have used the growth rates of (ix) the loans-to-deposits ratio as a measure of bank leverage and (x) total outstanding nominal loans to the private sector deflated by the CPI, which we believe are most appropriate for representing the flow of lending into the economy.¹

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 (except for the term spreads, taken in levels), which are further standardized

¹ All results remained essentially unchanged when using the credit impulse instead of credit growth (not reported). The credit impulse (see Biggs, Mayer, and Pick 2009) is measured as the year-on-year difference of credit growth in any given quarter as a percentage of nominal GDP.

in order to obtain meaningful aggregations of these series given our model (see next section).

Our sample of ten countries covers the bulk of the developed world, namely the G7, which includes the biggest economies in the euro area, as well as other relevant European economies. More precisely, the five euro countries included are France, Germany, Ireland, Italy and Spain. Beyond the euro area, two other EU countries (Sweden and the UK) are included, as well as the three non-European G7 economies, namely the US, Canada and Japan.

2.2 The empirical model

The variables described interact in a panel VAR framework as developed by Canova and Ciccarelli (2009) and Canova, Ciccarelli, and Ortega (2007). The model has the following form:

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

where $i=1, \dots, N$ indicates countries, $t=1, \dots, T$ indicates time and L is the lag operator; y_{it} is a $G \times 1$ vector of variables for each i and $Y_t = (y'_{1t}, y'_{2t}, \dots, y'_{Nt})'$; $D_{it,j}$ are $G \times NG$ matrices for each lag $j=1, \dots, p$; e_{it} is a $G \times 1$ vector of random disturbances. As we use demeaned variables in this analysis we can omit the constant term.

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; smooth changes in business cycle characteristics could be attributed to once-and-for-all breaks, which given the historical experience would be hard to justify. Second, the dynamic relationships are allowed to be country-specific. This avoids heterogeneity biases, which could easily distort economic conclusions. Third, whenever the $NG \times NG$ matrix $D_t(L) = [D_{1t}(L), \dots, D_{Nt}(L)]'$ is not block diagonal for some L , cross-unit lagged interdependencies matter. This makes dynamic feedback across countries possible and greatly expands the type of interactions our empirical model can account for.

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

$$Y_t = Z_t \delta_t + E_t \quad (2)$$

where Y_t and E_t are $NG \times 1$ vectors of endogenous variables and of random disturbances, respectively, while $Z_t = I_{NG} \otimes X'_t$; $X'_t = (Y'_{t-1}, Y'_{t-2}, \dots, Y'_{t-p})$, $\delta_t = (\delta'_{1t}, \dots, \delta'_{Nt})'$ and δ_{it} are $Gk \times 1$ vectors containing, stacked, the G rows of matrix D_{it} . Since δ_t varies in different time periods for each country-variable pair, it would be dif-

difficult to estimate it using unrestricted classical methods. And even if δ_t were time invariant, its sheer dimension (there are $k=NGp$ parameters in each equation) could prevent any meaningful unconstrained estimation.

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

$$\delta_t = \Xi \theta_t + u_t \quad (3)$$

where Ξ is a matrix of zeros and ones, $\dim(\theta_t) < \dim(\delta_t)$, and u_t is a vector of disturbances with mean zero, capturing unmodeled features of the coefficient vector δ_t . The vector θ_t is partitioned in 2 sub-blocks. The first sub-block accounts for elements in the coefficient vector δ_t , which are common across countries (global factors) but specific for groups of (i) real, (ii) credit and (iii) price variables. The second sub-block accounts for elements in the coefficient vector δ_t , which are country specific. Formally, we consider the following specification:

$$\Xi \theta_t = \Xi_1 \theta_{1t} + \Xi_2 \theta_{2t} \quad (4)$$

where Ξ_1 is a matrix of dimensions $NGk \times 3$, and Ξ_2 is a matrix of dimensions $NGk \times N$. The components in θ_{1t} and θ_{2t} are mutually orthogonal factors of dimensions 3×1 and $N \times 1$, respectively.

Factoring δ_t as in (3) reduces the problem of estimating NGk coefficients into the one of estimating for example, $N+3$ factors characterizing their dynamics. The 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

$$Y_t = Z_t \theta_t + v_t \quad (5)$$

where $Z_t = Z_t \Xi$ and $v_t = E_t + Z_t u_t$.

From an economic point of view, the decomposition in (5) is convenient since it allows us to measure the relative importance of global and country-specific influences in explaining fluctuations in Y_t and provides their evolution over time. In fact, $Z_t \Xi_1 \theta_{1t}$ is a vector of global indicators and, specifically, if $\theta_1 = (\theta_{11}, \theta_{12}, \theta_{13})'$ and $\Xi_1 = (\Xi_{11}, \Xi_{12}, \Xi_{13})$, then $Z_t \Xi_{11} \theta_{11t}$ is a global real indicator, $Z_t \Xi_{12} \theta_{12t}$ is a global loan indicator, $Z_t \Xi_{13} \theta_{13t}$ is a global financial price indicator; whereas $Z_t \Xi_2 \theta_{2t}$ is a vector of country specific indicators. Note that these indicators are correlated by construction, as Z_t enters in all of them, but should become uncorrelated as the number of countries and variables in the panel becomes large. Since they are smooth linear functions of the lagged endogenous variables, such indices are in fact leading indicators of global and country trends.

Note that if the factorization (3) is not exact (that is, the variance of u_t is not zero) the error term v_t contains a heteroschedasticity of known form. as is

common practice in this context (Canova and Ciccarelli 2009), we impose an exact factorization but assume that the error term E_t has a Student's- t distribution with α degrees of freedom and scale matrix Ω :

$$E_t \sim t_{\alpha}(0, \Omega). \quad (6)$$

This assumption is convenient because a Student's- t distribution on the error term is a robustification of the usual Normal distribution with fatter tails. In fact, it can be shown that a Student's- t is a mixture of a Normal and an inverse gamma. In other words we can re-write (6) as

$$\begin{aligned} E_t | \sigma_t &\sim N(0, \sigma_t \Omega) \\ \sigma_t &\sim IG\left(\frac{\alpha}{2}, \frac{\alpha}{2}\right) \end{aligned}$$

Therefore, we can introduce a general form of heteroscedasticity by simply replacing the Normal assumption with a Student's- t on the error term (see e.g. Koop 2003). This simple assumption makes our model specification robust to time heteroscedasticity and is consistent with the findings of widespread literature that suggests that the volatility of shocks has changed numerous times over the last 40 years (see, e.g. Cogley, Primiceri, and Sargent 2010). Note that large values of α makes the Student's- t converge to a Normal distribution and σ_t collapse to its prior mean of 1. This parameter therefore determines the degree of heteroscedasticity in the data: with small posterior values of α the data would support a departure from normality and therefore a high degree of heteroscedasticity.

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

$$\theta_t = \theta_{t-1} + \eta_t, \quad \eta_t \sim N(0, \bar{B}) \quad (7)$$

and specify $\bar{B}$ as a block diagonal matrix. We also assume, as is customary, that E_t and η_t are 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.² The block diagonality of $\bar{B}$ guarantees orthogonality of the factors, which is preserved *a-posteriori*, hence their identifiability.

The model is estimated with Bayesian techniques. In the Appendix we illustrate it with a simple example and provide the estimation details by describing the chosen priors and deriving the posterior distributions.

² See also Primiceri (2005) for a discussion on alternative specifications.

3 Results

Before presenting the results, it would be worthwhile to report on some of our searches around the proposed benchmark specification for our empirical model.

We conducted a limited number of preliminary checks on the model to examine the various features included in the specification. Our choice is based on the marginal likelihood of the model, that is $f(Y|M_i) = \int L(y|\psi_i, M_i) p(\psi_i|M_i) d\psi_i$ where ψ_i are the parameters of the model i . Model i is preferred to model j if its marginal likelihood is higher or, equally, if the Bayes factor $BF(i, j) = f(Y|M_i)/f(Y|M_j)$ substantially exceeds 1. We compute the marginal likelihood using the harmonic mean (Kass and Raftery 1995).

The benchmark specification includes three global variable-type components and ten country-specific factors. (The three global variable-type components comprise: one shared by all real variables across countries; another shared by loan market variables across countries; and a third shared by real asset prices, the real effective exchange rate and the term spread across countries.) This specification was chosen for its highest marginal likelihood (ML=−5931) as well as for its ease of interpretation and comparability with previous studies.

A restricted version of this benchmark, which does not distinguish between financial prices and lending but instead merges all financial variables into one financial factor, yields a much lower marginal likelihood (ML=−5990). The resulting financial factor is mostly insignificant. The data also strongly reject the model in which countries are grouped according to the euro area, the EU non-euro area and the rest of the world (ML=−7442), as has been previously found in the literature (Canova, Ciccarelli, and Ortega 2007). As a matter of fact, in the light of the recent (financial and sovereign) crisis, which has revealed hidden fragmentation and country heterogeneity among euro area countries, the result interestingly suggests that it might not be appropriate to merge several country factors into just a few. Thus, the statistical evidence confirms the existence of country heterogeneity. Investigating the causes goes beyond the scope of this paper and would require a structural model. Nevertheless, the evidence does seem to point towards the existence of diverging business and financial cycles within and between countries. It may well be that the diverging cycles are reinforced by the heterogeneous transmission of shocks.

Another restricted version of the benchmark with no variable-type factors, that is, with only a single global component and a set of country-specific factors, was equally rejected by the data (ML=−5964). Although the global factor was found to be significant throughout the sample, the data is clearly modeled best with a richer specification.

The benchmark specification is also better than a more rich factorisation that includes one global component across all variables and countries beside the variable and country-specific factors ($ML = -6015$). We used this factorisation in a previous version of the paper: this indeed confirmed the existence of a statistically significant common factor linking real and financial series across all countries throughout several cycles (Ciccarelli, Ortega, and Valderrama 2012). The data, however, is best modeled with the restricted specification which in any case gives a more straightforward interpretation.

Regarding the lag structure, in all specifications the Schwarz's Bayesian information criterion favors a single lag for the VAR dynamics.

Finally, we report in the Appendix (Figure A.1) the posterior distribution of the parameter that determines the degree of heteroscedasticity in the data, α . In line with findings in recent literature, suggesting that the volatility of shocks has changed numerous times over the last 40 years, the mode of the posterior distribution is between 3 and 4, therefore indicating a strong departure from normality and a high degree of time heteroscedasticity.

In the rest of this section we report the results organized according to our initial three sets of questions, namely: (i) commonalities and heterogeneity in macro-financial linkages (Section 3.1); (ii) the cross-country transmission of shocks (Section 3.2); and (iii) the relative role of financial versus real factors as well as global versus country specific factors in the Great Recession with respect to previous crises (Section 3.3).

3.1 What role do global and country-specific factors play in explaining macro-financial linkages?

In this section, we use the empirical model to check if macro-financial linkages differ across countries and over time. In particular, we check whether there are significant common components in the macro-financial interactions across the main developed economies and/or whether country-specific heterogeneities matter more in explaining fluctuations in domestic variables.

As discussed above (see Section 2.2), three distinct global components are identified: one common to all financial prices (real stock prices, house prices and term spreads); one common to all real variables (GDP, private consumption, gross fixed capital formation, the real effective exchange rate and trade); and one common to lending markets (ratio of total loans to deposits and credit growth).

From a visual inspection of the three global factors, reported in Figure 1, several observations can be made.

Figure 1: Evolution of global factors over time.

The charts plot the variable factors across all countries expressed in standard deviations from the historical average of annual growth rates. The solid black line represents the posterior median of the estimated distribution for the common factor at each point in time. The two dotted lines limit the 68% Bayesian credible interval. This corresponds to $Z_{\frac{\alpha}{2}}\hat{\sigma}_{\epsilon_t}$ in the paper (Section 2.2). “Loans” is a common factor for bank leverage (loans to deposit ratio) and the flow of credit into the economy (measured as the y-o-y growth of total outstanding nominal loans to the private sector deflated by the CPI). The “Real variables” are growth rates of GDP, private consumption, gross fixed capital formation, real effective exchange rates and trade (average of export and import). “Financial prices” are bonds spreads, and the prices of stocks and of real estate deflated by CPI.

First, and as found elsewhere in the literature (see, e.g. Kose, Otrok, and Prasad 2008; Claessens, Kose, and Terrones 2011), we confirm the existence of statistically significant global factors (real and financial) across all countries

throughout several cycles. The panels in Figure 1 show the evolution of these common components, expressed as standard deviations from the historical averages of annual growth rates. Each of these components is statistically significant for most of the sample, that is, the 68% posterior confidence interval is above or below zero, which means that each type of variable features a significant common movement across countries, and their fluctuations are most pronounced in the 2008–2009 recession.

Second, the common financial prices component is also found to be significant throughout the whole sample despite the inclusion of the evolution over time of the term spread. The term spread may be counter-cyclical, while the other two variables – real house and real stock prices – are mostly pro-cyclical. This component is particularly significant during recessions and from the year 2000 until the financial crisis. This may be a reflection of deeper financial integration across developed economies, related perhaps to the introduction of the common currency in Europe.

Third, the global real component appropriately captures both a slack in the early 1980s and the recession of the early 1990s and also identifies a recession in the years 2001–2002. It is noteworthy that the most recent global crisis appears to be by far the largest common fluctuation across countries and variables. Moreover, the posterior uncertainty is remarkably low towards the end of the sample, including the 2008–2009 recession as well as the incipient signs of a double dip recession in 2011. This finding of a significant global real component is in line with the international business cycle literature, which often finds stronger comovement among real aggregates both within and across countries (e.g. Crucini, Kose, and Otrok 2011).

Fourth, the global lending component is also very significant throughout the sample, in recessions as well as in expansions, showing a lending cycle that mimics the business cycle. In fact, unconditional lead-lag cross-correlations among the two estimated components confirm that the global real component leads the global lending component with a correlation peak of 0.62 at a three-quarter lead. This is a remarkable result which confirms and qualifies the common understanding that amplification mechanisms between macroeconomic fluctuations and financial constraints are in place at a global level (see Kiyotaki 1998; Claessens, Kose, and Terrones 2011). This pattern between real and lending variables changed during the last recession, when, unlike in previous recessions, the loans component started falling as early as in 2007 – that is, 1 year before the real component – coinciding with the tightening of credit supply as documented by, for example, the euro area Bank Lending Survey (BLS). It then dropped further after 2009, consistent with both the credit demand and supply

reductions reported in the BLS, and thus contributing to the dramatic fall in the real component.³

Fifth, both the loans and the real component also show the double dip recession that the world economy experienced in 2011, coinciding with the worsening European sovereign debt crisis. The charts confirm how, from a historical perspective, the last recession was particularly unique for both the financial and the real sectors of the world economy. It produced a much larger fluctuation compared with those observed in the preceding three decades for real variables, and a more persistent one for lending.

Finally, the analysis by global variable types confirms the leading nature of financial prices. We find that the common factor of financial prices leads fluctuations in both real and credit variables.⁴ In fact, in most recessions financial prices are usually the first to recover, followed by real variables, while the lending market is the last to recover, which is in line with stylised facts of the business cycle. Simple lead-lag cross-correlations among the three estimated factors suggest that financial prices lead real activity by three to four quarters and the loan market by five quarters, with a correlation peak at 0.5 in both cases.

Despite these findings at the global level, the country-specific component in fluctuations of real and financial variables remains significant. Figure 2 shows the country-specific components in our sample, which are very precisely estimated. The charts show that countries differ substantially in terms of the intensity and duration of their cycles and also, in some cases, in the timing of the phases. There are countries in which the fluctuations common to their own real and financial series, as shown by the 68% confidence intervals, lie well above zero in a particular period. In other countries, they are zero or even negative for the same period. The differences in the joint evolution of real and financial series across countries could be an indication of periods of non-synchronized business cycles across countries. The existence of such heterogeneity could be caused, for example, by the presence in one country of a financial bubble otherwise absent in another, while in other countries the business cycle is only being driven by real economic developments.

It is also interesting to note the difference in behavior of national factors relative to common factors. For instance, the intensity of the crisis during the early 1990s was very strong in Sweden, which was suffering a banking crisis that not only lasted longer than the recessions in the UK, US and Canada, but also started earlier than the European Exchange Rate Mechanism (ERM) crisis. On the other

³ Ciccarelli, Maddaloni, and Peydró (2015) found similar results with a Panel VAR model for euro area countries using similar macro data as well as BLS indicators of credit supply and demand over 2007–2010.

⁴ Giannone, Lenza, and Reichlin (2010) obtain similar results albeit with a different methodology.

Figure 2: Evolution of country factors over time.

The charts plot the country factors of all macroeconomic and financial variables expressed in standard deviations from the historical average of annual growth rates. The solid black line represents the posterior median of the estimated distribution for the common factor at each point in time. The two dotted lines limit the 68% Bayesian credible interval. These factors correspond to $Z_t \Xi_{2,t}$ in the paper (Section 2.2).

hand, the recession in 2001 was strong in Japan and France compared to other countries. As with the previous recession, the US and Sweden also experienced this recession earlier than euro area member countries.

Another point of interest is the long period of almost uninterrupted growth (financial and real) in Ireland and Spain prior to the sharp fall in both their economies during the Great Recession. This contrasts with the stagnation of the Italian economy during most of that same period and with the clear underperformance of the Japanese economy throughout the last two decades.

3.2 How important is the cross-country transmission of shocks?

In this section, we aim to look further into these linkages. We also consider whether these co-movements reflect significant spillovers between financial and real variables across countries or whether they are just the coincidence of simultaneous shocks. Also of interest is examining whether the spillovers of shocks across countries are greater if they are financial or real in origin. Finally, we look at whether the international transmission of shocks has changed during the great recession.

Modeling both real and financial series for several countries within the same empirical model makes it possible to understand better the role of cross-country spillovers in the linkages between financial and real variables. Thus, within the same panel VAR framework used to estimate the global and country factors, we compute some counterfactual impulse responses. This allows to determine how changes in a particular variable in a given country affect other variables in other countries.

To work out the impact of these spillovers, we compute impulse response functions as the difference between a conditional and an unconditional projection of, for example, GDP growth for each country in a given period. The unconditional projection is the model projection for GDP growth for that period based only on historical information and consistent with a model-based forecast path for the other variables. The conditional projection for GDP growth is the one the model would have obtained over the same period conditionally on the actual path of another variable, such as US stock prices, for that period. The difference between an unconditional forecast of US stock prices and their actual path over that horizon defines a shock to US stock prices.⁵

⁵ The approach is obviously not immune to Lucas' critique. However, in the context here, the short forecast horizons and the time-varying estimation – which makes the parameter structure change each quarter – should make results less subject to the critique. For similar counterfactuals see also Giannone, Lenza, and Reichlin (2012).

Clearly, the notion of shock here must be taken *cum grano salis*, for there is no identification of structural shocks as is often the case in the VAR literature. Furthermore the actual movement of the conditioning variables over the forecast horizon could be due to a variety of reasons. Nonetheless, this counterfactual exercise is helpful in answering certain questions. For example, based on actual US stock price developments as compared to a prediction based on the historical path of US stock prices, what rate of GDP growth would the model have predicted? Thus, the method provides a measure of the shock based on what actually occurred, with the defined shock starting at the observed peak of the series (US stock prices in this example) and lasting until its observed trough. The dating is somewhat arbitrary and differs across variables and countries. We report only the median impulse responses to highlight the heterogeneity across countries. The same responses with 90% Bayesian credible intervals are also reported in the Appendix for each country and time period (Figures A2–A7).

We first investigate whether negative shocks in the US, both in the financial and real sectors, were transmitted to real activity in the other countries in our sample. Moreover, by looking at three different periods, we can observe whether the extent of the spillover has changed over time.

Figure 3 shows the counterfactual responses of GDP growth in all countries to shocks that moved GDP in the US at three different points in time, which coincide with the start of the last three recessions in the US. The extent of cross-country interdependence is clear from the chart, as the fall in US GDP growth beyond the unconditional forecast (units are standard deviations of the demeaned series) causes a substantial fall in the real economy in every other country, although the reaction is always less pronounced than it is in the US. As expected, the spillover varies in intensity across countries, with Canada and the UK showing a larger response, reflecting their deeper economic linkages to the US, while Spain, Germany and Ireland show the smallest responses.⁶

It is also interesting to note that the size of the shock and the responses vary over time, with the latest recession showing both the largest shock and the largest responses. But neither the ranking of the spillovers of the US shock to other economies nor the proportionality of the responses to the shock have changed much over time. Indeed, the lower panel of Figure 3 shows the same responses as in the upper panel re-scaled by the size of the movement in US GDP (peak to trough) in each of the three periods of recession. As can be clearly seen, the intensity of the spillovers does not seem to have changed over time: however, it is the shock that has been more intense in the 2008–2009 recession. This result is consistent, for example, with Stock and Watson (2012) who, using a large scale dynamic factor

⁶ Figure A2 in the Appendix confirms that most GDP responses are significantly below zero.

Figure 3: GDP responses to US GDP shock.

The charts report counterfactual responses computed as the difference between a conditional and an unconditional projection of GDP growth for each country in a given period. The unconditional projection is the one the model would have obtained for GDP growth for that period based only on historical information, and consistent with a model-based forecast path for the other variables. The conditional projection for GDP growth is the one the model would have obtained over the same period conditionally on the actual path of US GDP growth for that period. The upper panel shows the responses of GDP growth in all countries to a US GDP shock at three different points in time. The lower panel shows the same responses re-scaled by the size of the “shock” to US GDP in each of the three recession episodes.

model for the US, find that the last recession could be characterized by a larger version of shocks previously experienced, to which the economy responded in a predictable way.

Figure 4 shows the GDP responses to a shock that negatively affected the stock market in the US at different points in time. The country responses are in general on a smaller scale than those to a US real shock (see Figure 4). However, the difference between the US response and those of the other countries is smaller than in the previous case. This could be taken as an indication that US financial shocks generate larger international spillovers than do real ones. Rescaling the GDP responses by the size of the shock as before, the lower panel of Figure 4 seems to show that there is no discernible change in the pattern of international transmission over time, with UK and Sweden reacting slightly more than all other countries.

3.2.1 How important are financial factors compared with real factors in the transmission of shocks?

In what follows, we study the spillover effects during selected episodes of intense deviations observed in the growth rate of real or financial series in other countries. The aim is to determine whether there is a pattern in the spillovers, such as increased intensity if the shock originates in a particular type of variable (e.g. financial versus real) or a particular country.

As for the real shocks, Figure 5 reports the GDP responses to the very country-specific downturn in Japan at the end of the 1990s, while Figure 6 shows the spillovers of the German recession in 2002. As expected, in both cases the country in which the shock originated transpires to be the one showing the largest response. However, in all other countries there is a significant and negative response to the unexpected contraction in economic activity in Japan or Germany and, as would be expected given our sample, the response to a German shock is slightly greater. The same partial transmission is observed for a positive real shock, such as the strong growth observed in private consumption in the UK in 1987–1988, which shows a similar (positive) response in all other countries (not reported). Nevertheless, the response is of course much smaller in the other countries. The response in the US to these shocks is surprisingly large and mostly significant, suggesting that our model also captures indirect effects (see Figures A4 and A5 in the Appendix).

We turn now to different periods of shocks to financial variables observed in different countries. Figure 7 reports the counterfactual responses of GDP growth and of total credit growth across countries to the unexpected credit contraction

Figure 4: GDP responses to US stock price shock.

The charts report counterfactual responses computed as the difference between a conditional and an unconditional projection of GDP growth for each country in a given period. The unconditional projection is the one the model would have obtained for GDP growth for that period based only on historical information, and consistent with a model-based forecast path for the other variables. The conditional projection for GDP growth is the one the model would have obtained over the same period conditionally on the actual path of US stock prices for that period. The upper panel shows the responses of GDP growth in all countries to a US stock price shock at three recessive episodes. The lower panel shows the same responses re-scaled by the size of the “shock” to US stock prices in each of the three periods.

Figure 5: GDP responses to Japanese GDP shock.

The chart reports countefactual responses computed as the difference between a conditional and an unconditional projection of GDP growth for each country over the period 1997:4–2000:1. The unconditional projection is the one the model would have obtained for GDP growth for that period based only on historical information, and consistent with a model-based forecast path for the other variables. The conditional projection for GDP growth is the one the model would have obtained over the same period conditionally on the actual path of Japan's GDP growth for that period.

in Sweden in the early 1990s. Although the spillover of this particular shock to real activity is not long-lasting and mostly insignificant even in the originating country, the shock had significant negative spillovers to credit markets in other countries.

Similar responses are obtained with regard to a positive shock to the stock market in Spain that occurred when the country joined the European Community in 1986Q2 (see Figure 8). While GDP responses are not economically significant, even in Spain, the temporary boom in the Spanish stock market was transmitted to stock markets of other developed economies, although with less intensity than might have been expected.

We find more or less the same pattern across the countries in our sample for other periods of financial shocks, such as housing price booms (e.g. the UK in 1986–1987) or busts (e.g. in Spain and Ireland from 2007 onwards). In all cases, we find partial but more economically and statistically significant spillovers to the same financial variable in other countries than to their real economy, even in the country of origin.

In sum, and as expected, we find not only that spillovers matter, but also that the international transmission of a shock may be faster and deeper between

Figure 6: GDP responses to German GDP shock.

The chart reports counterfactual responses computed as the difference between a conditional and an unconditional projection of GDP growth for each country over the period 2001:2–2003:4. The unconditional projection is the one the model would have obtained for GDP growth for that period based only on historical information, and consistent with a model-based forecast path for the other variables. The conditional projection for GDP growth is the one the model would have obtained over the same period conditionally on the actual path of Germany's GDP growth for that period.

financial variables than between real variables. On the other hand, it seems that for a shock to a financial variable to affect significantly the real economy elsewhere, that shock needs to be either common to all countries or to have originated in a systemic country, as could be seen in the case of shocks to the US stock market. Thus, shocks to financial variables in small countries do not affect the real economy much, whereas a financial shock that occurs in the US tends to affect the real economy not only in the US but elsewhere, too. This is in line with, for example, Eickmeier and Ng (2011), who find that negative credit supply shocks in the US have stronger negative effects on domestic and foreign GDP than do those which originated in other countries or areas such as the euro area and Japan.

Finally, we also find that, concerning the spillovers or transmission of shocks, the last recession has been very similar to past recessions except in terms of the size of the shock. These results are obtained with a non-structural model which allows for a general form of stochastic volatility – hence, one should not go too far in interpreting them. However, this last finding could indicate that larger co-movements or macro-financial linkages observed worldwide in the last recession

Figure 7: Responses to Swedish credit shock.

The charts report counterfactual responses computed as the difference between a conditional and an unconditional projection of GDP growth (upper panel) and credit growth (lower panel) for each country over the period 1990:1–1992:3. The unconditional projection is the one the model would have obtained for each variable for that period based only on historical information, and consistent with a model-based forecast path for the other variables. The conditional projection is the one the model would have obtained over the same period conditionally on the actual path of Sweden's credit growth for that period.

could, relative to previous recessions, be more closely related to the size of the shocks than to the intensification of their international transmission (see Stock and Watson 2012).

Figure 8: Responses to Spanish stock price shock. The charts report counterfactual responses computed as the difference between a conditional and an unconditional projection of GDP growth (upper panel) and stock prices (lower panel) for each country over the period 1985:3–1987:4. The unconditional projection is the one the model would have obtained for each variable for that period based only on historical information, and consistent with a model-based forecast path for the other variables. The conditional projection is the one the model would have obtained over the same period conditionally on the actual path of Spain’s stock prices for that period.

3.3 What mattered more in the last recession?

The sections above provide evidence of the existence of both real and financial factors that are common across a selection of developed economies. To comple-

Figure 9: Historical decomposition.

Sample 2005:1–2011:4.

The charts report historical decompositions based on the estimation of a country by country factor-augmented VAR for GDP growth and the three variable-type components displayed in Figure 1, which capture the common movements of financial prices, real activity and lending markets across countries. The decomposition shows the dynamic contributions of the different common components to GDP growth for each country in the sample over the period 2005:1–2011:4 and illustrates how much of the unexpected GDP growth in a given country is explained by the variable-type components that are common to all countries.

ment this analysis, this section aims to gage the relative weight of real and financial common factors in explaining real fluctuations across countries and over time. This is carried out by means of auxiliary historical decompositions, which answer the question of whether the real component of this common evolution matters more than the financial component in explaining GDP developments.

In order to answer this question, we estimate a country-by-country factor-augmented VAR for GDP growth and the three variable-type components displayed in Figure 1, these capture the common movements of financial prices, real activity and lending markets across countries. We then compute the dynamic contributions of the different common components to GDP growth for each country in the sample. Thus, we show how much of the unexpected GDP growth in a given country is explained by the variable-type components that are common to all countries. For the identification in this auxiliary VAR we use a simple Choleski and order the common factors first, followed by the country GDP. Among the factors, the ordering is consistent with the finding discussed in section 3 with financial prices placed first, followed by the real variables and the loans.⁷

Figure 9 shows this historical decomposition exercise for the 2005–2011 period. It is worth noting the large size of the common component, as captured by the sum of the contributions of the three variable-type factors to GDP growth fluctuations. Obviously, the relative weight of each of the three common factors changes across countries and over time. In particular, at the beginning of the last recession, the financial factors (see the bar in green bar and the bar in red, which represent financial prices loan markets, respectively) dominated, while the real component (the bars in blue) became more important as the recession

⁷ Note that the shock identification in multi-country models is still an area open to research. Therefore, studying the contributions of these factors directly in the full panel VAR is not feasible. For this reason, historical decompositions are computed in a second step for each country, following the idea and definition of factor-augmented VAR (FAVAR) introduced by Bernanke, Boivin, and Elias (2005). See also Canova and Ciccarelli (2012) for a similar FAVAR application to compute historical decompositions with the same model used here.

deepened. Nevertheless Stock and Watson (2012), when using a different methodology, also find that the shocks in the last recession were mainly associated with financial disruptions and heightened uncertainty. The real common downturn is very relevant in explaining the most recent recession, especially in the case of Japan, Germany, Italy or Canada, but gained momentum towards the end of the recession in all other countries, too. Despite all this, the common financial factors are also of relevance, confirming the widespread belief that GDP growth would have been much higher (that is, less negative) without the financial crisis. Comparing the role of the financial prices factor to the loan markets factor, we see that asset prices in most countries are more relevant in explaining the downturn, while the loan market factor played a role at the beginning of the recession, especially in Ireland, and was fairly relevant in explaining strong GDP growth pre-crisis in some countries such as Spain and Ireland, as would be expected.

Figures 10 and 11 show the same dynamic contributions for the periods that include the two previous recessions. Compared to the last recession, previous recessions had a smaller common component, be it of a real or financial nature, as can be seen by the larger size of the idiosyncratic components (see the bars in purple). This is not surprising, since the downturns of the early 1990s and of the early 2000s were much less synchronized than the 2008–2009 recession. Still, the common components undoubtedly played a role in previous recessions, especially the financial factors (see red and green bars), while the common real component was less relevant than in the 2008–2009 recession. A distinctive feature of the great recession, thus, seems to have been the large common real downturn across developed economies.

4 Summary of results and discussion

Summing up, the evidence found confirms the need to allow for cross-country and cross-variable interdependence when modeling real financial linkages. An empirical model that includes real and financial variables for the G7 as well as other European economies identifies statistically significant common real and financial components, which were especially evident during the Great Recession. As with other recessions, financial prices drop before the crisis sets in, while the loan market lags all other variables. We also find that, noticeably more than in previous recessions, real variables registered the greatest fall. However, country-specific factors remain very important, which is consistent with the heterogeneous behavior observed across countries.

Figure 10: Historical decomposition.

Sample 1999:1–2004:4.

The charts report historical decompositions based on the estimation of a country by country factor-augmented VAR for GDP growth and the three variable-type components displayed in Figure 1, which capture the common movements of financial prices, real activity and lending markets across countries. The decomposition shows the dynamic contributions of the different common components to GDP growth for each country in the sample over the period 1999:1–2004:4 and illustrates how much of the unexpected GDP growth in a given country is explained by the variable-type components that are common to all countries.

Figure 11: Historical decomposition.

Sample 1990:1–1994:4.

The charts report historical decompositions based on the estimation of a country by country factor-augmented VAR for GDP growth and the three variable-type components displayed in Figure 1, which capture the common movements of financial prices, real activity and lending markets across countries. The decomposition shows the dynamic contributions of the different common components to GDP growth for each country in the sample over the period 1990:1–1994:4 and illustrates how much of the unexpected GDP growth in a given country is explained by the variable-type components that are common to all countries.

Spillovers across countries are important drivers of macro-financial linkages. A shock to a real or financial variable in a given country is transmitted to all other countries (in our sample), albeit only partially and heterogeneously. These international spillovers seem to be faster and deeper between financial variables than between real variables. On the other hand, it seems that for a shock to a financial variable to affect significantly the real economy elsewhere that shock needs to be either common to all countries or to have been originated in a systemic country, as is the case with shocks to the US stock market.

We also find that while the Great Recession features the largest real and financial shocks in our sample, their spillovers are similar to those observed during previous recessions. Finally, we find that all recessions have a common and an idiosyncratic component. The common evolution was intensified in the more recent crisis, not only in its financial dimension but especially in its real dimension.

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 identifies significant effects of both country-specific and global factors in driving world cyclical fluctuations. This phenomenon seems to be a robust feature of the data, that is, it is not limited to countries in any particular geographic region, and is not a mechanical effect of crises episodes (see Kose, Otrok, and Prasad 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 also consistent with previous studies, although the joint estimation performed in this paper, which covers a number of countries and allows for interdependencies, might capture linkages that are stronger than those obtained in a country-by-country VAR analysis.

These results also carry considerable implications for theoretical models of the international business cycles as well as for policy-making. From a modeling perspective, the data appear to favor models that assign a prominent role to the international dimension, with countries endogenously reacting to foreign impulses. Also, time variation suggests important asymmetries in the shape and the dynamics of international cycles, such that linear models may miss policy-relevant features of the data.

From a policy perspective, some considerations are worth mentioning. First, despite substantial heterogeneity, countries share common financial shocks, suggesting that international financial markets are key to understanding co-movements in economic activity. Therefore, policy-makers should monitor developments in foreign financial markets. Second, since national

policy affects the national and not the common component, national authorities may be tempted to design domestic policies so as to counteract the effects caused by world conditions. However, the intense cross-country interdependencies may render such policies ineffective or, even worse, counter-productive to the domestic economy.

Clearly, these considerations instantly raise interesting questions that this paper has intentionally 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 still faces 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 real and financial variables 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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Appendix A. Data Appendix

The data used was collected by the Working Group on Econometric Modeling of the Eurosystem of Central Banks (ESCB) and used in Hubrich et al. (2013). It is available upon request under a confidentiality agreement.

Variable	Sources
Consumer prices	OECD, Eurostat, IMF, ECB
Gross Domestic Product (real)	OECD, Eurostat, NCB data
Gross Domestic Product (nominal)	OECD, Eurostat, NCB data
Private Final Consumption (real)	OECD, Eurostat, NCB data
Gross Capital Formation (real)	OECD, Eurostat, NCB data
3-month (interbank) interest rate	OECD, IMF, ECB
Export volumes	IMF DOTS
Import volumes	IMF DOTS
10-year government bond rate	OECD, IMF, ECB
Stock prices	OECD, IMF, ECB, NCB calculations
House prices	OECD, ECB, NCB
Term spread (10 year–3 month rates)	Own calculations
Real effective exchange rate	ECB
10-year government bond yields	ECB,
3-month Euribor	ECB
Loan/Deposit ratio	Own calculations
Loan	ECB, IFS
Deposits	ECB, IFS
Credit growth	ECB, IFS, own calculations (see below)

For euro area countries the data source is ECB, while for non-euro area countries data comes either from OECD or IMF. Note that all nominal variables (other than interest rates) were deflated by CPI prior to the calculation of year-on-year growth rates.

Appendix B. Model features

B.1 A simple example

To illustrate the structure of the matrices Ξ 's and of $\mathcal{Z}_{it}$, let us assume there were $G=2$ variables for each of $n=2$ countries and that the Panel VAR has $p=1$ lags and no intercept:

$$\begin{bmatrix} y_t^1 \\ x_t^1 \\ y_t^2 \\ x_t^2 \end{bmatrix} = \begin{bmatrix} d_{1,1,t}^{1,y} & d_{2,1,t}^{1,y} & d_{1,2,t}^{1,y} & d_{2,2,t}^{1,y} \\ d_{1,1,t}^{1,x} & d_{2,1,t}^{1,x} & d_{1,2,t}^{1,x} & d_{2,2,t}^{1,x} \\ d_{1,1,t}^{2,y} & d_{2,1,t}^{2,y} & d_{1,2,t}^{2,y} & d_{2,2,t}^{2,y} \\ d_{1,1,t}^{2,x} & d_{2,1,t}^{2,x} & d_{1,2,t}^{2,x} & d_{2,2,t}^{2,x} \end{bmatrix} \begin{bmatrix} y_{t-1}^1 \\ x_{t-1}^1 \\ y_{t-1}^2 \\ x_{t-1}^2 \end{bmatrix} + e_t \quad (8)$$

Here $\delta_t = [d_{1,1,t}^{1,y}, d_{2,1,t}^{1,y}, d_{1,2,t}^{1,y}, d_{2,2,t}^{1,y}, d_{1,1,t}^{1,x}, d_{2,1,t}^{1,x}, d_{1,2,t}^{1,x}, d_{2,2,t}^{1,x}, d_{1,1,t}^{2,y}, d_{2,1,t}^{2,y}, d_{1,2,t}^{2,y}, d_{2,2,t}^{2,y}, d_{1,1,t}^{2,x}, d_{2,1,t}^{2,x}, d_{1,2,t}^{2,x}, d_{2,2,t}^{2,x}]'$ is a (16×1) vector containing the time varying coefficients of the model. Note that the typical element of δ_t , $\delta_{t,s,t}^{i,j}$, is indexed by the country i , the variable j , the variable in an equation l (independent of the country) and the country in an equation s (independent of the variable).

Assuming a factorization with one global, two country specific and two variable components, the VAR (8) can be rewritten as

$$\begin{bmatrix} y_t^1 \\ x_t^1 \\ y_t^2 \\ x_t^2 \end{bmatrix} = \begin{bmatrix} Z_{1t} \\ Z_{1t} \\ Z_{1t} \\ Z_{1t} \end{bmatrix} \theta_{1t} + \begin{bmatrix} Z_{2t}^1 & 0 \\ Z_{2t}^1 & 0 \\ 0 & Z_{2t}^2 \\ 0 & Z_{2t}^2 \end{bmatrix} \theta_{2t} + \begin{bmatrix} Z_{3t}^1 & 0 \\ 0 & Z_{3t}^2 \\ Z_{3t}^1 & 0 \\ 0 & Z_{3t}^2 \end{bmatrix} \theta_{3t} + v_t \quad (9)$$

where $Z_{1t} = y_{t-1}^1 + x_{t-1}^1 + y_{t-1}^2 + x_{t-1}^2$, $Z_{2t}^1 = y_{t-1}^1 + x_{t-1}^1$, $Z_{2t}^2 = y_{t-1}^2 + x_{t-1}^2$, $Z_{3t}^1 = y_{t-1}^1 + y_{t-1}^2$, $Z_{3t}^2 = x_{t-1}^1 + x_{t-1}^2$. In the empirical application, all variables are measured in standardized and demeaned growth rates and therefore this type of averaging will indeed be appropriate. Note that if θ_{1t} is large relative to θ_{2t} , y_t^1 and x_t^1 comove with y_t^2 and x_t^2 . On the other hand, if θ_{1t} is zero, y_t^1 and x_t^1 may drift apart from y_t^2 and x_t^2 . In the general case when $p > 1$, lags could be weighted using a decay factor in the same spirit as Doan, Litterman, and Sims (1984).

B.2 Model estimation

If we assume an exact factorization for δ , the empirical model has the following state space hierarchical structure:

$$\begin{aligned} Y_t &= (Z_t \Xi) \theta_t + v_t \\ v_t | \sigma_t &\sim N(0, \sigma_t \Omega) \\ \theta_t &= \theta_{t-1} + \eta_t \\ \eta_t &\sim N(0, \bar{B}) \end{aligned}$$

Bayesian estimation requires the specification of further prior assumptions.

B.2.1 Prior information

We follow Chib and Greenberg (1995) to derive the posterior distributions of the parameter of interest. We first collect in the vector $\phi_0 = (\Omega^{-1}, \bar{B}, \sigma_t, \alpha)$ the unknown

parameters for which we assume a prior distribution conditional on $\{\theta_t\}_{t=0}^T$. We set $\bar{B}_i = b_i I_r$, $i=1, \dots, r$, where b_i controls the tightness of factor i in the coefficients and assume independence throughout, that is

$$p(\phi_0) = p(\Omega^{-1}) \prod_i p(b_i) \prod_t p(\sigma_t) p(\alpha)$$

We then assume the following prior distributions

$$\begin{aligned} p(\Omega^{-1}) &= W(z_1, Q_1^{-1}) \\ &\propto |\Omega^{-1}|^{(z_1 - ng - 1)/2} \exp\left(-\frac{1}{2} \text{tr}(Q_1 \Omega^{-1})\right) \\ \sigma_t &\sim IG\left(\frac{\alpha}{2}, \frac{\alpha}{2}\right) \\ &= \frac{(\alpha/2)^{\alpha/2}}{\Gamma(\alpha/2)} \sigma_t^{-(\alpha/2+1)} \exp\left[-\frac{\alpha}{2\sigma_t}\right] \\ p(b_i) &= IG\left(\frac{\varpi_0}{2}, \frac{S_0}{2}\right) \\ &\propto b_i^{-\left(\frac{\varpi_0}{2}+1\right)} \exp\left(-\frac{S_0}{2b_i}\right) \\ p(\alpha) &= \text{Expon}\left(\frac{1}{\varphi}\right) \\ &= \frac{1}{\varphi} \exp\left(-\frac{\alpha}{\varphi}\right) \end{aligned}$$

where $\propto$ means proportionality, W stands for Wishart, IG for inverse gamma and Expon for exponential distributions.

The hyperparameters $(z_1, Q_1, \varpi_0, S_0, \varphi)$ are known and their values are either obtained from the data to tune the prior to the specific application (this is the case for Q_1) or selected a-priori to produce relatively loose priors (this is the case for $z_1, \varpi_0, S_0, \varphi$). The values used are: $z_1 = NG + 5$, $Q_1 = \hat{Q}_1$, $\varpi_0 = 10^5$, $S_0 = 1.0$, and $\varphi = 20$. Here $\hat{Q}_1$ is a block diagonal matrix $\hat{Q}_1 = \text{diag}(Q_{11}, \dots, Q_{1N})$ and Q_{1i} is the estimated covariance matrix of the time invariant version for each country VAR.

B.2.2 Posterior distributions

The posterior distribution of $\phi_0 = (\Omega^{-1}, b_i, \sigma_t, \alpha)$ (conditional also on $\{\theta_t\}_{t=0}^T$) is proportional to the product of the prior and the likelihood of the data, i.e.

$$\begin{aligned}
p(\phi_0 | Y^T, \{\theta_t\}_{t=0}^T) &\propto \prod_t |\sigma_t \Omega|^{-1/2} \exp \left[-\frac{1}{2} \sum_t (Y_t - Z_t \Xi \theta_t)' (\sigma_t \Omega)^{-1} (Y_t - Z_t \Xi \theta_t) \right] \\
&\times \prod_t \frac{(\alpha/2)^{\alpha/2}}{\Gamma(\alpha/2)} \sigma_t^{-(\alpha/2+1)} \exp \left[-\frac{\alpha}{2\sigma_t} \right] \\
&\times \prod_i |b_i I_i|^{-T/2} \exp \left[-\frac{1}{2} \sum_i (\theta_t^i - \theta_{t-1}^i)' (b_i I)^{-1} (\theta_t^i - \theta_{t-1}^i) \right] \\
&|\Omega^{-1}|^{(z_i - ng - 1)/2} \exp \left(-\frac{1}{2} \text{tr}(Q_1 \Omega^{-1}) \right) \\
&\times \prod_i b_i^{\left(\frac{\varpi_0}{2} + 1\right)} \exp \left(-\frac{S_0}{2b_i} \right) \\
&\times \frac{1}{\varphi} \exp \left(-\frac{\alpha}{\varphi} \right)
\end{aligned}$$

where $Y^T = (Y_1, \dots, Y_T)$ denotes the data.

For the model we use, it is impossible to compute $p(\phi_0 | Y^T, \{\theta_t\}_{t=0}^T)$ analytically. A Monte Carlo technique which is useful in our context is the Gibbs sampler, since it only requires knowledge of the full conditional posterior distribution of ϕ_0 . Denoting $\phi_{-\kappa}$ the vector ϕ_0 excluding the parameter κ , it can be shown that the full conditional distributions are as follows

$$\begin{aligned}
\Omega^{-1} | Y^T, \phi_{-\Omega}, \{\theta_t\}_{t=0}^T &\sim \text{Wi} \left(z_1 + T, \left[\sum_t \frac{(Y_t - Z_t \Xi \theta_t)(Y_t - Z_t \Xi \theta_t)'}{\sigma_t} + Q_1^{-1} \right]^{-1} \right) \\
b_i | Y^T, \phi_{-b_i}, \{\theta_t\}_{t=0}^T &\sim \text{IG} \left(\frac{\varpi^i}{2}, \frac{\sum_t (\theta_t^i - \theta_{t-1}^i)' (\theta_t^i - \theta_{t-1}^i) + S_0}{2} \right) \\
\sigma_t | Y^T, \phi_{-\sigma_t}, \{\theta_t\}_{t=0}^T &\sim \text{IG} \left(\frac{\alpha + NG}{2}, \frac{(Y_t - Z_t \Xi \theta_t)' \Omega^{-1} (Y_t - Z_t \Xi \theta_t) + \alpha}{2} \right) \\
\alpha | Y^T, \phi_{-\alpha}, \{\theta_t\}_{t=0}^T &\propto \left(\frac{\alpha}{2} \right)^{T\alpha/2} \Gamma(\alpha/2)^{-T} \exp \left[-\alpha \left(\frac{1}{\varphi} + \frac{1}{2} \sum_i [\ln \sigma_t + \sigma_t^{-1}] \right) \right]
\end{aligned}$$

where $\varpi^i = K + \varpi_0$ and $K = T$, if $i=1$, $K = Tg$, if $i=2$, $K = TN$, if $i=3$, etc. Note that the conditional distribution of α is not standard and a Metropolis step should be included within the Gibbs algorithm (see e.g. Koop 2003, for details).

Finally, the simulation of θ_t given the other parameters is derived following Chib and Greenberg (1995). It can be shown that the conditional posterior distribution is given by

$$\theta_t | Y^T, \phi_{-\theta_t} \sim N(\bar{\theta}_{t|T}, \bar{R}_{t|T}) \quad t \leq T$$

where $\bar{\theta}_{t|T}$ and $\bar{R}_{t|T}$ 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). In particular, given θ_0 and R_0 the Kalman filter gives the recursions

$$\begin{aligned}\theta_{t|t} &= \theta_{t-1|t-1}^* + (R_{t-1|t-1}^* \mathcal{Z}_t' F_t^{-1})(Y_t - \mathcal{Z}_t \theta_{t-1|t-1}^*) \\ R_{t|t} &= (I - (R_{t-1|t-1}^* \mathcal{Z}_t' F_t^{-1}) \mathcal{Z}_t)(R_{t-1|t-1}^* + \bar{B}) \\ F_{t|t-1} &= \mathcal{Z}_t R_{t-1|t-1}^* \mathcal{Z}_t' + \Upsilon_t\end{aligned}\quad (10)$$

where $\theta_{t-1|t-1}^*$ and $R_{t-1|t-1}^*$ are, respectively, the mean and the variance covariance matrix of the conditional distribution of $\theta_{t-1|t-1}$. To obtain a sample $\{\theta_t\}$ from the joint posterior distribution $(\theta_1, \dots, \theta_T | Y^T, \varphi_{-\theta T})$, the output of the Kalman filter is used to simulate θ_T from $N(\theta_{T|T}, R_{T|T})$, θ_{T-1} from $N(\theta_{T-1}, R_{T-1})$, and θ_1 from $N(\theta_1, R_1)$, where $\theta_t = \theta_{t|t} + R_{t|t} R_{t+1|t}^{-1} (\theta_{t+1} - \theta_{t|t})$, and $R_t = R_{t|t} - R_{t|t} R_{t+1|t}^{-1} R_{t+1|t}$. The recursions can be started choosing R_0 to be diagonal with elements equal to small values, while θ_0 is estimated with OLS on a time invariant version of (1) over the entire sample.

Under regularity conditions (see Geweke 2000), cycling through the conditional distributions above produces in the limit 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 68% interval for the common indicator is obtained ordering the draws of $Z_{1t} \theta_{1t}$ for each t and taking the 16th and the 84th percentile of the distribution. The results we present are based on chains with 150,000 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 .

Figure A1: Posterior distribution of α .

The chart plots the posterior degrees of freedom of the Student's-t distribution of the reduced-form innovations, Eq. (6) Section 2.2.

Figure A2: GDP responses to US GDP shock.
The charts report the same median responses as in Figure 3 by country and with 90% Bayesian credible interval.

Figure A3: GDP responses to US stock price shock. The charts report the same median responses as in Figure 4 by country and with 90% Bayesian credible interval.

Figure A4: GDP responses to Japanese GDP shock. The charts report the same median responses as in Figure 5 by country and with 90% Bayesian credible interval.

Figure A5: GDP responses to German GDP shock. The charts report the same median responses as in Figure 6 by country and with 90% Bayesian credible interval.

Figure A6: Responses to Swedish credit shock. The charts report the same median responses as in Figure 7 by country and with 90% Bayesian credible interval.

Figure A6 (continued)

Figure A7: Responses to Spanish stock price shock. The charts report the same median responses as in Figure 8 by country and with 90% Bayesian credible interval.

Figure A7 (continued)

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