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Heterogeneity and cross-country spillovers in macroeconomic-financial linkages

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HETEROGENEITY AND CROSS-COUNTRY SPILLOVERS IN MACROECONOMIC- FINANCIAL LINKAGES

Matteo Ciccarelli, Eva Ortega
and Maria Teresa Valderrama



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Abstract

We investigate heterogeneity and spillovers in macro-financial linkages across developed economies, with a particular emphasis in the most recent recession. A panel Bayesian VAR model including real and financial variables identifies a statistically significant common component, which turns out to be very significant during the most recent recession. Nevertheless, country-specific factors remain important, which explains the heterogeneous behaviour across countries observed over time. Moreover, spillovers across countries and between real and financial variables are found to matter: 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. Finally, shocks spill over in a heterogeneous way across countries.

JEL classification: C11, C33, E32, F44

Key words: Financial crisis, Macro-financial linkages, panel VAR models

Non-technical summary

There are many channels through which macroeconomic and financial linkages can arise. For instance, a deterioration of financial conditions will affect the economy through a negative wealth effect on consumption and investment decisions, or through credit rationing given the difficulty to identify solvent borrowers. On the other hand, an economic downturn can affect the valuation of financial assets, since the present value of future cash flows decreases. The final effect on the economy depends not only on agents' behavior but also on the institutional framework they operate in, both of which vary across countries and over time.

This paper addresses the topic of heterogeneous macro-financial linkages across countries and over time and quantifies the importance of country spillovers from real and financial shocks. We analyze the evolution and heterogeneity in macro-financial linkages and international spillovers over the last three decades for some developed economies in a unified framework. We build a time-varying panel VAR model where real and financial variables are jointly modelled for a set of countries including the G7 and other relevant European economies. Of a total of 10 countries, 7 belong to the European Union and of those, 5 are euro area members. Although tight institutional and economic interdependencies may have made euro area countries more alike, the recent recession has shown that hand in hand with some common behavior, there may still be a substantial degree of heterogeneity in macro-financial linkages across countries within the euro area and the European Union and that those linkages may have changed over time.

The evidence found confirms the need to allow for cross-country and cross-variable interdependence when studying real-financial linkages. The empirical model including real and financial variables for the G7 and other European economies identifies a statistically significant common component which turned out to be larger during the 2008-2009 recession. However, country-specific factors remain very important, which explains the presence of a heterogeneous pattern in macroeconomic-financial linkages.

The fact that heterogeneity across countries matters, despite the common evolution of the business cycles around the world found in previous studies, is also consistent with the more recent literature on international business cycles, which recognizes the importance of both group-specific and global factors in driving world cyclical fluctuations. We also find that all GDP recessions since the 1980s have a common and an idiosyncratic component, but the common component was larger during the more recent crisis in its financial dimension (including asset prices and loan markets) and even more in its real dimension. Finally, there is substantial evidence of significant spillovers. A shock to a variable in a given country affects all other countries and the transmission seems to be more intense among financial

variables. Moreover, shocks spill over in a heterogeneous way across countries.

These results cast a new perspective for theoretical models of the international business cycle, as well as for policy making. From a modelling perspective, the data appear to favour 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, 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, policy makers should monitor foreign financial developments. Second, since national policy affects the national component more than the common component, national authorities may be tempted to design domestic policies so as to counteract world conditions. However, the intense cross-country interdependencies may make such policies ineffective or, even worse, counter-productive for the domestic economy.

1 Introduction

The recent crisis has been a worldwide phenomenon in which shocks to the financial system of one country or economic area have spread rapidly not only to the real economy but also across borders, showing the deep interdependence between the financial and real sectors. This paper addresses two main questions: first, whether macro-financial linkages differ across countries and over time and second, how important are cross-country spillovers from real and financial shocks.

There are many channels through which macroeconomic and financial linkages can arise. For instance, a deterioration of financial conditions may affect the economy through, among others, a negative wealth effect on consumption and investment decisions, or through credit rationing as it is harder to identify solvent borrowers, or the other way around, an economic downturn will affect the valuation of financial assets since the present value of future cash flows decreases. The final effect on the economy depends not only on agents' behavior but also on the institutional framework they operate in, both of which vary across countries and over time.

Regarding international macro-financial spillovers, there is a vast literature reporting their intensification in the last decades. On one hand, over the past quarter century global trade flows have been growing at a much faster rate than world output. As noted in Hirata et al. (2011), there has been an intensification of the processes of economic unification in different regions, including an explosion in the number of regional trade agreements, but also a rapid growth of intra-industry trade through international vertical specialization, especially in North America, Europe and Asia. On the other hand, the volume of global financial flows has grown even faster than 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 surely increased the magnitude of international spillovers, the relative importance of the real sector compared to the financial sector, may have changed over time.

In this paper, we analyze the evolution and heterogeneity in macro-financial linkages and international spillovers over the last three decades for some developed economies in a unified framework. We build an empirical model where real and

financial variables are jointly modelled for a set of countries including the G7 and other relevant European economies. Of a total of 10 countries, 7 belong to the European Union and of those, 5 are euro area members. Although tight institutional and economic interdependencies may have made euro area countries more alike, the recent recession has shown that hand in hand with some common behavior there may still be a substantial degree of heterogeneity in macro-financial linkages across countries within the euro area and the European Union and that those linkages may have changed over time.

A time-varying Panel BVAR (of the type developed in Canova and Ciccarelli, 2009 and Canova, Ciccarelli and Ortega, 2007) is used to study interdependence and time variation simultaneously across a panel of countries. The aim is to understand common or heterogeneous patterns in the interactions between financial and real variables over the last three decades and in particular during the recent crisis. Moreover, those possible commonalities can be analyzed jointly for all variables and countries, or alternatively for groups of variables (e.g., real variables versus financial variables on average across countries).

With such an econometric tool we can explore further issues like (i) what is the role of country-specific vs. common factors in explaining economic fluctuations, (ii) how much does the transmission of shocks across countries matter, (iii) whether shocks matter more if they are of real or financial origin and (iv) did commonalities prevail more in the 2008-2009 recession compared to previous recessions. 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. The empirical model including real and financial variables for the G7 and other European economies identifies a statistically significant common component which turned out to be larger during the 2008-2009 recession. However, country-specific factors remain very important, which explains the presence of a heterogeneous pattern in macroeconomic-financial linkages. 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 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, 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).

We find evidence of significant spillovers: a shock to a variable in a given country affects all other countries. We also find that shocks may also spill over in a heterogeneous way across countries, which is consistent with evidence from more standard VAR studies (Guarda and Jeanfils, 2011). Regarding whether the transmission of shocks changed during the great recession, we find evidence that it is not the case: while the great recession features the largest real and financial shocks in our sample, their spillovers are similar to those observed during previous recessions. However, by jointly estimating a system including many countries, we may find stronger linkages than those in country-by-country VAR analyses, due to the amplification effect that results from allowing interdependence. Finally, we find that all GDP recessions since the 1980s have a common and an idiosyncratic component, but the common evolution was intensified in the more recent crisis, both in its financial dimension (including asset prices and loan markets) and even more in its real dimension.

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 compares the relative role of financial vs. real factors and common vs. specific factors in the 2008-2009 crisis with previous crises and section 7 concludes and discusses some implications for modelling and policy.

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:

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

where $i = 1, \dots, N$ indicates countries, $t = 1, \dots, T$ time and L is the lag operator; y_{it} is a $G \times 1$ vector of variables for each i and $Y_t = (y'_{1t}, y'_{2t}, \dots, y'_{Nt})'$; $D_{it,j}$ are $G \times NG$

matrices for each lag $j = 1, \dots, p$; e_{it} is a $G \times 1$ vector of random disturbances. As the variables used in this analysis are demeaned, we can omit the constant term.

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 $D_t(L) = [D_{1t}(L), \dots, D_{Nt}(L)]'$, is not block diagonal for some L , cross-unit lagged interdependencies matter. Thus, dynamic feedback across countries is possible and this greatly expands the type of interactions our empirical model can account for.

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

$$Y_t = Z_t \delta_t + E_t \quad E_t \sim N(0, \Omega) \quad (2)$$

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

$$\delta_t = \Xi \theta_t + u_t \quad u_t \sim N(0, \Sigma \otimes V) \quad (3)$$

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

$$\Xi \theta_t = \Xi_1 \theta_{1t} + \Xi_2 \theta_{2t} + \Xi_3 \theta_{3t} \quad (4)$$

where Ξ_1, Ξ_2, Ξ_3 are matrices of dimensions $NGk \times 1, NGk \times N, NGk \times G_1$, respectively. $\theta_{1t}, \theta_{2t}, \theta_{3t}$ are mutually orthogonal factors capturing, respectively, movements in the coefficient vector which are common across all 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, where $G_1 \leq G$ denotes the number of variable groups.

Factoring δ_t as in (3) reduces the problem of estimating NGk coefficients into the one of estimating for example, $1+N+G_1$ 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

$$Y_t = \mathcal{Z}_t \theta_t + v_t \quad (5)$$

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

Economically, the decomposition in (5) is convenient since it allows us to measure the relative importance of common, country-specific and variable-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 and $\mathcal{Z}_{3t} \theta_{3t}$ 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. Since they are smooth linear functions of the lagged endogenous variables, such indices are in fact leading indicators of common, country and variable tendencies.

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

$$\theta_t = \theta_{t-1} + \eta_t \quad \eta_t \sim N(0, \bar{B}) \quad (6)$$

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 block diagonality of \bar{B} guarantees orthogonality of the factors, which is preserved a-posteriori and hence their identifiability. Finally, independence among the errors is standard.

In the appendix we illustrate the model with a simple example, relate it with the existing literature and provide all the estimation details.

3 The data

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

The sample period is 1980q1-2011q4. This span of data includes several business cycles and in particular a large number of quarters before and after the introduction of the Euro. 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 (see Canova, Ciccarelli and Ortega, 2012).

The real variables included are growth rates of 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 in the lending market: bank leverage (loans to deposit ratio) and the flow of credit into the economy. The latter is measured as the y-o-y growth of total outstanding nominal loans to the private sector deflated by the CPI.²

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 spread which is taken in levels), which are further standardized in order to obtain meaningful aggregations of these heterogeneous series.

¹On this, see Primiceri (2005), also for a discussion on alternative specifications.

²All results remained essentially unchanged when using the credit impulse instead of credit growth (not reported). The credit impulse (see Biggs et al., 2009) is measured as the y-o-y difference of credit growth in any given quarter as a percentage of nominal GDP.

Our sample of 10 countries covers the bulk of the developed world. That is, 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: US, Canada and Japan.

3.1 Selected features of the data

Before proceeding to the empirical analysis, it is useful to present some stylized facts about the variables in our study. In particular, we are interested in the degree of heterogeneity across countries and over time that we observe by just looking at the first and second moments of the data. In the appendix, we show annual average growth rates and the standard deviation for each variable for the periods from 1981 to 1998 and from 1999 to 2011. Although our sample includes non-member countries, it is fair to say that EMU could have potentially influenced other parts of the world, in particular through financial markets and thus we split our sample along this criterion to illustrate variation across time.

In Table A1, we present average growth rates and standard deviations for the real variables in our study (GDP, private consumption and gross fixed capital formation). Despite focusing mainly on the largest world economies, we still observe a wide range of possible values for the pace of economic growth: there are rapid growing countries (above 3%) before 1999 like US, Japan and Ireland together with countries experiencing average growth rates under 2% (Italy and Sweden). In the following period, between 1999 and 2011 the dispersion in growth rates increases slightly, in particular because the lower bounds move to the left, where we find countries with average growth rates below 1% (Italy and Japan). In general, we find that average GDP growth rates were higher before 1999 while volatility was lower. The only exception is Sweden, whose economy grew slower before 1999 due probably to the banking crisis it suffered in the early 1990's.

Turning to private consumption, the picture becomes more heterogeneous. We find that about half of the countries show higher average growth rates before 1999 while a bit less than half show larger growth before 1999. The change in volatility

of the growth rates is also not uniform, for only about half of the countries volatility is lower after 1999. A similar pattern is found for gross fixed capital formation. Although average growth rates of total investment fell strongly for most countries, there are some exceptions (France, Sweden and Canada) and also for 6 out of 10 countries volatility was lower after 1999. Also the range of growth rates of gross fixed capital formation is much wider than in the case of private consumption or GDP both before and after 1999, showing more clearly the differences between fast and slow growing economies.

Looking at financial prices (table A2), the heterogeneity across countries and across time is even larger. Average annual growth rates in real stock prices range from 24.3% in Sweden to 7.2% in Japan during the period 1981 to 1998, while in the period between 1999 and 2011 the range shifted to 8.2% in Sweden to -0.6% in Italy. In general, while all countries in this study experienced very strong stock price performance in the first period, almost all of them with the exception of Canada and Sweden saw a strong reversal of this trend in the following period and at the same time volatility increased from an already high level in most (but not all) countries after 1999.

Real house prices show again a very mixed picture across countries. In our sample, we have countries like Spain, Ireland and Italy where average growth rates in house prices stood at 9.5% and 8.1% (both Ireland and Italy), respectively and countries like Japan and Germany with average annual growth rates of 2% and 2.9%, respectively. While for most countries the pace of growth fell in the following period (except in France, UK and Sweden) the range widened from 8.2% in Spain to -3.7% in Japan. Volatility in house prices is also extremely heterogeneous going from 14.5% for Italy to 1.8% in the US before 1999 and from 29.4% in Canada to 1.4% in Germany in the period since 1999 and volatility increased after 1999 only for about half of the countries.

Despite the widening in most other variables, the range of values of the term spread actually narrowed after 1999, reflecting perhaps the convergence of interest rates (and inflation rates) observed across most of the countries in our sample in the last years. In the period between 1981 and 1998 the range of the term spread was between -0.2 in Spain to 2.8 in Japan. After 1999 all spreads increased, while

the range narrowed to 1.2 in Japan and 2.5 in Sweden and volatility decreased for all countries except Ireland and US.

To investigate macro-financial linkages we use the loan to deposits ratio to capture the banking structure in each country (table A3). Here again, we find that despite focusing on highly developed economies there is a wide range of possible levels for this indicator. Indeed the highest level of this indicator in the period before 1999 was found in Germany (1.6%) followed by France (1.4%) while the lowest level was registered in the US (0.8%) followed by Japan (0.9%). In the following period Japan and the US switched places for the two countries with the lowest level of loans to deposits ratio. At the same time, we observe a strong increase in Sweden, which reaches 2.1% followed by Ireland with 1.8%. For almost all countries except Germany, UK and Japan, the ratio increased after 1999 reflecting partly a slower pace of growth of deposits in the second period since at the same time credit growth was also falling for most countries in our sample.

In fact, credit growth was strong for most countries between 1981 and 1999 with annual growth rates ranging from 14.8% in the UK to 5.8% in the US. In the period from 1999 to 2011 the pace of credit growth decreased in almost all countries except Spain (14.4%), Ireland (13.6%) and the US (6.1%) and in some countries like Germany and Japan the fall in the growth rate was very strong.

In summary, simple descriptive statistics reveal differences in the evolution of the real and financial variables in this study. A very crude description of the situation shows that while the pace of growth of almost all variables, especially real variables, asset prices and credit, in the majority of countries was slower in the period after 1999, the volatility of many variables and countries in our sample increased. However, this result seems to be mostly driven by the large drop and heightened uncertainty in almost all variables during the last recession.

4 Commonality vs. heterogeneity

In this section, we aim at measuring whether there are significant co-movements among these countries and variables that simple summary statistics cannot identify, by estimating the empirical model explained in section 2.

After estimating different specifications of this model, 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 markets variables across countries and a third shared by real asset prices and the term spread across countries.³ These common, country-specific and variable-type components quantify the relative contribution 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 main developed economies or do country-specific heterogeneities matter more?

Despite the heterogeneous behavior showed in the previous section, there is indeed a significant common component, especially in the last recession. As found elsewhere in the literature (see for example Kose et al., 2008), we confirm the existence of a statistically significant common factor linking these seemingly heterogeneous real and financial series across all countries and throughout several cycles. Figure 1 displays the evolution of this common factor, expressed as the standard deviation from the historical average of annual growth rates. The common component estimated captures appropriately the recession in the early 80s, that of the early 90s and it also identifies the recession of 2001-02. It is noteworthy that the most recent crisis appears by far as the largest common fluctuation. Moreover, the posterior uncertainty is remarkably low towards the end of the sample, including the 2008-2009 recession as well as signs of a possible “double dip” in 2011.

[FIGURE 1 HERE]

However, the country-specific component in fluctuations of real and financial variables remains significant and this explains some of the heterogeneous behavior observed over time across countries as summarized in section 3. Figure 2 shows the country-specific components for each country in our sample, which are very precisely

³An alternative specification with only two variable-type factors (one for the real variables and another for the financial ones) yields a lower marginal likelihood. 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.

estimated. The charts 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 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. 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 at the same time in other countries only real economic developments drive the business cycle.

[FIGURE 2 HERE]

It is interesting to note the different behavior of national factors relative to the common factor. For instance, the intensity of the crisis during the early 90's is very strong in Sweden and not only lasts longer than the recessions in the UK, US and Canada, but it also starts earlier than the EMS crisis, like in France or in Spain. On the other hand, the recession around 2001 was strongest in Japan and Germany compared to the other countries. As in the previous recession, the US and Sweden experienced this recession earlier than euro area member countries.

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.

[FIGURE 3 HERE]

Besides the common and country-specific factors, three distinct variable-type components are identified: 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 lending markets (ratio of total loans to deposits and credit growth). The panels in Figure 3 show that each of these components is statistically significant for most of the sample, 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 and their fluctuations are most significant in the 2008-09 recession.

The financial prices component is found to be less significant throughout the whole sample than the other two variable-type components. One possible reason is that it includes the evolution over time of the term spread, which may be counter-cyclical, while the other two variables, real house and real stock prices are mostly pro-cyclical. But, also, as we observed already in section 3, there has been more heterogeneity in real asset prices across countries and over time than in macro aggregates. Despite this, significant common developments in financial prices across countries are found during all recessions. Moreover, since the year 2000 the significance of this common component has increased, which may be a reflection of deeper financial integration across developed economies, related perhaps to the introduction of the common currency in Europe.

The analysis by variable groupings confirms that the last recession was particularly unique from a historical perspective both for the financial and real sectors of the world economy. Figure 3 shows 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. The loan market component started falling as early as 2007, coinciding with the credit supply tightening documented by e.g., the euro area Bank Lending Survey (BLS) indicators, then dropped even more after 2009 when the BLS reported both credit demand and supply reductions. Ciccarelli et al. (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 for the euro area and found similar results. We can also observe in all three components the “double dip” the world economy is experiencing since 2011, coinciding with the intensification of the European sovereign debt crisis.

The analysis by variable type also confirms previous findings on the leading nature of financial prices. We find that the common factor of financial prices leads fluctuations in real variables, while loan ratios are lagging.⁴ In fact, in most recessions financial prices are usually the first to recover, followed by real variables

⁴Giannone, et al. (2010) find the same result with a different methodology.

and the last to recover is the lending 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 2-quarter lead). In turn, real variables appear to lead the loan market (correlation peaks at 0.7 with a 2 or 3-quarter lead). 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 common component is the real variable component and in a synchronized manner: the maximum correlation coefficient between these two series of 0.9 is the contemporaneous one. 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, Crucini et al. (2011).

5 Cross-country transmission of shocks

The last section showed evidence of commonalities among macroeconomic and financial variables across countries and over time, not least in the most recent recession. In this section, we aim at deepening further into these linkages and try to answer the following questions: Do these co-movements reflect important spillovers between financial and real variables across countries or just the coincidence of shocks in time? Are the spillovers larger if they have a financial origin or a real one? And has the international transmission of shocks changed during the great recession?

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 particular variable in a given country affect other countries, using generalized impulse response functions. With this methodology we can assess, for example, whether a negative financial shock in one country affects other countries.

To measure spillovers, we compute generalized impulse response functions as the difference between a conditional and an unconditional projection of, for example, GDP growth for each country in a particular period (see e.g., Pesaran and Shin, 1998, for a definition of generalized impulse responses). 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 another variable, say 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.

Clearly, the notion of shock here must be taken *cum grano salis*, for there is no identification of “structural shocks” as it is typically done in the VAR literature and the actual movement of the conditioning variables over the forecast horizon can be due to a variety of reasons. Nonetheless, this counterfactual exercise is a very helpful tool to answer the question: what rate of GDP growth would the model have predicted based on the historical path of the US stock prices compared to a prediction based on actual stock prices developments? 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 market prices in this example) and lasting until its observed trough. The dating is somewhat arbitrary and can differ across variables and country of origin.

We first investigate whether exceptionally negative developments in the US, both in the financial and real sectors, have had similar effects on real activity across other countries. Moreover, by looking at 3 different periods, we can study whether the intensity of the spillover has changed over time.

Figure 4 shows the generalized impulse responses of GDP growth in all countries to a US GDP shock at three different points in time. 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 significant fall in the real economy in every country, although the reaction is always

smaller than the one in the US.⁵ Of course the spillover is of different intensity across countries, with Canada and the UK showing a larger response corresponding to their deeper economic linkages to the US and Spain, Germany and Ireland showing the smallest responses.

[FIGURE 4 HERE]

It is also interesting to note that the size of the shock and the responses vary over time, with the latest recession experiencing 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 4, shows the same responses of the upper panel re-scaled by the size of the shock to US GDP in each of the three recession episodes. As can be clearly seen, the intensity of the spillovers does not seem to have changed over time, it is the shock that has been more intense in the 2008-09 recession. This result is consistent e.g., with Stock and Watson (2012) who, using a large scale dynamic factor 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 5 shows the GDP responses to a negative shock to US stock market in different periods. The country responses are in general smaller than those to a US real shock (see Figure 4). However, the distance between the US GDP response and that 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 real ones. Rescaling the GDP responses by the size of the shock as before, the lower panel of Figure 5 seems to show that there is no significant change in the pattern of international transmission over time, with UK and Sweden reacting more and faster than all other countries.

[FIGURE 5 HERE]

⁵Confidence intervals are not shown for clarity but are available upon request. They confirm that all GDP responses are significantly below zero.

The last two figures showed a large albeit heterogenous spillover from a US shock to other economies. 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, in particular, whether they are more intense if the shock originates in a particular type of variable (e.g., financial vs. real) or a particular country.

As for the real shocks, Figure 6 reports the GDP responses to the very country-specific downturn in Japan at the end of the 1990s, while Figure 7 shows the spillovers of the German recession in 2002. In both cases the country suffering the shock is the one showing the largest reaction, but in all other countries GDP responds negatively to the unexpected contraction in economic activity in Japan or Germany. The transmission of such real shocks, hence, seems to be significant but partial. The same partial transmission is observed for a positive real shock, like the strong growth observed in private consumption in the UK in 1987-88, which shows a similar (but positive) response in all other countries (not reported).

[FIGURES 6 AND 7 HERE]

We turn now to shocks to financial variables observed in different countries and different episodes. Figure 8 reports the generalized impulse responses of GDP growth and of total credit growth across countries to the unexpected credit contraction in Sweden in the early 1990s. Although the spillover of this particular shock to real activity is mostly not significant even in the originating country, the shock had significant negative spillovers to credit markets in other countries.

[FIGURE 8 HERE]

Similar responses are obtained to the positive shock to the stock market in Spain that occurred when the country joined the European Communities in 1986Q2 (see Figure 9): while GDP responses are not significant even in Spain, the temporary boom in the Spanish stock market was transmitted to the stock markets of other developed economies, although with less intensity as could be expected and like in the case of the credit shock in Sweden.

[FIGURE 9 HERE]

We find more or less the same pattern across the countries in our sample for other episodes of financial shocks, like housing prices booms (like in the UK in 1986-87) or busts (like in Spain and Ireland since 2007). In all cases, we find partial but more significant spillovers to the same financial variable in other countries than to their real economy. Moreover, the transmission across countries throughout a variety of episodes seems stronger between stock markets or credit variables than between spreads, house prices or loan-to-deposit ratios across countries.

In sum, and as expected, we find that spillovers matter. We find also some signs that the international transmission of a shock may 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 have been originated in a systemic country, as could be seen in the case of shocks to the US stock market.

Very importantly, we find that while the recent recession has shown the largest shocks both in financial and real variables for the period analyzed, at the same time spillovers across countries seem to have been as sizeable as in previous episodes of large financial or real downturns. These results are obtained with a non-structural model which does not allow for stochastic volatility and hence one should not go very far in interpreting them, but this last finding could be consistent with the possibility that larger co-movements or macroeconomic-financial linkages observed worldwide in the last recession could be more related to the size of the shocks than to the intensification of their international transmission relative to previous recessions (see Stock and Watson 2012).

6 What mattered more in the last recession?

Previous sections provide evidence of significant common factors, both real and financial, across developed economies. The aim of this section is to gauge the relative weight of real and financial common factors in explaining real fluctuations across countries and over time. Does the real component of this common evolution matter more than the financial component in explaining GDP developments?

In order to answer these questions, we estimate a country by country factor-augmented VAR for GDP growth and the three variable-type components displayed in Figure 3, which 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.⁶

[FIGURE 10 HERE]

Figure 10 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. Naturally, the relative weight of each of the three common factors changes across countries and over time. In particular, at the beginning of the recession, the financial factors (the green bar for financial prices and the red one for loan markets) dominated, while the real component (blue bars) gained weight as the recession deepened. Although with a different methodology, Stock and Watson (2012) find also 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 weight towards the end of the recession in all other countries too. Nevertheless, the common financial factors are also relevant, 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 in most countries, asset prices 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 quite relevant in explaining strong GDP growth pre-crisis in some countries like Spain and Ireland.

Figures 11 and 12 show the same dynamic contributions for the periods including the two previous recessions. Compared to the last recession, previous ones had

⁶See Bernanke, B., Boivin, J. and P. Elias (2005) for the definition of FA-VAR, and Canova and Ciccarelli (2012) for a FA-VAR application to compute historical decompositions with the model used here.

a smaller common component, be it of real or financial nature, as can be seen by the larger size of the idiosyncratic components (purple bars). This is not surprising since the downturn of the early 1990s and of the early 2000s were much less synchronized than the last crisis. Still, the common components played a significant role in previous recessions, especially the financial factors (red and green bars), while the common real component was less relevant than in the 2008-09 recession. A distinctive feature of the great recession, thus, seems to have been the large common real downturn across developed economies.

[FIGURES 11 AND 12 HERE]

7 Summary of results and discussion

Summing up, 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 the G7 as well as other European economies, identifies a statistically significant common component, especially during the most recent recession. However, country-specific factors remain very important, which explains the heterogeneous behavior observed across countries. In addition, there are common components of real variables across countries, as well as for loan market variables and for financial prices. As in other recessions, financial prices seem to have entered the recent crisis somewhat earlier, while the loan market lags even real variables. Also we find that, more intensely than in other recessions, real variables registered the greatest fall.

Spillovers are found to matter in macroeconomic-financial linkages: a negative shock to a real or financial variable in a given country also affects all other economies, although the transmission is only partial. 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 have been originated in a systemic country, as could be seen in the case of 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, both in its financial dimension and, 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 finds 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, i.e., it is not limited to countries in any particular geographic region and is not a mechanical effect of crises episodes (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 also consistent with previous studies, although the joint estimation performed in this paper, which includes many countries and allows for interdependences, might yield stronger linkages than those obtained in a country-by-country VAR analysis.

These results carry also important implications for theoretical models of the international business cycles as well as for policy making. From a modelling perspective, the data appear to favour 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, 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, policy makers should monitor foreign financial developments. Second, since national policy affects the national component more than the common component, national authorities may be tempted to design domestic policies so as to counteract world conditions. However, the intense cross-country interdependencies may make such policies ineffective or, even 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 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.

References

- [1] Biggs, M., Mayer, T. and A. Pick (2009) “Credit and Economic Recovery”, DNB Working Paper No. 218.
- [2] Bernanke, B., Boivin, J. and P. Elias (2005), “Factor-Augmented Vector Autoregressions (FAVARs) and the Analysis of Monetary Policy”, *Quarterly Journal of Economics*, 120 (1), 387-422.
- [3] Canova, F. and M. Ciccarelli (2009) “Estimating Multi-country VAR models”, *International Economic Review*, 50, 929-961.
- [4] Canova, F. and M. Ciccarelli (2012), “ClubMed? Cyclical fluctuations in the Mediterranean basin,” *Journal of International Economics*, forthcoming
- [5] Canova, F., Ciccarelli, M. and E. Ortega (2007) “Similarities and Convergence in G-7 Cycles”, *Journal of Monetary Economics*, 54, 850-878.
- [6] Canova, F., Ciccarelli, M. and E. Ortega, (2012) “Do institutional changes affect business cycles? Evidence from Europe”, *Journal of Economics Dynamics and Control*, forthcoming.
- [7] Ciccarelli, M., Maddaloni, A. and J. L. Peydró (2010) “Trusting the Bankers: A New Look at the Credit Channel of Monetary Policy”, ECB WP no. 1228.
- [8] Chib, S. and E. Greenberg (1995) “Hierarchical Analysis of SUR Models with Extensions to Correlated Serial Errors and Time-Varying Parameter Models” *Journal of Econometrics*, 68, 409-431.
- [9] Crucini, M., A. Kose and C. Otrok, (2011) “What are the driving forces of international business cycles?” *Review of Economic Dynamics*, vol. 14(1), pages 156-175.
- [10] Forni, M. and L. Reichlin (1998), “Let’s get real: A factor analytic approach to disaggregated business cycle dynamics,” *Review of Economic Studies* 65, 453-473.
- [11] Geweke, J. (2000) “Simulation Based Bayesian Inference for Economic Time Series” in Mariano, R., Schuermann, T. and Weeks, M. (eds.). *Simulation Based Inference in Econometrics: Methods and Applications*, Cambridge, UK: Cambridge University Press.

- [12] Giannone, D., Lenza, M. and L. Reichlin (2010) “Money, credit, monetary policy and the business cycle in the euro area.” In Papademos, L. and J. Stark (eds.), *Enhancing monetary analysis*, ECB, Frankfurt am Main, October 2010, pp. 252-262.
- [13] Guarda P. and P. Jeanfils (2011) “Macro-Financial Linkages: country-specific VARs”, mimeo, National Bank of Luxembourg.
- [14] Hirata, H., M. A. Kose and C. Otrok (2011), “Regionalization vs. Globalization”, mimeo.
- [15] Hubrich, K., A. D’Agostino, M. Cervena, M. Ciccarelli, P. Guarda, M. Haavio, P. Jeanfils, C. Mendicino, E. Ortega, M.T. Valderrama and M. V. Endresz (2012), “Heterogeneity and Nonlinearities in the Transmission of Financial Shocks to the Macro-economy”, ECB Occasional Paper, forthcoming.
- [16] Kadiyala, K.R. and S. Karlsson (1997) “Numerical Methods for Estimation and Inference in Bayesian-VAR Models”, *Journal of Applied Econometrics* 12, 99–132.
- [17] Kose A., C. Otrok and E. S. Prasad, (2008). “Global Business Cycles: Convergence or Decoupling?” NBER Working Papers 14292, National Bureau of Economic Research.
- [18] Lane, P. and G. Milesi-Ferretti (2007) “The External Wealth of Nations Mark II: Revised and Extended Estimates of Foreign Assets and Liabilities: 1970-2004”, *Journal of International Economics* 73(2), 223-250.
- [19] Pesaran, M. H. and Y. Shin (1998), “Generalized Impulse Response Analysis in Linear Multivariate Models”, *Economics Letters*, 58, 17–29.
- [20] Pesaran, H., T. Schuerman and S. Weiner (2005), “Modelling Regional Interdependencies using a Global Error Correction Macroeconomic Model,” *Journal of Business and Economic Statistics* 22, 129-162.
- [21] Primiceri, G. (2005) “Time varying structural vector autoregressions and monetary policy”, *The Review of Economic Studies*, 72, 821–852.
- [22] Sargent, T. (1989) “Two models of measurement and the investment accelerator,” *Journal of Political Economy* 97, 251-287.

- [23] Stock, J.H. and M.W. Watson (2012), “Disentangling the Channels of the 2007-2009 Recession”, NBER Working Papers 18094, National Bureau of Economic Research.

Appendix

A Data appendix

The data used was collected by the Working Group on Econometric Modelling of the Eurosystem of Central Banks (ESCB) and used in Hubrich et al. (2012). It is available upon request under a confidentiality agreement.

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.

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
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
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)

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

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

where L_t is nominal loans and P_t is the CPI.

B Model features

B.1 A simple example and relationship with the literature

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

$$\begin{bmatrix} y_t^1 \\ x_t^1 \\ y_t^2 \\ x_t^2 \end{bmatrix} = \begin{bmatrix} d_{1,1,t}^{1,y} & d_{2,1,t}^{1,y} & d_{1,2,t}^{1,y} & d_{2,2,t}^{1,y} \\ d_{1,1,t}^{1,x} & d_{2,1,t}^{1,x} & d_{1,2,t}^{1,x} & d_{2,2,t}^{1,x} \\ d_{1,1,t}^{2,y} & d_{2,1,t}^{2,y} & d_{1,2,t}^{2,y} & d_{2,2,t}^{2,y} \\ d_{1,1,t}^{2,x} & d_{2,1,t}^{2,x} & d_{1,2,t}^{2,x} & d_{2,2,t}^{2,x} \end{bmatrix} \begin{bmatrix} y_{t-1}^1 \\ x_{t-1}^1 \\ y_{t-1}^2 \\ x_{t-1}^2 \end{bmatrix} + e_t \quad (7)$$

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 , $\delta_{l,s,t}^{i,j}$, 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).

Given the factorization (4), the VAR (7) can be rewritten as

$$\begin{bmatrix} y_t^1 \\ x_t^1 \\ y_t^2 \\ x_t^2 \end{bmatrix} = \begin{bmatrix} \mathcal{Z}_{1t} \\ \mathcal{Z}_{1t} \\ \mathcal{Z}_{1t} \\ \mathcal{Z}_{1t} \end{bmatrix} \theta_{1t} + \begin{bmatrix} \mathcal{Z}_{2t}^1 & 0 \\ \mathcal{Z}_{2t}^1 & 0 \\ 0 & \mathcal{Z}_{2t}^2 \\ 0 & \mathcal{Z}_{2t}^2 \end{bmatrix} \theta_{2t} + \begin{bmatrix} \mathcal{Z}_{3t}^1 & 0 \\ 0 & \mathcal{Z}_{3t}^2 \\ \mathcal{Z}_{3t}^1 & 0 \\ 0 & \mathcal{Z}_{3t}^2 \end{bmatrix} \theta_{3t} + v_t \quad (8)$$

where $\mathcal{Z}_{1t} = y_{t-1}^1 + x_{t-1}^1 + y_{t-1}^2 + x_{t-1}^2$, $\mathcal{Z}_{2t}^1 = y_{t-1}^1 + x_{t-1}^1$, $\mathcal{Z}_{2t}^2 = y_{t-1}^2 + x_{t-1}^2$, $\mathcal{Z}_{3t}^1 = y_{t-1}^1 + y_{t-1}^2$, $\mathcal{Z}_{3t}^2 = x_{t-1}^1 + x_{t-1}^2$. 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 et al. (1984).

As the notation we have used makes it clear, the regressors in (5) are combinations of lags of the right hand side variables of the VAR, while θ_{it} play the role of time varying loadings. Using averages as regressors is common in the signal extraction literature (see e.g., Sargent, 1989) and in the factor model literature (Forni and Reichlin, 1998). However, there are several important differences between (5) and standard factor models. First, the indices we use here weight equally the information in all variables while in factor models the weights generally depend on the variability of the components. Second, the indices dynamically span lagged interdependencies

across units and variables while in standard factor models they statically span the space of the variables of the system. Third, these indices are directly observable while in factor models they are estimated. Moreover, they are correlated by construction because the factorization is applied on the coefficient vector rather than on the variables. Finally, this averaging approach creates moving average terms of order p in the regressors of (5), even when y_{it} are serially independent. Therefore, contrary to what occurs in factor models, our indicators implicitly filter out from the right hand side variables of the VAR high frequency variability. The fact that the regressors of the SUR model emphasize the low frequencies movements in the variables of the VAR is important in forecasting in the medium run and in detecting turning points of GDP growth (Canova et al., 2007).

The SUR model we use has also some similarities with the global VAR model used by e.g., Pesaran et al. (2005) to model global interdependencies, even though the starting point, the underlying specification and the estimation technique differ. In fact, in the global VAR models the estimated specification looks like a set of unrelated single country VARs where common factors are proxied by averages of the variables across countries. Our approach shares the idea of using arithmetic averages as regressors and can be interpreted as an F-factor generalization of these authors' approach, where each factor spans a difference space, when we allow for lagged interdependencies in the error term and for time-varying loading.

B.2 Model estimation

The empirical model has the state space structure:

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

Bayesian estimation requires the specification of prior assumptions. As said in section 2, we specify \bar{B} as a block diagonal matrix and assume that $\Sigma = \Omega$, $V = \sigma^2 I_k$, with E_t , u_t and η_t being mutually independent.

B.2.1 Prior information

We assume prior densities for $\phi_0 = (\Omega^{-1}, \bar{B}, \theta_0)$ and let σ^2 be known. We set $\bar{B}_i = b_i * I$, $i = 1, \dots, r$, 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 $p(\Omega^{-1}) = W(z_1, Q_1)$, $p(b_i) = IG(\frac{\varpi_0}{2}, \frac{S_0}{2})$ and $p(\theta_0 | \mathcal{F}_{-1}) = N(\bar{\theta}_0, \bar{R}_0)$ 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 $p(\theta_t | \mathcal{F}_{t-1}) = N(\bar{\theta}_{t-1|t-1}, \bar{R}_{t-1|t-1} + B_t)$.

We collect the hyperparameters of the prior in the following vector

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

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 $z_1, \varpi_0, S_0, \bar{R}_0$) 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 $\bar{R}_0 = I_r$. 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; $\hat{\theta}_0$ 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 $\sigma^2 \rightarrow 0$, we present results assuming an exact factorization of δ_t .

B.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

$$L \propto |\Omega|^{-T/2} \exp \left[-\frac{1}{2} \sum_t (Y_t - Z_t \Xi \theta_t)' \Omega^{-1} (Y_t - Z_t \Xi \theta_t) \right] \quad (9)$$

where $Y^T = (Y_1, \dots, Y_T)$ denotes the data. Using the Bayes rule, $p(\phi | Y^T) = \frac{p(\phi) L(Y^T | \phi)}{p(Y^T)} \propto p(\phi) L(Y^T | \phi)$. Given $p(\phi | Y^T)$, the posterior distribution for the elements of ϕ , can be obtained by integrating out nuisance parameters from $p(\phi | Y^T)$. 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 $p(\phi | Y^T)$ 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

$$\begin{aligned}\theta_t \mid Y^T, \phi_{-\theta_t} &\sim N(\bar{\theta}_{t|T}, \bar{\mathbf{R}}_{t|T}) \quad t \leq T, \\ \Omega^{-1} \mid Y^T, \phi_{-\Omega} &\sim Wi\left(z_1 + T, \left[\sum_t (Y_t - Z_t \Xi \theta_t)(Y_t - Z_t \Xi \theta_t)' + Q_1^{-1}\right]^{-1}\right) \\ b_i \mid Y^T, \phi_{-b_i} &\sim IG\left(\frac{\varpi^i}{2}, \frac{\sum_t (\theta_t^i - \theta_{t-1}^i)'(\theta_t^i - \theta_{t-1}^i) + S_0}{2}\right)\end{aligned}\tag{10}$$

where $\bar{\theta}_{t|T}$ and $\bar{\mathbf{R}}_{t|T}$ 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 (10) 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 $\mathcal{Z}_{1t}\theta_{1t}$ 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 .

Table A1. Descriptive statistics: Real variables

	GDP growth				Private Consumption				Total Investment			
	1981-1998		1999-2011		1981-1998		1999-2011		1981-1998		1999-2011	
	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.
Germany	2.05	1.83	1.36	2.54	2.04	1.73	0.73	1.05	1.53	4.80	0.97	8.12
Spain	2.54	1.66	2.40	2.43	2.32	2.32	2.34	2.83	3.85	8.19	1.53	7.53
France	2.05	1.32	1.52	1.71	1.93	1.33	1.79	1.16	1.82	7.35	2.30	6.70
Ireland	3.88	4.18	3.36	4.93	2.93	3.23	3.07	5.07	4.12	10.27	-1.37	15.33
Italy	1.89	1.54	0.75	2.22	2.14	1.88	0.77	1.19	1.61	5.17	0.46	6.38
United Kingdom	2.56	1.97	1.97	2.62	3.09	2.42	2.04	2.76	5.62	12.62	1.68	9.00
Sweden	1.95	2.11	2.61	3.02	1.40	2.55	2.47	1.88	2.16	7.92	3.32	6.99
Canada	2.65	2.54	2.41	2.10	2.47	2.12	3.14	1.30	3.07	7.75	4.48	6.11
United States	3.24	2.09	1.98	2.22	3.44	1.60	2.42	1.98	4.46	5.91	0.95	8.92
Japan	3.14	2.52	0.73	2.65	2.98	2.04	0.81	1.28	2.91	5.44	-1.41	3.78
Average	2.60	2.18	1.91	2.64	2.47	2.12	1.96	2.05	3.12	7.54	1.29	7.89

Table A2. Descriptive statistics: Financial prices

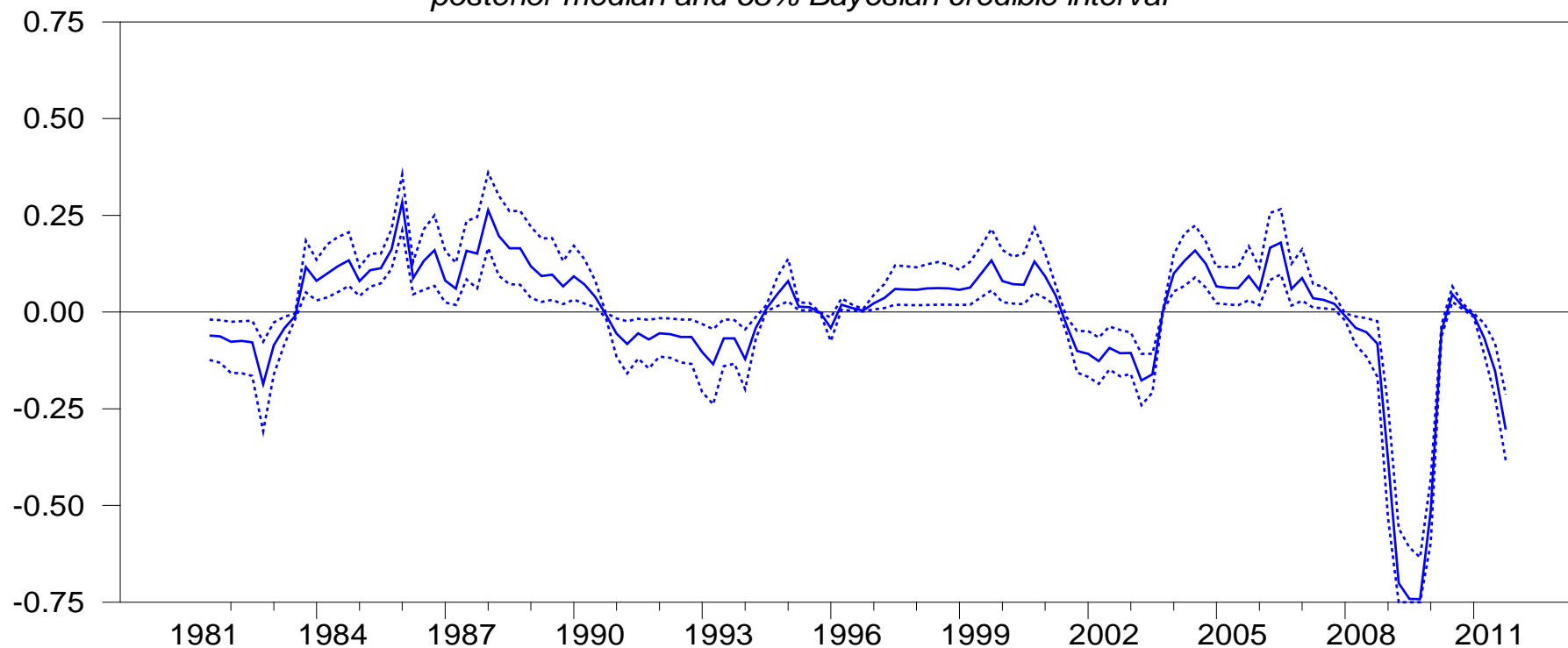
	Stock prices growth				House prices growth				Term spread			
	1981-1998		1999-2011		1981-1998		1999-2011		1981-1998		1999-2011	
	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.
Germany	13.03	21.29	3.25	25.44	2.02	3.33	0.31	1.40	0.93	1.52	1.11	0.90
Spain	21.55	31.86	3.43	20.70	9.50	8.36	8.24	9.24	-0.17	1.73	1.64	1.26
France	14.86	23.44	3.36	23.93	3.94	4.79	7.75	5.98	0.80	1.39	1.31	0.92
Ireland	17.93	26.09	-0.40	24.77	8.09	8.07	3.97	12.82	0.10	1.69	2.20	2.35
Italy	22.09	45.01	-0.56	21.70	8.07	14.47	5.05	4.82	0.11	1.26	1.75	1.20
United Kingdom	14.31	12.04	1.28	16.14	7.53	8.68	7.57	7.85	-0.10	1.78	0.50	1.34
Sweden	24.35	30.68	8.24	30.12	4.77	7.99	7.35	4.09	0.21	2.51	1.50	0.84
Canada	7.81	17.46	7.43	19.82	4.96	8.00	-1.20	29.41	0.63	1.83	1.33	1.11
United States	13.16	13.70	3.89	17.86	4.08	1.81	3.61	5.48	1.20	1.38	1.43	1.46
Japan	7.19	21.80	0.04	23.31	2.90	5.29	-3.73	1.44	2.83	1.16	1.18	0.30
Average	15.63	24.34	3.00	22.38	5.59	7.08	3.89	8.25	0.65	1.63	1.39	1.17

Table A3. Descriptive statistics: loan market variables

	Loans-to-deposits ratio				Credit growth			
	1981-1998		1999-2011		1981-1998		1999-2011	
	mean	st. dev.	mean	st. dev.	mean	st. dev.	mean	st. dev.
Germany	1.65	0.09	1.15	0.09	6.88	1.97	2.51	3.12
Spain	1.21	0.10	1.33	0.07	11.23	6.18	14.36	8.54
France	1.36	0.21	1.45	0.09	7.28	5.55	7.21	4.37
Ireland	1.09	0.12	1.79	0.26	12.83	7.77	13.55	13.72
Italy	1.01	0.15	1.56	0.12	10.47	5.32	8.73	3.73
United Kingdom	1.36	0.30	1.23	0.05	14.85	10.73	8.77	5.58
Sweden	1.01	0.21	2.11	0.50	7.88	10.34	7.89	3.41
Canada	1.04	0.03	1.10	0.05	8.72	8.24	5.85	5.11
United States	0.78	0.03	0.78	0.03	5.84	4.61	6.06	4.19
Japan	0.90	0.04	0.58	0.13	6.67	4.56	-1.63	2.87
Average	1.14	0.13	1.31	0.14	9.27	6.53	7.33	5.46

Figure 1. Evolution of common factor over time

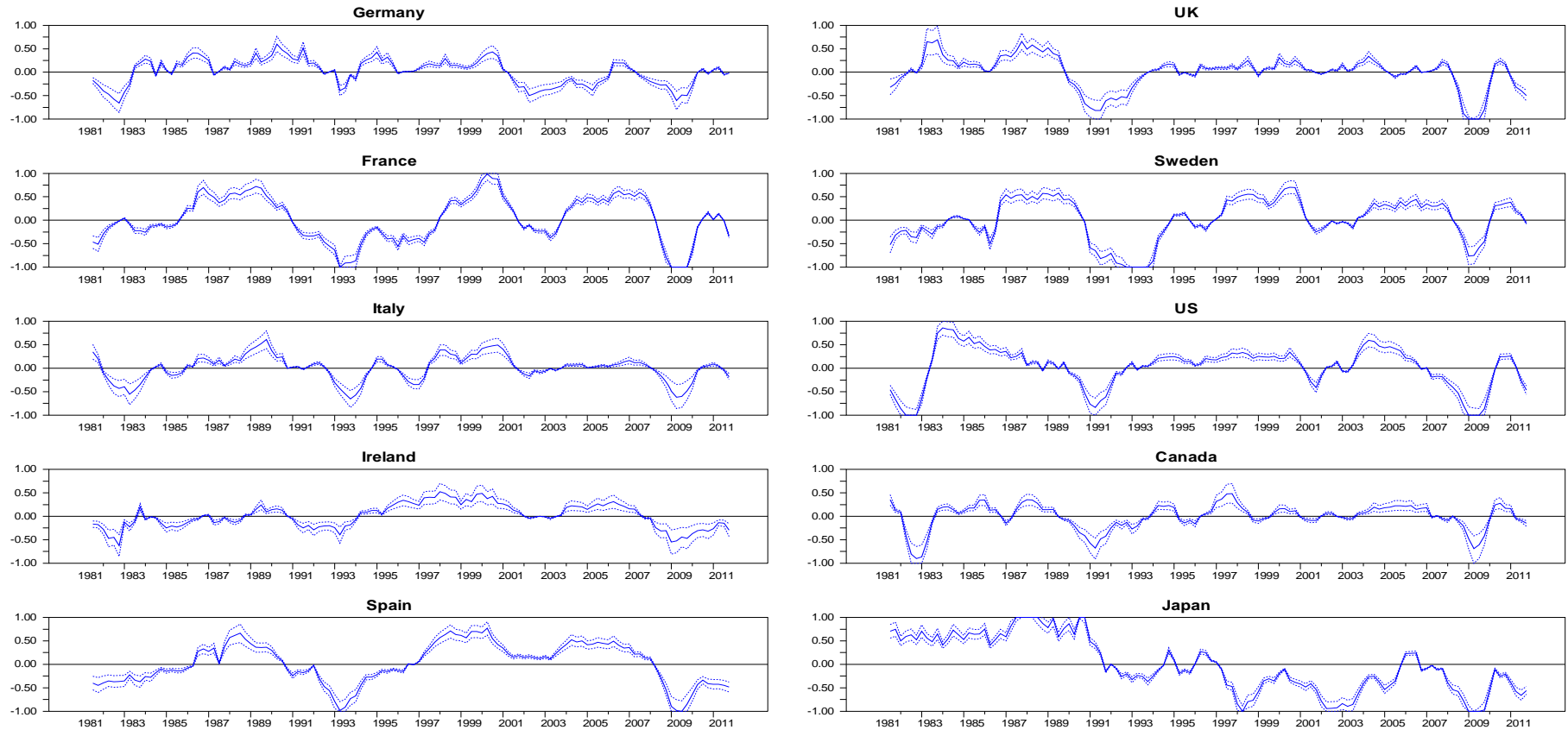
posterior median and 68% Bayesian credible interval



Note: 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. This common factor corresponds to $Z_{1t}\theta_{1t}$ in the paper (section 2).

Figure 2. Evolution of country factors over time

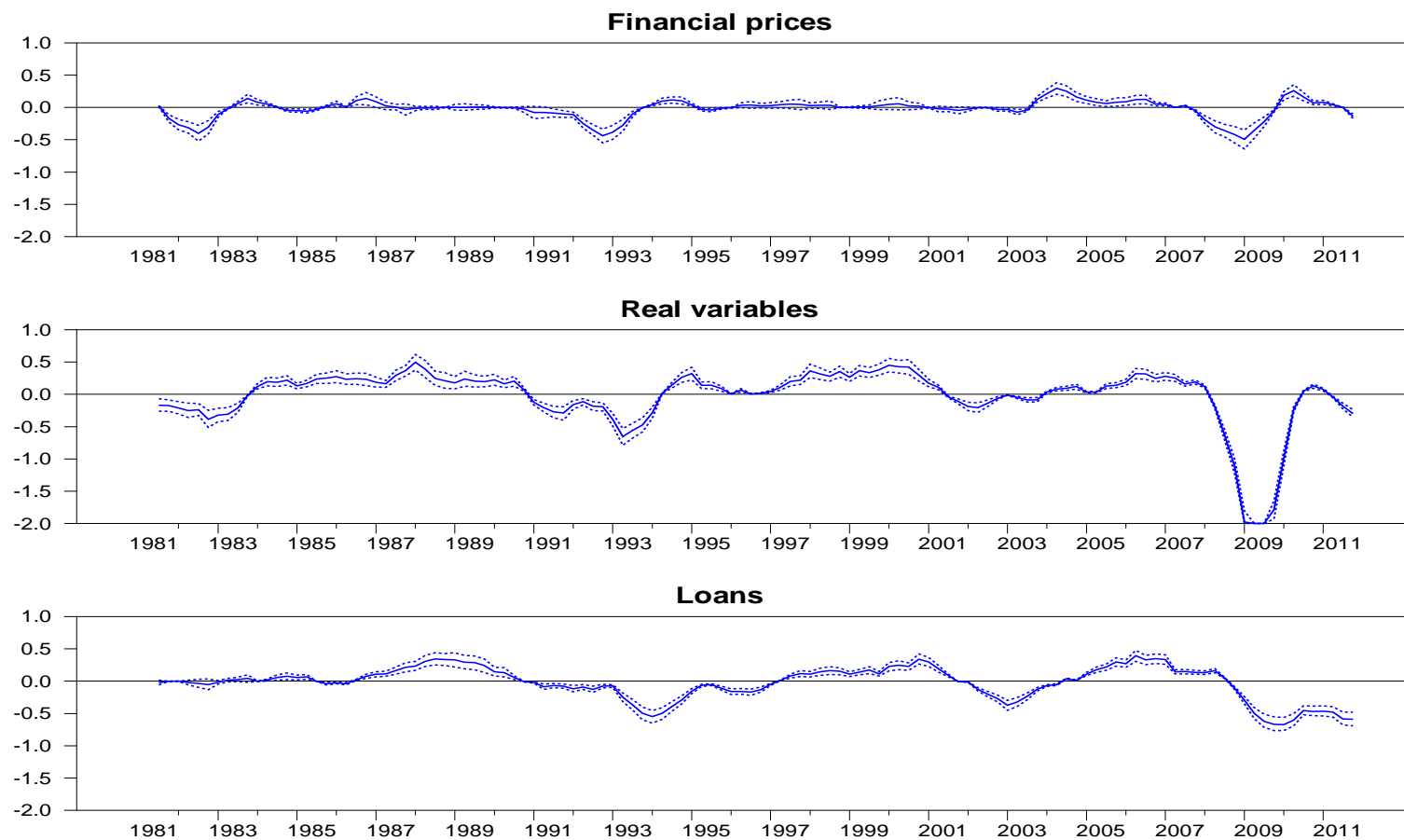
posterior median and 68% Bayesian credible interval



Note: 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 $Z_{2t}\theta_{2t}$ in the paper (section 2).

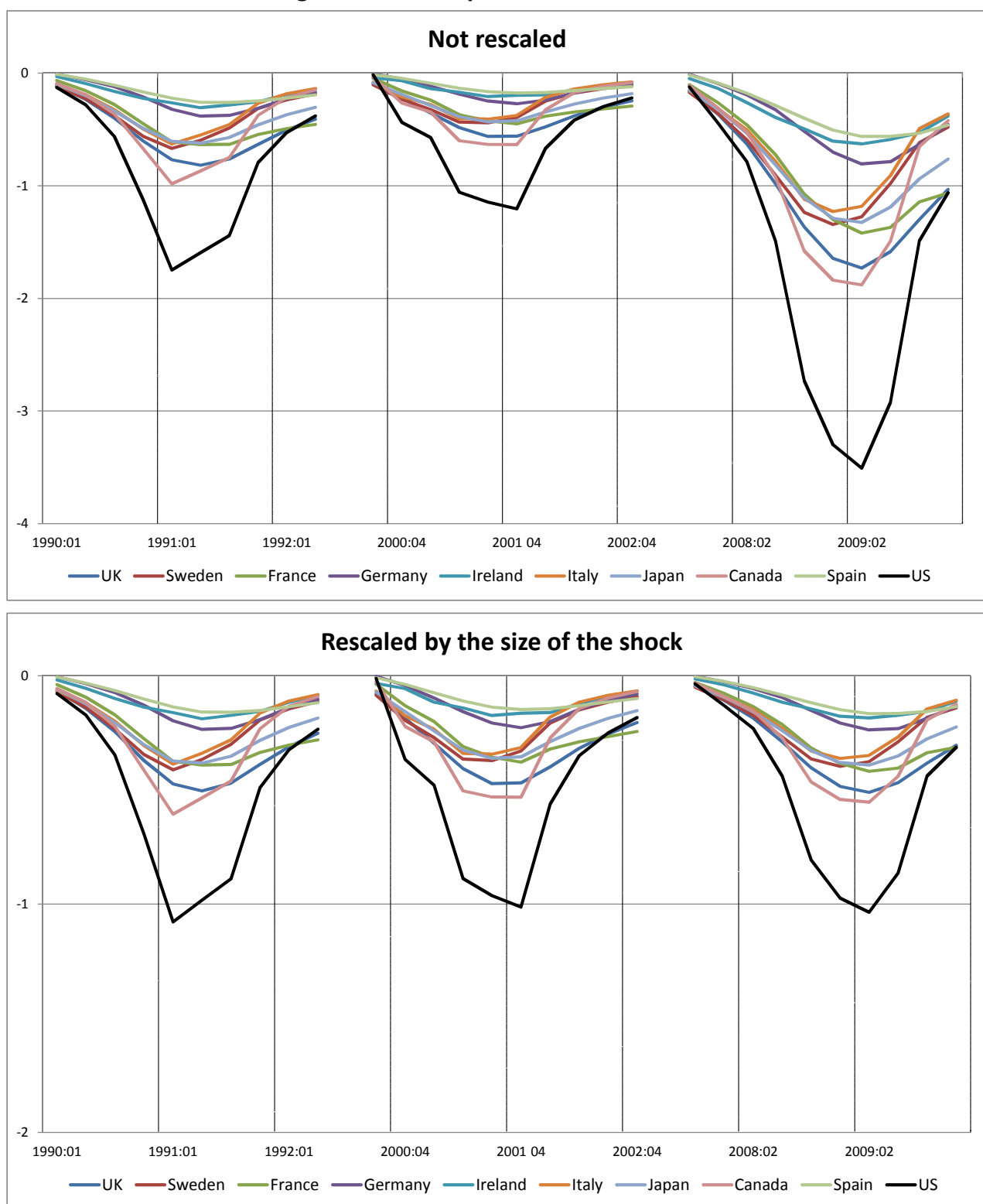
Figure 3. Evolution of common factors over time

posterior median and 68% Bayesian credible intervals



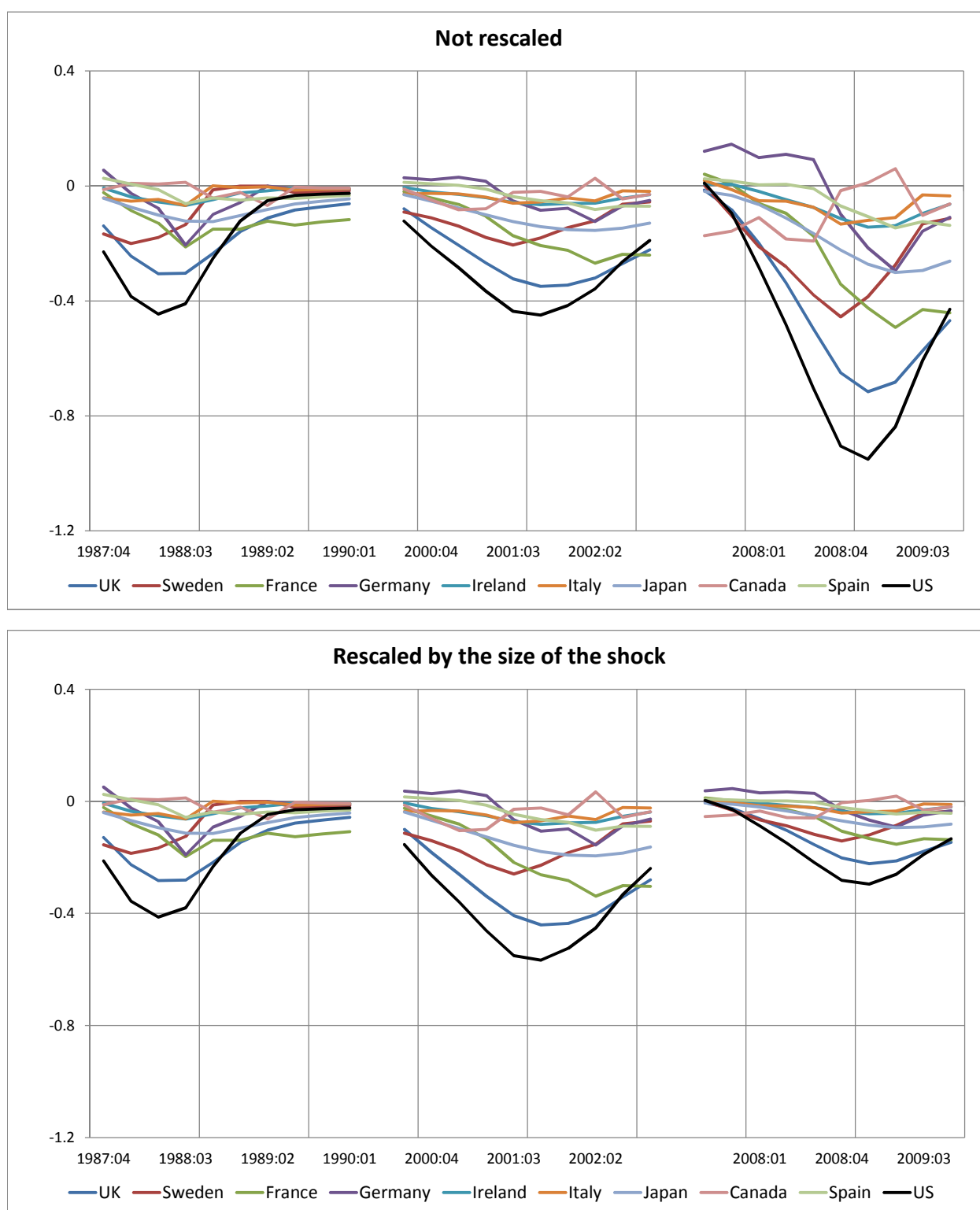
Note: The charts plot the variable factors across all countries expressed in standard deviations from the historical average of annual growth rates. The solid black line represents the posterior median of the estimated distribution for the common factor at each point in time. The two dotted lines limit the 68% Bayesian credible interval. This corresponds to $Z_{.34}\theta_{3t}$ in the paper (section 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 and gross fixed capital formation. "Financial prices" are bonds spreads, and the prices of stocks and of real estate deflated by CPI.

Figure 4. GDP responses to US GDP shock

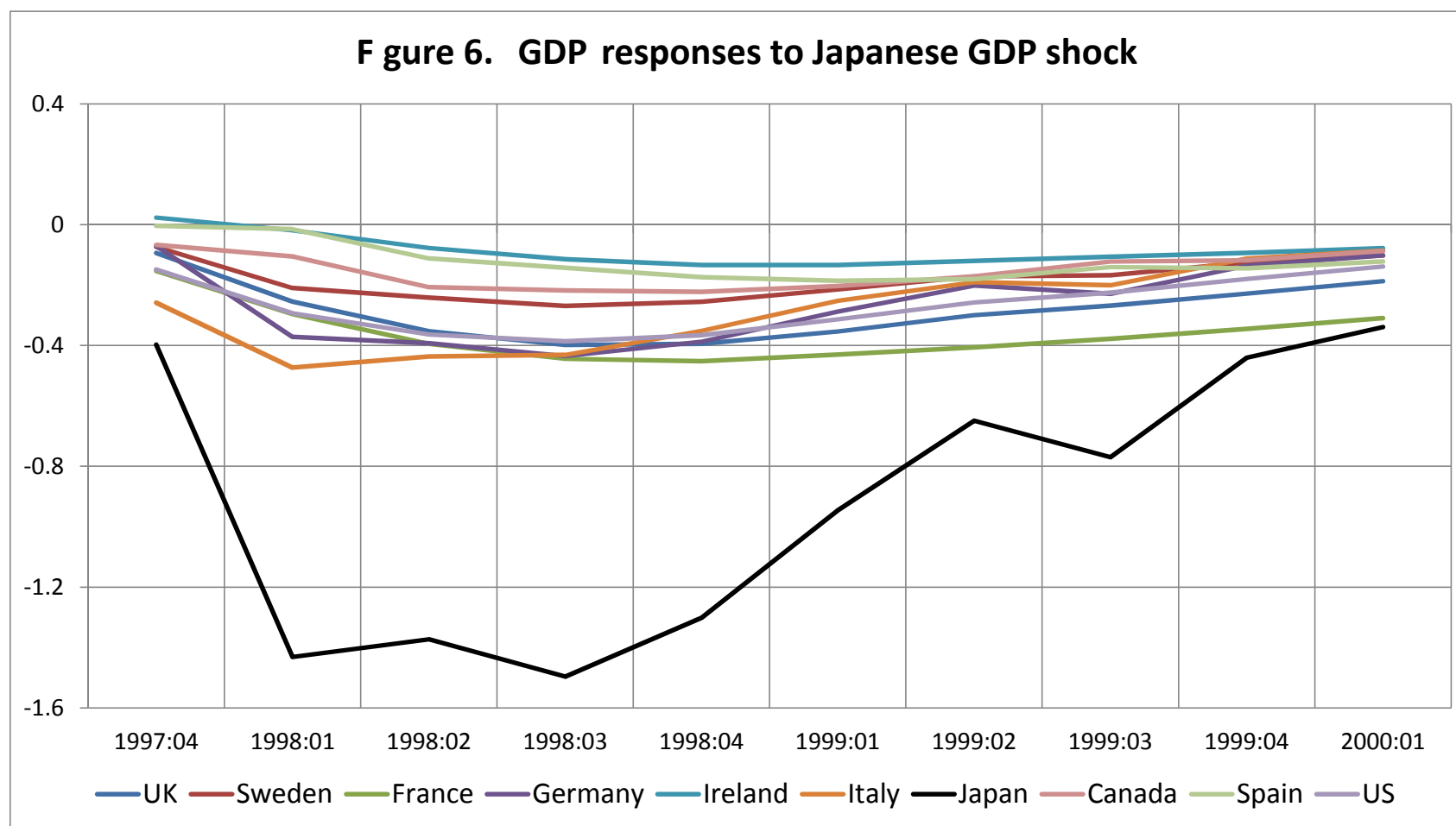


Note: The charts report generalised impulse response functions computed as the difference between a conditional and an unconditional projection of GDP growth for each country in a given period. The unconditional projection is the one the model would have obtained for GDP growth for that period based 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.

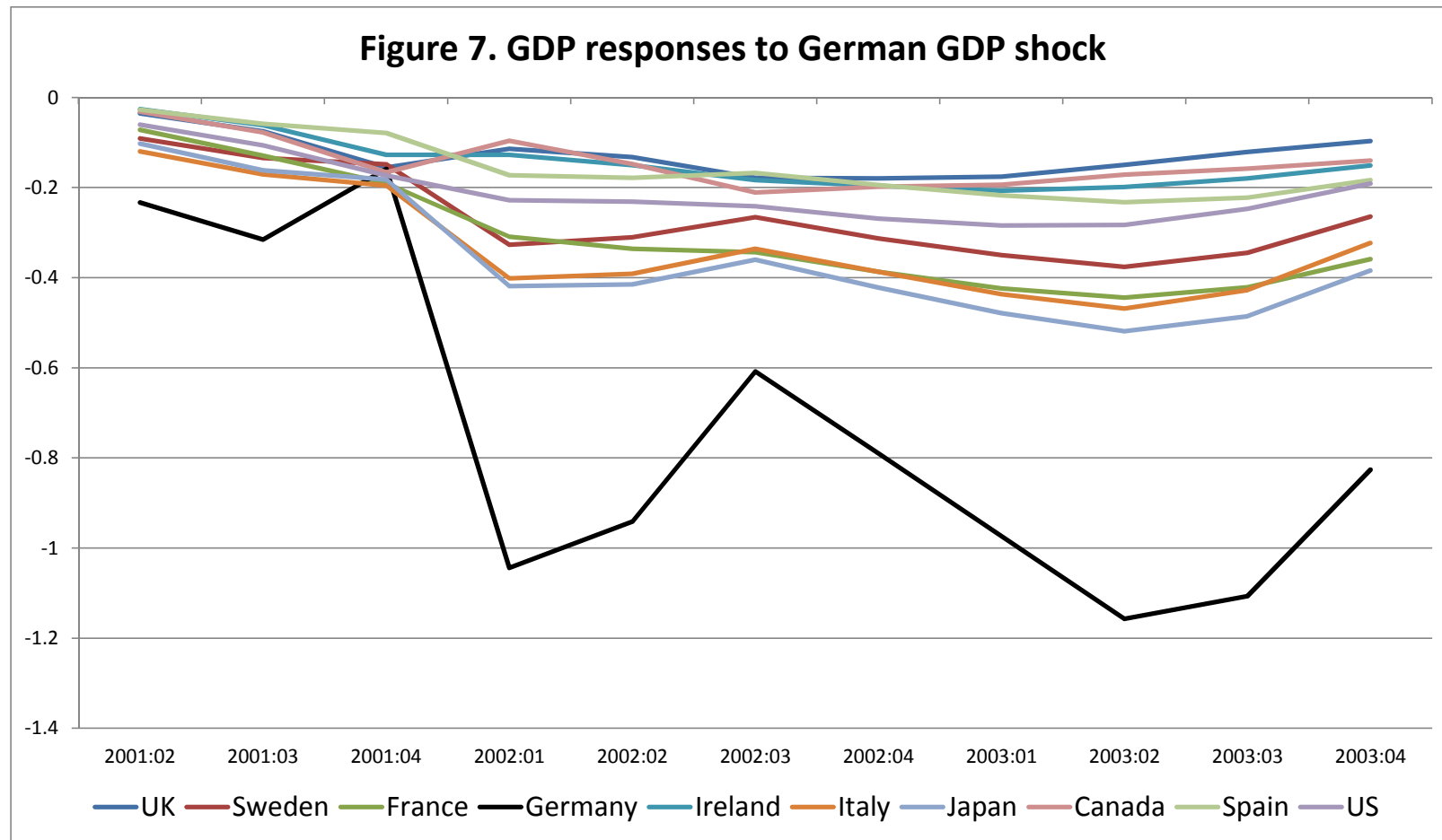
Figure 5. GDP responses to US stock price shock



Note: The charts report generalised impulse response functions 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.

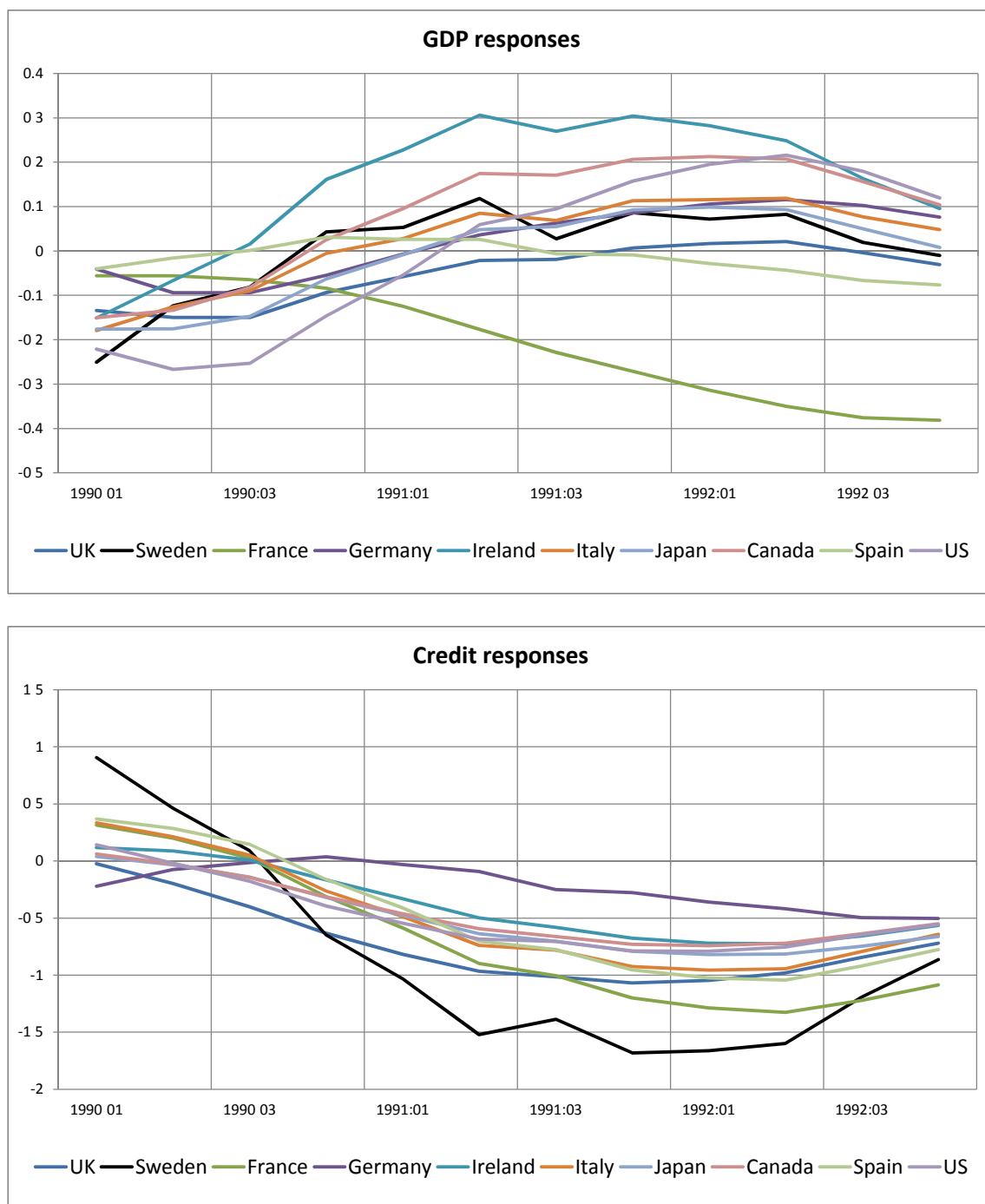


Note: The chart reports generalised impulse response functions computed as the difference between a conditional and an unconditional projection of GDP growth for each country over the period 1997:4-2000:1. The unconditional projection is the one the model would have obtained for GDP growth for that period 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.



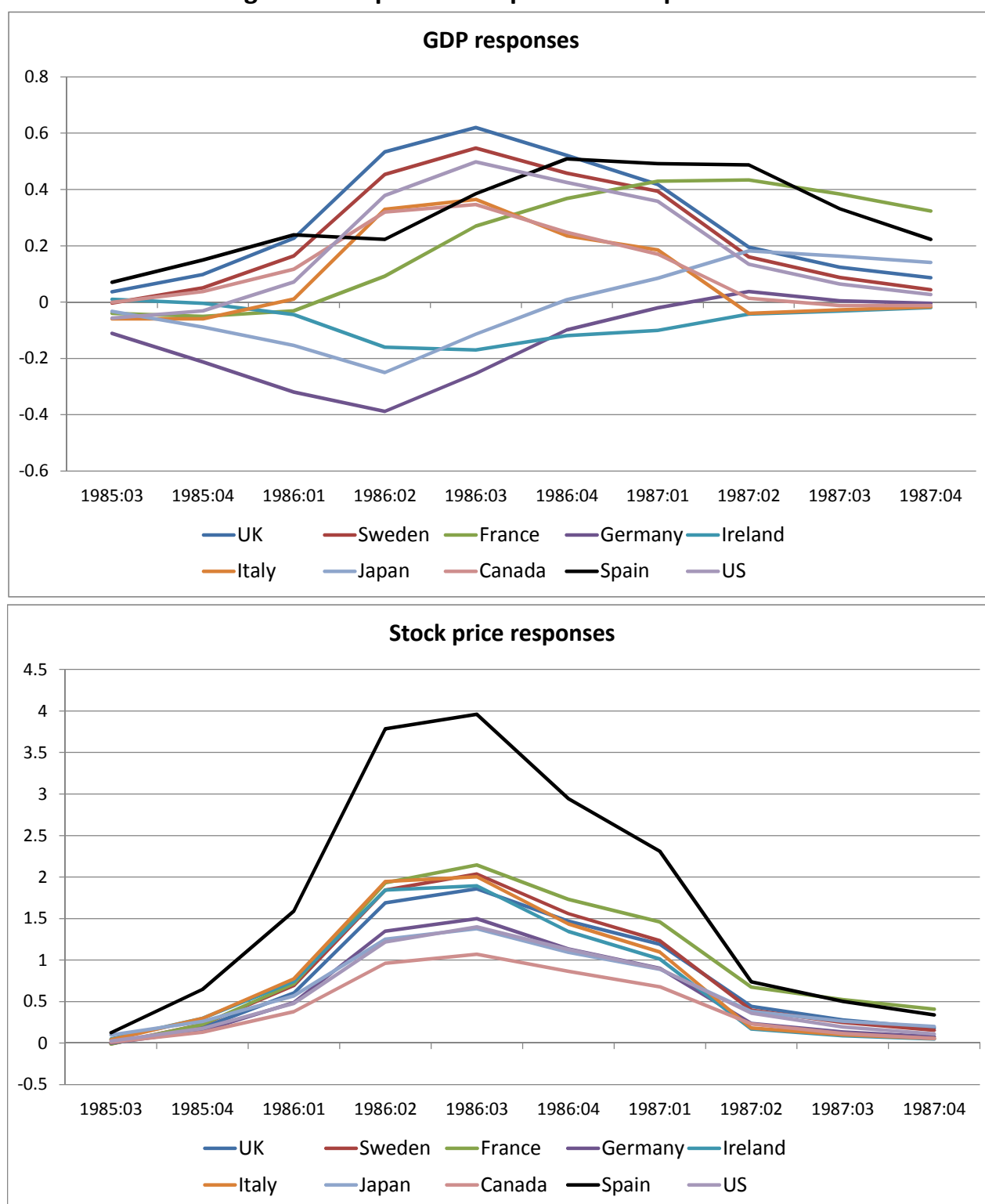
Note: The chart reports generalised impulse response functions computed as the difference between a conditional and an unconditional projection of GDP growth for each country over the period 2001:2 2003:4. The unconditional projection is the one the model would have obtained for GDP growth for that period 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.

Figure 8. Responses to Swedish credit shock



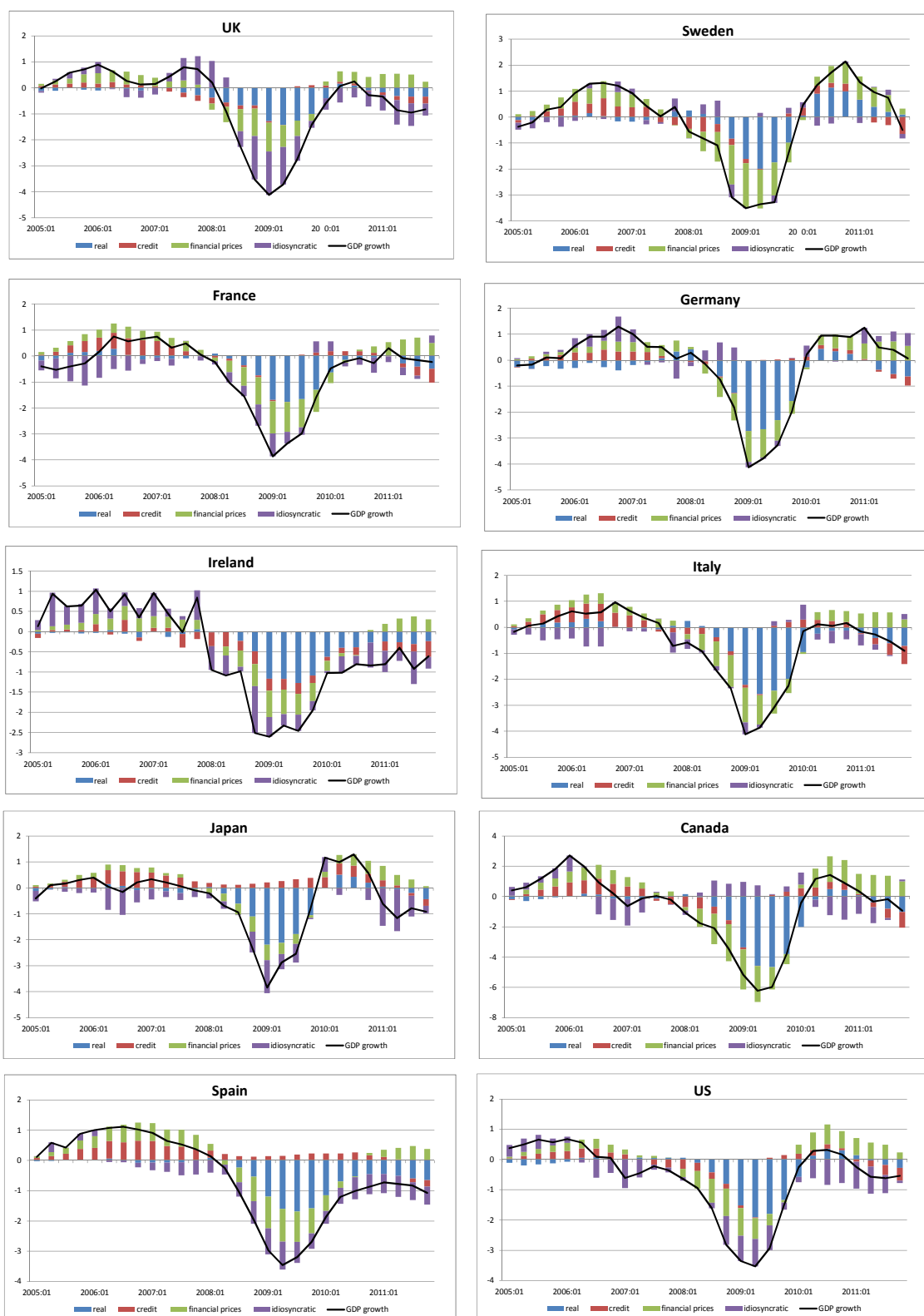
Note: The charts report generalised impulse response functions computed as the difference between a conditional and an unconditional projection of GDP growth (upper panel) and credit growth (lower panel) for each country over the period 1990:1-1992:3. The unconditional projection is the one the model 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.

Figure 9. Responses to Spanish stock price shock



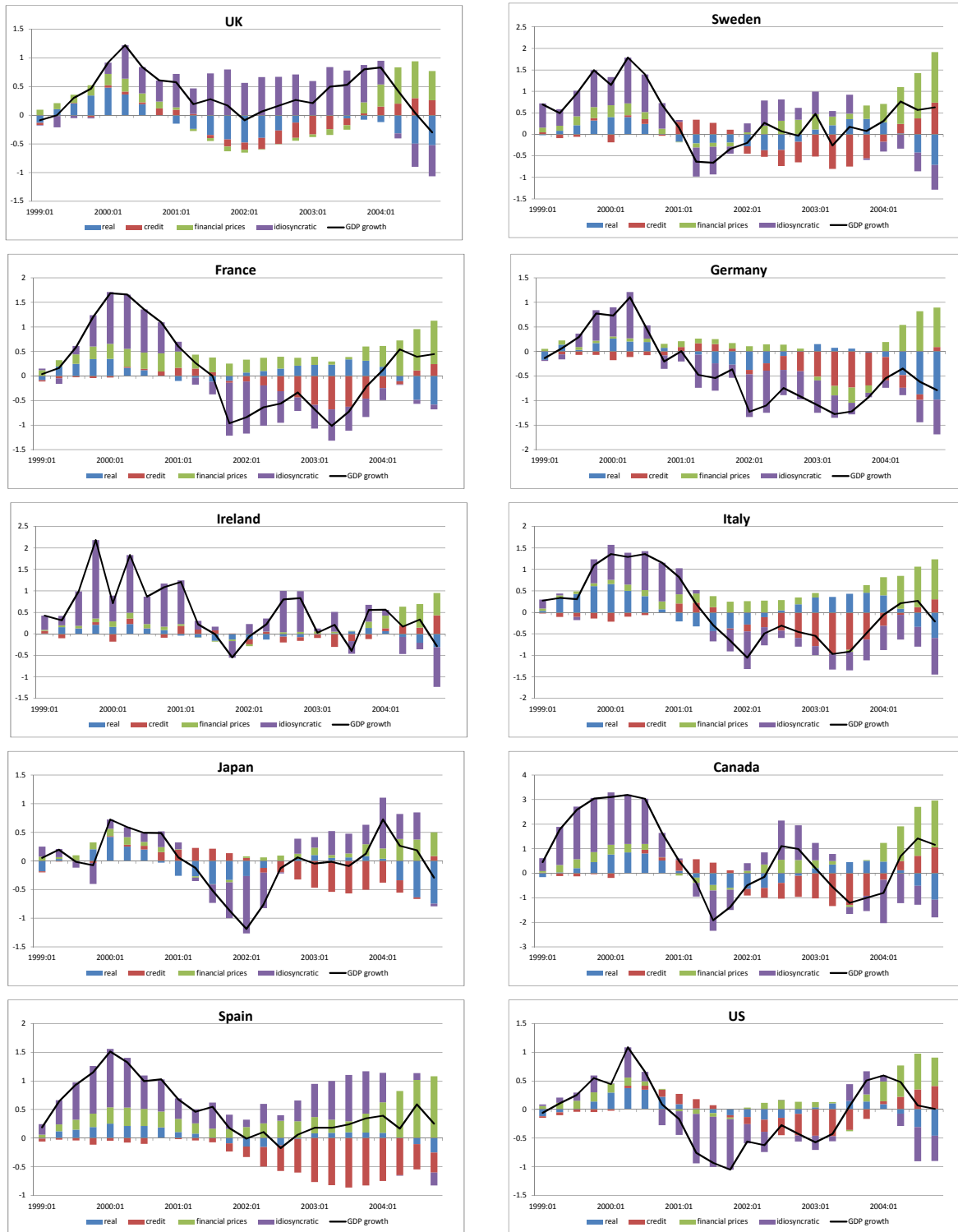
Note: The charts report generalised impulse response functions computed as the difference between a conditional and an unconditional projection of GDP growth (upper panel) and stock prices (lower panel) for each country over the period 1985:3-1987:4. The unconditional projection is the one the model 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.

Figure 10. Historical decomposition. Sample 2005:1 - 2011:4



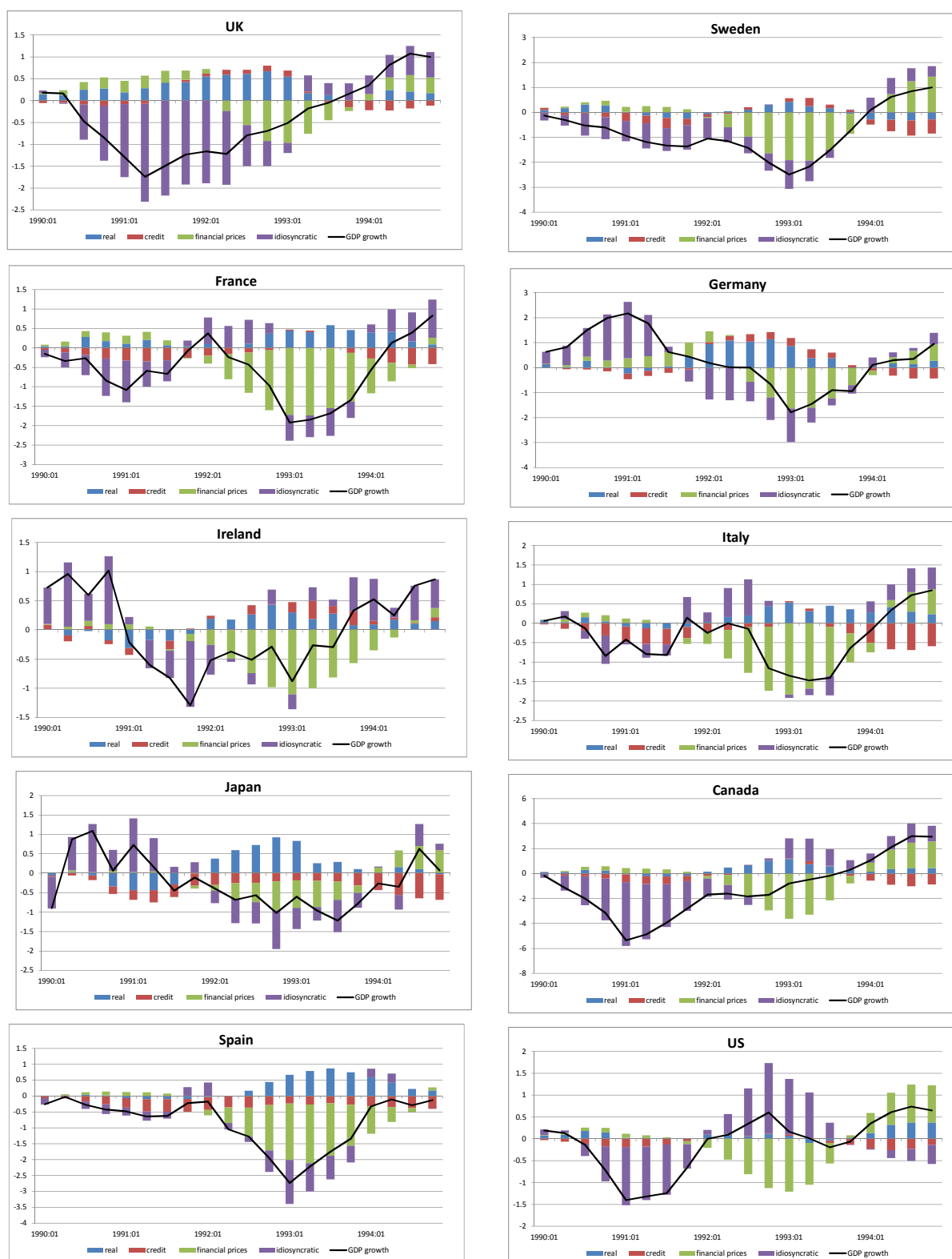
Note: The charts report a historical decomposition based on the estimation of a country by country factor-augmented VAR for GDP growth and the three variable-type components displayed in Figure 3, which capture the common movements of financial prices, real activity and lending markets across countries. 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.

Figure 11. Historical decomposition. Sample 1999:1 - 2004:4



Note: The charts report a historical decomposition based on the estimation of a country by country factor-augmented VAR for GDP growth and the three variable-type components displayed in Figure 3, 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 12. Historical decomposition. Sample 1990:1 - 1994:4



Note: The charts report a historical decomposition based on the estimation of a country by country factor-augmented VAR for GDP growth and the three variable type components displayed in Figure 3, 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.