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MACRO-FINANCIAL LINKAGES:
EVIDENCE FROM COUNTRY-SPECIFIC VARs

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Macro-Financial Linkages: evidence from country-specific VARs[1]

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Abstract

This paper estimates the contribution of financial shocks to fluctuations in the real economy by augmenting the standard macroeconomic vector autoregression (VAR) with five financial variables (real stock prices, real house prices, term spread, loans-to-GDP ratio and loans-to-deposits ratio). This VAR is estimated separately for 19 industrialised countries over 1980Q1-2010Q4 using three alternative measures of economic activity: GDP, private consumption or total investment. Financial shocks are identified by imposing a recursive structure (Choleski decomposition). Several results stand out. First, the effect of financial shocks on the real economy is fairly heterogeneous across countries, confirming previous findings in the literature. Second, the five financial shocks provide a surprisingly large contribution to explaining real fluctuations (33% of GDP variance at the 3-year horizon on average across countries) exceeding the contribution from monetary policy shocks. Third, the most important source of real fluctuations appears to be shocks to asset prices (real stock prices account for 12% of GDP variance and real house prices for 9%). Shocks to the term spread or to leverage (credit-to-GDP ratio or loans-to-deposits ratio) each contribute an additional 3-4% of GDP variance. Fourth, the combined contribution of the five financial shocks is usually higher for fluctuations in investment than in private consumption. Fifth, historical decompositions indicate that financial shocks provide much more important contributions to output fluctuations during episodes associated with financial imbalances (both booms and busts). This suggests possible time-variation or non-linearities in macro-financial linkages that are left for future research.

Résumé non-technique

La crise financière a mis en évidence l'importance des liens entre le secteur financier et l'économie réelle. En tirant des leçons pour l'analyse économique, Kenny et Morgan (2011) invitent à une meilleure prise en compte des canaux de transmission et d'amplification liés aux marchés financiers et à l'incertitude. Ces canaux de transmission, du secteur financier à l'économie réelle (mais aussi vice versa), sont le sujet d'une vaste littérature théorique et empirique qui est bien recensée dans un récent rapport du comité de Bâle (BCBS, 2011).

La présente étude se concentre sur l'impact des chocs financiers sur l'activité réelle, en adressant plusieurs interrogations. Premièrement, quels chocs financiers ont été les plus importants historiquement ? Deuxièmement, les liens macro-financiers sont-ils hétérogènes à travers les pays ? Troisièmement, quelle part des fluctuations réelles peut-on attribuer aux chocs financiers ? Quatrièmement, quelles composantes de la production sont les plus vulnérables aux chocs financiers ?

Nous utilisons un modèle vecteur autorégressif (VAR), un outil standard pour analyser les liens dynamiques entre variables macro-économiques, ce qui nous permet de prendre en compte de possibles effets de retour du secteur réel au secteur financier. En plus des variables macro-économiques classiques, nous intégrons cinq variables financières (cours boursiers, prix immobiliers, l'écart des taux d'intérêt à long et à court terme, le rapport du crédit bancaire au PIB et le rapport des prêts bancaires aux dépôts bancaires). Ce modèle VAR est estimé individuellement pour 19 pays développés sur la période 1980T1-2010T4 en utilisant trois mesures différentes de l'activité économique: le PIB, la consommation privée et l'investissement total.

Le VAR nous permet d'extraire la partie des fluctuations des variables financières qui ne peut pas être anticipée à l'aide du passé de l'ensemble des variables, ce qu'on appelle les « innovations » dans une variable. Cependant, ces innovations sont généralement corrélées à travers les différentes variables, ce qui empêche une interprétation économique. Il est possible de filtrer ces innovations (décomposition de Choleski), afin de récupérer les « chocs structurels » susceptibles d'interprétation. Cette opération présuppose un ordre récursif dans lequel nous plaçons les variables financières en derniers, c'est-a-dire nous supposons qu'elles sont relativement endogènes et peuvent réagir simultanément aux développements macro-économiques étrangers ou domestiques. Les **chocs financiers** identifiés de cette façon représentent la partie des fluctuations des variables financières qui ne peut pas être anticipée à l'aide des observations passées et qui n'est pas corrélée avec les fluctuations contemporaines des variables macro-économiques.

Parmi les variables financières que nous considérons, il est naturel d'inclure les prix des actifs (boursiers et immobiliers), dont l'impact sur la production est appelé « accélérateur

financier » (Bernanke, Gertler & Gilchrist, 1999). En effet, les fluctuations des prix des actifs modifient les bilans financiers des ménages et des entreprises, ce qui peut déterminer leur accès au crédit en présence d'asymétries informationnelles. Ce canal peut passer par l'impact sur la valeur nette de l'emprunteur ou sur la valeur des garanties dont il dispose. Les fluctuations des prix d'actifs peuvent également déterminer l'accès au crédit par leur impact sur les bilans financiers des banques. Dans ce cas, le canal passe par les effets sur le levier d'endettement de l'intermédiaire financier ou sur les conditions associées à de nouveaux apports en capital. Finalement, d'éventuels chocs de confiance pourraient aussi être capturés par les fluctuations des cours boursiers étant donné leur ajustement rapide aux nouvelles informations.

Entre les sources possibles de chocs financiers, nous retenons également l'écart entre taux d'intérêt (à court et à long terme). Les fluctuations de cet écart ont un impact sur les bilans des banques, dont l'actif et le passif sont composés d'instruments à maturités différentes. D'ailleurs, des études empiriques indiquent que les modifications de la pente de la courbe de rendements peuvent servir à anticiper les retournements d'activité économique (e.g. Ang, Piazzesi & Wei, 2006). Finalement, les mesures du levier financier (rapport crédit/PIB ou rapport prêts bancaires/dépôts) sont associées plus directement au canal de transmission par le crédit (Bernanke & Gertler, 1995) et figurent également dans des modèles plus récents du cycle d'endettement et de la liquidité (e.g. Adrian & Shin, 2009).

Plusieurs conclusions découlent de nos résultats. Premièrement, l'effet des chocs financiers sur l'activité économique est assez hétérogène entre pays, ce qui est cohérent avec d'autres résultats dans la littérature. Deuxièmement, l'effet combiné des cinq chocs financiers identifiés par notre méthode représente une contribution importante aux fluctuations de l'activité réelle (33% de la variance du PIB à l'horizon de 3 ans, en moyenne à travers les pays), dépassant celle des chocs de politique monétaire. Troisièmement, entre les différents chocs financiers, il apparaît que la plus importante contribution aux fluctuations de l'activité réelle provient des chocs dus aux prix des actifs financiers (les cours boursiers expliquent 12% de la variance du PIB en moyenne et les prix immobiliers 9%). L'écart des taux ou le levier d'endettement (rapport crédit-PIB ou rapport prêts bancaires-dépôts) contribuent chacun pour 3 à 4% supplémentaire (en moyenne à travers pays). Quatrièmement, en général l'effet combiné des cinq chocs financiers est plus important pour les fluctuations de l'investissement que pour celles de la consommation privée. Cinquièmement, il ressort des décompositions historiques que la contribution des chocs financiers aux fluctuations de l'activité est plus importante lors des épisodes associés aux déséquilibres financiers (les crises mais aussi les périodes de forte expansion). Il est donc possible que l'intensité des liens macro-financiers varie à travers le temps ou de façon non-linéaire. Cependant, ce dernier point nécessiterait d'autres méthodes, que nous prévoyons pour des travaux futurs.

1. Introduction

The global financial crisis stressed the need to improve our understanding of the links between the financial sector and the real economy. Kenny and Morgan (2011) highlight the central role financial shocks played in the crisis and attribute much of the forecasting failures to inadequate attention paid to "…key transmission and amplification channels, especially those linked to financial markets and uncertainty." These channels, both from the financial sector to the real sector and vice versa, are described in a useful survey of recent theoretical and empirical work by the Basel Committee on Banking Supervision (BCBS, 2011). Here we focus on the impact of financial shocks on real activity, but in a framework that allows for feedback in both directions. We use standard reduced form methods (identified vector auto-regressions or VARs) to address several relevant questions. First, which financial shocks have been more important historically? Second, is there heterogeneity across countries in terms of macro-financial linkages? Third, how much do financial shocks contribute to real economic fluctuations? Fourth, which components of output are most affected by financial shocks?

Since we use standard VARs and a country-by-country approach, the underlying assumptions are that (i) international spillovers are captured by an indicator of foreign demand for exports, (ii) nonlinearities are negligible, and (iii) parameters are constant through time. While these simplifications are not meant to be realistic, they make it possible to consider a relatively wide set of 19 economies (most members of the euro area, the area-wide aggregate and the main other OECD countries), suggesting a range of answers to our main questions.

Using the VAR reduced form approach, we define a financial shock as a movement in a financial variable that is unpredictable from past information (an innovation) and is uncorrelated with contemporary movements in main macro-economic variables (orthogonal). For each country, we estimate separate VARs using three different measures of real output: GDP, private consumption or total investment. Each VAR also includes a consumer price index, short-term interest rates, an international index of commodities prices and an indicator of foreign demand. VAR models based on this set of variables have become a standard tool to capture macro-economic dynamics (Christiano et al. 1999). Structural shocks can be identified using short-term restrictions, long-term restrictions, sign restrictions or a combination of these. Below, we rely on short-term restrictions using the standard Choleski decomposition of the innovation covariance matrix, which implies a recursive exogeneity structure among the variables (see discussion below and details in appendix). Similar methods have been applied to study the transmission of monetary policy in euro area

aggregates (e.g. Peersman & Smets, 2001) as well as in individual euro area countries (e.g. Mojon & Peersman, 2001).

In principle, a macro-economic VAR can correspond to the reduced form of a general class of dynamic stochastic general equilibrium (DSGE) models. However, Fernandez-Villaverde et al. (2007) show that not every DSGE will have a VAR representation (and the opposite is also true). Kilian (2011) also warns that caution is required in comparing structural VAR and DSGE results, but both these studies conclude that VAR and DSGE approaches can be complementary. Since a given VAR can be compatible with a whole class of DSGE models, VARs are especially useful when there is uncertainty about the most appropriate DSGE specification, as is the case in the relatively new field of modelling macro-financial linkages.

We augment each VAR to also include five different financial variables: two asset prices (real house prices and real stock prices), the term spread (difference between long and short-term interest rates), and two leverage indicators (ratio of private sector credit to GDP and ratio of aggregate loans to aggregate deposits in the banking sector). The inclusion of asset prices is natural, given their impact on output through the financial accelerator (Bernanke, Gertler & Gilchrist, 1999). Changes in asset prices can act through borrowers' balance sheets, by affecting their net worth or collateral values, but also through banks' balance sheets, by affecting their leverage and their ability to raise new capital. Since stock prices adjust rapidly to incorporate new information, they may also capture confidence shocks. Changes in the term spread (between short- and long-term interest rates) also affect bank balance sheets, given the maturity mismatch between assets and liabilities. The term spread also links to a separate literature on the slope of the yield curve as a predictor of economic activity (e.g. Ang, Piazzesi & Wei, 2006). Finally, the leverage indicators may capture credit channel effects (Bernanke & Gertler, 1995) more directly than asset prices. They also figure in models of liquidity and the leverage cycle (e.g. Adrian & Shin, 2009).

Several other financial variables could have been considered but were eliminated because data was only available for a shorter sample or a more limited set of countries. It is also difficult to include more than five financial variables in a macro-economic VAR given limited degrees of freedom. Therefore we do not consider credit spreads across different classes of borrowers, sovereign spreads across different countries, non-performing loans, loan-loss provisions or other measures of liquidity or volatility. Still, we consider a sufficiently broad set of financial variables to benefit from several advantages. First, we can allow for possible interactions between financial variables as well as between real and financial variables. Second, the set of five different financial variables allows us to better identify innovations as fluctuations that are unpredictable from a larger information set. Third, joint analysis of several financial variables (especially including both house prices and credit) is important

given the finding by Borio & Lowe (2002, 2004) that financial imbalances are better identified through a combination of different financial indicators.

There exists a growing literature extending the standard macroeconomic VAR to incorporate financial variables.[2] The analysis below extends this in three directions. First, as mentioned above, we simultaneously include **five** different financial variables. Among the studies cited in the footnote, only Abildgren (2010) includes more than three financial variables. Second, we provide a broader cross-country perspective, repeating the exercise for each of 19 industrialised economies (including euro area aggregate data) with consistent samples and data definitions. Among the studies cited, only three are comparable in country coverage: Chirinko et al. (2004) consider 13 economies, Assenmacher-Wesche & Gerlach (2008) consider 17 economies and Fornari & Stracca (2010) consider 21 advanced economies. However, these authors only include two or three financial variables. Third, we use a longer sample period to capture a greater number of financial imbalance episodes, starting in 1980Q1 and ending in 2010Q4, which includes the global financial crisis. Again, only Abildgren (2010) uses a longer sample, but limited to a single country (Denmark).

As is well known, shock identification by the standard Choleski decomposition[3] of the innovation covariance matrix assumes a recursive exogeneity structure that is explicit in the ordering of the variables in the VAR. At the top of this ordering, we place place the two external variables (a country-specific foreign demand indicator[4] and an international commodities price index), treating them as more exogenous. These are followed by domestic output, inflation and interest rates, a fairly standard sequence in the literature going back to Christiano et al. (1999). The five financial variables are placed lower in the ordering, allowing them to react to contemporaneous shocks in all the macro-economic variables. Assenmacher-Wesche & Gerlach (2008) argue that financial variables should follow interest rates because monetary policy only reacts to asset price movements if these are prolonged, while asset prices react immediately to changes in monetary policy. The exact ordering

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[2] For example, Iacoviello (2002), Giuliodori (2005), Neri (2004), Adalid & Detken (2007), den Haan et al. (2007), Goodhart & Hofmann (2008), Chirinko et al. (2008), Assenmacher-Wesche & Gerlach (2008), Baumeister et al. (2008), Musso et al. (2010), Giannone et al. (2010), Abildgren (2010) and Fornari & Stracca (2011). Most of these studies focus on monetary policy transmission.

[3] This is also implemented by Giuliodori (2005), Adalid & Detken (2007), Goodhart & Hofmann (2008), Assenmacher-Wesche & Gerlach (2008), Abildgren (2010) and Musso et al. (2010). See appendix.

[4] For EU27 countries this was drawn from the Eurosystem BMPE trade consistency exercise. For non-EU countries it was constructed as a weighted average of real imports of trading partners, with the trade weights used to calculate effective exchange rates at the ECB.

within the block of financial variables is less clear-cut. We follow the suggestion by Goodhart & Hofmann (2008) that house prices should appear first among the financial variables because they are probably stickier. We place the leverage indicators last among the financial variables as do Adalid & Detken (2007), Goodhart & Hofmann (2008) and Musso, Neri & Stracca (2010). These authors argue that this ordering implies a conservative approach to the endogeneity of money and credit growth, allowing them to react contemporaneously to shocks in all the other endogenous variables[5].

All VARs were estimated with two lags[6] of each of ten endogenous variables. The estimation sample usually[7] covered 1981Q2 to 2010Q4. With the exception of interest rates, the term spread, the loans-to-deposits ratio and the loans-to-GDP ratio (expressed as a "credit growth" indicator[8]), all variables are expressed in log-levels and seasonally adjusted. As also observed in other studies, the credit data from the IMF International Financial Statistics suffer from level shifts, so these were eliminated using the TRAMO software package before calculating the leverage ratios.

2. 3.1. How much do financial shocks explain?

The forecast error variance decompositions from the VARs serve as a natural tool to compare the relative importance of different shocks across countries with different output volatility. Three results stand out. First, the contribution of financial variables to real fluctuations is fairly heterogeneous across countries (confirming findings in Chirinko et al. 2008). Second, the combined contribution from the five financial shocks is surprisingly high (33% of GDP variance at the 3-year horizon, averaging across countries) and it increases with the horizon (see Table 1 below). Third, among the financial shocks (see Table 2 for details), those to asset prices appear to contribute more to real fluctuations.

Averaging across countries, shocks to real stock prices contribute more than 12% of output variance at the 3-year horizon, shocks to real house prices contribute 9%, shocks to the term

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[5] Our results are robust to alternative orderings of the financial variables. Since there are five of these variables, there are 5!=120 possible orderings. For each estimated VAR, all 120 variance decompositions were generated. Results in the text are close to the average across these 120 decompositions. See appendix for standard deviations across the 120 decompositions.

[6] Considering up to 5 lags, the Schwarz Bayesian Information Criterion favours only 1 lag in all cases.

[7] For Italy, Denmark, Japan and New Zealand, our quarterly house price series ends in 2010Q3. Loans data for Canada ends in 2008Q4. See appendix for the exact estimation sample for each VAR.

[8] See Biggs, Mayer & Pick (2009). Our main conclusions are unaffected by using their "credit impulse" indicator instead.

spread 5%, and shocks to the leverage ratios around 3%-4% each. However, this ranking of financial shocks is uncertain as differences are often small and may be insignificant. In addition, the ranking varies across countries, reflecting different institutional features and financial structures (see discussion in Assenmacher-Wesche & Gerlach, 2008). These institutional features may either dampen or amplify the impact of financial shocks on the behaviour of household and firms (see Bernanke & Gertler, 1995).

Table 1: % of forecast variance explained by combined effect of five financial shocks

	BE	DE	ES	FI	FR	IE	IT	LU	NL	EA	DK	GB	SE	AU	CA	CH	US	JP	NZ	AVG
							Gross Domestic Product													
1y	28	36	35	29	25	18	14	14	32	35	23	24	32	32	18	14	23	16	27	25.0
2y	35	45	39	36	32	29	19	18	40	37	34	27	34	40	24	27	26	30	34	31.9
3y	34	44	39	36	37	30	20	19	39	40	40	25	37	43	31	25	29	32	35	33.4
6y	34	45	40	39	37	32	21	19	39	43	39	30	39	43	34	26	29	34	37	34.7
							Private Consumption													
1y	3	29	39	11	13	17	7	8	15	4	29	14	11	16	29	14	12	19	29	16.7
2y	11	40	45	19	21	35	16	22	27	11	35	15	13	26	29	19	20	25	36	24.4
3y	13	41	46	24	26	36	20	25	33	17	39	16	16	27	30	21	24	28	36	27.3
6y	16	42	48	27	30	38	23	27	38	23	39	20	17	28	38	22	27	31	37	30.1
							Gross Fixed Capital Formation													
1y	3	17	30	23	15	25	17	13	18	20	20	19	37	31	7	17	20	9	44	20.4
2y	14	22	43	41	25	38	30	18	31	30	33	29	44	34	15	25	29	25	53	30.5
3y	17	24	42	43	26	40	32	18	33	39	38	28	43	37	18	26	34	31	55	32.9
6y	18	25	43	47	30	50	35	19	34	45	38	31	44	38	23	27	34	36	56	35.3

Note: see appendix 1 for country codes

Table 1 is divided in separate panels for GDP, Private Consumption and Gross Fixed Capital Formation. Each panel reports the share of forecast variance explained at different horizons by the combined contribution of shocks to the five financial variables considered (real house prices, real stock prices, long-short spread, loans-to-GDP ratio and loans-to-deposit ratios). For GDP, the cumulative contribution of the five financial shocks appears to be clearly higher for Germany, Spain, and the Netherlands in the euro area, and Australia, Denmark and Sweden outside. For Private Consumption, the cumulative contribution is again highest for Germany and Spain in the euro area, followed by the Netherlands and Ireland. Outside the euro area, the combined contribution is highest in Denmark, Canada and New Zealand. For Investment, the cumulative contribution of financial shocks is highest for Spain, Finland and Ireland in the euro area, and for New Zealand, Sweden, Denmark and Australia outside.

Focussing on the (unweighted) cross-country average in the final column, the combined contribution of the five financial variables appears to be slightly higher for GDP than for investment and is lower for consumption at all horizons. Looking across countries, there is no clear pattern, with the combined contribution sometimes similar across measures of output and sometimes very dissimilar. For some countries financial shocks contribute more to fluctuations in consumption and for others to those in investment or GDP.

At first sight, it may seem surprising that three countries known for their large financial sector (Switzerland, Luxembourg, United Kingdom) appear to be among the less vulnerable to financial shocks. There are several explanations for this result. First, these three countries export much of the financial services they produce. In so far as financial shocks originate (or propagate) abroad, they may affect foreign demand for these services within the same quarter. Given the ordering in the Choleski decomposition, such a shock will then be classified as a foreign demand shock rather than a financial shock (foreign financial shocks are foreign shocks first and financial shocks second). Furthermore, to focus on the link between domestic lending and domestic activity, the leverage ratios were constructed using bank loans to the domestic private sector.

Second, most of the financial shocks considered (house price shocks, stock price shocks and shocks to the term spread) can affect household and firm decisions directly even in the absence of a banking sector. As observed by Bernanke and Gertler (1995), the credit channel is an amplification mechanism, not really a separate channel.

Finally, the variance decomposition normalises output volatility of different countries (in Ireland or Luxembourg it is 8 to 10 times larger than in France, Germany or the euro area), but important differences remain within the decomposition (Figure 3.1). In Luxembourg and Switzerland the own-shock (exogenous) contribution to GDP growth is much higher. This may reflect higher measurement error, since in smaller economies idiosyncratic shocks to individual sectors or even firms are more likely to distort aggregate measures. On the other hand, the United Kingdom ranks first in terms of the contribution from foreign shocks, consistent with its status as a larger open economy. Therefore the smaller contribution of financial shocks in these three countries partly reflects the larger role of exogenous or external factors in driving their GDP.

Another puzzling result is that Germany appears to have the highest combined contribution from financial shocks. In part this is explained by the observation above: adjusting for its higher contribution from external shocks, Germany falls five places in the ranking. Germany also stands out because its contribution of financial shocks is much higher for private consumption than for investment (where the contribution actually falls below the cross-country average). This is consistent with the common view that German industry is largely

composed of smaller firms that finance their investment through long-standing banking relationships that insulate them from shocks. On the other hand, private consumption fluctuations in Germany appear to be largely driven by real house price shocks (see below).

Figure 1: GDP (% of variance explained after 3 years)
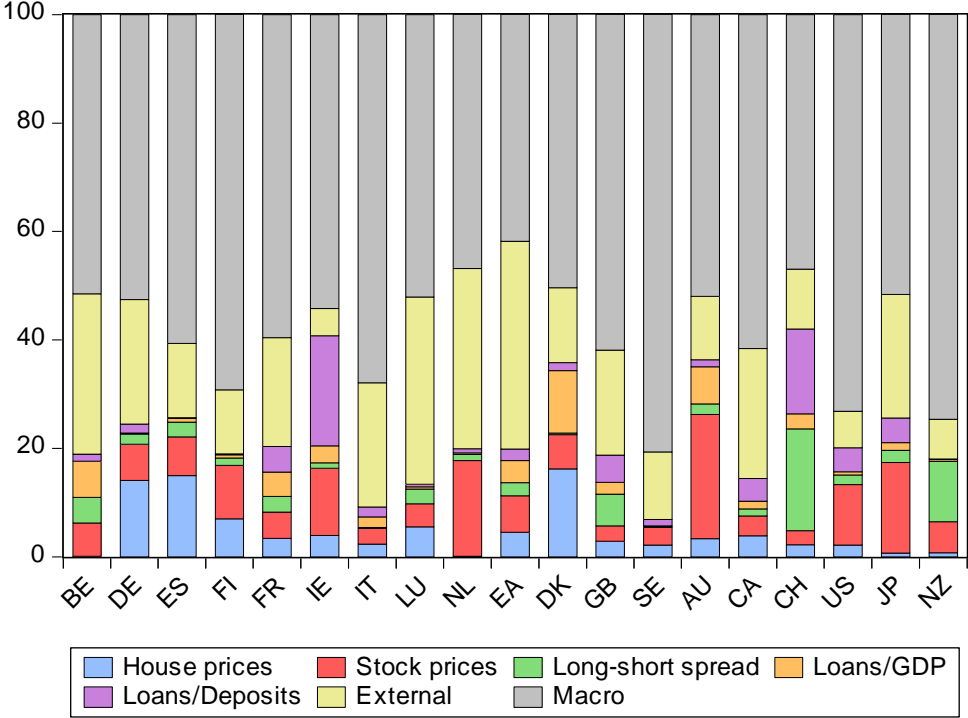
As reported in Figure 1, the relative contribution of individual financial shocks varies significantly across countries. This figure reports the forecast error decomposition for Gross Domestic Product at the 3-year horizon. At the bottom of the graph are the financial variables: real house prices (blue bars), real stock prices (red bars) long-short term spread (green), bank loans to GDP ratio (orange) and bank loans to deposits ratio (purple). Above this appear the combined contributions from external variables (light yellow bars), meaning the country-specific foreign demand indicator and the international commodities price index. Finally, at the top of the graph appear the combined contributions from domestic macroeconomic variables (grey bars), which include the own-shock to GDP, as well as shocks to consumer prices, and short term interest rates.

The contribution from the own-shock to GDP reflects the exogenous component in output movements. This may be exaggerated by omitted variable bias and the particular identification scheme chosen (since output is ordered first among domestic variables, the own-shock will absorb any shocks to other domestic and financial variables that are contemporaneously correlated with those in output). On the other hand, since the financial variables appear last in the Choleski ordering (at the bottom of the graph) it is natural that they contribute relatively less to output fluctuations (they are only the residual component of

innovations after accounting for correlation with contemporaneous shocks in all variables higher in the ordering). This "limitation" of our identification scheme suggests that our results only provide a lower bound estimate for the contribution of financial shocks to output fluctuations, emphasising the fact that they are estimated to be surprisingly large.

Table 2: % of forecast variance at 3-yr horizon explained by individual financial shocks

	BE	DE	ES	FI	FR	IE	IT	LU	NL	EA	DK	GB	SE	AU	CA	CH	US	JP	NZ	AVG
									Gross Domestic Product											
House prices	6	22	18	9	7	16	1	4	8	12	11	5	5	15	13	1	3	7	12	9.2
Stock prices	9	10	14	15	7	8	11	10	14	8	12	14	23	19	7	9	10	20	14	12.4
Term spread	3	8	3	4	11	1	4	0	8	14	8	1	4	2	4	1	9	1	1	4.6
Loans/GDP	3	2	2	5	11	2	0	1	2	5	6	4	3	3	4	12	4	1	5	3.9
Loans/deposits	12	1	3	3	0	4	3	4	6	2	3	2	2	3	3	3	2	4	3	3.3
									Private Consumption											
House prices	3	18	14	6	10	25	2	2	0	9	7	6	3	15	15	2	1	5	11	8.0
Stock prices	2	10	15	5	3	5	8	11	12	0	20	9	8	6	4	5	5	15	11	8.2
Term spread	7	5	12	1	7	0	2	2	4	1	1	1	1	2	5	6	10	1	2	3.6
Loans/GDP	0	7	1	4	1	5	1	6	16	3	4	0	1	2	4	5	6	4	11	4.3
Loans/deposits	2	1	4	8	5	2	6	4	1	4	7	1	3	1	2	4	3	3	1	3.1
									Gross Fixed Capital Formation											
House prices	2	12	12	21	10	19	11	6	5	14	19	4	7	13	8	1	3	3	24	10.2
Stock prices	1	4	19	8	6	13	5	7	8	6	7	12	31	14	2	9	9	17	16	10.3
Term spread	8	1	7	6	4	1	4	1	10	2	6	3	3	5	1	0	7	1	3	3.8
Loans/GDP	0	5	3	2	6	4	6	2	6	16	2	0	1	1	2	8	12	3	6	4.4
Loans/deposits	6	2	1	5	1	3	7	2	4	1	3	8	1	4	5	8	3	8	5	4.1

Table 2 reports the forecast variance decomposition at the 3-year horizon by financial shock. Real house price shocks explain more GDP fluctuations in Germany (22%), Spain (18%) and Ireland (16%). Real stock price shocks affect GDP most in Sweden (23%), Japan (20%), Australia (19%), the Netherlands (14%), and Spain (13%). Shocks to the term spread explain more GDP fluctuations in the euro area aggregate (14%), France (11%), and the US (9%). Shocks to credit growth are more important in Switzerland (12%), France (11%) and Denmark (6%). Shocks to the loans-to-deposits ratio account for more GDP fluctuations in Belgium (12%), the Netherlands (6%), and Japan (4%).

In the final column of Table 2, the cross-country average suggests that asset price shocks contribute much more than the other financial variable shocks. This may not be surprising, given that credit aggregates are determined jointly by supply and demand, with credit

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demand containing "a significant countercyclical component" (Bernanke & Gertler, 1995). Among asset prices, real stock price shocks appear to contribute more on average than real house price shocks, although this is not the case in all countries. In fact, for Germany and Ireland the contribution of house prices is nearly twice that of stock prices, and it is also higher in Spain, Canada and the euro area aggregate. There is no a priori reason why house price shocks or stock price shocks should contribute more. This will depend on several characteristics of the economy under question, including the structure of firm and household finance[9], the relative size of stock-market capitalisation and mortgage debt, the distribution of stock ownership among households, corporations and non-residents. Institutional features of the housing market will also matter, such as the typical loan-to-value ratio, use of fixed or variable mortgage rates, typical mortgage duration in years, mortgage equity withdrawal possibilities and role of state mortgage companies[10].

Focussing on the euro area aggregate and the US, GDP fluctuations in the former are more sensitive to shocks to the term spread (13.8%) and real house prices (12%), followed by shocks to real stock prices (7.5%), to credit growth (4.7%) and to the loans-to-deposits ratio (2.2%). In the US, real stock prices tops the ranking (10.2%) followed by the term spread (9%), credit growth (4.4%), real house prices (3%), and the loans-to-deposits ratio (2.3%).

In the middle panel of Table 3.2, when Private Consumption replaces GDP in the VAR as the indicator of economic activity, the leverage indicators for euro area countries were calculated using long series on loans to households provided by the ECB[11]. Starting with real house price shocks, their contribution to fluctuations in private consumption is highest in Ireland (24%), Germany (18%), Australia (15.4%), Canada (14.6%) and Spain (14%). Real stock price shocks contribute most to consumption fluctuations in Denmark (20%), Japan (15%) and Spain (14.6%). Shocks to the term spread contribute more to consumption fluctuations in Spain (12%), the US (10%), Belgium and France (both 7%). Shocks to credit growth contribute most in the Netherlands (16%), New Zealand (11%) and Germany (7%). Shocks to the loans-to-deposits ratio contribute most in Finland (8%), Denmark (7%), and Italy (6.5%).

For euro area aggregate data, fluctuations in consumption are explained more by shocks to real house prices (9%), to the loans-to-deposits ratio (4%), and to credit growth (3%).

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[9] See ECB (2007) and ECB (2009).

[10] See Calza et al (2009), ECB (2009) and CGFS (2006).

[11] This may reduce the comparability of results for euro area countries to those for other countries, and also to euro area country results in the VARs using GDP, which used IMF data on loans.

Shocks to the term spread (0.6%) or to real stock prices (0.5%) are less important. By contrast, in the US consumption fluctuations are explained more by shocks to the term spread (10%), to credit growth (6%), and to real stock prices (5%), than by shocks to the loans-to-deposits ratio (3%) or to real house prices (0.6%).

The bottom panel of Table 2 provides the variance decomposition at the 3-year horizon when Investment replaces GDP in the VAR as the measure of economic activity. In this case, for euro area countries the leverage indicators are calculated using loans to non-financial corporations. Shocks to real house prices make the largest contribution to investment fluctuations in New Zealand (24%), Finland (21%), Ireland (19%) and Denmark (18.6%). The contribution of house price shocks in Spain is above average at 12%. Shocks to real stock prices appear to have a much larger role in Sweden (31%) and Germany (19%), followed by Japan (17%) and New Zealand (16.5%). Shocks to the term spread contribute more to investment fluctuations in the Netherlands (10%), Belgium (8%), the US (7%) and Spain (6.5%). Shocks to credit growth have the largest effects on investment in the euro area aggregate (16%), the US (12%), Switzerland (8%) and Italy (6%). Shocks to the loans-to-deposits ratio contribute more to investment fluctuations in the United Kingdom (8.5%) Switzerland (8.2%), Japan (7.6%) and Italy (6.8%).

For the aggregate euro area data, fluctuations in investment are affected more by shocks to credit growth (16%), followed by real house price shocks (14%), real stock price shocks (6%), shocks to the term spread (2%) and to the loans-to-deposits ratio (1%). For the US, investment fluctuations are also more sensitive to credit growth shocks (12%), followed by real stock price shocks (8%), shocks to the term spread (7%), to real house prices (2.7%) and to the loans-to-deposits ratio (2.6%).

3. When were financial shocks important?

While the forecast error variance decomposition provided an indication of the relative importance of financial shocks for output growth, historical decompositions can provide an indication of when in the sample those shocks were most present. In the figures below, euro area and US GDP growth are decomposed into the contributions of three groups of variables. The blue bars represent the contribution of shocks to the macro-economic variables (GDP, inflation and interest rates). The red bars represent the combined contribution of the five financial variables and the green bars represent the contribution of the external variables (foreign demand and commodities prices).

Contributions to GDP growth were calculated by recovering the residuals (innovations) from each equation, transforming these to structural shocks by multiplying by the Choleski factor and then using the resulting shocks at each point in time to scale the impulse response

functions forward to the end of the sample. These impulses from shocks at different periods were then summed at each point in the sample so that the effect of the current shock and all past shocks were combined to obtain the contribution to growth from that particular kind of shock.
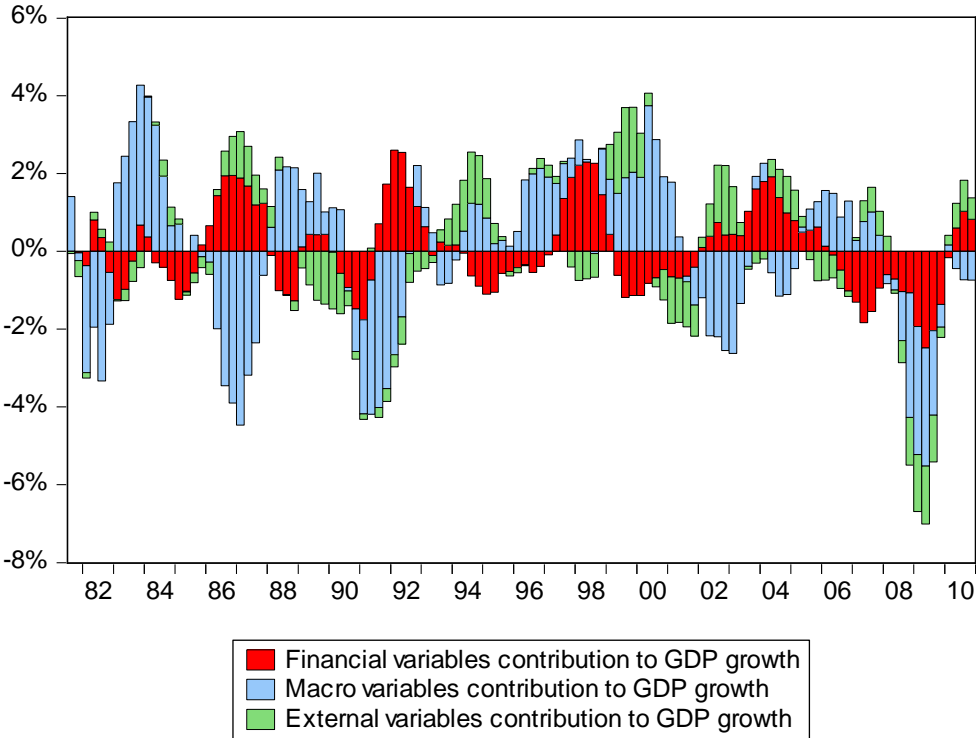
Only the historical decompositions for the euro area and the US are discussed below. The historical decompositions for other countries appear in the appendix.

Figure 2: Euro Area GDP growth Historical Decomposition
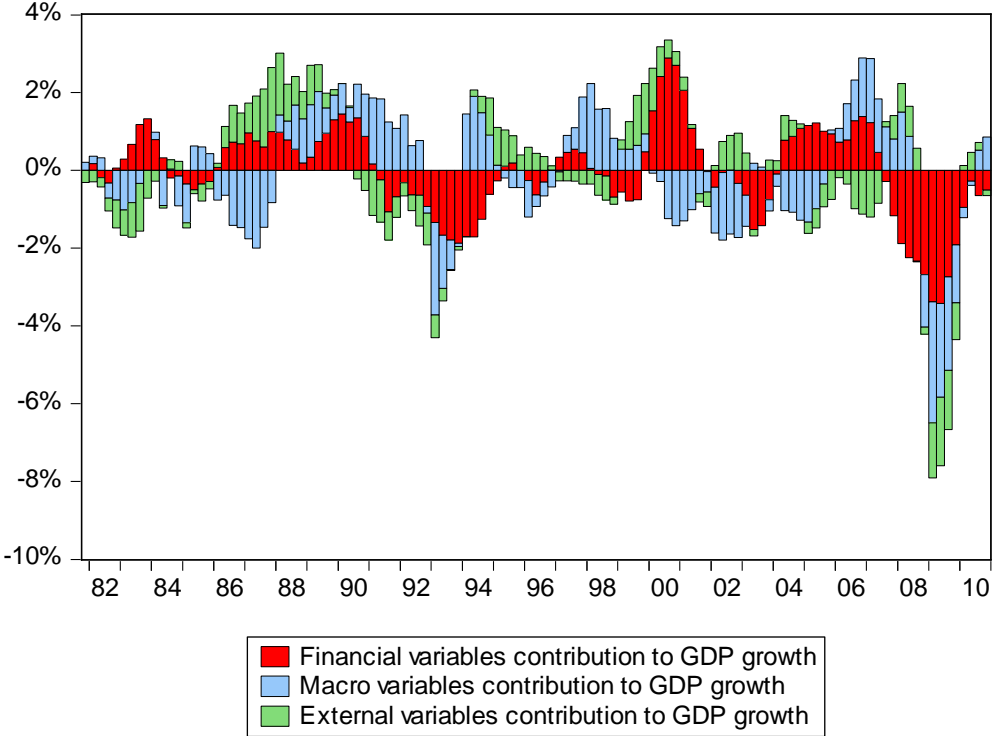
For the euro area, the contributions from financial variable shocks were limited in the early 1980s and tended to be positive following the peak in the US dollar associated with the Plaza accord. The positive contributions picked up in 1989Q2-1990Q3 during the house price boom. The financial shock contributions turned negative in 1991 and plunged through the ERM crisis of September 1992 and the ensuing recession. From 1995 to 1999 the contribution to growth from financial shocks was limited, but it gained consistency during the "new technology" stock market bubble from 1999Q4 peaking in 2000Q3. In 2001 the stock market bubble burst and contributions fell to zero. There is another string of positive contributions starting in 2004Q2 when real house prices boomed and lasting until the first signs of financial turmoil in 2007Q2. The contribution turned negative in 2007Q3 and plunged until 2009Q2 as GDP collapsed. The negative contribution to growth from financial shocks diminished until 2010, when they remained mildly negative.

Figure 3: US GDP growth Historical Decomposition

Legend:
- Financial variables contribution to GDP growth (red)
- Macro variables contribution to GDP growth (light blue)
- External variables contribution to GDP growth (green)

In the US, financial shocks contributed little to output fluctuations in the early 1980s. The Tax Reform act of 1986 contributed to end the property price boom visible as a string of positive contributions from 1985Q4 to 1987Q4. The ensuing Savings & Loan crisis is visible as negative contributions during 1988 and again in 1990Q2-1991Q2. As could be expected, the 1992 ERM crisis visible in Europe coincides with a string of positive contributions in the US data as house prices began to recover. However, by 1994Q3 the contribution turned negative as real asset prices stagnated and the term spread began to fall. A string of large positive contributions reappears starting in 1997Q2 when asset prices rallied and the term spread recovered. This episode peaked in 1998Q2 as the term spread fell to zero and real stock prices paused. Macro variables seem to dominate during the ensuing "new technology" stock market bubble until it burst in 2001. Financial shocks provided no serious contribution to growth until 2003Q3 when real stock prices recovered, although the contribution to growth peaked shortly afterwards in 2004Q2 and then declined. By 2006Q2 it was negative and weighed increasingly on growth during 2008, reaching a trough in 2009Q2. Since 2010Q2 the contribution to growth from financial shocks is modestly positive.

4. Conclusions

Conventional VAR methods estimated in a single-country setting provide a standard and flexible framework to analyse the links between financial variables and real variables. Variance decompositions based on the conventional Choleski identification suggest several

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conclusions. First, the contribution of financial variables to real fluctuations is fairly heterogeneous across countries. Second, on average across countries, this contribution is rather large (up to 33% of GDP variance at the 3-year horizon) and exceeds the contribution of monetary policy shocks. Third, shocks to real asset prices (house prices and stock prices) often have greater real effects than those to the term spread or to leverage (loans-to-GDP ratio or loans-to-deposits ratio). Fourth, comparing GDP, private consumption or investment, the latter is often most responsive to financial shocks. However, our results suggest that for some countries financial shocks may affect consumption more strongly than investment. When introducing financial frictions in DSGE models, the modelling of firm and household decisions should reflect country-specific characteristics.

Our main conclusions are robust to several changes in specification (see appendix), including estimating the VAR with longer lags, using log-levels instead of year-on-year growth rates, and dropping the volatile periods at the start and end of the estimation sample. When we re-estimate our VARs with other specifications or using only subsamples, shocks to asset prices continue to contribute more to real fluctuations (on average across countries).

We have also checked the robustness of our results to alternative orderings of the financial variables (see appendix); however, the Choleski identification scheme does assume that within the same observation period shocks to a given variable are orthogonal to those of variables placed higher in the ordering. This assumption is clearly more appropriate at monthly frequency than at the quarterly frequency that we adopt in order to use national accounts data. In fact, Gilchrist et al. (2009) use monthly data and find a higher contribution of financial shocks to real fluctuations. They identify credit shocks in the US corporate bond market that account for up to 30% of the variability of monthly employment and industrial production at the 2-4 year horizon.

We should draw attention to several limitations of our analysis. First, we use a longer sample than in many previous studies in order to include as many financial imbalance episodes as possible, but this also increases the number of potential regime shifts (such as EMU). In addition, there may be theoretical reasons to expect the relation between real and financial variables to vary at different points in the business cycle. Both these remarks suggest that methods allowing for time-varying parameters may be more appropriate. Second, our approach ignores possible cross-country spillovers that could be captured by panel VAR methods (e.g. Ciccarelli, Ortega & Valderrama, 2012). Finally, our standard VAR framework is only a linear approximation to the data, while the relation between real and financial variables may be subject to nonlinearities (e.g. Hartmann et al 2012).

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Appendix 1: Structural VAR identification by short-run restrictions

Let y_t, $t = 1,\ldots,T$ denote a K-dimensional vector of variables. This can be approximated by a vector autoregression of finite order p with the following structural form:

$$B_0 y_t = B_1 y_{t-1} + \ldots + B_p y_{t-p} + u_t$$

Where u_t denotes a mean zero serially uncorrelated error term, also known as structural innovation or structural shock. The error term is usually assumed to be unconditionally homoskedastic (constant variance). Constants and deterministic trends have been suppressed for notational convenience. This structural form can be expressed compactly as

$$B(L)y_{t-1} = u_t$$

Where L denotes the lag operator ($Ly_t = y_{t-1}$) and $B(L) = B_0 - B_1 L - B_2 L^2 - \ldots - B_p L^p$ is the autoregressive lag polynomial of order p. The standard normalization of the variance-covariance of the structural error term is

$$E(u_t u_t') = \Sigma_u = I_K$$

Meaning (i) there are as many structural shocks as variables in the model, (ii) these shocks are mutually uncorrelated so that Σ_u is diagonal and (iii) the variance of all structural shocks is equal to unity. The latter normalization involves no loss of generality as long as the diagonal elements of B_0 are unrestricted.

The reduced form representation of the model is required for estimation, expressing y_t as a function of lagged y_t only. Premultiplying both sides of the structural form by B_0^{-1},

$$B_0^{-1} B_0 y_t = B_0^{-1} B_1 y_{t-1} + \ldots + B_0^{-1} B_p y_{t-p} + B_0^{-1} u_t$$

So the reduced form can be written

$$y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + \varepsilon_t \quad \text{where } A_i = B_0^{-1} B_i, \ i = 1,\ldots,p \quad \text{and } \varepsilon_t = B_0^{-1} u_t$$

Equation-by-equation ordinary least squares regression provides consistent estimates of the reduced form parameters A_i, reduced form errors ε_i and their covariance matrix $E(\varepsilon_t \varepsilon_t') = \Sigma_\varepsilon$. However, since the reduced form errors are $\varepsilon_t = B_0^{-1} u_t$ they are likely to be mutually correlated ($\Sigma_\varepsilon \neq I_K$). An estimate of B_0^{-1} is required to recover the orthogonal structural shocks (u_t) from the correlated reduced form errors (ε_t). The most common approach is to assume a recursive structure, applying the Choleski decomposition to the covariance matrix Σ_ε of the estimated residuals to obtain the lower triangular K x K matrix P such that

$$PP' = \Sigma_\varepsilon$$

Assuming $P = B_0^{-1}$ we can recover the structural shocks as $\quad u_t = P^{-1} \varepsilon_t$

Appendix 2: Data description and sources

	Description	Sources
CPI	Consumer Prices	OECD, Eurostat, IMF, ECB
YER	Gross Domestic Product (real)	OECD, Eurostat, NCB data or interpolations
PCR	Private Final Consumption (real)	OECD, Eurostat, NCB data or interpolations
ITR	Gross Capital Formation (real)	OECD, Eurostat, NCB data or interpolations
STN	Short-term (interbank) interest rate	OECD, IMF, ECB
LTN	Long-term Interest Rate (nominal)	OECD, IMF, ECB
SP	Stock prices	OECD, IMF, ECB, NCB calculations
HP	House prices	OECD, ECB, NCB calculations
Loan	Loans to private sector	IMF, ECB
LHH	Loans to households	ECB
LNFC	Loans to nonfinancial corporations	ECB
Fin1	Interest rate spread	difference between short-term/long-term interest rates
Fin2	Loan/GDP ratio	calculated by team members
Fin3	Loan/Deposit ratio	calculated by team members

Note: house prices and stock prices are deflated by consumer prices, the long-short interest rate spread is nominal and the leverage ratios do not need deflation.

Sample periods for the VAR estimates appear below.

		Real GDP	Real private consumption	Real investment
Belgium	BE	1981Q3 2010Q4	1981Q4 2010Q4	1981Q4 2010Q4
Germany	DE	1981Q3 2010Q4	1981Q4 2010Q4	1981Q4 2010Q4
Spain	ES	1981Q3 2010Q4	1981Q4 2010Q4	1981Q4 2010Q4
Finland	FI	1981Q3 2010Q4	1981Q4 2010Q4	1981Q4 2010Q4
France	FR	1981Q3 2010Q4	1981Q4 2010Q4	1981Q4 2010Q4
Ireland	IE	1981Q3 2010Q4	1981Q4 2010Q4	1981Q4 2010Q4
Italy	IT	1981Q3 2010Q3	1981Q4 2010Q3	1981Q4 2010Q3
Luxembourg	LU	1981Q3 2010Q4	1981Q4 2010Q4	1981Q4 2010Q4
Netherlands	NL	1981Q3 2010Q4	1981Q4 2010Q4	1981Q4 2010Q4
Euro area	EA	1981Q4 2010Q4	1981Q4 2010Q4	1981Q4 2010Q4
Denmark	DK	1981Q3 2010Q3	1981Q4 2010Q3	1981Q4 2010Q3
United Kingdom	GB	1981Q3 2010Q4	1981Q3 2010Q4	1981Q3 2010Q4
Sweden	SE	1981Q3 2010Q4	1981Q3 2010Q4	1981Q3 2010Q4
Australia	AU	1981Q3 2010Q4	1981Q3 2010Q4	1981Q3 2010Q4
Canada	CA	1981Q3 2008Q4	1983Q3 2008Q4	1983Q3 2008Q4
Switzerland	CH	1981Q3 2010Q4	1981Q3 2010Q4	1981Q3 2010Q4
United States	US	1981Q3 2010Q4	1981Q3 2010Q4	1981Q3 2010Q4
Japan	JP	1981Q3 2010Q3	1981Q4 2010Q3	1981Q4 2010Q3
New Zealand	NZ	1981Q3 2010Q3	1981Q4 2010Q3	1981Q4 2010Q3

Appendix 3: alternative orderings of five financial variables

This appendix examines the robustness of results to alternative orderings of the financial variables included in the VAR. Since there are five of these variables, there are 5!=120 possible orderings. For each country-output measure, the variance decomposition of the estimated VAR was repeated for all 120 of these orderings. Results presented above (based on the ordering in the text) are close to average results across these 120 variance decompositions. The graphs in this appendix report standard deviations taken across the 120 sets of results. Notice that these indicate uncertainty about the relative contribution of the five financial variables. By definition, the combined contribution of the financial variables is not affected by alternative orderings within their set.

Figure 4:   Standard Deviation (%) of contributions to GDP variance after 3 years (across 5!=120 possible orderings of financial variables)
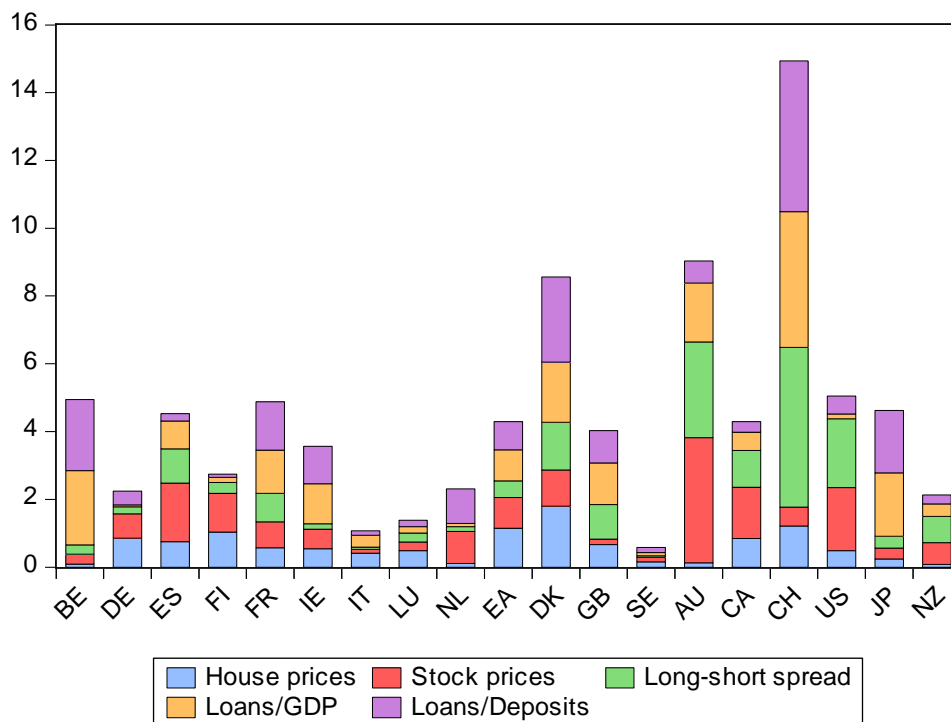
For most countries, the range of the y-axis on these graphs is limited, suggesting a relatively concentrated distribution across the 120 sets of results. However, from the first graph above, it is apparent that in Switzerland, Australia or Denmark the relative ranking of financial shocks for GDP fluctuations is much more sensitive to alternative orderings of the financial variables, while that for Sweden, Italy or Luxembourg is particularly robust.

Figure 5: Standard Deviation (%) of contributions to Private Consumption variance after 3 years (across 5!=120 possible orderings of financial variables)
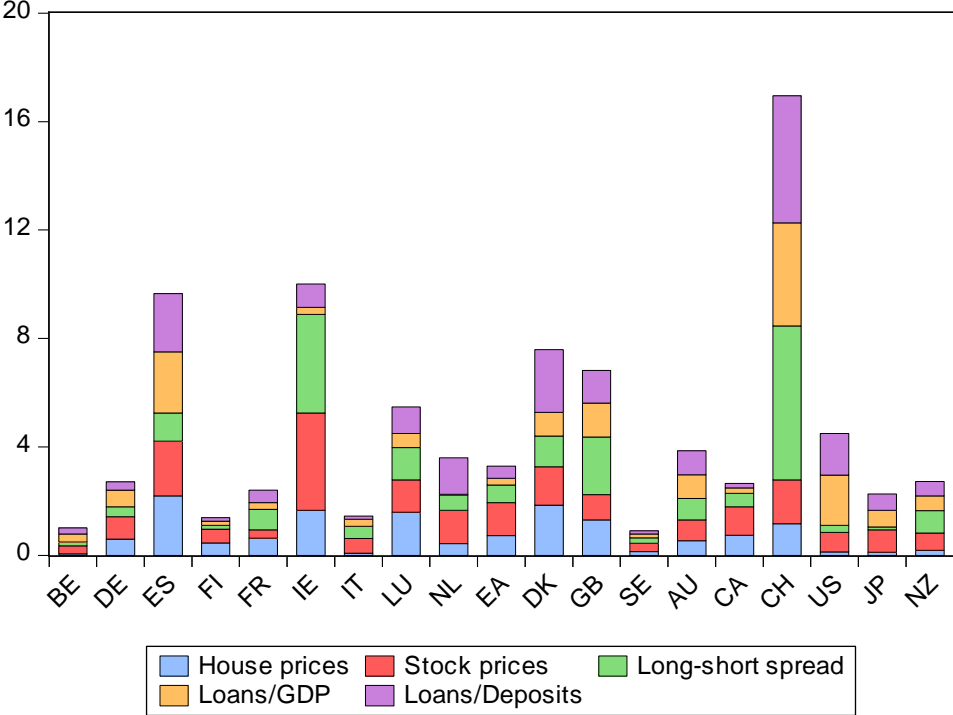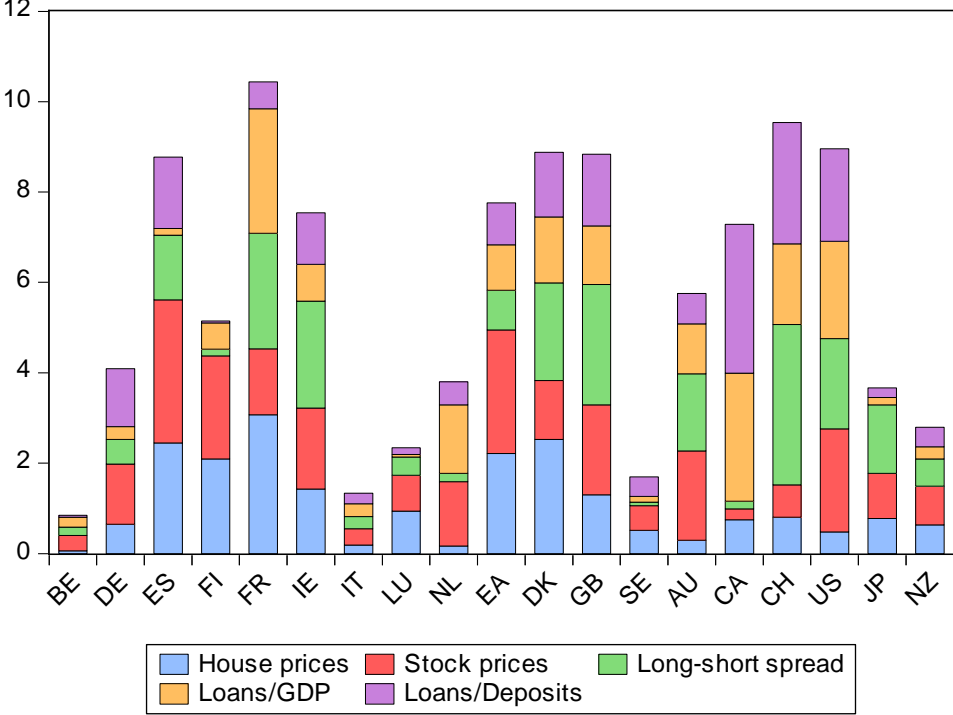

Figure 6: Standard Deviation (%) of contributions to Investment variance after 3 years (across 5!=120 possible orderings of financial variables)

Appendix 3: Sensitivity analysis

This appendix performs sensitivity analysis by estimating the VARs with alternative lag lengths, estimating the VAR in log-levels (with and without a deterministic trend) and estimating the baseline VAR(2) in year-on-year growth rates over subsamples (excluding the volatile period up to 1984Q4 or excluding the recent financial crisis since 2008Q1). The figures below focus on the share of GDP forecast error variance at the 3-year horizon that is explained by the combined contribution of the five financial shocks. Each figure compares this result under different model specifications. In each case, the main results carry through: there is heterogeneity across countries and financial shocks contribute significantly to output fluctuations. Although not reported, asset prices are still the most important financial shocks.

Figure 7: Lag length (GDP variance explained by financial shocks after 3 years)

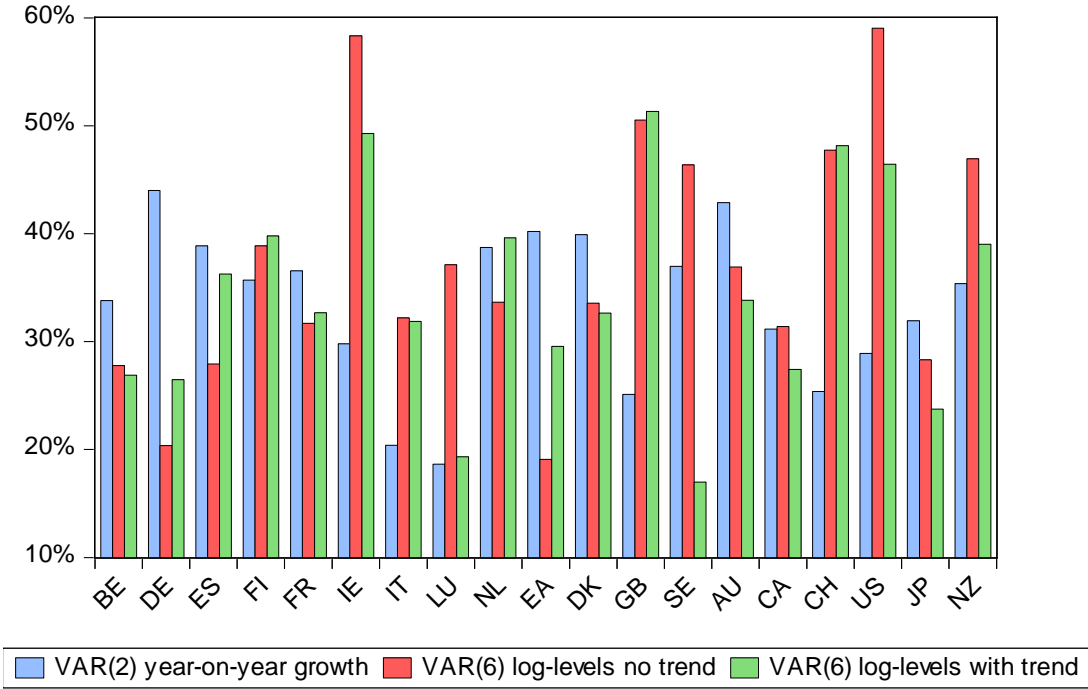| ■ VAR(2) year-on-year growth | ■ VAR(3) year-on-year growth | ■ VAR(4) year-on-year growth |
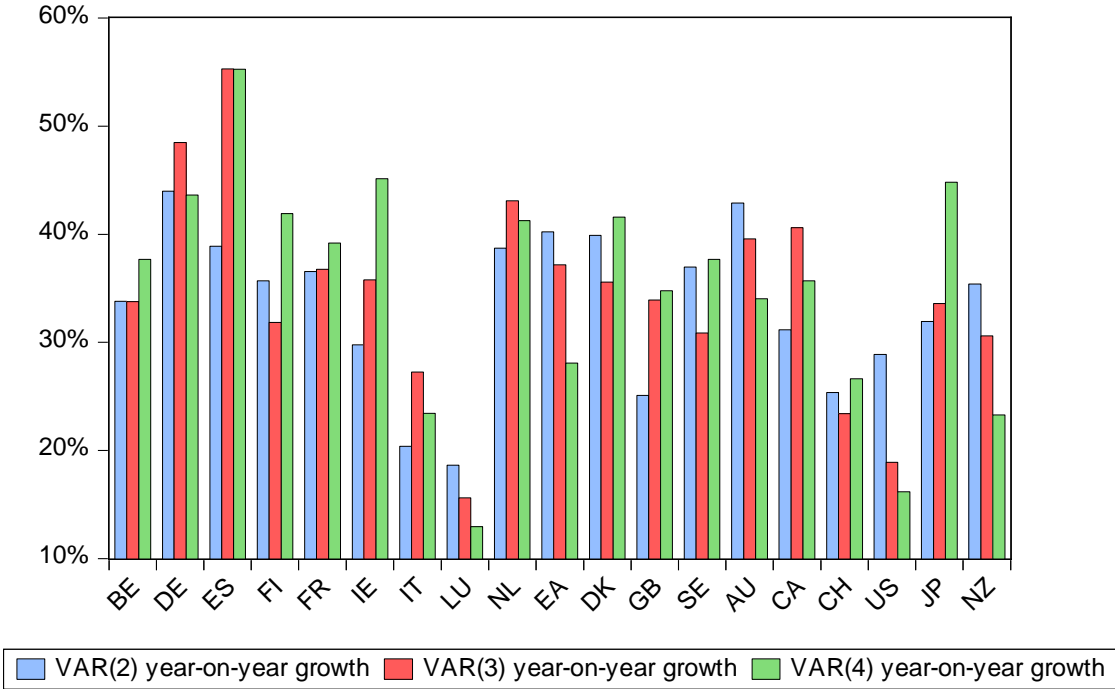
Figure 9 compares results when the baseline VAR in year-on-year growth rates is extended from 2 to 4 lags. If the VAR is overparameterized, estimates should be less efficient but remain consistent. However, if the baseline VAR is misspecified by including too few lags then estimators will be inconsistent. The figure does not suggest that results are changed substantially by including additional lags. For several countries there is an increase in the combined contribution of financial shocks (Spain, Ireland, Japan) but for others there is a fall (Luxembourg, euro area, Australia, New Zealand). The (unweighted) average across countries rises from 32% (2 lags) to 34% (3 lags) to 35% (4 lags), which does not seem significant.

Figure 8: Specifications (GDP variance explained by financial shocks after 3 years)

Our baseline specification includes two lags of year-on-year growth in GDP. This can be considered a restricted form of a VAR(6) in log-levels. Figure 10 compares baseline results to those from a VAR estimated in log-levels, both omitting and including a deterministic trend. For some countries the restrictions implied by the baseline specification do seem to have a large effect, raising the combined contribution of financial shocks (Germany, euro area, Denmark, Japan) or lowering them (Ireland, Italy, United Kingdom, Switzerland, US). The cross-country average rises from 32% to 34% (no trend) or 37% (with trend).

Figure 9: Subsamples (GDP variance explained by financial shocks after 3 years)
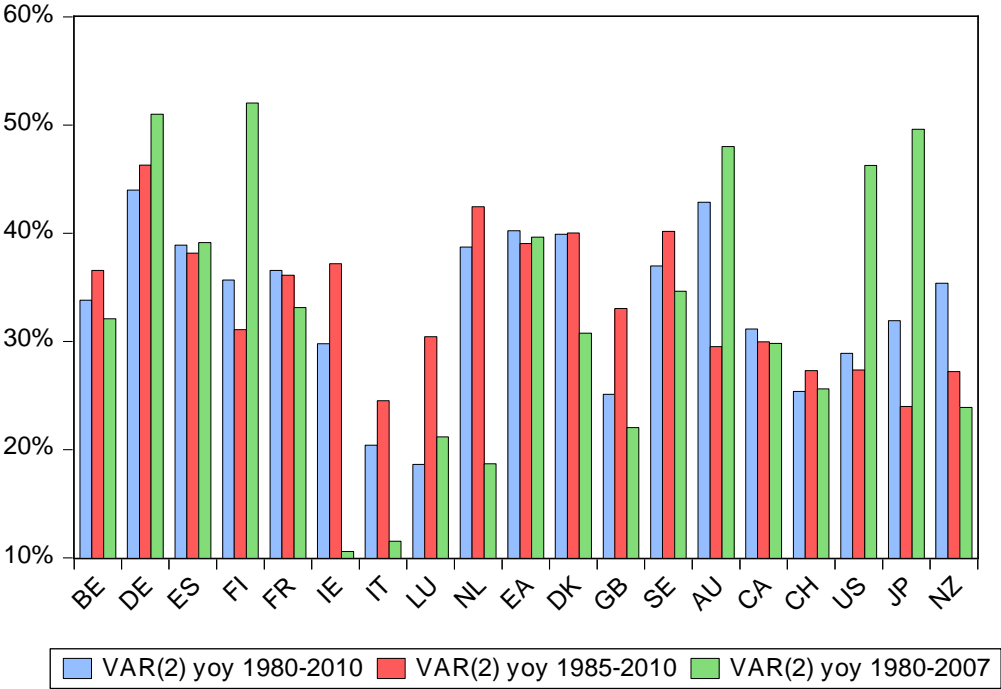

Some of the authors cited drop the period up to 1985 on the argument that it was exceptionally volatile. Others do not include the volatile period associated with the global financial crisis starting in 2007. Figure 11 indicates that for some countries the results are largely affected by dropping the turbulence at the start or the end of the sample. In Germany, the contribution of financial shocks is actually higher when the start or the end of the sample is dropped. In Finland, Australia, the US and Japan, dropping the start of the sample lowers the contribution of financial shocks, while dropping the end of the sample increases it dramatically. This suggests that for these countries, the correlation between financial and macro-economic variables differed across these two periods. The unweighted cross-country average rises from 32% in the full-sample analysis to 34% when dropping 1980-1984 and to 33% when dropping 2008-2010.

Appendix 4: Average Impulse Response Functions

It is difficult to compare impulse response functions across countries, as they are based on a shock of a "representative" size for the individual economy. For example, Mojon & Peersman (2001) note that a one standard-deviation shock will have different size across countries depending on the relative volatility of the underlying data. Alternatively, imposing a shock of the same size across countries may imply a large shock for one country and a small shock for another. In this annex we adapt the approach in Canova and Pappa (2007) and report a weighted average of impulse response functions across countries, with country weights that are proportional to the inverse of the variance (precision of the estimate) at each horizon.

Figure 10: GDP Impulse Response Function (weighted average across countries)
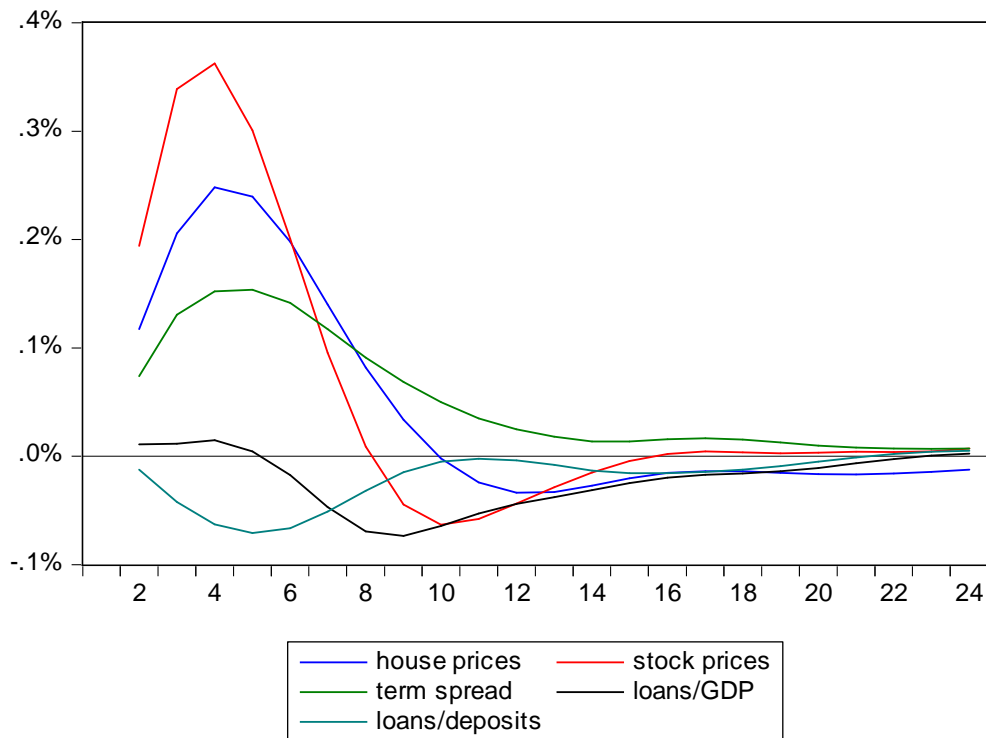
The initial response of GDP growth to a one standard deviation shock to real stock prices is highest, followed by its response to the real house price shock and the shock to the term spread. All three have a hump-shaped response, however, the response to the stock price shock dies away more rapidly, which may partly explain its lesser contribution to total variance explained. GDP responses to the remaining two shocks are generally closer to zero and therefore unlikely to be statistically significant. These impulse response functions should be interpreted with caution, since each line is a weighted average (with country weights unrelated to the size of their economies). The country weights are also changing over the horizon of the shock, since the relative precision of the estimate may vary at different horizons across countries.

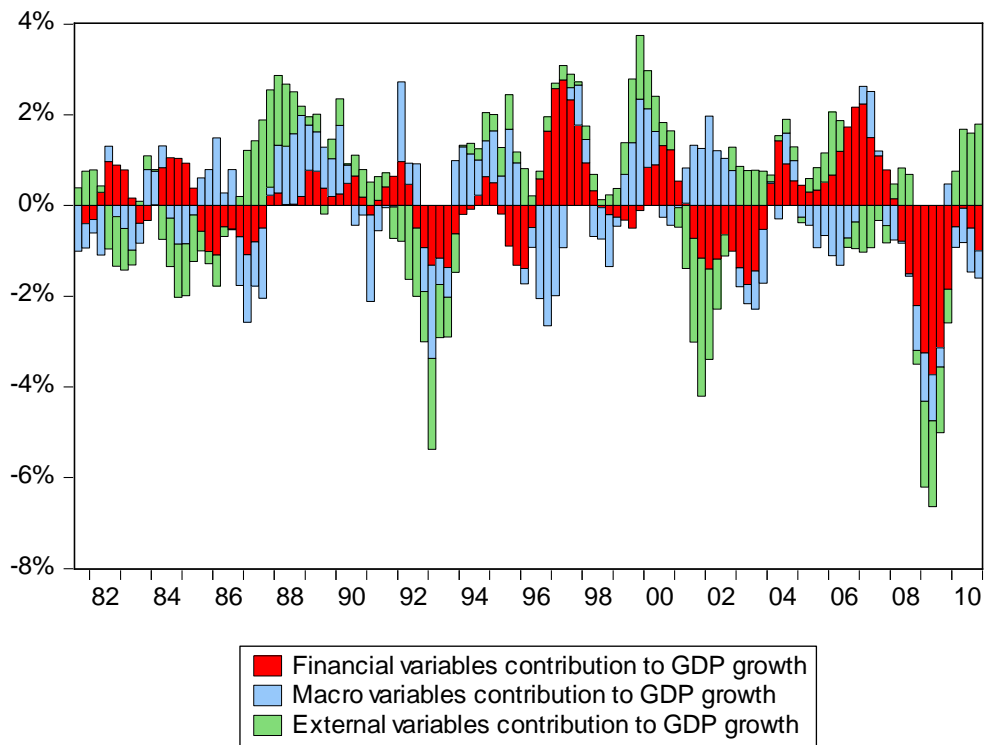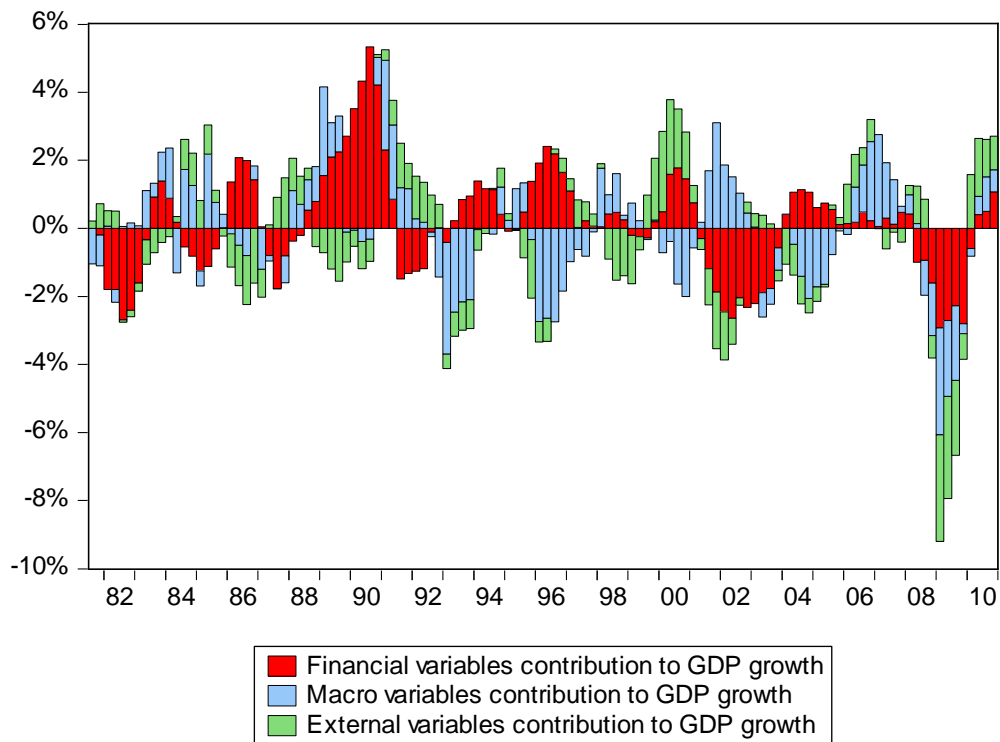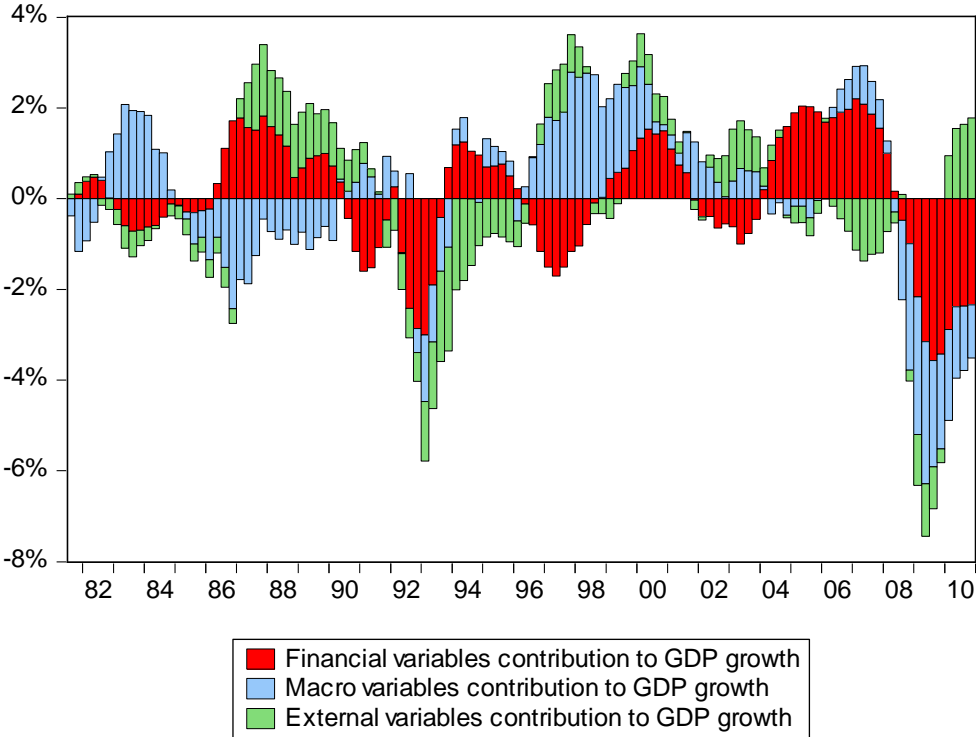## Appendix 5: Additional historical decompositions

Figure 11: Belgium

Financial variables contribution to GDP growth
Macro variables contribution to GDP growth
External variables contribution to GDP growth

Figure 12: Germany

Financial variables contribution to GDP growth
Macro variables contribution to GDP growth
External variables contribution to GDP growth

Figure 13: Spain

- Financial variables contribution to GDP growth
- Macro variables contribution to GDP growth
- External variables contribution to GDP growth

Figure 14: Finland

- Financial variables contribution to GDP growth
- Macro variables contribution to GDP growth
- External variables contribution to GDP growth

Figure 15: France

Legend:
- ■ (red) Financial variables contribution to GDP growth
- ■ (blue) Macro variables contribution to GDP growth
- ■ (green) External variables contribution to GDP growth

Figure 16: Ireland

Legend:
- ■ (red) Financial variables contribution to GDP growth
- ■ (blue) Macro variables contribution to GDP growth
- ■ (green) External variables contribution to GDP growth

Figure 17: Italy

Legend:
- Financial variables contribution to GDP growth
- Macro variables contribution to GDP growth
- External variables contribution to GDP growth

Figure 18: Luxembourg

Legend:
- Financial variables contribution to GDP growth
- Macro variables contribution to GDP growth
- External variables contribution to GDP growth

Figure 19: Netherlands

Legend:
- ■ Financial variables contribution to GDP growth (red)
- ■ Macro variables contribution to GDP growth (blue)
- ■ External variables contribution to GDP growth (green)

Figure 20: Denmark

Legend:
- ■ Financial variables contribution to GDP growth (red)
- ■ Macro variables contribution to GDP growth (blue)
- ■ External variables contribution to GDP growth (green)

Figure 21: United Kingdom

Legend:
- Financial variables contribution to GDP growth
- Macro variables contribution to GDP growth
- External variables contribution to GDP growth

Figure 22: Sweden

Legend:
- Financial variables contribution to GDP growth
- Macro variables contribution to GDP growth
- External variables contribution to GDP growth

Figure 23: Australia

Legend:
- Financial variables contribution to GDP growth
- Macro variables contribution to GDP growth
- External variables contribution to GDP growth

Figure 24: Canada

Legend:
- Financial variables contribution to GDP growth
- Macro variables contribution to GDP growth
- External variables contribution to GDP growth

Figure 25: Switzerland

Financial variables contribution to GDP growth
Macro variables contribution to GDP growth
External variables contribution to GDP growth

Figure 26: Japan

Financial variables contribution to GDP growth
Macro variables contribution to GDP growth
External variables contribution to GDP growth

Figure 27: New Zealand

Legend:
- Financial variables contribution to GDP growth
- Macro variables contribution to GDP growth
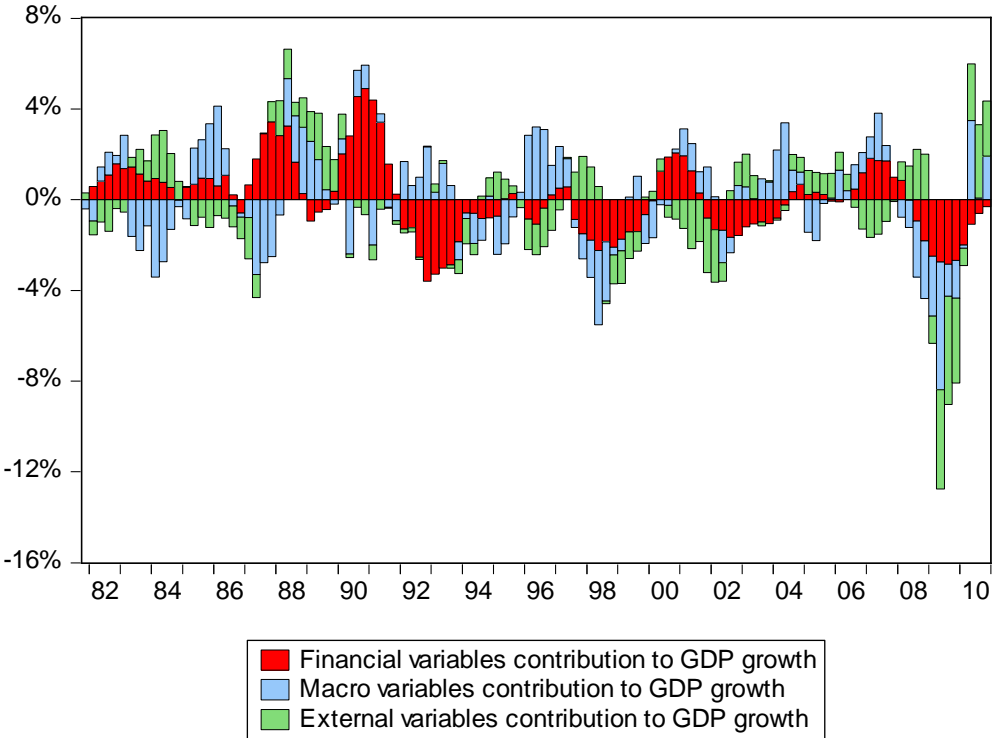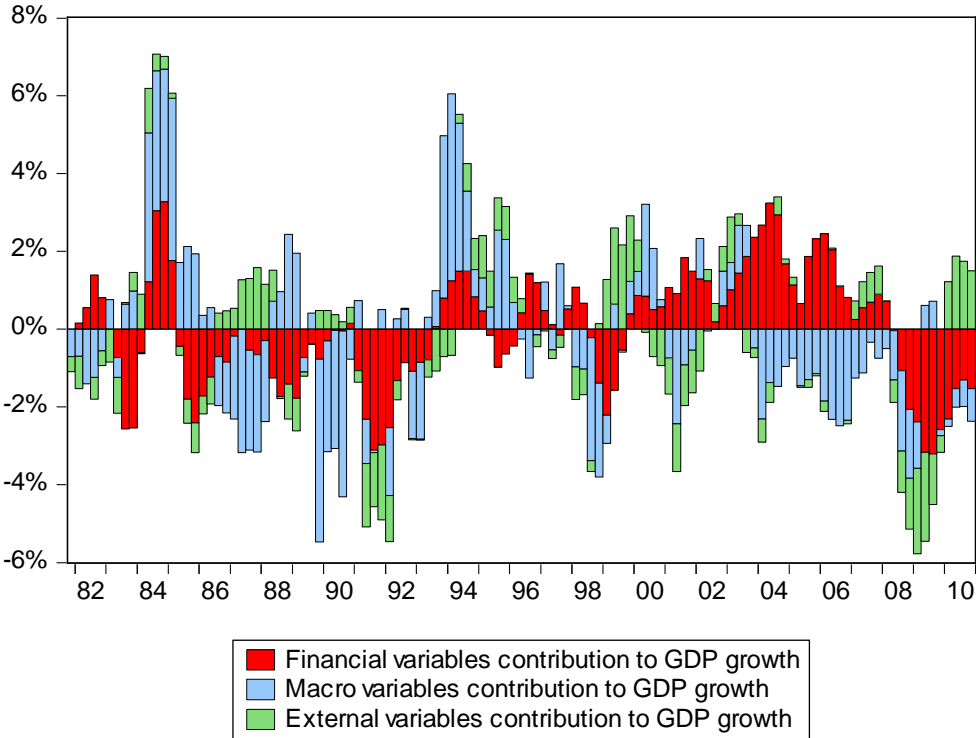- External variables contribution to GDP growth

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