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Dynamic Interactions Between Financial and Macroeconomic Imbalances: A Panel VAR Analysis

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Abstract

We use Bayesian and GMM panel VAR frameworks to study interactions between financial cycles and macroeconomic imbalances based on a global sample of 24 countries spanning the period 1998–2012. We find that financial cycles play an important role in shaping macroeconomic imbalances with expansions inducing economic overheating and a downward pressure on public debt-to-GDP ratios, and vice versa. Bank-based economies exhibit a deeper and faster response of business cycles to financial misalignments, while the impact in market-based economies is milder, but more persistent, as well as more significant for current account and public debt dynamics. Financial cycles invoke a particularly strong reaction of current account balances and especially public debt ratios in the euro area.

Keywords: financial cycles, macroeconomic imbalances, financial stability, business cycles, panel VAR, Bayesian VAR

JEL classification: E44, F32, G15, F4

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1 Introduction

The global financial crisis of 2007–2008 has given an impetus to the debate among economists and policymakers revisiting the macroeconomic effects of activity in financial markets. Although the "finance-growth nexus" literature has documented a positive link between financial development and economic growth (see Goldsmith, 1969; McKinnon, 1973; Shaw, 1973 for earlier contributions and Beck and Levine, 2004; Beck et al., 2000; Demetriades and Hussein 1996; King and Levine, 1993; Levine, 1997; Levine and Zervos, 1998; Rousseau and Wachtel, 2011 for more recent empirical evidence), it has become apparent now that financial market dynamics also have strong implications for the stability of economic growth.

In particular, financial markets are prone to persistent long-run cyclical fluctuations reflecting the build-up of imbalances as credit rapidly expands and asset prices rise to overinflated levels, followed by market corrections often taking the form of sharp adjustments—financial crises (Adarov, 2018a,b; Borio 2013, 2014). These boom-bust cycles, also referred to as financial cycles, also appear to be an important driver of business cycles and contribute to external and internal macroeconomic imbalances. This assertion offers a perspective complementary yet rather different from the well-established "financial accelerator" literature (Bernanke and Gertler, 1989; Bernanke et al., 1999; Kiyotaki and Moore, 1997; Mendoza, 2010), which postulates that financial markets may act merely an amplifier of real shocks, rather than a possible driving force of business cycle dynamics.

Moreover, shocks initially limited to a rather narrow financial market segment may quickly sprawl to other segments and lead to devastating impacts not only at the national, but also at the global level in light of increasingly complex and deepening macro-financial linkages and cross-border spillovers. Indeed, the overheating housing market in the USA triggered a subprime mortgage market crisis in 2007, which further unraveled a chain of events leading to a large-scale national banking and "shadow" banking sector meltdown, and, ultimately, to cross-border financial contagion and the global economic recession. Financial market overheating and formation of asset bubbles instigating adverse macroeconomic repercussions is surely not a unique feature of the recent crisis, and history has seen many other destructive boom-bust episodes—the Dutch Tulip Mania of the 1630s, the South Sea Bubble of 1720, the US Stock Market Crash of 1929, Japan's Real Estate and Equity Market Bubble of the late 1980s, the the Dot-Com Bubble of 2000, to name just a few prominent ones. What is special and alarming about the recent crisis episode is that, despite decades of research on business cycles and financial markets, it still has largely caught economists and policymakers by surprise. Therefore, de facto far-reaching macroeconomic consequences of financial shocks met by lacking empirical consensus or an established theoretical framework that could anticipate or robustly explain these phenomena highlight the surging need for further research focusing on the impacts, specific transmission mechanisms and feedback effects of financial cycles.

While the idea of inherent instability and cyclical nature of financial market dynamics conceptually is not new per se, going back to Minsky (1978, 1982), Kindleberger (1978) and related works, the recent crisis has renewed the interest in the topic, and a growing body of research has been devoted to documenting and analyzing financial cycles (Adarov 2017, 2018a,b; Aikman et al, 2015; Borio, 2013, 2014; Borio et al., 2013, 2014; Claessens et al., 2011, 2012; Drehmann et al., 2012; Miranda-Agrippino and Rey, 2015; Nowotny et al., 2014; Schüler et al., 2015; Schularick and Taylor, 2012; Stremmel, 2015).[1] The reported empirical evidence generally points at long-run cyclical patterns observed in the dynamics of asset prices, credit market activity and the housing sector, as well as their close association with crisis episodes, accentuating the importance of further analysis on the macroeconomic effects of financial cycles. In this paper we further expand on the debate by assessing the interactions between financial cycles and key external and internal macroeconomic imbalances—the dynamics of the output gap, the current account balance and the general government debt.

In this regard, besides the empirical literature on financial cycles outlined above, our study is most closely related to a broader body of research investigating the role of financial factors in economic crises and macroeconomic imbalances. Among the key contributions showing a connection between financial misalignments and business cycles, Jordá et al. (2011) based on 14 advanced countries over the period of 1870–2008 suggest that credit growth is "the single best predictor of financial instability", also noting that recessions accompanied by financial crises tend to be deeper. The correlation between credit booms and current account imbalances is also shown to have increased significantly during the recent decades. The conclusion that credit booms are indeed among the strongest predictors of financial crises is also confirmed in Schularick and Taylor (2012) and Gourinchas and Obstfeld (2012). Using a threshold method Mendoza and Terrones (2014) identify credit boom episodes in a sample of 61 economies over the period 1960–2010 and show their close association with economic expansions, rising equity and housing prices, real exchange rate appreciations and widening external deficits (vice versa in the contraction phase). Among the most recent studies attempting to identify potential causal relationship among macro-financial imbalances, Comunale (2017), applying panel and Bayesian techniques to a sample of EU countries, reports that that financial gaps can have a greater influence on current account misalignments than output gaps.

Our study comes closest to the latter work as regards the methodology and research objectives, but further expands the analysis to the global sample of countries. This allows for a more general understanding of macroeconomic implications of financial cycles and interactions among macro-financial imbalances, which has not been addressed so far empirically. In addition to this, we contribute to the literature along other dimensions concerning the devised measure of financial cycles and the estimation methodology. Importantly, we use a novel financial cycle measure derived as a synthetic index aggregating information from a large number of observable market characteristics conveying price, quantity and risk dynamics in four key financial market segments—credit, housing, equity and bond markets. This allows to capture general financial market dynamics and imbalances in a more comprehensive and unbiased manner in contrast to conventional approaches exercised in the literature relying on a single (or several) proxy variables.[2] Finally, the paper employs panel vector autoregression (PVAR) methods along with Bayesian shrinkage techniques for extra robustness and to address sample size limitations. This

[1] A related strand of literature is also concerned with financial conditions indexes, financial stress and asset bubbles—see Hatzius et al. (2010), Claessens and Kose (2017) for further discussion.

[2] More specifically, most studies focus either exclusively on credit cycles or use a proxy variable, usually private credit-to-GDP ratio, to measure financial cycles (Aikman et al., 2015; Claessens et al., 2012; Dell'Arriccia et al., 2012; Schularick and Taylor, 2012). In some recent empirical works private credit growth is also combined with housing prices to arrive at a single financial cycle indicator (Borio, 2014).

estimation framework allows to make use of variation in both the time and the cross-sectional dimensions of the data and infer dynamic relationships among macro-financial imbalances allowing for fully endogenous covariates, in contrast to conventional panel data methods.

More specifically, we study dynamic interactions between financial cycles and macroeconomic imbalances measured by output gap, current account balance and public debt variables, all taken as a percentage of GDP. While the three measures of external and internal imbalances have been widely used in the literature and the data are obtained from publicly available sources, the financial cycle measure is an original metric, which we estimate on a country-by-country basis as a normalized latent dynamic factor[3] summarizing common variation in a range of indicators reflecting the state of credit, housing, equity and debt securities markets—the key financial market segments.[4]

Based on these data we construct a strongly balanced panel dataset comprising 24 advanced and developing countries over the period 1998–2012 at an annual frequency and then quantify mutual impacts among the macro-financial imbalances using the generalized method of moments (GMM) PVAR estimator following Abrigo and Love (2016) and the Bayesian PVAR estimator in line with Dieppe et al. (2016). The application of the GMM-style PVAR is more common in empirical macroeconomic research and the baseline estimations using the global sample also take advantage of this approach. However, given our relatively small sample we also make use of Bayesian techniques to address overparametrization issues. The sample size is particularly limiting for the two additional case studies the paper explores—(i) implications of financial market structure, i.e. bank-based and market-based financial systems,[5] and (ii) the euro area—necessitating the use of Bayesian shrinkage. To further alleviate the degrees of freedom issue we use a parsimonious four-variable PVAR setup involving the financial cycle index, the output gap as a percentage of GDP, the current account balance as a percentage of GDP and the general government debt as a percentage of GDP, which results in a stable first-order PVAR model.[6]

Having estimated the GMM and the Bayesian PVAR versions of the model and drawing on panel Granger causality test results, impulse-response profiles and other empirical exercises, we find that financial cycles do have non-trivial impacts on macroeconomic imbalances. Most importantly, the analysis strongly indicates in favor of the hypothesis that financial cycles indeed constitute an important driver of business cycles, as well as influence the dynamics of fiscal imbalances.

The magnitude of the impact is also non-negligible: a one-standard deviation shock in the financial cycle variable[7] induces macroeconomic overheating equivalent to 0.5 percent of

[3] To this end we use dynamic factor models and state-space estimation techniques (Kalman filter).

[4] To the extent possible owing to the data constraints, the indicators used as observable input variables in dynamic factor models are chosen to reflect price, quantity and risk characteristics that are instrumental for gauging unsustainable dynamics in a given financial market segment: for instance, credit to GDP ratio, credit growth, interest rates and spreads in the case of credit cycles; benchmark stock market index returns, stock market volatility, stock market capitalization to GDP ratio in the case of equity cycles.

[5] For the discussion on the relative merits of the bank-based and market-based systems see Beck and Levine (2004), Demirgüç-Kunt and Maksimovic (2002), and Levine (2003).

[6] The variables are taken in year-on-year differences, which ensures their stationarity as verified by Im-Pesaran-Shin (2003) and Fisher-type panel unit root tests. The ordering of the variables in the PVAR models and Cholesky decompositions follows the order listed here. Alternative identification schemes were also tested for robustness. The lag order is identified using conventional information criteria—see the methodology section for further technical details.

[7] This corresponds to a change of 0.7 in the financial cycle index. To facilitate interpretation of the financial

potential GDP (positive output gap) and a decline by 0.7 percentage points in the public debt-to-GDP ratio (in percent); vice versa for the negative shock. The response to financial cycle innovations is also fast, peaking in the first year after the initial shock, and persistent, taking about 4 years to peter out in the case of the output gap and up to 6 years for the public debt ratio. Overall, across the global sample, innovations in the financial cycle variable explain up to 7.1% of variation in the output gap and 9.1% of variation in the public debt ratio over the 10-year horizon. The existence of a pro-cyclical feedback from output gaps to financial cycles is not confirmed to be statistically and economically significant across empirical exercises and robustness tests.

In contrast to the reaction of the fiscal position and the output gap variables, the direct impact of financial cycles on external imbalances appears to be weak and statistically insignificant. Indirectly, however, financial shocks still matter for the current account balance (positive shocks deepening the deficit) via pass-through effects mediated by the stimulus financial overheating induces on domestic aggregate demand, which, in turn, translates to surging imports and hence deteriorating current account. The latter is evidenced by a statistically significant negative response of the current account balance variable to positive output gap shocks in our PVAR model, consistent with economic theory and empirical literature.

Evidence from the first case study, which focuses on the implications of financial market structure, suggests that the interactions among macro-financial imbalances follow similar fundamental patterns in both bank-based and market-based systems, but yet a number of differences can be noted as regards the depth and the duration of the impacts. First, financial cycles tend to explain a higher share of forecast error variance of other endogenous model variables in market-based economies as opposed to bank-based economies, particularly in the public debt dynamics (8.7% versus 4.3%, respectively).[8] The greater role of financial cycles in shaping external and internal imbalances in the former group is also confirmed by impulse response profiles and stronger Granger-causal effects. Second, the reaction of output gaps to financial cycle shocks is deeper on impact (greater by a factor of 1.7) and more statistically significant in the case of the bank-based economies. This, however, is offset by a more persistent effect in the market-based sample: it takes up to two additional years for a response to phase out in comparison with the bank-based countries. In other words, the impact of financial cycles is more lasting and broad-based, i.e. affecting more significantly external and internal imbalances, in the case of market-based economies, while in the case of bank-based economies it is rather more focused on output gaps with a greater initial momentum.

The inquiry into the euro area case study to reveal possible differences in macro-financial spillovers under a monetary union framework points at rather similar patterns of mutual interactions among the output gap, the current account and the public debt variables in the bloc

cycle index in terms of magnitudes (in addition to its direction and duration), it is standardized to have a zero mean and a standard deviation of unity for each country, so that its changes can be interpreted in terms of the number of standard deviations from the mean. As a reference point, for instance, the late 2000s global financial crisis and the Great Recession episode is associated with the US financial cycle index tumbling by 4.7 units (standard deviations) from the 2005 peak to the 2009 trough—see the discussion in Section 3.

[8] The market-based sample is also the only case when financial cycles invoke a stronger relative impact on public debt ratios than output gap shocks. With this exception, across all samples investigated in the study, the output gap variable has a greater significance in explaining both current account and public debt dynamics.

to those of the bank-based sample. This is not surprising given that the euro area is mostly a subset of the bank-based economies sample.[9] However, the impact of financial cycles on current account and public debt dynamics is, by contrast, much stronger in terms of statistical and economic significance. In fact, the proportion of their forecast error variance explained by financial cycles (3% and 10%, respectively, for the current account and the public debt ratio) is also greater than in the case of the market-based and the global samples. The response also exhibits high persistence, especially for the public debt ratio: a one-standard-deviation positive shock to the financial cycle variable reduces the debt ratio by about one percent of GDP on impact (peak response), gradually phasing out only after 10 years.

Summarizing, the paper presents new empirical evidence on important dimensions along which developments in financial markets affect economies. Our key finding is that financial markets are prone to cyclical slow-moving dynamics, which can be inferred by summarizing information on the empirical patterns of credit aggregates, asset prices, interest rates, market risk and volatility dynamics, and these financial cycles do have strong implications for business cycles and macroeconomic imbalances. This serves a useful purpose of better informing policy debates and encouraging further research on related issues. In particular, the results highlight the importance of tackling the buildup of financial imbalances as one of the roots of macroeconomic overheating leading to crises. Inter alia, this implies that macroeconomic policy focusing exclusively or predominantly on targeting inflation as the principal nominal anchor may be a suboptimal framework and needs to be adjusted to allow for a more proactive monitoring and policy response to the buildup of financial misalignments: one may certainly envision a situation when an inflation target is achieved, and monetary policy therefore takes a neutral stance, while financial market imbalances may still be building up. Failure to recognize and address these additional challenges is a sure path to another crisis. As a related matter, and more generally and importantly, further efforts along this line of research may help revisit our economic beliefs and arrive at a more informed understanding of business cycles and macroeconomic imbalances given the gaps in the existing paradigm revealed by the global financial crisis.

The rest of the paper is organized as follows. Section 2 describes the sample, data and methodology. Section 3 presents empirical results, outlining the general findings and case studies focusing on the financial structure and the euro area. Section 4 presents concluding remarks.

2 Data and empirical strategy

2.1 Sample and data

The econometric analysis is based on a panel dataset constructed for a global sample of 24 advanced and developing countries over the period 1998–2012 at an annual frequency. Table 1 outlines the composition and other particulars of the full global sample of countries, as well as subsamples that are used for additional empirical exercises focusing on the euro area and the implications of financial market structure for macro-financial imbalances. The sample composition is largely motivated by the availability of sufficiently long series, among others, estimates of financial cycles, such that the panel dataset is strongly balanced with sufficiently large number

[9] The Netherlands is the only country included in the euro area sample, but not in the bank-based group.

of cross-sections N for a meaningful econometric analysis.[10]

Table 1: Sample composition and characteristics

Sample	Countries included, ISO3 codes	Period	N	T	Obs.
A. Global sample (strongly balanced)	Australia (AUS), Austria (AUT), Belgium (BEL), Canada (CAN), Switzerland (CHE), Chile (CHL), Czech Republic (CZE), Germany (DEU), Spain (ESP), Estonia (EST), Finland (FIN), France (FRA), United Kingdom (GBR), Hungary (HUN), Italy (ITA), Japan (JPN), Republic of Korea (KOR), Mexico (MEX), Netherlands (NLD), Norway (NOR), Poland (POL), Slovakia (SVK), Sweden (SWE), United States (USA)	1998–2012	24	15	360
B. Market-based financial systems	AUS, CAN, CHE, CHL, GBR, KOR, MEX, NLD, SWE, USA	1998–2012	10	15	150
C. Bank-based financial systems	AUT, BEL, CZE, DEU, ESP, EST, FIN, FRA, HUN, ITA, JPN, NOR, POL, SVK	1998–2012	14	15	210
D. Euro area	AUT, BEL, DEU, ESP, EST, FIN, FRA, ITA, NLD, SVK	1998-2012	10	15	150

The data for the variables measuring macroeconomic imbalances are obtained from publicly available IMF, World Bank and OECD databases—specific data sources and descriptive statistics are listed in Table 2. Output gap estimates are sourced primarily from the IMF World Economic Outlook and complemented by the data from the OECD Economic Outlook in the cases when the series are either missing or shorter. Likewise, general government debt data from the IMF Historical Public Debt Database has been complemented by the IMF Global Debt Database.

Table 2: Descriptive statistics and data sources, full sample

Variable name	Variable description	N	Mean	Std. dev.	Min	Max	Source
FC	Financial cycle index	360	0.01	0.85	-2.36	2.48	Own estimates
$YGAP$	Output gap, percent of potential GDP	360	0.03	2.49	-11.36	11.86	IMF World Economic Outlook, OECD Economic Outlook
CA	Current account balance, percent of GDP	360	0.29	5.51	-14.98	16.23	IMF World Economic Outlook
$DEBT$	General government debt, percent of GDP	360	56.44	37.46	3.66	238.01	IMF Historical Public Debt Database, IMF Global Debt Database

The measure of financial market imbalances—financial cycles—is obtained from Adarov (2018a,b), in which financial cycles are estimated as standardized indexes summarizing joint dynamics across key financial market segments: the banking sector, housing, equity and debt security markets. These, in turn, are based on financial market data from a wide range of sources, including Bank for International Settlements databases, IMF International Financial Statistics, OECD Main Economic Indicators, OECD Housing Statistics, Federal Reserve Economic Data, World Bank Global Financial Development Database, Investing.com, Yahoo Finance, complemented by data from Haver Analytics and national monetary authorities. A brief

[10] The original unbalanced sample includes more countries and spans the period 1985–2015. However, for the purposes of robust PVAR analysis the sample was reshaped to arrive at a strongly balanced dataset maximizing jointly the number of countries in the sample and the number of observations at the cost of shorter time dimension T.

recap of the financial cycle index and its estimation methodology is described further (for an in-depth discussion of technical details and estimation results see Adarov, 2018a).

2.2 Estimation of financial cycles

Financial cycles reflect the buildup and correction of imbalances in financial markets taking an empirical pattern of repeated boom-bust cycles due to changing risk perceptions, liquidity conditions, and other demand and supply factors. Our measure of financial cycles is obtained for each country in the sample by extracting a latent dynamic common factor from a range of observable variables conveying price, quantity and risk characteristics of activity across four key financial market segments—credit, housing, debt securities and equity markets.

More specifically, aggregate national financial cycles characterizing the overall financial market dynamics in a given country c are estimated via a two-step procedure performed separately for each country in the sample: first, segment-specific financial cycles are obtained for each of the four financial market segments using relevant observable market characteristics; then, national aggregate financial cycles are derived as a common factor from the four previously estimated segment-specific cycles (see Figure 1 for a stylized representation).

Figure 1: Estimation of aggregate financial cycles

$$\left.\begin{array}{l}
\left.\begin{array}{r}\text{private credit by banks}\\ \text{lending, deposit and other interest rates}\\ \text{maturity and risk interest rate spreads}\end{array}\right\} FC_c^{CR} \text{ (credit cycle)}\\
\left.\begin{array}{r}\text{real housing price index}\\ \text{price to rent and price to income ratios}\end{array}\right\} FC_c^{H} \text{ (housing cycle)}\\
\left.\begin{array}{r}\text{maturity and risk bond yield spreads}\\ \text{government and corporate bond yields}\\ \text{bond market capitalization}\end{array}\right\} FC_c^{B} \text{ (bond cycle)}\\
\left.\begin{array}{r}\text{benchmark stock market index returns}\\ \text{volatility of returns}\\ \text{stock market capitalization}\end{array}\right\} FC_c^{EQ} \text{ (equity cycle)}
\end{array}\right\} FC_c^{AG} \text{ (aggregate cycle)}$$

In practice, estimation of financial cycles is more nuanced in light of significant cross-country heterogeneity and availability of data, and, while the key variables used in the estimation are the same across the countries in the sample (for instance, private credit by banks, stock market capitalization), the composition of variables may differ depending on actual availability of sufficiently long relevant series. The supplementary online appendix lists specific variables used for each country and segment, and also reports dynamic factor model parameter estimates.

Dynamic factor models (Geweke, 1977; Sargent and Sims, 1977) are formulated in a state-space form and estimated via the Kalman filter and smoother. In particular, in the estimations of segment-specific financial cycles in a country c, the vector of observable signal variables

$\mathbf{y}_{c,t} = [y_{c1t} \; ... \; y_{cNt}]'$ for $t = 1...T$—that is, the vector of financial variables[11] characterizing price, quantity and risk dynamics of a respective financial market segment indexed by S—is modeled as the sum of the unobservable common factor $f^S_{c,t}$ and the vector of idiosyncratic shocks $\mathbf{v^S_{c,t}}$:

$$\begin{cases} f^S_{c,t} = \alpha^S_c \times f^S_{c,t-1} + u^S_{c,t} \\ \mathbf{y}_{c,t} = \mathbf{B^S_c} \times f^S_{c,t} + \mathbf{v^S_{c,t}} \end{cases} \tag{1}$$

where $f^S_{c,t}$ follows a first-order autoregressive process with the persistence parameter α^S_c. The $N \times 1$ vector of factor loadings $\mathbf{B^S_c}$ links N observable input financial variables to the latent common factor; $u^S_{c,t}$ and $\mathbf{v^S_{c,t}}$ are the state and the measurement equation *i.i.d.* error terms. Separate estimations are carried out individually for each of the four financial market segments and each country in the sample, and the resulting $\hat{f}^S_{c,t}$ in a standardized form constitutes a corresponding segment-specific financial cycle index.

Estimation of aggregate national financial cycles then proceeds using country-specific dynamic factor models of a similar structure with the four previously estimated segment-specific financial cycles included as observed variables, comprising the vector $\hat{\mathbf{f}}^S_{c,t}$, in the measurement equation of the following state-space system:

$$\begin{cases} f^{AG}_{c,t} = \alpha^{AG}_c \times f^{AG}_{c,t-1} + u^{AG}_{c,t} \\ \hat{\mathbf{f}}^S_{c,t} = \mathbf{B^{AG}_c} \times f^{AG}_{c,t} + \mathbf{v^{AG}_{c,t}} \end{cases} \tag{2}$$

The (aggregate) financial cycle index further used in the analysis is then the common factor $\hat{f}^{AG}_{c,t}$ estimated in equation (2) for each country in the sample, detrended and standardized (scaled to have a zero mean and a standard deviation of unity), which allows to interpret its magnitude in terms of standard deviations from the mean. The financial cycle measures computed originally at a quarterly frequency are converted to an annual frequency for the PVAR analysis. For reference, original financial cycles are reported for selected systemic economies in Appendix Figure 8, and annualized financial cycles expressed in year-on-year changes as used in the PVAR analysis are also reported in Appendix Figure 7 for all countries in our global sample.

2.3 Panel VAR model setup

The interactions between financial cycles and macroeconomic imbalances are analyzed using a panel VAR framework, which accounts for individual country heterogeneity while allowing for dynamic relationships between multiple endogenous variables. In general, VAR models have been found to be an especially useful tool to estimate dynamic interactions between endogenous variables of interest. However, in empirical macroeconomic applications sufficiently long data is

[11] Prior to entering a respective state-space model the variables are standardized (demeaned and divided by their sample standard deviation) to ensure symmetric contribution to the variance of the latent factor regardless of their measurement scale and historical volatility.

typically a major constraint and "the curse of dimensionality" frequently becomes a problem. In our case it is also an issue as the length of the series is not sufficiently long to robustly estimate separate VAR models for each country. Therefore, when setting up a model we limit the focus to a possibly small number of variables conveying the dynamics of key macroeconomic imbalances, in addition to the derived financial cycle measure, and also opt for a joint estimation pooling all countries in the sample via a panel VAR framework, which also generally improves estimation quality by increasing the cross-sectional dimension.[12]

Formalizing, given N countries indexed $i = 1, ..., N$ and time $t = 1, ..., T$, the model is defined as follows:

$$\mathbf{X}_{it} = \mu_i + \mathbf{\Theta}(\mathbf{L})\mathbf{X}_{it} + \epsilon_{it} \tag{3}$$

where the vector $\mathbf{X}_{it} = \begin{bmatrix} FC_{it} & YGAP_{it} & CA_{it} & DEBT_{it} \end{bmatrix}'$ consists of the financial cycle index (FC), output gap as a percent of potential GDP ($YGAP$), current account as a percent of GDP (CA) and public debt as a percent of GDP ($DEBT$). $\mathbf{\Theta}(\mathbf{L})$ is a matrix polynomial in the lag operator L, μ_i is the vector of time-invariant country effects, ϵ_{it} is the error term. The specified four-variable setup represents a most parsimonious model allowing for efficient estimation in light of our relatively small number of observations. Yet, for robustness we also estimate alternative models, including specifications with real effective exchange rate ($REER$) as an additional variable and real GDP growth rate ($GROWTH$) instead of $YGAP$ in the vector $\mathbf{X}_{it}$ (discussed in the robustness checks section of the paper).

The variables enter the model in first differences, which ensures their stationarity. We use Im-Pesaran-Shin (2003) and Fisher-type panel unit root tests to confirm stationarity (results are reported in Appendix Table 7). Lag order is selected based on the Schwarz Bayesian information criterion (SBIC), Akaike information criterion (AIC) and Hannan and Quinn information criterion (HQ).

The model is first estimated via the generalized method of moments (GMM) with the Helmert forward mean-differencing transformation following Love and Zicchino (2006). The method is known to yield consistent estimates in panel data settings, and has been used in the past for similar applications (Gnimassoun and Mignon, 2016 and Comunale, 2017). The GMM estimation framework, however, is well-suited for panels with a relatively short time dimension, i.e. $N > T$. Therefore, for baseline estimations we transform the original longer unbalanced data to a strongly balanced panel dataset by maximizing the number of observations over $\{N, T\}$, s.t. $N > T$. The Helmert transformation controls for country fixed effects while preserving the orthogonality between the endogenous variables and their lags allowing the latter to be used as instruments in GMM estimations.[13]

In addition, we estimate the model via Bayesian panel VAR estimation techniques for robustness[14], given a relatively small number of observations, particularly in the case study analyses involving subsets of the global sample—the euro area, countries with market-based and bank-

[12] For an in-depth survey of PVAR applications see Canova and Ciccarelli (2013).
[13] Technical implementation of GMM PVAR is based on the Stata codes developed in Abrigo and Love (2016).
[14] To this end we use the MATLAB version of the Bayesian Estimation, Analysis and Regression (BEAR) toolbox developed by the ECB and documented in Dieppe et al. (2016).

based financial systems. The Bayesian shrinkage allows one to estimate a model with a limited sample avoiding overparametrization issues noted above. Under the Bayesian VAR approach (Litterman, 1979 and Doan et al., 1984), model parameters are treated as random variables, characterized by some underlying probability distribution. The method provides a framework to incorporate prior information about the model parameters and update these probability distributions conditional on the observed data. We use the standard normal-Wishart prior with default hyperparameter values. The normal-Wishart prior assumes that the model parameters (panel VAR coefficients and the residual covariance matrix in Equation 3) are unknown and in this respect it is superior to another popular choice—the Minnesota (Litterman) prior—which assumes that the residual covariance matrix is known. As the objective of our empirical exercise is to infer average dynamic responses to shocks of interest, the Bayesian PVAR pooled estimator is used, which is the Bayesian counterpart of the mean-group estimator and implies that the coefficients are homogeneous across countries. Heterogeneity in coefficients across different country subsets sharing similar relevant characteristics is explored in the two case studies discussed following the baseline results in the next section.

3 Results

3.1 Evidence from the global sample

In order to infer the general relationship between financial cycles and macroeconomic imbalances, we estimate the model using a global sample of countries as a baseline case. To this end we first estimate a homogeneous PVAR model via the GMM estimator and then also validate the results using Bayesian PVAR estimation techniques reported separately in the robustness section.

As mentioned in the methodology section, for the full sample of countries over the period 1985–2015 only unbalanced panel dataset is available as a range of variables contain spans of missing observations and for transition economies the data starts only in the 1990s. Therefore, the original unbalanced panel data is adjusted to maximize the number of observations, so that the dataset is a strongly balanced panel with $N > T$ to allow for a consistent GMM estimation avoiding the instrument proliferation issue. In this case we end up with a global sample of 24 countries observed over the period of 15 years (1998–2012), adding up to 360 observations. The sample is nevertheless diverse and includes both advanced and developing economies from different regions around the world and different financial systems, which allows for a more general inference. The detailed sample composition is reported in Table 1 in the data section.

Given a purposely small number of endogenous variables included in the baseline model (four) and an identified lag order of 1, as indicated by conventional AIC, BIC and HQ criteria, GMM estimations should yield robust results without imposing additional restrictions. The baseline model and other PVAR models employed in the paper are stationary and satisfy the eigenvalue stability conditions.

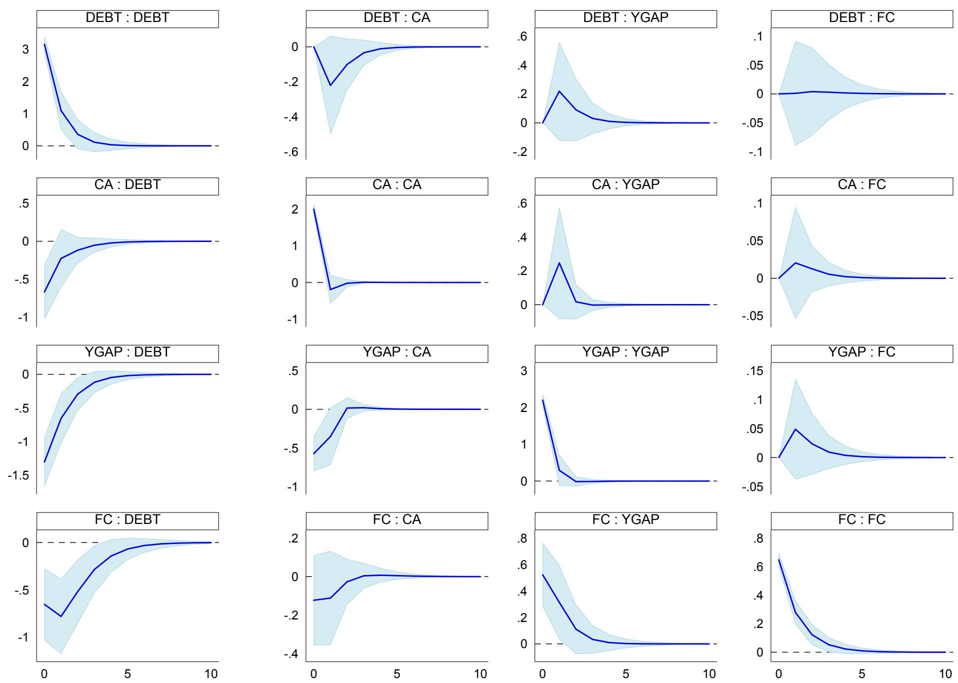
Following the estimation of the PVAR model we compute orthogonalized impulse response functions (IRFs)[15] and forecast error variance decomposition (FEVD) to track the impact of

[15] IRF error bands are also generated by Monte-Carlo simulations with 1000 iterations for the horizon of 10 years.

each variable in the system over time. While for reference generalized IRFs are also reported in Appendix Figure 10, for economic interpretation the main interest lies in uncorrelated shocks. Orthogonal IRFs are obtained via Cholesky factorization scheme. The ordering of the variables for Cholesky decomposition is the same as appears in the PVAR specification, that is, $\mathbf{X}_{it} = \begin{bmatrix} FC_{it} & YGAP_{it} & CA_{it} & DEBT_{it} \end{bmatrix}'$. This implies that the variables lower in the ordering may affect the variables of higher order only with a lag. In this particular arrangement, the fiscal position variable $DEBT$ is treated as the most endogenous, adjusting to the financial cycle FC, the business cycle $YGAP$ and the current account CA shocks contemporaneously (in the same year). On the other hand, the financial cycle variable is assumed to be the most exogenous among the variables included in $\mathbf{X}_{it}$ as it is heavily driven by self-reinforcing dynamics of financial markets underpinned by risk and value perceptions (Borio, 2014), which empirically translates to highly persistent movements of the financial cycle index: the fitted autoregressive parameter is generally very high, exceeding 0.8–0.9 (Adarov, 2018a). Financial misalignments are nevertheless assumed to be influenced by other variables with a lag in this setup. The main results, however, remain robust to alternative ordering schemes.

Figure 2: Impulse response functions, global sample, GMM PVAR

Note: The figure shows orthogonalized impulse response functions ("impulse variable : response variable") with 95% confidence intervals (bootstrapped with 1000 iterations) associated with the baseline GMM PVAR model.



The results show that, notably, financial cycles do have strong implications for macroeconomic imbalances and constitute an important driver of business cycles, supporting our original conjecture. As can be seen from the (orthogonal) IRF profiles in Figure 2, a positive shock in the financial cycle index FC leads to a statistically significant positive response of the output gap $YGAP$, as well as a negative change in the public debt ratio $DEBT$ (vice versa for the negative shocks).

The economic significance of the effects is also non-trivial: a shock of one standard deviation in the financial cycle variable (equivalent to a magnitude of 0.7) induces macroeconomic overheating with the output gap widening by 0.5 percent of GDP and a decline in the debt-to-GDP ratio by 0.7. The response to financial cycle innovations is also fast, peaking in the first year, and persistent, taking about four years to phase out in the case of the output gap and up to six years for the public debt ratio.

One challenge in interpreting the financial cycle dynamics in general and its innovations in the IRF context in particular, is a lack of an objective measurement scale for the derived financial cycle index. As noted in the methodology section, in order to circumvent this shortcoming, the financial cycle index is standardized to have a zero mean and a standard deviation of unity, and therefore its dynamics can be interpreted in terms of standard deviations from the mean. This, in turn, jointly with the sequencing of phases and their duration, can be related to known boom-bust events in country-specific historical contexts. For illustration, the late 2000s global financial crisis and the Great Recession episode is associated with the US financial cycle index tumbling by 4.7 units (standard deviations) from the 2005 peak to the 2009 trough (see Figure 8 in the Appendix), and, more generally, systemic financial market events are typically reflected in financial cycle fluctuations of at least one standard deviation in magnitude. The relative importance of variable shock contributions can also be inferred from the historical decomposition of shocks based on panel VAR results—a US example is illustrated in Figure 9 in the Appendix, highlighting the significance of financial cycles for business cycle developments. As one could see from the $YGAP$ shock decomposition, the US financial cycle was a major factor driving economic overheating prior to the 2007 crisis; then, while in 2007 the financial cycle was already far into the contraction phase as housing, credit and capital markets plummeted contributing negatively to the output gap, the recession unfolded fully in 2008.

In contrast to the observed effects on the output gap and the public debt dynamics, the direct impact of financial cycles on the current account balance CA appears to be weak and statistically insignificant, albeit the direction of the response is consistent with expectations. Indirectly, however, financial shocks still matter for the current account (positive shocks deepening the current account deficit) via pass-through effects as financial overheating stimulates aggregate demand, which, in turn, translates to surging imports and hence deteriorating current account. This conjectured transmission mechanism is supported by a statistically significant negative response of the current account balance variable to positive output gap shocks in our PVAR model (see IRFs in Figure 2 and Granger causality test results discussed next), which is also consistent with economic theory and empirical literature.

Complementing the IRF analysis, we also examine potential causal linkages among the variables via Granger causality tests. First, we carry out Granger causality tests based on the homogeneous PVAR model in line with Abrigo and Love (2016). The results, reported in Table 3, strongly indicate in favor of rejecting the hypothesis of non-causal relationship from FC to $YGAP$ and from FC to $YGAP$ (at the 10% and 5% levels of statistical significance, respectively). In addition, for robustness, we run a battery of Dumistrescu and Hurlin (2012) causality tests for heterogeneous panels,[16] which yield even more statistically significant results,

[16] The test is based on individual Wald statistics of Granger non-causality averaged across the cross-section units

confirming strong causal linkages extending from the financial cycle to the output gap and the public debt variables—see the robustness section and a related Table 5. Although the Dumistrescu and Hurlin test points also at a possible causality from FC to CA, this observation is not confirmed by other evidence from the homogeneous PVAR results (both GMM and Bayesian) and associated Granger causality tests.

Table 3: Granger causality test results

Note: The table shows the results of the Granger causality Wald test based on the baseline GMM PVAR specification in line with Abrigo and Love (2016). Null-hypothesis: variable X (first row) does not Granger-cause variable Y (first column). ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

Y ↓	X →	*FC*	*YGAP*	*CA*	*DEBT*
FC	χ^2		1.27	0.28	0.00
	p-value		0.26	0.60	0.98
YGAP	χ^2	3.27*		3.43*	1.63
	p-value	0.07		0.06	0.20
CA	χ^2	0.15	6.12**		2.35
	p-value	0.70	0.01		0.13
DEBT	χ^2	7.8**	0.87	0.00	
	p-value	0.01	0.35	0.98	

Finally, we report forecast error variance decomposition (FEVD) for each variable to measure the proportion of forecast error variance explained by innovations in itself and other model variables. Table 4 shows the relative importance of variable fluctuations at selected time horizons—1, 5 and 10 years following the initial shock—sorted first by the impulse variable and then by the response variable in the same order as they appear in the PVAR setup. FEVD results pertaining to the baseline global sample estimations are reported in column 4 (other columns outline results for additional empirical exercises discussed later in the section). As expected, most of the forecast error variance is attributed to own innovations, yet fluctuations in other variables do have notable explanatory power, and the patterns are consistent with the insights from the IRFs and the Granger causality tests. Focusing on the impact of financial misalignments, FC fluctuations contribute notably to the variance of $YGAP$ and $DEBT$, but not CA. Most of the impact on $YGAP$ manifests itself in the first year after the initial shock with 5.3% of its total variance explained, and remains persistent gradually increasing over the following decade, eventually reaching 7.1%. Innovations in FC explain up to 9.1% of variation in $DEBT$ over the 10-year horizon, peaking at about 7% in the second year.

While the impact of FC on other variables proves to be significant, by contrast, the feedback from macroeconomic imbalances to financial cycles appears to be negligible in statistical and economic terms based on the results collected across empirical exercises and robustness checks. An exception is the Dumistrescu and Hurlin (2012) Granger causality test, pointing at the

and has been reported to show good small sample properties. See also the robustness section for further discussion.

statistical significance of a possible effects of $YGAP$ and CA on FC, but this result is not confirmed by evidence from other exercises, while the IRF and the FEVD profiles show that the economic significance of this impact in any case is negligible.

Table 4: Forecast error variance decomposition

Note: The table shows forecast error variance decomposition for the PVAR variables for the baseline results based on strongly balanced panel dataset, as well as for the unbalanced full sample of countries.

			Share of variance explained				
			A. Global balanced sample		B. Market-based	C. Bank-based	D. Euro area
Horizon	Impulse variable	Response variable	GMM PVAR	Bayesian PVAR	Bayesian PVAR	Bayesian PVAR	Bayesian PVAR
1	FC	FC	100.0%	100.0%	100.0%	100.0%	100.0%
5	FC	FC	99.3%	98.0%	96.3%	97.8%	96.5%
10	FC	FC	99.3%	97.9%	95.9%	97.7%	96.2%
1	FC	YGAP	5.3%	3.8%	2.6%	3.4%	3.2%
5	FC	YGAP	7.1%	4.5%	4.6%	3.7%	3.8%
10	FC	YGAP	7.1%	4.5%	4.6%	3.7%	3.9%
1	FC	CA	0.3%	0.6%	1.2%	0.4%	0.3%
5	FC	CA	0.6%	1.0%	2.0%	1.0%	2.9%
10	FC	CA	0.6%	1.0%	2.0%	1.0%	3.0%
1	FC	DEBT	3.4%	2.8%	4.2%	1.7%	9.1%
5	FC	DEBT	9.1%	6.3%	8.5%	4.2%	9.8%
10	FC	DEBT	9.1%	6.4%	8.7%	4.3%	9.8%
1	YGAP	FC	0.0%	0.0%	0.0%	0.0%	0.0%
5	YGAP	FC	0.6%	0.2%	0.4%	0.4%	0.5%
10	YGAP	FC	0.6%	0.2%	0.4%	0.4%	0.5%
1	YGAP	YGAP	94.7%	96.2%	97.4%	96.6%	96.8%
5	YGAP	YGAP	90.7%	92.5%	86.4%	93.5%	91.9%
10	YGAP	YGAP	90.7%	92.5%	86.2%	93.3%	91.4%
1	YGAP	CA	7.6%	6.1%	3.1%	7.6%	11.6%
5	YGAP	CA	10.0%	7.3%	3.8%	8.7%	12.9%
10	YGAP	CA	10.0%	7.3%	3.8%	8.7%	12.9%
1	YGAP	DEBT	13.5%	12.1%	6.8%	15.1%	15.1%
5	YGAP	DEBT	14.4%	11.0%	6.5%	13.2%	13.3%
10	YGAP	DEBT	14.4%	11.0%	6.4%	13.2%	13.1%
1	CA	FC	0.0%	0.0%	0.0%	0.0%	0.0%
5	CA	FC	0.1%	0.2%	0.4%	0.3%	0.9%
10	CA	FC	0.1%	0.2%	0.4%	0.3%	1.0%
1	CA	YGAP	0.0%	0.0%	0.0%	0.0%	0.0%
5	CA	YGAP	1.1%	1.7%	6.7%	0.4%	1.3%
10	CA	YGAP	1.1%	1.7%	6.7%	0.4%	1.3%
1	CA	CA	92.0%	93.1%	95.1%	91.5%	87.7%
5	CA	CA	88.1%	91.1%	92.8%	89.3%	82.3%
10	CA	CA	88.1%	91.1%	92.7%	89.2%	82.1%
1	CA	DEBT	3.6%	1.9%	5.4%	0.6%	1.0%
5	CA	DEBT	3.3%	1.7%	4.9%	1.0%	1.5%
10	CA	DEBT	3.3%	1.7%	4.8%	1.0%	1.6%
1	DEBT	FC	0.0%	0.0%	0.0%	0.0%	0.0%
5	DEBT	FC	0.0%	1.2%	2.1%	0.6%	0.9%
10	DEBT	FC	0.0%	1.3%	2.4%	0.7%	1.0%
1	DEBT	YGAP	0.0%	0.0%	0.0%	0.0%	0.0%
5	DEBT	YGAP	1.0%	0.7%	0.8%	1.4%	1.6%
10	DEBT	YGAP	1.0%	0.7%	0.9%	1.5%	1.9%
1	DEBT	CA	0.0%	0.0%	0.0%	0.0%	0.0%
5	DEBT	CA	1.3%	0.1%	0.4%	0.3%	0.5%
10	DEBT	CA	1.3%	0.2%	0.4%	0.3%	0.5%
1	DEBT	DEBT	79.5%	82.8%	82.4%	81.4%	73.9%
5	DEBT	DEBT	73.2%	80.4%	78.2%	80.1%	74.0%
10	DEBT	DEBT	73.1%	80.3%	77.9%	80.0%	74.0%

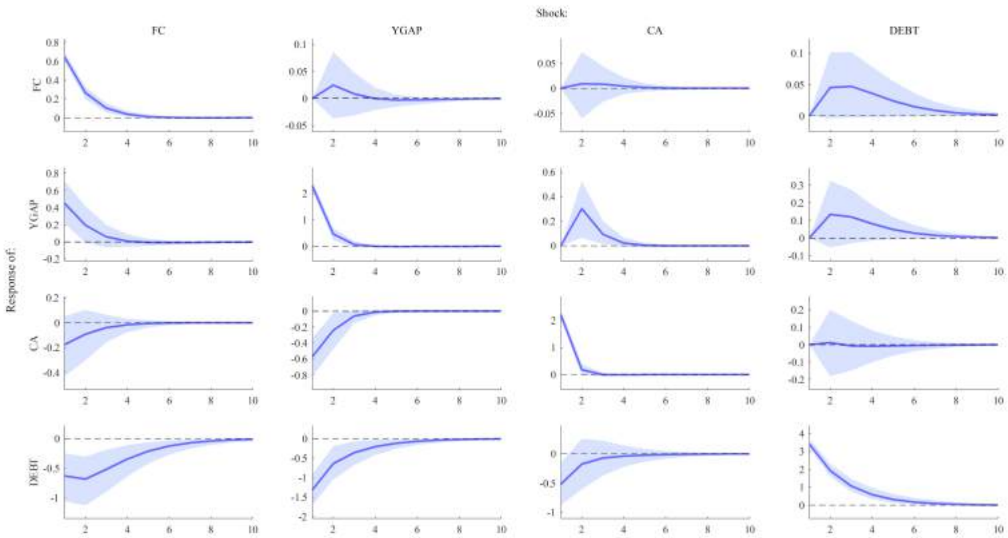
Although we are interested primarily in the impacts involving financial cycles, some results concerning mutual spillovers between external and internal macroeconomic imbalances are also worth a brief mention. Among statistically significant effects, positive output gap shocks lead to: (i) the worsening of the current account balance as expected given that rising real incomes stimulate, inter alia, demand for imports, and (ii) a decline in the public debt-to-GDP ratio, which is consistent with possible valuation effects, outcomes of a counter-cyclical fiscal policy and attempts to steer the public debt burden towards fiscally sustainable targets during economically tranquil periods. Adjustments in current account balances in response to business cycle shocks occur over the course of two years following the initial impulse and are spread over five years for public debt ratios. Output gap shocks explain a total of 10% of forecast error variance in the current account and 14.4% in the public debt variable over a ten-year horizon. Current account shocks contribute up to 3.3% of variance in the public debt ratio, invoking a negative response, which is consistent with the "twin deficits" hypothesis. However, in terms of the magnitudes, the impact is not significant, and the existence of a possible causal link in this case is strongly rejected by Granger causality tests.

3.2 Robustness checks

To ensure robustness of the results, we perform a variety of additional empirical exercises with alternative model specifications, estimators and variables, check sensitivity to sample composition and period considered, as well as test alternative shock identification schemes. To keep the paper at compact length, this section only briefly showcases selected results.

Figure 3: Impulse response functions, global sample, Bayesian PVAR

Note: The figure shows orthogonalized impulse response functions along with the 95% confidence intervals. The impulse variables are listed in the first row, the response variables are listed in the first column.



Bayesian PVAR estimation for the global sample. As discussed in the methodology section, complementing the GMM PVAR analysis, we also estimate a Bayesian panel VAR version of the model utilizing the same global balanced sample of countries. Overall, the estimation results are virtually identical to those obtained using the GMM PVAR estimator in terms of the impulse-response profiles (Figure 3) and also similar as regards the relative share of forecast error variance explained (Table 4). Among others, the impact of FC on $YGAP$ and $DEBT$ is confirmed to be strong with fast and persistent response, as well as the magnitudes identical to the baseline results. Likewise, FC does not have a significant effect on CA. The interactions among other variables also mirror the baseline results. In FEVD, in comparison with the GMM

PVAR estimation, for all variables the Bayesian model generally attributes a greater share of forecast error variance to own shocks and, conversely, a lower share of variance to innovations in other model variables. For instance, shocks in FC explain 4.5% of variation in $YGAP$ and 6.4% of variation in $DEBT$ over the 10-year horizon in the Bayesian PVAR setup, as opposed to 7.1% and 9.1% in the GMM PVAR setup, respectively (the impact of FC on CA remains insignificant). The relative importance of shocks, however, remains the same.

Alternative Granger causality tests. As an additional approach to gauge the predictive power of the variables in the baseline PVAR model, in addition to the Granger causality tests in line with Abrigo and Love (2016), we also perform a sequence of pairwise Dumistrescu and Hurlin (2012) Granger causality tests for all model variables. The test is developed for heterogeneous panels based on individual Wald statistics of Granger non-causality computed for each cross-section unit and then averaged over all cross-section units in the sample. Besides computational simplicity and allowing for cross-country heterogeneity, the test reveals other instrumental advantages: the power of the test is preserved even for small N and T, the test does not require running panel estimations and can be implemented in unbalanced panels. The results of this exercise, outlined in Table 5, confirm the findings from the homogeneous GMM PVAR-based Granger causality tests. In particular, they also point at a possible causal link from FC to $YGAP$ and $DEBT$ (the hypothesis of Granger non-causality is rejected at the 1% and 10% levels, respectively). In contrast to the baseline results, the Dumistrescu and Hurlin (2012) test also suggests a (Granger) causal relationship from $YGAP$ and CA to FC. These additional findings, however, are not supported by either the GMM PVAR or the Bayesian PVAR IRF profiles, as well as associated FEVD results. The feedback from other macroeconomic variables to financial cycles, therefore, appears to be weak.

Table 5: Dumistrescu and Hurlin (2012) Granger causality test results

Note: The table shows the results of the Dumistrescu and Hurlin (2012) Granger causality test for heterogeneous panel data models. Null-hypothesis: variable X (first row) does not Granger-cause variable Y (first column). ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

Y ↓	X →	*FC*	*YGAP*	*CA*	*DEBT*
FC	$\tilde{Z}$		6.04***	2.13**	1.00
	p-value		0.00	0.03	0.32
YGAP	$\tilde{Z}$	9.66***		0.60	0.42
	p-value	0.00		0.55	0.67
CA	$\tilde{Z}$	2.66**	3.80***		-0.64
	p-value	0.01	0.00		0.52
DEBT	$\tilde{Z}$	1.89*	0.79	-1.16	
	p-value	0.06	0.43	0.24	

Sensitivity to the Cholesky decomposition schemes. It is clear that the variables reflecting the dynamics of financial and macroeconomic imbalances used in our PVAR framework are interrelated. The ordering of variables used in the Cholesky identification schemes to arrive at orthogonal shocks may potentially lead to different results due to underlying assumptions about the sequencing of innovations and invoked responses of endogenous variables. The sequencing of the spillovers is a non-trivial issue particularly in the context of financial cycles as there is established theoretical framework that could provide clear guidance and the empirical literature on the interactions between financial cycles and real economic variables is scarce. Therefore, besides the factorization scheme that puts FC first in the ordering, that is, assuming it is "most exogenous" of the rest of the vector $\mathbf{X}_{it}$ variables, we test alternative ordering schemes. The results remain robust, and even when FC is ordered last in the vector $\mathbf{X}_{it}$, and thus assumed to be the "most endogenous", reacting in the same period to innovations in all other variables, the results still hold, although in some cases with lower significance. In particular, the impact of FC on $YGAP$ is still positive, but is significant at the 10% level of statistical significance. The impact of FC on $DEBT$ remains significant at the 1% level with the same impulse-response profile, except that the peak response occurs a period later than in the baseline model. The response of CA to FC innovations remains insignificant. This ordering also increases the statistical significance of the reverse feedback from $YGAP$ to FC, however, the magnitude of this impact is still negligible.

Additional variables. We further check whether the use of additional or alternative variables in the PVAR model may affect the result for the relationships of interest. The use of variables expressed in relative terms—as a percentage of GDP and in first differences—allows to mitigate the scale effects associated with significant cross-country heterogeneity that would be present when using the variables in levels, as well as helps avoid introducing additional uncertainty to the model due to the imprecision that variables measuring macroeconomic imbalances as deviations from a hypothetical equilibrium level would bring to the model. With reference to the latter issue, the output gap variable we use is subject to such measurement uncertainty, although it is used in first-differences and potential output is not expected to change much at business cycle frequencies. Nevertheless, as an alternative to the output gap measure $YGAP$, we also check the model with real GDP growth rates ($GROWTH$) for robustness. Estimation results (see sample results in Appendix Figure 11), however, remain largely the same as regards the impact of financial cycle shocks on other variables, and vice versa. Among others, the impact of financial cycles on business cycles, this time measured in terms of real GDP growth rates, remains significant both statistically and economically, with similar magnitudes of the responses to shocks. Another exercise—incorporating the real effective exchange rate variable (year-on-year differences), $REER$, in addition to the four baseline variables—does not improve the explanatory power of the model and the macroeconomic spillover effects involving financial misalignments remain the same as in the baseline specification (see Figure 12 in the Appendix for additional insights).

Sensitivity to the sample period and country composition. One may wonder also to what extent the results could be influenced by the recent global financial crisis and the Great Recession. Indeed, it is a valid concern as the crisis was characterized by a simultaneous downturn in financial markets and business cycles across many countries globally, and, given the panel data setting of our analysis, the significance of the results linking FC to $YGAP$ possibly could be unduly influenced by the recent crisis episode, as opposed to reflecting a more general relationship holding also robustly for pre-crisis dynamics and diverse idiosyncratic movements in financial and business cycles that could be tracked in different countries. To address this, we reestimate the model in both the GMM and the Bayesian PVAR versions using the same global sample, but observed only in the pre-crisis period, up to the year 2007, and compare the results with the baseline full-period estimations. The results still hold and the effects of financial cycles remain important and statistically significant. The magnitude of the impact in response to a one-standard deviation shock in FC reduces only slightly in the case of $YGAP$—from 0.4 to 0.3 percent of GDP (the peak response, occurring in the first period).

Finally, we test whether the results may differ for subsamples of countries with the following two case studies reported in the next sections: (i) potentially heterogeneous effects for countries having predominantly bank-based as opposed to market-based financial systems and (ii) implications for the euro area. As these results are instructive about important policy-relevant aspects of financial misalignments, specifically, may inform about possible externalities of deeper capital markets and shock spillover patterns within monetary union frameworks, they are formulated further as separate case studies with a relatively more detailed exposition.

3.3 Market-based versus bank-based financial systems

The section reviews whether the composition of financial markets matters for the strength of macro-financial spillovers, thus also relaxing the assumption of homogeneous effects within the global sample. This empirical exercise also adds to the literature debating on the implications of financial structure for economic growth and its stability (Beck et al., 2000; Beck and Levine, 2004; Demirgüç-Kunt and Maksimovic, 2002; Levine, 2003). Empirical analysis so far could not consistently suggest whether bank-based or market-based financial systems are better for economic growth and development. Against these inconclusive results, some studies argue that neither type of financial system is actually superior but, rather, the overall level of financial development matters (Rajan and Zingales, 1998).

The importance of capital markets also has received much attention in the aftermath of the Global Recession in the context of European financial markets. Overreliance on banks for financial intermediation, while capital markets remain relatively underdeveloped, has been recognized as one of the vulnerabilities in many European economies, giving rise to the Capital Markets Union initiative to facilitate development of deep and integrated capital markets in the EU. While capital markets indeed may help diversify funding sources and facilitate risk-sharing, they are also prone to the risks associated with procyclicality and formation of asset bubbles, especially when taking into account newly developed financial instruments for which risks are not well understood yet.

Therefore, in the context of the study it may be of interest to review whether the composition of financial markets had any implications so far for shaping transmission channels of financial cycle shocks. To address this empirically the global sample is split into two groups following the literature on financial structure: (i) bank-based financial systems, which rely on traditional financial intermediation via bank loans, and (ii) market-based financial systems, which have a relatively more prominent role of capital markets. The country composition and sample properties have been reported in Table 1 in the data section.

Splitting the global sample into smaller subgroups further exacerbates the degrees-of-freedom problem and necessitates the use of shrinkage techniques. To tackle this challenge, we again resort to Bayesian PVAR estimation with data resampling via bootstrap (Gibbs sampling) to arrive at robust estimates. For both samples we estimate compact homogeneous Bayesian PVAR models with the identified lag order 1,[17] which follow the structure of the baseline model as specified in Equation 3. The time period covered, data transformations (first-differences), Cholesky factorization schemes for shock orthogonalization are also identical to the baseline case to ensure complete comparability of results.

Combined evidence from the impulse-response functions (Figures 4 and 5), forecast error variance decomposition (Table 4) and Granger causality tests[18] (Table 6) suggests that the interactions among macro-financial imbalances follow similar fundamental patterns in both bank-based and market-based systems. Nevertheless, a number of important differences can be noted as regards the depth and the duration of the impacts.

First, financial cycles tend to explain a higher share of forecast error variance of other endogenous model variables in market-based economies in contrast to bank-based economies (see Table 4). In the case of the impact of FC on $YGAP$ the difference is not high: financial cycles explain 4.6% of variation in the output gaps of market-based economies, as opposed to 3.7% estimated for the bank-based sample. However, the share of variance in CA and $DEBT$ ascribed to FC dynamics is twice as much in market-based economies in comparison with that in bank-based economies. This is especially noteworthy for the $DEBT$ variable (8.7% versus 4.3% of variance explained by FC in the market-based and the bank-based samples, correspondingly), as the impact on CA is negligible in absolute values for both samples (2% versus 1% of variance explained). The greater role of financial cycles in shaping external and internal imbalances in market-based economies is also supported by the evidence from the Granger causality tests summarized in Table 6 and the IRF profiles reported in Figures 4 and 5.

The market-based sample is also the only case when financial cycle shocks trigger a stronger response of public debt-to-GDP ratios than output gap innovations. With this exception, across all samples investigated in the study (global, bank-based systems, market-based systems, euro area), the output gap variable has a greater significance in explaining both current account and public debt dynamics.

Second, the reaction of output gaps to financial cycle shocks is deeper on impact (greater by a factor of 1.7) and more statistically significant in bank-based economies in comparison with the market-based sample. In particular, as can be seen from the IRFs in Figures 4 and 5, a one-standard deviation shock in FC, equivalent to a magnitude of 0.7, invokes a response of $YGAP$ of about 0.5 (percent of potential GDP) in the case of the bank-based sample and about 0.3 in the market-based sample in the first year, which is the period of the peak impact. This, however, is offset by a more persistent effect in the market-based sample: it takes up to two additional years for a response in $YGAP$ to phase out in comparison with the bank-based countries, which is also mirrored in a greater proportion of variance in $YGAP$ explained by FC in market-based economies over a horizon of ten years in FEVD.

[17] The lag order is chosen based on SBIC, AIC and HQ information criteria. The models are stationary and satisfy the eigenvalue stability criteria.

[18] We use pairwise Dumistrescu and Hurlin (2012) Granger tests for non-causality for all model variables. As the N dimension becomes particularly small for the subsamples considered in the case studies the test results should be interpreted with caution and with the evidence from other empirical exercises in mind.

Figure 4: Impulse response functions, market-based country sample, Bayesian PVAR

Note: The figure shows orthogonalized impulse response functions along with the 95% confidence intervals. The impulse variables are listed in the first row, the response variables are listed in the first column.

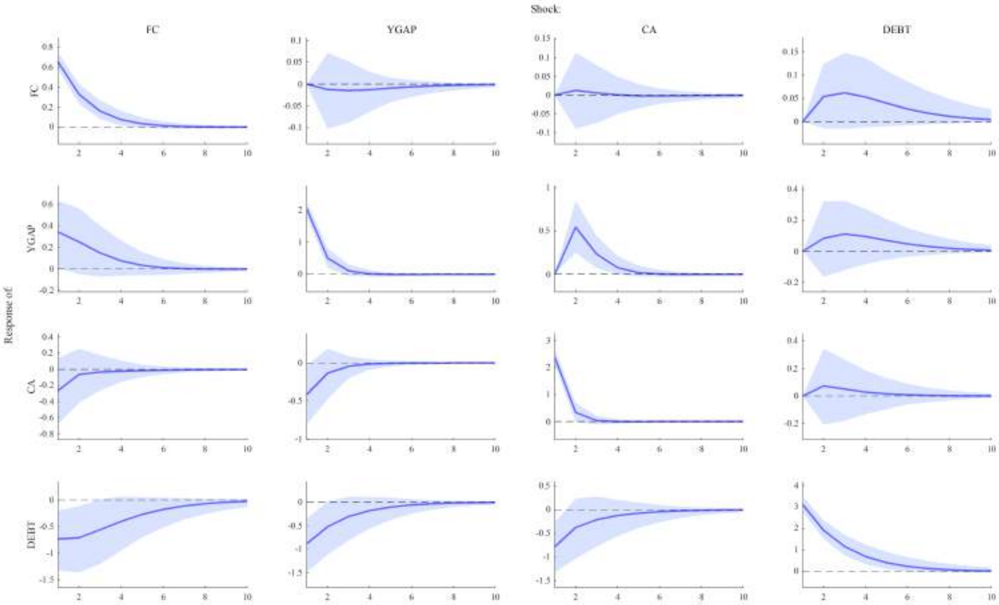


Figure 5: Impulse response functions, bank-based country sample, Bayesian PVAR

Note: The figure shows orthogonalized impulse response functions along with the 95% confidence intervals. The impulse variables are listed in the first row, the response variables are listed in the first column.

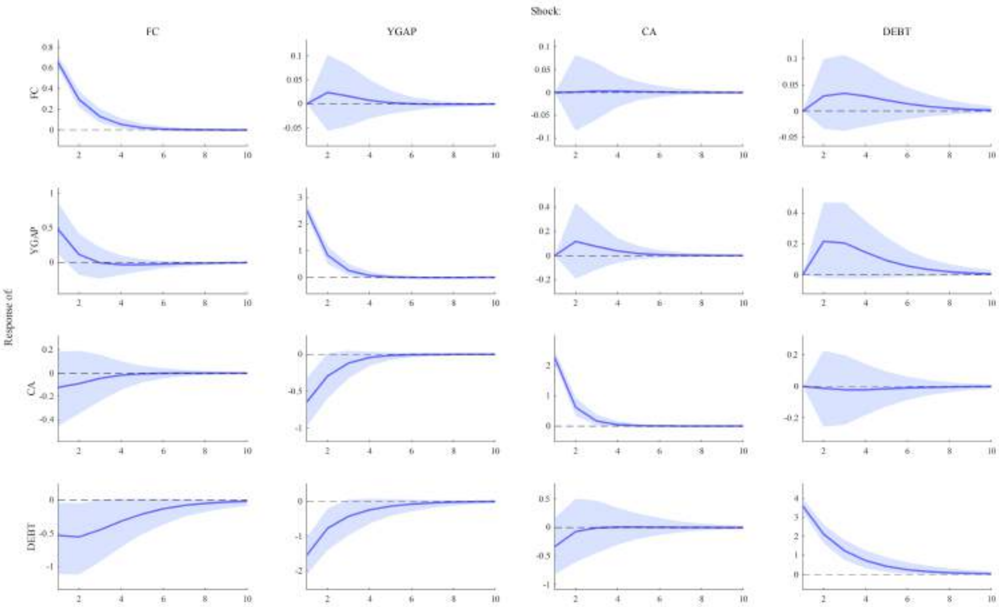


Table 6: Granger causality test for market-based, bank-based and euro area samples

Note: The table shows the results of the Dumistrescu and Hurlin (2012) Granger causality test for heterogeneous panel data models. Null-hypothesis: variable X (first row) does not Granger-cause variable Y (first column). ***, **, * indicate statistical significance at the 1%, 5% and 10% levels.

I. Market-based financial systems

Y ↓	X →	*FC*	*YGAP*	*CA*	*DEBT*
FC	$\tilde{Z}$		6.34***	1.52	0.16
	p-value		0.00	0.13	0.87
YGAP	$\tilde{Z}$	9.14***		1.53	0.76
	p-value	0.00		0.13	0.45
CA	$\tilde{Z}$	3.02***	4.62***		0.14
	p-value	0.00	0.00		0.89
DEBT	$\tilde{Z}$	2.31**	-0.87	-0.37	
	p-value	0.02	0.38	0.71	

II. Bank-based financial systems

Y ↓	X →	*FC*	*YGAP*	*CA*	*DEBT*
FC	$\tilde{Z}$		2.56**	1.51	1.17
	p-value		0.01	0.13	0.24
YGAP	$\tilde{Z}$	4.92***		-0.50	-0.09
	p-value	0.00		0.61	0.93
CA	$\tilde{Z}$	0.92	1.07		-0.95
	p-value	0.36	0.29		0.34
DEBT	$\tilde{Z}$	0.52	1.78*	-1.20	
	p-value	0.60	0.08	0.23	

III. Euro area

Y ↓	X →	*FC*	*YGAP*	*CA*	*DEBT*
FC	$\tilde{Z}$		3.82***	1.06	0.13
	p-value		0.00	0.31	0.89
YGAP	$\tilde{Z}$	4.81***		-0.30	0.03
	p-value	0.00		0.76	0.98
CA	$\tilde{Z}$	1.55	2.03**		-0.10
	p-value	0.12	0.04		0.92
DEBT	$\tilde{Z}$	0.71	2.11**	-1.11	
	p-value	0.48	0.04	0.27	

The response of the fiscal position variable to innovations in financial cycles is slightly deeper in market-based economies, as well as more statistically significant: the peak response of -0.7 is reached in the second period after the initial shock, as opposed to -0.5—also a peak response occurring in the second period—in the bank-based sample.

Supporting the evidence from the IRFs and FEVD, Granger causality tests also strongly indicate in favor of the hypothesis that FC Granger-causes $YGAP$ at the 1% statistical significance level in both bank-based and market-based samples. In market-based economies FC also Granger-causes CA and $DEBT$, in contrast to the bank-based sample.

In summary, financial cycles do have a strong impact on business cycles regardless of the financial market structure. The macroeconomic impact of financial cycles is also more lasting and broad-based, i.e. affecting more significantly external and internal imbalances, in the case of market-based economies, while in the case of bank-based economies it is rather more focused on output gaps with a greater initial momentum.

3.4 Implications for the euro area

As a final step of the analysis, we zoom in on euro area countries. Our sample includes ten out of nineteen euro area members (see Table 1) observed over the period 1998–2012 to facilitate comparability of the results with the baseline model outcomes and other case studies. All countries included in the euro sample are the founding members of the bloc established in 1999 with the exception of Estonia (joined in 2011) and Slovakia (joined in 2009). The latter two countries were however obliged to adhere to the euro convergence criteria (the Maastricht criteria) and participated in the European Exchange Rate Mechanism II before the accession, and therefore can be safely included in the sample.

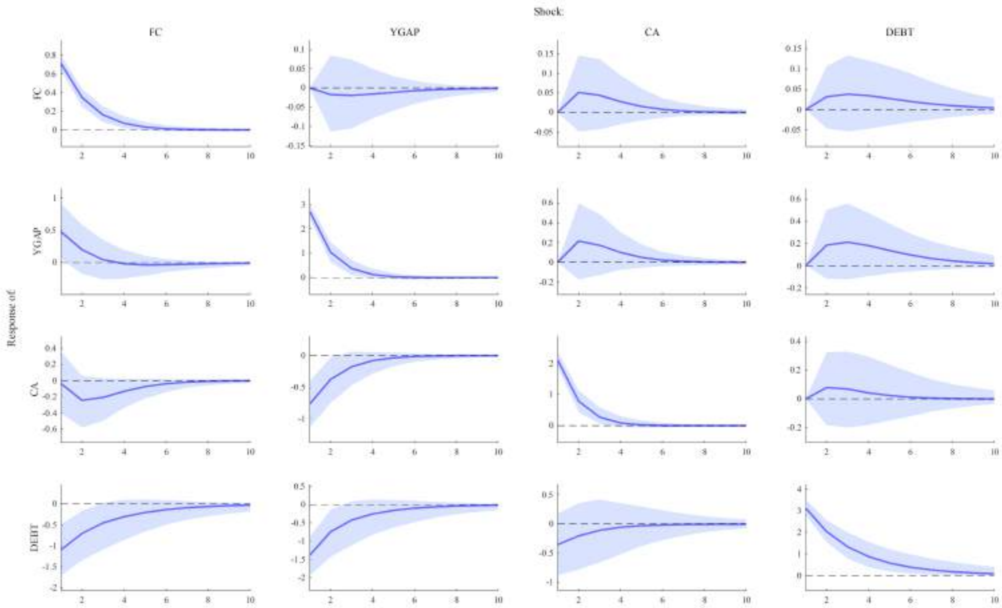
While the financial systems of the euro area countries are dominated by banks (the Netherlands is the only country in the sample classified as a market-based economy, but it also has a large active banking system), macro-financial spillover patterns may still differ from those in the broader bank-based sample as monetary union regulations may shape the adjustment paths of macroeconomic imbalances and impose additional constraints on policy responses to macroeconomic shocks on account of a common currency and explicit limits on macroeconomic imbalances imposed by the Maastricht criteria. Moreover, heterogeneity of euro area countries—particularly, deep structural differences between the "North" and the "South"—along with a lack of optimal currency area characteristics (Mundell, 1961 and McKinnon, 1963) have contributed to the persistence of macroeconomic imbalances within the bloc. Lasting macroeconomic misalignments along with unchecked booming credit prior to the Great Recession have led to the "twin crisis" of banks and sovereigns contributing to the depth of the recession in Europe (see also Lane, 2012 for discussion).

To study the dynamics of macro-financial imbalances in the euro area we also use the Bayesian PVAR approach and related empirical exercises discussed above. The orthogonal IRF plots are reported in Figure 6, FEVD results are outlined in Table 4 and Granger causality test results are listed in Table 6.

Empirical evidence suggests that the impact of financial cycles on output gaps in the euro area countries proves to be positive and significant as well, consistent with the baseline results and the case studies examined earlier. In terms of the dynamics, magnitudes and significance it is largely identical to the impact of financial cycles on output gaps in bank-based economies: a one-standard deviation shock in FC leads to a positive change in $YGAP$ of about 0.5 (percent of potential GDP) in the first period with the impact phasing out over 3 years.

Figure 6: Impulse response functions, euro area sample, Bayesian PVAR

Note: The figure shows orthogonalized impulse response functions along with the 95% confidence intervals. The impulse variables are listed in the first row, the response variables are listed in the first column.



However, the effects of financial misalignments on the current account and the public debt dynamics are much stronger in the euro area in terms of both economic and statistical significance. This is also reflected in a relatively high share of forecast error variance explained by financial cycle fluctuations: 3% in CA and 10% in $DEBT$ variation are attributed to FC shocks, which, in fact, is also greater than in the case of the market-based and the global samples.

The impulse-response profiles indicate a high persistence of the impact, especially for the public debt ratio: a one-standard-deviation positive shock in the financial cycle variable reduces the debt ratio by about one percentage point on impact (peak response), gradually phasing out only after 10 years. Moreover, the initial response of $DEBT$ also carries a greater momentum, peaking faster, already in the first period after the shock, as opposed to the second period observed in the global or bank-based samples. This much more significant response of $DEBT$ to FC innovations constitutes the principal difference in the reactions in the euro area sample in comparison with the broader bank-based sample.

The impact of FC on CA, although more significant than in other cases examined, nevertheless is not sizable in terms of the economic magnitudes and the proportion of variance explained. Interestingly enough, however, the peak response to a one-standard-deviation shock in FC of CA (-0.2 percent of GDP) is observed not on impact, as in the other samples examined and the baseline case, but in the second year gradually phasing out in the next six years. The same pattern is observed in Comunale (2017), which studies macro-financial imbalances in the euro area with partial-pooling Bayesian PVAR estimator. We however find that output gaps play on average a more important role as a driver of the current account balance and the fiscal position dynamics that financial cycles.

4 Conclusion

Financial markets are prone to repeated boom-bust cycles. The recent global financial crisis has highlighted the importance of better understanding these financial cycles and their impacts. In this paper we provide new empirical evidence on the macroeconomic implications of financial cycles estimated for a global sample of countries by summarizing information contained in the empirical patterns of credit aggregates, asset prices, interest rates, market risk and volatility dynamics of financial markets. Importantly, we show empirically the significance of financial cycles as a driver of business cycles and their strong implications for shaping macroeconomic imbalances, which is instrumental for informing policy debates.

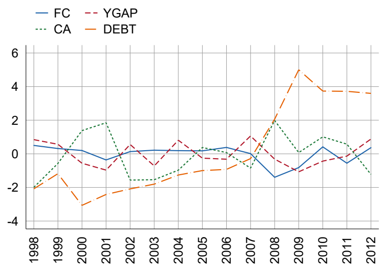
The risks posed by financial cycles are by no means unmanageable, and the results emphasize the importance of tackling the buildup of financial imbalances as one of the roots of macroeconomic overheating leading to crises. This implies that macroeconomic policy focusing exclusively or predominantly on targeting inflation as the principal nominal anchor may need to be revisited to allow for a more proactive monitoring and policy response to the buildup of financial imbalances. It is certainly possible to envision a situation when, for instance, an inflation target is achieved and the economy is at its potential as measured by conventional capacity utilization and employment indicators, and monetary policy therefore takes a neutral stance, while financial market imbalances may still be building up breeding systemic risks. As a related matter, the diagnostic tools and measures used to gauge macroeconomic stance, for instance, output gap estimation frameworks, would gain more relevance if adjusted to incorporate information on financial market dynamics. Significant advances have been made along these lines in the recent years, and regulatory authorities have been active in implementing new macroprudential policy instruments in attempt to tame financial cycles and related systemic risks, yet more needs to be done to understand better and address the vulnerabilities stemming from increasingly complex financial markets. In this regard, it is also critical to further advance research efforts in this direction to enable a thorough understanding of how economies function as the recent global financial crisis has clearly shown the gaps still existing in the established macroeconomic paradigm despite decades of research. It appears that further empirical and theoretical research on financial cycles, their macroeconomic implications and specific transmission channels, still lacking in the literature, is a promising way forward and constitutes a highly welcome research agenda.

Appendix

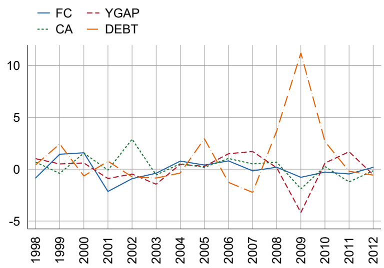
Figure 7: Dynamics of macro-financial imbalances

Note: The figure shows the dynamics of the variables used in the empirical analysis, including the financial cycle index (FC), the output gap as a percentage of potential GDP ($YGAP$), the current account as a percentage of GDP (CA), the general government debt as a percentage of GDP ($DEBT$), all expressed in first-differences. The countries in the global sample are arranged alphabetically by their ISO3 codes.

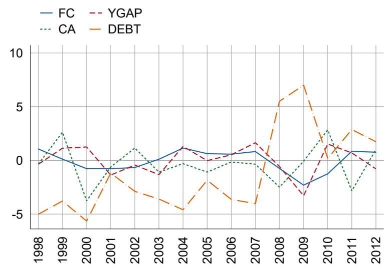
(a) AUS



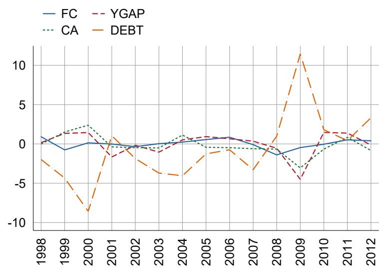
(b) AUT



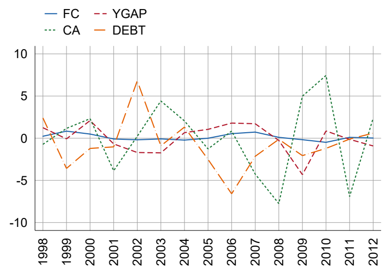
(c) BEL



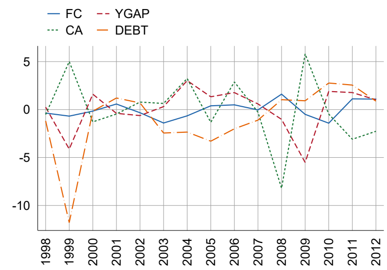
(d) CAN



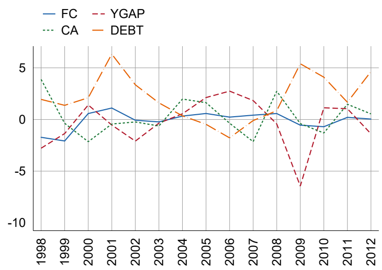
(e) CHE



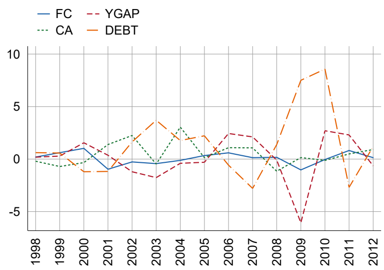
(f) CHL



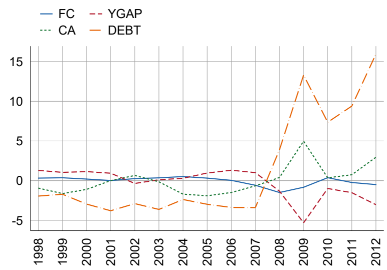
(g) CZE



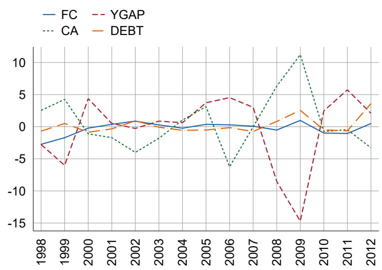
(h) DEU



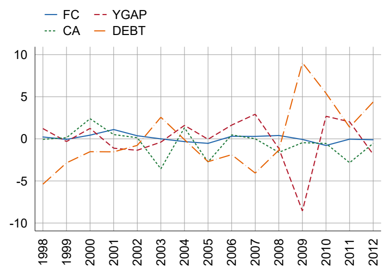
(i) ESP



(j) EST



(k) FIN



(l) FRA

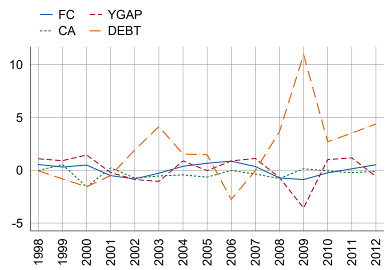
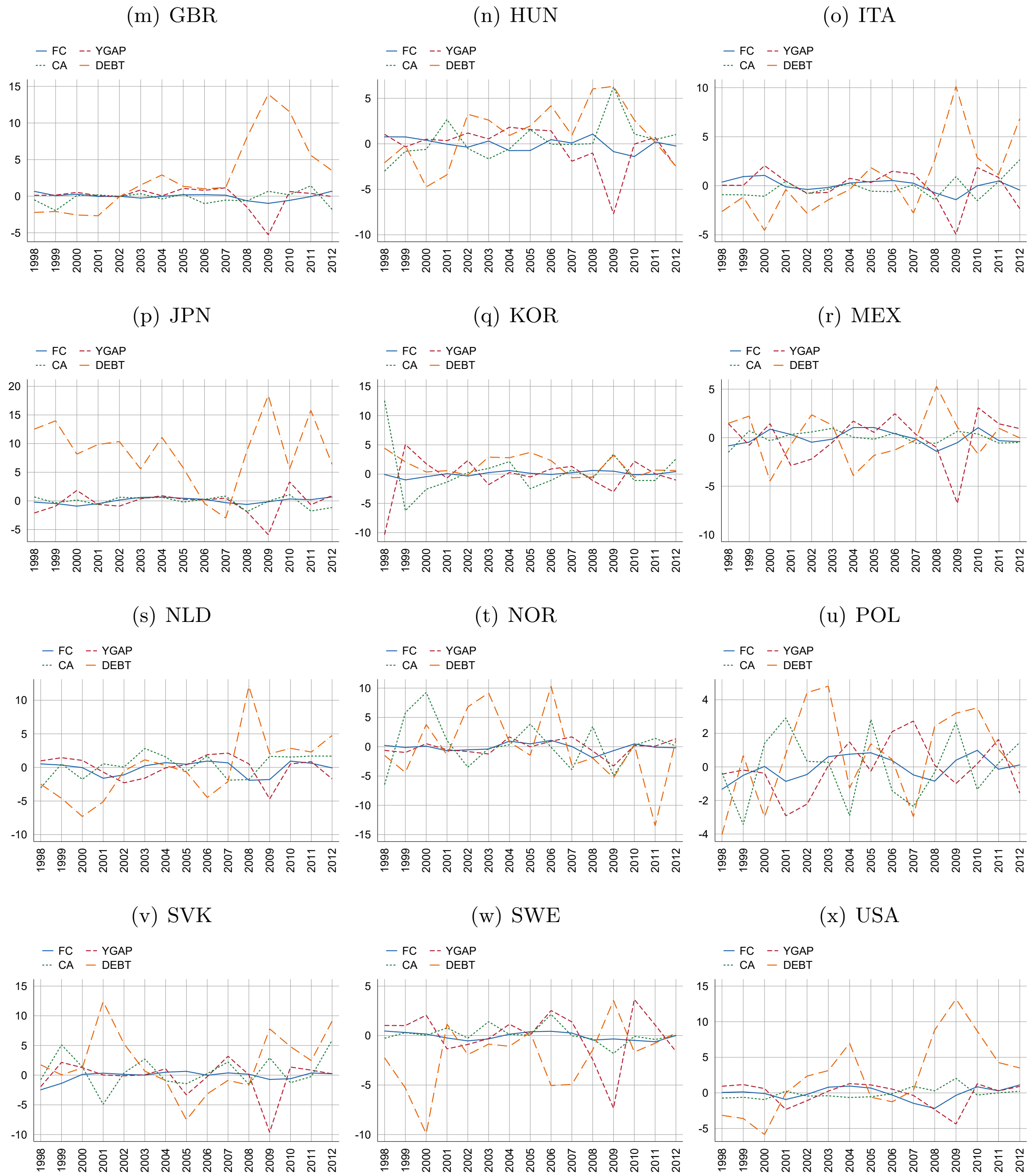


Figure 7 (cont.): Dynamics of macro-financial imbalances

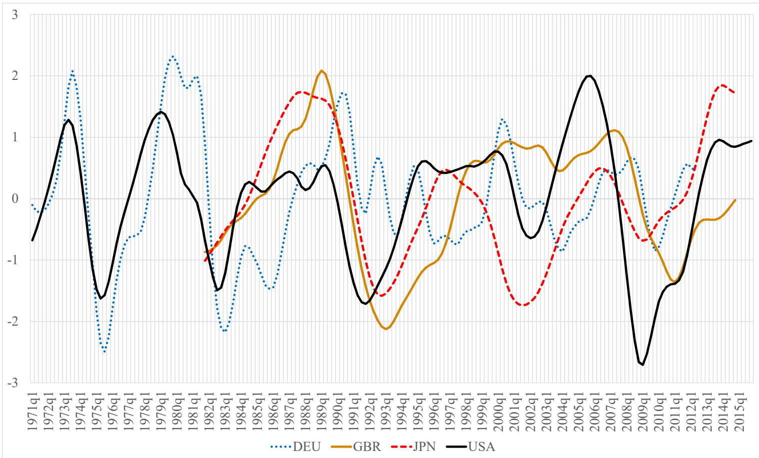


(m) GBR (n) HUN (o) ITA (p) JPN (q) KOR (r) MEX (s) NLD (t) NOR (u) POL (v) SVK (w) SWE (x) USA

Figure 8: Financial cycles of systemic economies

Note: The figure shows the financial cycles of four systemic economies (the United Kingdom, Germany, Japan and the United States). The top panel shows the original financial cycle index estimated at a quarterly frequency, the bottom panel shows the annualized financial cycle in first-differences as used in the PVAR models.

(a) Financial cycles, quarterly, levels



(b) Financial cycles, annual, year-on-year differences

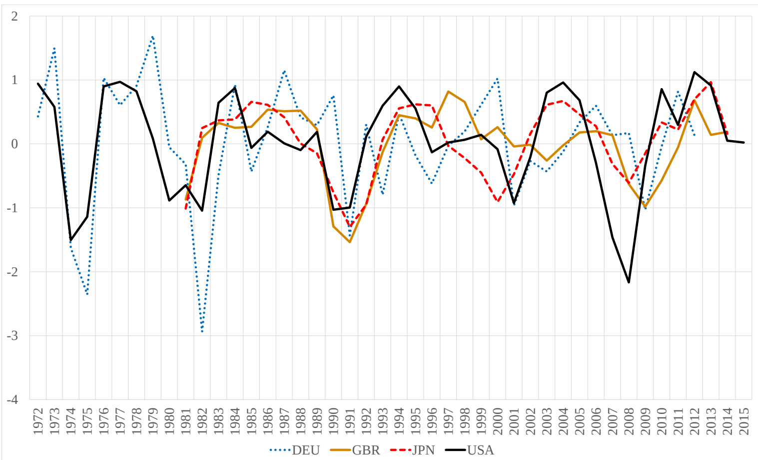
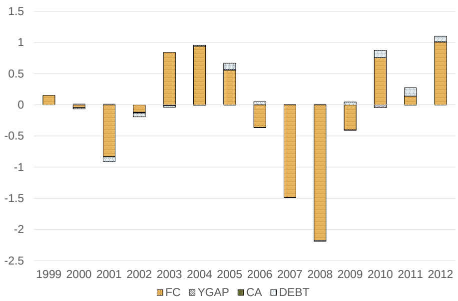


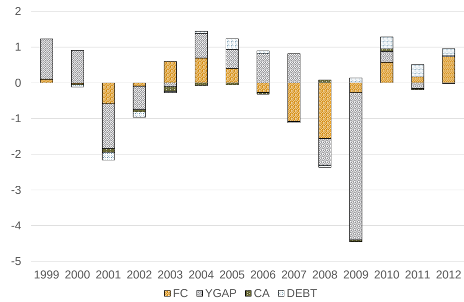
Figure 9: Historical decomposition of variable shocks, USA

Note: The figure shows historical decomposition of shocks to endogenous PVAR model variables—the financial cycle index (FC), the output gap as a percentage of GDP ($YGAP$), the current account balance as a percentage of GDP (CA) and the general government debt as a percentage of GDP ($DEBT$)—based on the baseline estimation results using the global sample.

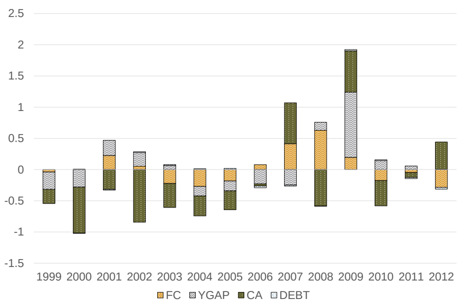
(a) FC



(b) $YGAP$



(c) CA



(d) $DEBT$

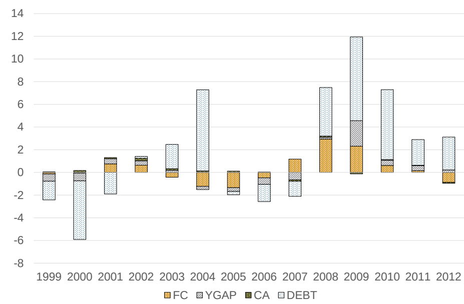


Table 7: Panel unit root test results

Note: The table shows the results of the Im-Pesaran-Shin (2003) and the Fisher-type ADF (see Choi, 2001) panel unit root tests for the model variables based on the global sample. Test statistics relevant for finite panels and associated p-values are reported. Null hypothesis: all panels have a unit root. Specifications assume panel-specific means and autoregressive parameters; lags are selected based on the SBIC criterion.

Test	Test statistic	FC	$YGAP$	CA	$DEBT$
Im-Pesaran-Shin (2003) test	W_{t-bar}	-9.43	-8.26	-7.80	-3.29
	p-value	0.00	0.00	0.00	0.00
Fisher-type tests	inverse χ^2 (P)	250.23	200.34	214.47	95.45
	p-value	0.00	0.00	0.00	0.00
	inverse normal (Z)	-11.19	-9.96	-9.21	-3.87
	p-value	0.00	0.00	0.00	0.00
stationary		yes	yes	yes	yes

Figure 10: Generalized impulse response functions, global sample, GMM PVAR

Note: The figure shows generalized impulse response functions (“impulse variable : response variable”) with 95% confidence intervals associated with the baseline GMM PVAR estimation.

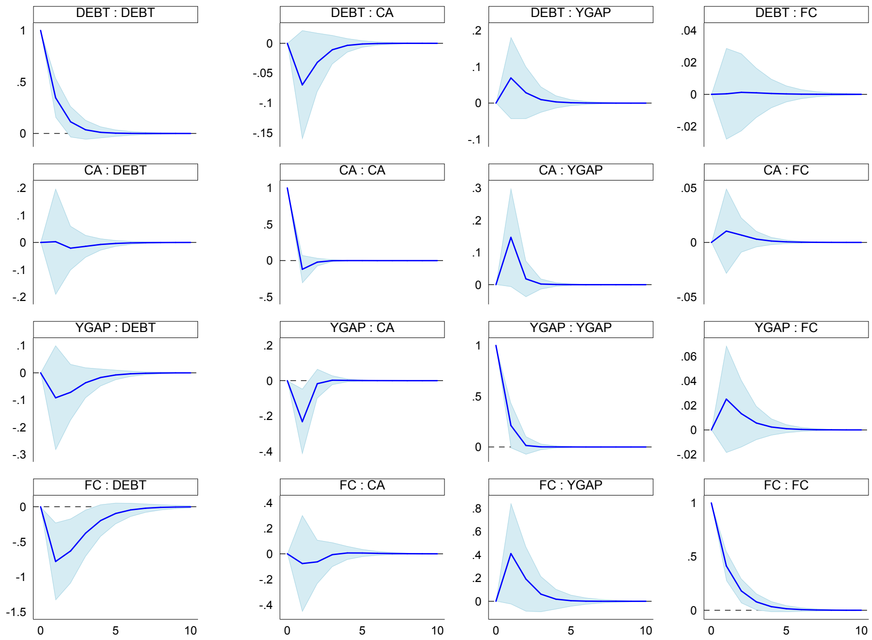


Figure 11: Impulse response functions, GMM PVAR with real GDP growth rates

Note: The figure shows orthogonalized impulse response functions (“impulse variable : response variable”) with 95% confidence intervals. The specification includes real GDP growth variable ($GROWTH$) instead of $YGAP$ used in the baseline specification. The ordering of the variables in the Cholesky decomposition is otherwise the same: $\mathbf{X}_{it} = \begin{bmatrix} FC_{it} & GROWTH_{it} & CA_{it} & DEBT_{it} \end{bmatrix}'$.

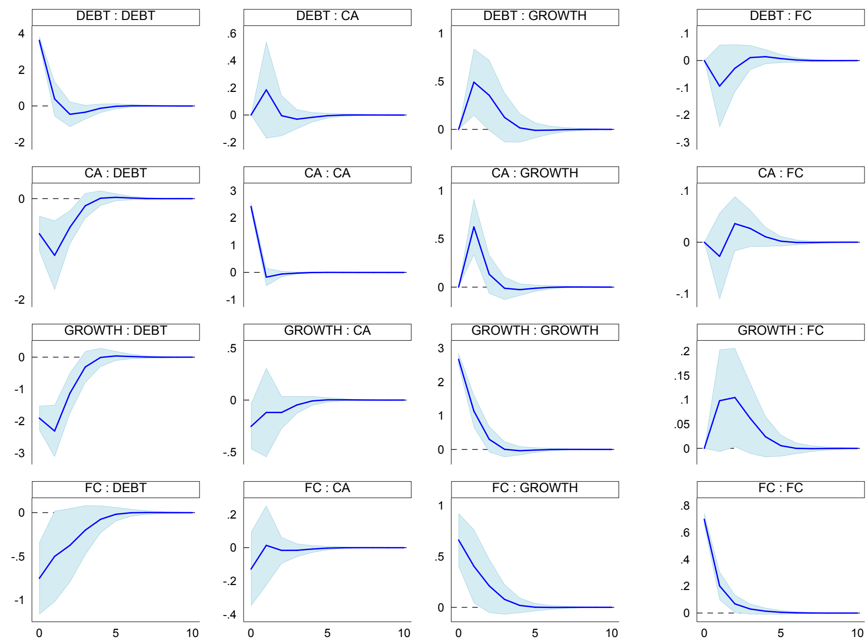
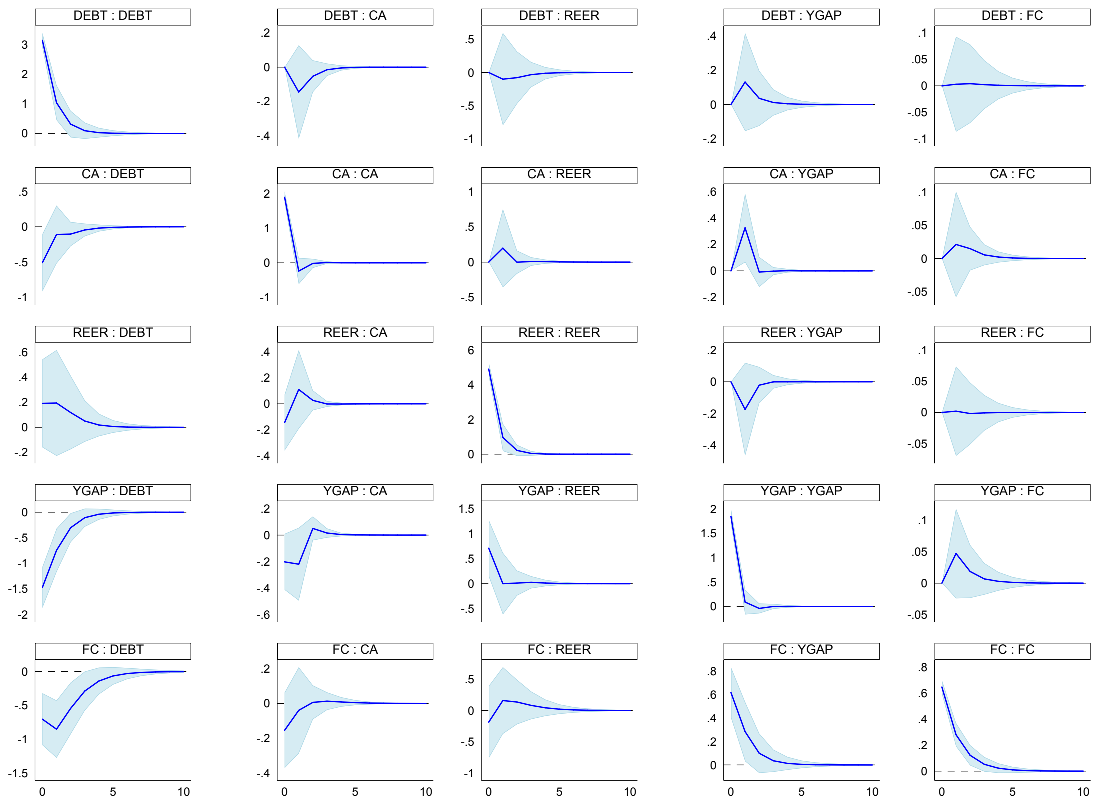


Figure 12: Impulse response functions, GMM PVAR with REER

Note: The figure shows orthogonalized impulse response functions ("impulse variable : response variable") with 95% confidence intervals. The specification includes real effective exchange rate ($REER$), expressed in year-on-year changes, augmenting the baseline specification. The ordering of the variables in the Cholesky decomposition is as follows: $\mathbf{X}_{it} = \left[FC_{it} \quad GROWTH_{it} \quad REER_{it} \quad CA_{it} \quad DEBT_{it}\right]'$.



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