Bank-specific shocks and aggregate leverage: Empirical evidence from a panel of developed countries

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ABSTRACT

This paper investigates the link between shocks in the banking sector and aggregate leverage measured by the credit-to-GDP gap. Using a balanced panel of 15 countries for the period 1989-2016, we exploit the approach due to Gabaix (2011) and consider banking granular shocks as an indicator of banking distress. We find that banking shocks Granger-cause aggregate leverage. In particular, banking shocks tend to increase the level of leverage and cause departures of the credit-to-GDP ratio from its long-term trend.

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Keywords: banking shocks; granularity model; credit-to-GDP gap; Panel VAR; Granger causality

1. Introduction

The pivotal role of the banking system in the 2008 financial crisis has led to a resurgence of interest in the role of the banking channel in smoothing or exacerbating financial and real shocks. From the theoretical standpoint, several studies have incorporated the behaviour of banks in standard Dynamic Stochastic General Equilibrium (DSGE) and agent-based models to describe the endogenous propagation of shocks between financial and credit markets and the rest of the economy (see, e.g., Gerali et al. (2010); Greenwood and Jovanovic (1990); Laeven et al. (2015)). Empirical studies have extensively focused on gauging the link between credit shocks and the real economy, triggering intense debates on the influential role of credit in driving global activity during recessions (Helbling et al., 2011). Many scholars agree that stock market bubbles are accompanied by credit market booms (Miao and Wang, 2018), and that the main source of interaction between financial and real variables is financial markets' imperfections. Since firms' balance sheets and households' creditworthiness are both likely to be procyclical, they are core determinants and amplifiers of macroeconomic activity. Variations in the constraints that limit the ability of firms to borrow are described as financial shocks (Jermann and Quadrini, 2012). Such financial shocks – originating from asset prices, stock markets and corporate bond spreads – have their effects on production and spending, and are believed to convey important signals regarding risks to the economic outlook (Gilchrist and Zakrajšek, 2012).

However, scholars have devoted less attention to the role that banking shocks play for the overall risk in the economy, albeit their relevency. This issue is crucial for policymakers, particularly when such shocks originate from large banks, posing systemic and contagion risks to the economy. In this paper, we fill this gap in the literature and investigate the link between shocks originating from the banking system and aggregate leverage, which is essential for financial stability.

Our analysis builds on the Granular Shocks Hypothesis introduced by Gabaix (2011) in the context of the relationship between large firms and aggregate output, where the hypothesis posits that idiosyncratic shocks to large firms have the potential to generate nontrivial aggregate shocks that affect GDP growth. Such impact can be sizeable when firms are highly concentrated within an economy, and their size follows a power-law distribution. Similar hypotheses have been formulated in the banking literature, where the argument is that if the banking system is highly concentrated – i.e., few large banks own and produce a large share of loans in the market– the shocks generated by these banks do not average out over time, and they may have an impact on the real economy.

In this regard, Buch and Neugebauer (2011) find a positive link between banking granular shocks constructed out of the total loans aggregate and the real economy. Bremus and Buch (2017) look at the relationship between banking granular shocks and financial openness, and show that banking shocks tend to be stronger in financially closed economies. Recently, a boost to the existing literature has come from Bremus et al. (2018), who provide both theoretical foundations and empirical evidence that banks' size follows a Pareto distribution, especially when there are a few large banks that dominate the market, so that their size matters for aggregate outcomes. This result is significant, as it is one of the main assumptions of Gabaix's model. The authors, then, use standard panel regressions and find that banking shocks positively affect output growth and the growth of domestic credit.

In this paper, we uncover the link between banking granular shocks and aggregate leverage – as measured by the credit-to-GDP gap. More specifically, we follow Gabaix's approach and analyze whether shocks to large banks – measured in terms of their lending and size – have any effect on the credit-to-GDP gap.[1] The latter is considered in the literature as an important leading indicator of financial crises as well as a measure of aggregate leverage (see, among the others, Giese et al. (2014); Jokivuolle et al. (2015). Our focus is on 15 developed economies and main international banking centres. In these countries, the interplay between finance and the real economy has been particularly relevant, with economic downturns affecting the soundness of financial institutions, and vice versa, as witnessed in the Global Financial Crisis. For these economies, we gather data between 1989 and 2016, a period interspersed with episodes of financial distress and economic slowdowns.

To the best of our knowledge, this is the first time that the credit-to-GDP gap is considered in the empirical literature of banking shocks. Moreover, from the methodological standpoint, while previous studies mostly use single equation frameworks, here we exploit a Panel Vector Autoregreesive (hereafter PVAR) approach that, coupled with a long time span of data, allows to better model the time dynamics and interactions among the observed variables, accounting for possible endogeneity.[2] As discussed in the existing literature, accounting for the dynamic interaction and feedback effects between banking and macro aggregates can be particularly

[1] The unequal distribution of banking firms in terms of size motivates the empirical analysis and the strategy in calculating the shocks variable. See, e.g.,Bremus et al. (2018).

[2] As explained in section 3.1, unlike previous authors, we do not compute banking granular shocks as residuals obtained from regressions that filter out the effects of GDP and its time lags. Instead, we follow the original approach proposed by Gabaix (2011) which does not remove such effects. Then, we use PVAR methods to account for any feedback effect among the variables under scrutiny. In this respect, we believe that our approach is more general than alternatives used in the literature.

important when banks face cyclical macroeconomic conditions as well as simultaneous and correlated regulatory changes (Kanngiesser et al., 2017).

Our analysis presents a contribution to the banking literature on the granular hypothesis. We find that shocks originating from large banks have positive effects on aggregate leverage.[3] The empirical results suggest that shocks originating from large banks increase the credit-to-GDP gap by as much as 4.5 percentage points over a time horizon of two years. We also find that such dynamics are unidirectional, with banking shocks affecting the leverage but not vice versa, and asymmetric in terms of length and magnitude, as positive shocks boost the gap while negative shocks dampen it. These results are of relevance for policymakers and regulators for several reasons. First, they emphasize the importance of monitoring the supply of credit from large banks, as these can lead to increased levels of leverage that can generate financial instability and crises. Second, they show that the credit-to-GDP gap conveys useful information about the dynamics of lending – especially from large banks – giving support to its use as an early warning indicator. Finally, Granger-causality tests show that banking shocks can anticipate the occurrence of peaks and troughs in the gap. As such, they might be able to flag instances of financial distress in a timelier way than the gap itself. The use of banking shocks in this direction could become particularly intriguing in the phenomenon of the zero lower bound and in the presence of unconventional monetary policies that may distort the ability of the term structure to predict the fluctuations of real and financial aggregates.

The remainder of the paper is organized as follows. Section 2 discusses the literature on banking shocks and the real economy. Section 3 describes the dataset. Section 4 presents the empirical methods, and Section 5 discusses the empirical results. Finally, Section 6 concludes.

2. **Literature review**

This paper builds on the recent strand of research on the "Granularity Hypothesis", first formulated by Gabaix (2011), in which idiosyncratic shocks to individual large firms do not average out in the aggregate. In this seminal paper, the author investigates the behaviour of large firms in a theoretical context with model calibration and tests the above hypothesis empirically using US annual data from 1951 to 2008. He finds that the idiosyncratic fluctuations, calculated using balance sheet ratios for productivity and size of the 100 largest firms, explain about one-third of the variation

[3] We define leverage as the private sector (i.e., non-financial corporations and household) debt outstanding in relation to GDP at the country level, which is common in the macro-finance literature. A detailed explanation on how to measure aggregate leverage is given in section 3.2.

in output growth.[4] He then concludes that idiosyncratic shocks are an important part of business cycle fluctuations and that a higher degree of firm concentration makes the relationship between firm shocks and macroeconomic fluctuations stronger.

Some scholars have applied Gabaix's concept of granularity to the banking sector (Amiti and Weignstein, 2017; Blank et al., 2009; Bremus and Buch, 2017; Bremus et al., 2018; Bremus et al., 2017; Buch and Neugebauer, 2011). While these applications validate the importance of looking at granularity, their focus has been on the effects of such shocks on output, house prices, and aggregate firm-level investment.

Blank et al. (2009), for example, explore whether shocks originating from large banks affect the probability of distress of small banks, and thus the stability of the banking system. In calculating banking granular shocks, they argue that bank loans and deposits are increasingly biased measures of banks' activities because of the growing importance of investment banking and the so-called universal banking. Consequently, they use banks' total operating income as a proxy for banks' size and use the cost-to-income ratio as a measure of the origins of shocks. Using annual data from 1991 to 2005 for the 10 largest banks in Germany, they present two main findings. First, size matters in banking, i.e., German banks follow an uneven size distribution. Second, the soundness of the whole banking system is affected by adverse shocks to large financial institutions. As a result, shocks originating from large banks increase the probability of distress for small and medium-size banks. Buch and Neugebauer (2011) generalize the previous finding by applying the concept of banking granularity to a larger sample of 35 European countries for the pre-crisis years from 1996 to 2006. In order to identify the largest banks, they choose only those banks that generate at least 5% of the total operating income of the industry in each country. They point out that a 5% threshold ensures that large and systemically important banks are included. Also, they choose net loans as a measure of productivity for the largest banks. Their findings can be summarized as follows. First, idiosyncratic shocks in the loan growth of large banks have a statistically and economically significant impact on the rate of economic activity, explaining about 16% of the cyclical variation of GDP growth. Second, they find strong evidence of a positive link between shocks from loan growth to real GDP in Eastern European countries compared to Western European countries. They claim that the lower degree of financial development in Eastern Europe and the difficulties in switching to alternative financial sources due to severe information asymmetry can explain such dichotomy in the results.

[4] Such cohort of firms excludes however firms in the oil, energy and financial sectors.

In the case of Japan, Amiti and Weignstein (2017) study the effects of banking granularity on investment. Their work incorporates three major distinguishing features. First, they exploit the heterogeneity in sources of firms' financing to aid the identification of time-varying banking shocks hitting firms. Second, their approach to the estimation of banking shocks accounts for the impact of new lending relationships between banks and firms. Third, they estimate the shocks directly from the loan data and do not rely on the use of instruments in their shock's identification strategy, because such instruments may be correlated with firm-borrowing and bank-supply shocks. By developing a new methodology on a unique dataset from 1990 to 2010, they separate bank-supply shocks from firm-borrowing shocks. Using Weighted Least Squares, they show that idiosyncratic granular bank supply shocks explain 30-40% of aggregate loans and investment fluctuations.

In another study, Bremus and Buch (2017) focus on the relationship between granularity in banking and economic growth, while accounting for an economy's financial openness and market concentration. They use a panel of 79 countries from 1996 to 2009 and calculate banking granular shocks from the banks' assets and credit volumes. They find that financial openness affects the strength of granular shocks: the different availability of alternative credit options means that these shocks produce smaller (larger) effects on macro fluctuations in more (less) financially open countries.

Integrating the housing market with banking granularity, Bremus et al. (2017) study the relationship between mortgage supply shocks at the bank level and regional house prices in the US from 1990 to 2014. They point out that there is a positive and statistically significant link between idiosyncratic mortgage shocks and house price growth and that the stronger concentration is in the mortgage market, the more micro-level shocks spread across the housing market.

In a similar vein, Bremus et al. (2018) model granularity in a theoretical context, considering banks as heterogeneous in terms of their cost of intermediation while competing to provide homogenous loans. They test the model empirically employing panel regressions on annual data from 1996 to 2009 for 83 countries. Using total loans to calculate banking shocks, they find support for the hypothesis that bank size follows a power-law distribution. Their study concludes that banking granular shocks are positively and significantly associated with the growth rate of domestic credit and real GDP. While our paper focuses on banking granular shocks, it differs from theirs in three ways. First, from the methodological standpoint, whereas they rely on single-equation methods (panel fixed-effects), we exploit a multivariate panel equation setting (PVAR). Second, while their sample includes a broader cross-section of countries but a shorter period of 14 years, we investigate a smaller set of developed countries but for a more extended period of 28 years. Third, while they test the effects of the shocks on the growth rate of credit, we test for their role on the credit-to-GDP gap that, as mentioned before, is considered a measure of leverage.

In summary, motivated by the above applications, our study aims to shed light on the granularity hypothesis in banking by considering its role on a measure of leverage, namely the credit-to-GDP gap, often considered as a leading indicator of impending financial crises and used by policymakers as a component of the macroprudential toolkit to enhance banking system resilience and mitigate systemic risk through bank capital regulations. Specifically, we test the hypothesis that banking granular shocks accelerate the economy's financial leverage. In contrast to previous studies, we contribute to the current debate by investigating the ability of the gap to convey information about the banking industry and by using PVAR methods. Unlike conventional panel data methods, PVARs account for possible endogeneity among the variables under scrutiny.

3. Data

We gather balance sheet annual data for the largest banks operating in 15 developed economies for the period 1989-2016. We then retrieve the time series of macroeconomic variables, such as real GDP, interest rates and consumer prices, over the same period.

First, we use *Datastream* to identify the largest banks operating in each country and then calculate a measure of shocks' granularity.[5] Similarly to Buch and Neugebauer (2011) and Bremus et al. (2018), we select for each country all commercial and universal banks that generate an average of 5% of net operating income of the industry in each of the selected countries during the sample period. In some cases, countries are too small and have a very concentrated banking system, so setting the threshold at 5% would select only one bank. In this case, we drop such countries from our data set and we only include countries with at least three banks in the sample.[6] We also exclude large banks whose data are available only for shorter time spans or are missing, and replace them with banks of similar size from the same country. By applying such criteria, we are able to gather a balanced panel, which is advantageous especially in terms of efficiency gains when using PVAR methods. Table 1 reports the countries and the number of banks considered in the empirical analysis, as well as the percentage of banks from the total sample in each country considered for the computation of the banking shocks variable.

[5] Compared to alternatives, *Datastream* allows us to construct a dataset with a sufficiently large cross-section of countries and a time period that spans more than 25 years. Since data for Japanese banks are available only from the year 2000, we have decided to drop this country from our dataset.

[6] This restricts the cohort of countries under scrutiny to 15.

Table 1. Total number of banks used in the analysis and banking market concentration

Country	Number of banks	% of the Total	Market concentration
Austria	4	6.452	55.39
Belgium	3	4.839	63.98
Canada	6	9.677	61.05
Denmark	4	6.452	86.60
France	5	8.065	57.67
Germany	3	4.839	66.94
Greece	4	6.452	77.04
Ireland	3	4.839	66.44
Italy	5	8.065	59.40
Portugal	3	4.839	80.93
Spain	4	6.452	62.12
Sweden	3	4.839	92.07
Switzerland	4	6.452	64.09
United Kingdom	5	8.065	51.12
United States	6	9.677	35.12
Total	62	100	

Notes: This table reports for each country, the number of large banks used to calculate the banking shocks variable, their percentage over the whole sample of banks (commercial and universal banks) and banking market concentration. Concentration is calculated using the assets of the largest banks within a country divided by the total assets in the banking system. Calculations are based on balance sheet data for the year 2016 (source: *Datastream*).

Even though the total number of banks varies widely among countries, the last column of Table 1 shows that all considered countries have a relatively high degree of concentration. On the one hand, the US has the lowest concentration of 35.12%, which is expected for a more market-oriented economy. On the other hand, Sweden has the highest concentration of 92.07%, supposedly due to considerable economies of scale and substantial barriers to entry in the banking system. Moreover, the substantial level of concentration (i.e., >35%, with an average of about 55-60%) suggests that large banks play a pivotal role in the countries under analysis. It is, therefore, quite possible that shocks emanating from such large banks might have an impact on the macroeconomic conditions of such countries, and possibility on the credit-to-GDP gap.

3.1 Computing banking granular shocks

We start our analysis by identifying the variables that can be used to calculate the banking granular shocks (BGS) variable. In line with Gabaix (2011), one input must be a measure of a bank's output and the second a measure of a bank's size. We, therefore, choose total operating income, including interest and non-interest income, as a proxy for the size. This variable will also help us identify and select the largest banking firms in each country. The rationale behind this analogy is that larger banks are expected to generate more profits than smaller banks and that the market share (i.e., bank concentration) is positively related to profits (Berger et al., 1993). We then choose total loans – a broad measure including consumer, real estate, C&I loans – to account for bank productivity. Although their traditional lending services have declined, loan contracts remain a significant element of a bank's balance sheet as a measure of its output (Allen and Santomero, 2001), as well as a key indicator for the credit channel of monetary policy (Kashyap and Stein, 2000). Also, using loans to work out our measures of granular shocks is consistent with previous studies such as Blank et al. (2009); Blank et al. (2009); Bremus et al. (2018); Buch and Neugebauer (2011).

The following three steps describe the procedure we follow to compute shocks of large banks in each country. In the first step, we calculate the annual growth rate of output of bank *i* in country *j* by taking the natural logarithm of its total loans:

$$\mathrm{g}_{\mathrm{ij,t}} = \ln(\mathrm{loans})_{\mathrm{ij,t}} - \ln(\mathrm{loans})_{\mathrm{ij,t-1}}, \tag{1}$$

In the second step, we calculate the average growth rate of total loans of the largest *L* banks in country *j*:

$$\bar{\mathrm{g}}_{\mathrm{j,t}} = \frac{1}{\mathrm{L}} \sum_{\mathrm{i=1}}^{\mathrm{L}} \mathrm{g}_{\mathrm{ij,t}}, \tag{2}$$

Finally, we obtain a measure of the banking granular shocks by summing up the weighted differences between the bank *i* growth rate and the mean growth of largest L banks, where the weights are calculated as the ratio between the total operating income for each bank *i* ($\mathrm{S}_{\mathrm{ij,t}}$) and the total operating income of all largest banks in the country ($S_{\mathrm{j,t}}$).[7]

$$\mathrm{BGS}_{\mathrm{j,t}} = \sum_{\mathrm{i=1}}^{\mathrm{L}} \frac{\mathrm{S}_{\mathrm{ij,t}}}{\mathrm{S}_{\mathrm{j,t}}} \left(\mathrm{g}_{\mathrm{ij,t}} - \bar{\mathrm{g}}_{\mathrm{j,t}}\right). \tag{3}$$

To account for possible outliers due to merger and acquisitions activities among banks in our sample, we follow Buch and Neugebauer (2011) and winsorize the values of banking shocks that fall outside the range [-0.5, +0.5]. This procedure affects only 3% of our observations. Fig. 1 displays the banking shocks obtained for each country. Noticeably, only few banking shocks take values outside the above band, mostly during the 07/08 crisis.[8]

[7]Because some countries in our sample have fewer banks compared to others, we have tried to calculate BGS in Eq. (3) both including and excluding bank *i* from the average growth rate of banks in country *j*. Since the two BGS figures feature a correlation of 99% or above for the full cohort of countries considered, we report here only the results based on the former method of calculation.

[8] Unlike Buch and Neugebauer (2011) we do not calculate BGS as residuals of a regression of the bank loan growth on average country loan growth and current and lagged values of GDP growth. We instead use the standard BGS indicator, as in Gabaix (2011), which does not remove such macroeconomic effects.

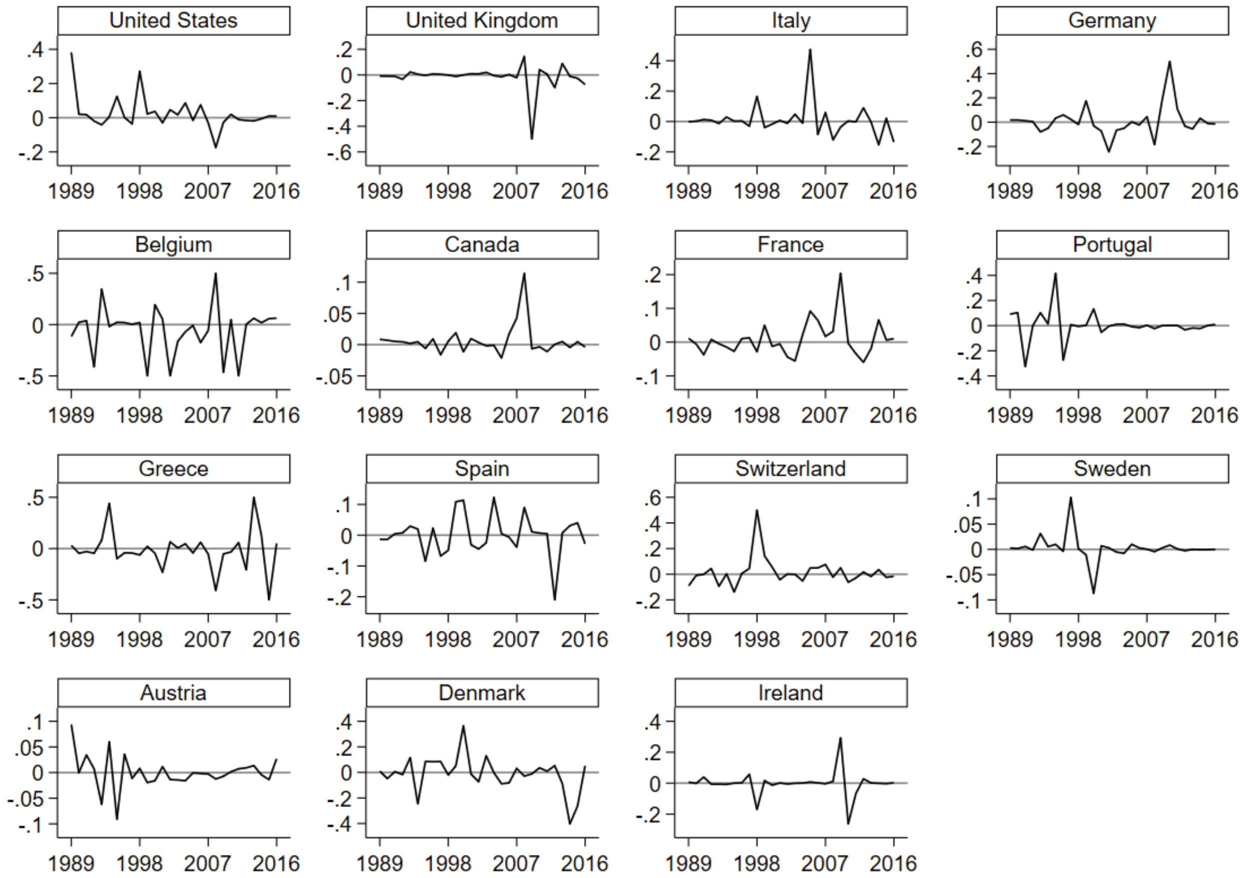

Fig. 1. Banking granular shocks for 15 countries during the period 1989-2016 (*N*=15, *T*=28). These figures display the evolution of banking granular shocks calculated following Gabaix (2011) as set out in Eq. (3).

3.2 Credit-to-GDP gap

We gather the data on the credit-to-GDP ratio from the Bank for International Settlements database, which also specifies the credit-to-GDP gap as the difference between the credit-to-GDP ratio and its long-run trend.

$$\mathrm{GAP}_{j,t} = \frac{\mathrm{credit}_{j,t}}{\mathrm{output}_{j,t}} - \mathrm{trend}_{j,t}. \tag{4}$$

The credit figure is the total credit to the private non-financial sector, capturing total borrowing from all domestic and foreign sources. The trend component to generate the gap in Eq. (4) is derived using the Hodrick and Prescott (1997) filter. Many scholars stress the importance of the credit-to-GDP gap as an Early Warning Indicator for banking crises. Drehmann and Yetman (2018) argue that the credit-to-GDP gap outperforms other gap measures across many forecast horizons as the best predictor of crises. Other authors use the credit-to-GDP gap to predict periods of excessive leverage and banking crisis (see, e.g., Alessi and Detken (2018); Jokivuolle et al. (2015); Teimouri and Dutta (2016).

Since our banking data are at annual frequency, our credit-to-GDP gap is calculated by first taking the annual average of the quarterly ratio. We then measure its long-term trend using an HP filter with an appropriate smoothing parameter and finally compute the difference between the ratio and its trend.[9] Fig. 2 displays the series of the credit-to-GDP gap for each country.

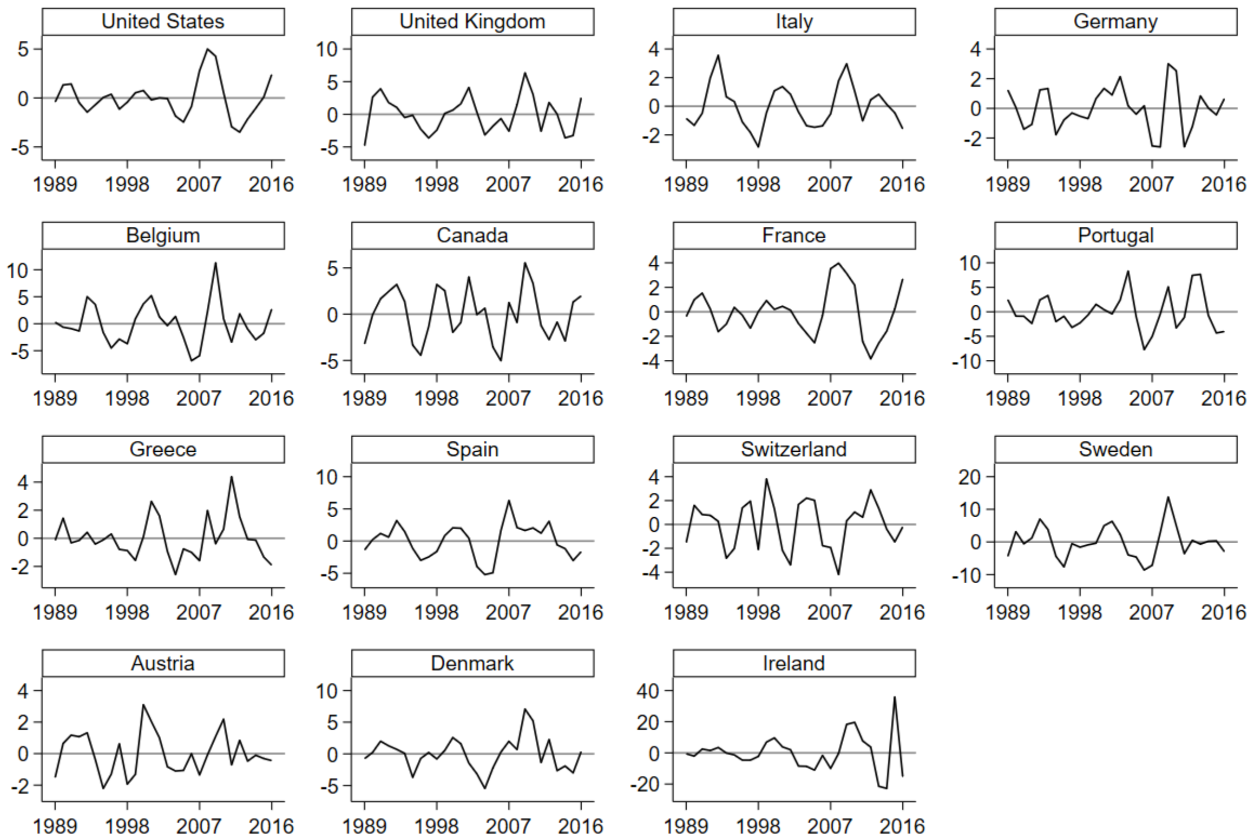

Fig. 2. Credit-to-GDP gap for 15 countries during the 1989-2016 period (N=15, T=28). These figures display the credit-to-GDP gap calculated as the difference between credit-to GDP ratio and its long-term trend as set out in Eq. (4), with the trend being calculated using the HP filter.

3.3 Macroeconomic control variables

Several factors can affect the relationship between banking shocks and leverage. The most notable are the business cycle, inflation, and monetary policy. In line with the literature, we control for the cycle by considering the growth rate of real GDP (see, e.g., Albertazzi and Gambacorta (2009)). We compute inflation as the annual percentage change in the Consumer Price Index. In order to account for the monetary policy stance, we include the interest rate spread, calculated by

[9] Hodrick and Prescott (1997) use a smoothing parameter of 1600 in calculating the filter. However, since we use annual observations, we set the smoothing parameter to 6.4 as suggested by Ravn and Uhlig (2002).

taking the difference between yields of five-year government bonds and three-month bills.[10] Table 2 provides descriptive statistics for the variables under scrutiny.

Table 2. Summary statistics

	Mean	Std. Dev.	Minimum	Maximum	Obs.
Credit-to-GDP gap	0.000	3.992	-22.80	35.91	420
Banking shocks	0.000	0.117	-0.500	0.500	420
GDP growth	0.020	0.031	-0.241	0.262	420
Inflation rate	0.025	0.025	-0.050	0.228	420
Spread	0.013	0.021	-0.055	0.285	420

Note: Sample period 1989-2016 for 15 countries (N=15, T=28). Credit-to-GDP gap is the difference between credit-to-GDP ratio and its long-term trend as specified in Eq. (4), where the trend is calculated using the HP filter. GDP growth (real) is the year-on-year growth rate of GDP deflated using current prices. The inflation rate is the annual percentage change in the consumer price index. Interest rate spread is the difference between five-year government bonds and three-month bills yields.

4. Empirical methodology

Panel Vector Autoregression

To investigate whether shocks generated by large banks affect credit-to-GDP ratios, we use a Panel Vector Autoregression (PVAR) methodology estimated using Generalized Methods of Moments (GMM) framework. In particular, our approach follows that of Abrigo and Love (2016), who introduce a PVAR estimation based on the early work of Sims (1980). In a VAR setting, all variables are treated as endogenous and interdependent, although in some cases exogenous variables might be included. This approach can be particularly important, as the banking system is vulnerable to macroeconomic fluctuations, simultaneously or with lags, with feedback effects of banks instability on economic activity that are amplified during periods of extreme credit booms and busts (Baltas et al., 2017). Because all variables are treated as endogenous, feedback effects are not a problem in our estimation. Such feedback effects can arise from the dynamic interaction between the two sides of the economy and among banking and macro variables. For example, inflation might distort the allocation of bank loans, as bank managers behave “conservatively” when inflation is high (Caglayan and Xu, 2016). Another macro variable that could potentially affect the supply of loans of large banks – and hence shocks originating from the banking sector – is the interest rate spread, which is a proxy for monetary policy (Barraza et al., 2019).

[10] Our source for macroeconomic control variables is the *Global Financial Database*.

Furthermore, modelling the dynamics of banking shocks, and financial and macroeconomic variables into a PVAR allows us to look at the Impulse Response Functions (IRFs) of different types of shocks, observing the response of the credit-to-GDP gap after simulating innovations to the banking granular shocks. We apply orthogonalized IRFs because the actual variance-covariance matrix of the errors is unlikely to be diagonal. A careful identification procedure for the PVAR is needed to isolate shocks to each of the variables. We choose a causal ordering of the variables and follow the standard procedure of Cholesky decomposition. It is relatively standard in the monetary transmission and macro-finance literature to adopt an ordering where real variables are placed before financial variables, i.e., output and prices before interest rates (see, e.g., Christiano et al. (1998) and Assenmacher-Wesche and Gerlach (2008)).

The inclusion of the credit-to-GDP gap and banking shocks variables, however, is new to the literature and warrants further assumptions. Goodhart and Hofmann (2008) place credit as last in the VAR they estimate under the assumption that monetary variables respond immediately to a real shock. On the contrary, Leroy and Lucotte (2019) place credit before interest rates and after real output as the bank interest rate pass-through is sluggish in the short term, hence the lack of immediate response from credit to a shock in interest rates. In our case, we use the deviations of credit relative to output and not the absolute term of credit as done by previous authors.

In our specification, we assume current shocks to the interest rate spread to affect the credit-to-GDP gap and banking shocks with a lag, in line with the notion that the channels through which monetary policy operates exhibit a lag before influencing the cyclical fluctuations in economic activity, as proposed by Friedman (1961). The interest rate spread, therefore, is ordered at the bottom of our PVAR setting and after inflation rate and output. We also place the credit-to-GDP gap after banking shocks and output for a similar reason. Indeed, according to the Basel Committee guide on Banking Supervision when the gap reaches two points or above, policymakers are advised to take buffer decisions, which allow banks to adjust their countercyclical capital buffer accordingly. Hence, the banking sector responds with a lag to regulatory changes. Real GDP growth is placed at the front-end of the PVAR before the banking shocks and credit-to-GDP gap variables, reflecting that the banking system responds immediately to a shock in output and, if there is a feedback effect, this is likely to happen with a lag.[11] The resulting order of a five variable PVAR model is, therefore: real GDP growth, banking shocks, credit-to-GDP gap, inflation rate,

[11]Following the standard approach in the literature, the assumption here is to follow a causal ordering of the variables. For example, the variables that come earlier in the ordering affect the subsequent variables contemporaneously as well as with a lag, while the variables that come later affect the previous variables only with a lag.

interest rate spread. We also aim to study the direction of transmission and causality between our variables using Granger (1969) causality tests.

Following Love and Zicchino (2006), we can specify a first-order PVAR model as follows:[12]

$$Z_{it} = \Gamma_0 + \Gamma_1 Z_{it-1} + \varepsilon_{it}, \tag{5}$$

where, Z_{it} is a (k × 1) vector of stationary variables of each of the i countries, i = 1, 2, 3, … 15. The subscript t denotes the time observations. Γ_0 is a vector of constants, Γ_1 is a matrix of parameters corresponding to the coefficients attached to Z_{it-1}, the vector of lagged endogenous variables. The disturbance ε_{it} is a vector of residuals, which encompasses the country-specific variance, σ_i^2.

Eq. (5) imposes the restriction that the underlying structure is the same for each cross-sectional unit. However, this constraint is likely to be violated in practice, and the identification would be affected by unobserved heterogeneity. To account for this issue, it is possible to introduce fixed effects, f_i:

$$Z_{it} = \Gamma_0 + \Gamma_1 Z_{it-1} + f_i + \varepsilon_{it}. \tag{6}$$

However, introducing fixed effects would create biased coefficients, especially when the mean-difference procedure is used to estimate the model since the fixed effects are correlated with the regressors when including lags of the dependent variables. To avoid this problem, we use forward mean-differencing, also known as the Helmert procedure (Arellano and Bover, 1995). This procedure removes only the forward mean, i.e., the mean of all the future observations available for each country-year, and preserves the orthogonality between the transformed variables and the lagged regressors so that the application of GMM becomes valid when using lagged regressors as instruments to estimate the coefficients.

5. Results

5.1 Pre-testing for stationarity

Before presenting our estimation results, we determine the time-series properties of the variables under scrutiny. We first test for the presence of unit-roots by using a battery of standard panel unit-root tests. Specifically, we make use of the statistics proposed by Choi (2001), Im et al. (2003) and Levin et al. (2002). We then test for the presence of unit-root by using the panel LM test proposed by Im et al. (2005) which allows for shifts in the levels of the series.

[12] A lag length of one was selected based on the minimization of the Akaike Information Criterion (AIC). This lag order is also supported by the Bayesian Information Criterion (BIC) and Quasi Information Criterion (QIC).

Empirical results, presented in Table 3, show that the null of unit-root is rejected at the 1% level for all the series of our panel. Therefore, in the remainder of the analysis, we consider the series in levels.[13]

Table 3. Panel unit-root tests for credit-to-GDP gap, banking shocks, GDP growth, inflation rate, and interest rate spread.

Variable	Fisher type	Im-Pesaran-Shin	Levin-Lin-Chu	Im-Lee-Tieslau
Credit-to-GDP gap	-10.74***	-9.844***	-10.13***	-22.87***
Banking shocks	-9.847***	-8.910***	-6.997***	-35.53***
GDP growth	-7.858***	-7.079***	-4.379***	-30.34***
Inflation rate	-7.197***	-6.434***	-6.698***	-20.82***
Spread	-3.303***	-3.142***	-4.208***	-26.70***

Notes: Sample period 1989-2016 for 15 countries (N=15, T=28). *** indicates rejection of the null of unit root at the 1% significance level. Im-Lee-Tieslau test allows for one shift in levels. The reported values are the t-statistic for each test. Lag length is based on the minimum of the AIC. Critical values at 1, 5 and 10 percent significance levels for all tests are respectively -2.326, -1.644 and -1.281.

5.2 Impulse response functions

Having checked for stationarity, we proceed by estimating the above mentioned PVAR specification for the above set of variables across the 15 countries. Our interest is to study the response of the credit-to-GDP gap series following innovations in the banking granular shocks variable. Fig. 3 illustrates the IRFs obtained from the PVAR estimation.[14] We find that a one-standard-deviation shock to banking granular shocks triggers a positive and statistically significant response of the gap of about 4.5 percentage points after one year. This result is significant for three reasons. Firstly, it shows that the credit-to-GDP gap can convey information on the build-up of systemic vulnerabilities that may arise from banks' lending. This finding is expected as banks tend to increase their intermediation activities through rapid credit growth and by taking on risks (Drehmann et al., 2011). Secondly, positive shocks originating from large banks may trigger a credit boom – as detected by high values of the credit-to-GDP gap – and may tend to amplify the business cycle. Such an impact lasts as long as four years, with a cumulative effect raised to 9.4%. Thirdly, we provide empirical insight into the impact of banking shocks on a leading indicator of

[13] We then consider one series at time and compute several univariate unit-root tests, namely, Ng and Perron (2001), Dickey and Fuller (1979); Phillips and Perron (1988). Similarly, in this case, empirical results consistently reject the null of unit-root for all the series. These results are available upon request.

[14] All eigenvalues of the dynamic matrix in the PVAR system are within the unit circle.

financial crises. To the best of our knowledge, this is the first time that this result is highlighted in the literature.

Additionally, the response of the gap following a shock to real output growth is positive and significant up to two years. This finding supports the idea that the expansion of credit is procyclical and that banks may behave in a way that collectively undermines the stability of the financial system during the expansionary phases of the cycle (Brunnermeier et al., 2009). This result is in line with the literature that documents the positive link between the credit cycle and the economy.[15] Furthermore, the response of the gap to a one-standard-deviation shock in the interest rate spread is negative and statistically significant, which can be interpreted as implying that expectations of future growth, or a looser monetary stance, are associated with a reduction in the gap, and hence the risk in the economy. We then find that a positive shock to inflation triggers a negative and statistically significant response of the credit-to-GDP gap. This result is in line with a number of previous studies. For instance, Boyd et al. (2001) show that an inflationary cycle would adversely affect the allocation of credit, as it can intensify informational asymmetries leading to less intermediary activity and deterioration in borrowers' ability to meet payment obligations. Caglayan and Xu (2016) argue that bank credit tends to decrease when inflation hits higher levels. Our results provide empirical support for this argument and highlight the importance of price stability for the supply of credit. We then report in the Appendix (Fig. A1) the response of the other macro variables to an impulse in the banking shocks variable. Initially, output responds positively by up to 0.15% to a positive banking shock, which then turns insignificant for a time horizon beyond two years. This positive response of output to banking shocks is consistent with the results of Buch and Neugebauer (2011). Furthermore, it can be seen that the interest rate spread responds negatively to a positive shock to the banking shocks variable, which is in line with the literature on monetary policy where regulators decrease interest rates in response to banking crises (Taylor, 2009). Lastly, inflation responds negatively to a shock in the banking shocks variable, but this is not significant during the observed period.

[15] For a detailed review on this topic see Borio (2014).

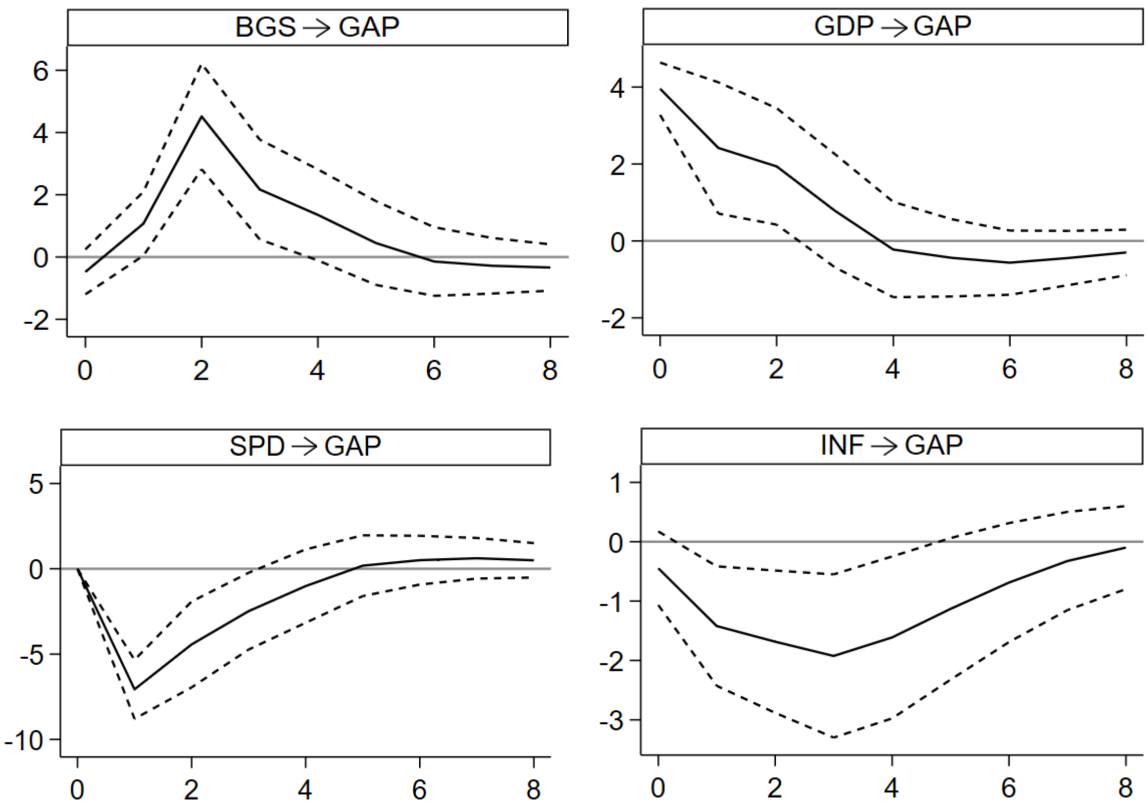

Fig. 3. Credit-to-GDP gap IRFs (solid lines) following a one-standard-deviation shock in the banking shocks, real output, interest rate spread, and inflation rate variables. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. IRFs obtained from PVAR model estimated on the panel data of 15 countries over the period 1989-2016 (*N*=15, *T*=28).

Following the baseline estimation, we then re-estimate our PVAR specification for the same set of variables while separating banking granular shocks based on their sign, i.e., positive and negative ones. In particular, we introduce an interaction term between banking shocks and an indicator variable for positive and negative shocks. By doing so, we should be able to document whether the credit-to-GDP gap responds differently to positive and negative banking shocks. [16] The left panel of Fig. 4 reports the response of the credit-to-GDP gap to positive banking shocks. As expected, positive shocks lead to a positive response of the gap. The right panel of the same figure shows that the gap responds negatively to a negative banking shocks impulse. The two diagrams display some degree of asymmetry in terms of the length and magnitude of the responses.

[16] We find that the number of positive shocks is substantially greater than that of negative shocks, as the latter are mainly concentrated in the years surrounding the Subprime crisis.

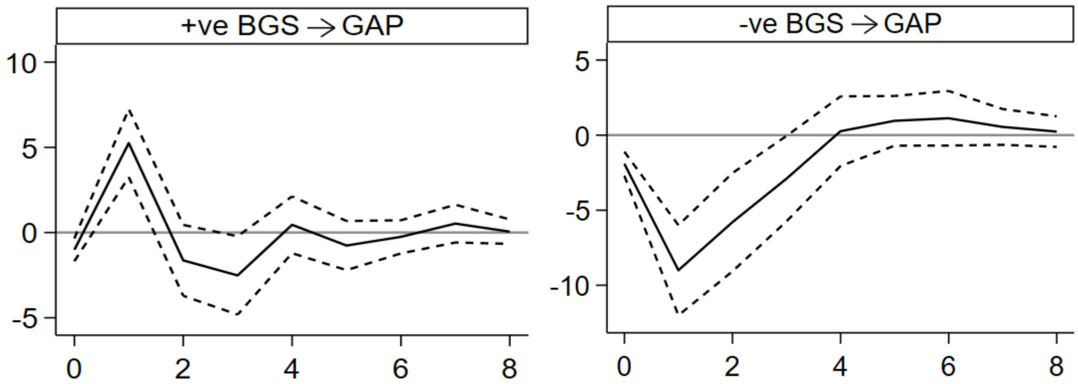

Fig. 4. Credit-to-GDP IRFs (solid lines) following a one-standard-deviation shock in positive (left panel) and negative (right panel) banking granular shocks. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. IRFs obtained from PVAR model estimated on the panel data of 15 countries over the period 1989-2016 (*N*=15, *T*=28).

5.3 Granger- causality tests

We then proceed to test for the direction of causality among our variables. Table 4 displays the results of the Granger-causality tests obtained from the PVAR estimation.[17] As anticipated by the IRFs previously set out, we find that banking shocks Granger-cause the credit-to-GDP gap. However, such a relationship is not bi-directional, so that the credit-to-GDP gap does not Granger-cause banking shocks. Furthermore, all macroeconomic variables in our model Granger-cause the gap, in particular real GDP growth, supporting our previous evidence obtained from the impulse responses. This result is also in line with the recent literature on the procyclicality of credit, which documents how credit is amplified and becomes more attractive to borrowers during the expansionary phases of the cycle (Leroy and Lucotte, 2019). We also find that Granger-causality results highlight the presence of feedback effects between some of the variables under scrutiny, most importantly, between GDP growth and banking shocks, and between inflation and credit-to-GDP gap. Such feedback effects are accounted for by our PVAR setting.[18]

[17] A possible alternative would be to test for Granger-causality in a frequency domain in the spirit of Breitung and Candelon (2006) in a panel OLS context, rather than the PVAR setting adopted in the paper. We would like to thank an anonymous Reviewer for this suggestion that we have implemented as robustness analysis, following the approach suggested by Croux and Reusens (2013). Our results confirm that banking shocks significantly Granger-cause the gap at both low and high frequencies. However, even if favorable, the results of this approach should be taken with caution given that, as pointed by Croux and Reusens (2013), the method is not robust when the time dimension is small, as it is in our case. For brevity, we do not fully report the results of this analysis, although they are available upon request.

[18] Refer to Table A1 in the Appendix for comprehensive results of Granger-causality tests.

Table 4. Granger-causality tests

Null hypothesis	χ^2	p-value
Banking shock does not Granger-cause credit-to-GDP gap	19.74***	0.000
GDP growth does not Granger-cause credit-to-GDP gap	11.09***	0.000
Inflation rate does not Granger-cause credit-to-GDP gap	17.86***	0.000
Interest rate spread does not Granger-cause credit-to-GDP gap	63.95***	0.000
Credit-to-GDP gap does not Granger-cause banking shock	0.314	0.575

Notes: Sample period 1989-2016 for 15 countries (N=15, T=28). *** indicates rejection of the null at the 1% significance level. Lag length = 1 which is selected based on the minimum of AIC. Granger-causality test are based on a likelihood ratio statistic that follows a χ^2 distribution with one degree of freedom.

5.4 Variance decomposition analysis

In Table 5, we report the results of the variance decompositions analysis, which highlights the importance of banking shocks and the other macroeconomic variables in explaining the credit-to-GDP gap. Specifically, approximately between 13% and 15% of the forecast error variance of the credit-to-GDP gap, over a time horizon from three to nine years, can be explained by banking shocks. Unsurprisingly, there is some degree of variation in the ability of each variable to forecast the credit-to-GDP gap; variations in the interest rate spread account for the highest percentage and can explain up to 43% of the variation in the gap. This finding is likely a reflection of the importance that expectations of future growth or monetary policy stance, as embedded in the spread, have on leverage. This result is in line with previous studies on the information content of the term structure and its predictive power in relation to the real cycle and financial conditions (see, e.g., Estrella and Hardouvelis (1991); Gertler and Lown (1999)).

Table 5. Variance decomposition of the credit-to-GDP gap over different time horizons.

Horizons	Banking Shocks	GDP	Inflation	Spread	GAP
3	13.40	15.53	3.101	42.77	25.17
6	15.40	14.10	6.812	41.44	22.23
9	15.31	14.24	7.042	41.38	22.01

Notes: Sample period 1989-2016 for 15 countries (N=15, T=28). Each time horizon (in years) shows the share of forecast error variance of the credit-to-GDP gap explained by banking shocks, GDP growth, inflation rate, interest rate spread, and credit-to-GDP gap itself. For each row figures add up to 100.

5.5 *Robustness checks*

We carry out an extensive sensitivity analysis of our baseline results by estimating alternative specifications of our PVAR model. We begin by testing whether a different ordering of the Cholesky decomposition has any effect on the estimation of our baseline specification. We do so by first placing the banking shocks variable after GDP growth and credit-to-GDP gap, and then by placing it before both of them. We also place the banking shocks and credit-to-GDP gap variables at the bottom end of the PVAR ordering after output, inflation and interest rate spread, assuming that financial variables respond immediately to shocks originating from the real economy (Christiano et al., 1998). For each of the three cases, we estimate the PVAR specification, obtain the IRFs and compute the Granger-causality tests. Since we do not observe substantial changes to the baseline results, these robustness checks are not reported but are available upon request.

We then investigate whether our main results are driven by a specific year or period. We do so by estimating the PVAR model on a shorter dataset where we drop one year at the time. Empirical results suggest that the estimated coefficients of the PVAR model, as well as the related IRFs results, remain substantially unaffected. We carry out a similar task by dropping one country at the time. This exercise can be particularly important for two reasons. Firstly, our sample combines countries with different credit and banking systems, as well as levels of financial development. Secondly, as mentioned in the data section, there can be robustness implications when the small size of a country implies that very few banks are included in the calculation of the granularity shocks. Again, this analysis delivers results that are very similar to those of Fig 3. These results are not reported but available upon request.

We then check whether our results are sensitive to the Global Financial Crisis. We do this, first, by using a dummy for the second part of the sample from 2008 onwards. Again, this analysis returns results broadly similar to those in Fig. 3 (results are available upon request). Second, we split the sample into pre-crisis (up to 2006) and post-crisis (from 2007) sub-samples. The IRFs of Figs. A2 and A3 in the Appendix confirm the baseline results of a positive and negative response of the gap to banking shocks and yield spread respectively, as previously seen in Fig.3, with some differences in the response of the other variables.[19]

We also acknowledge that, especially in the 2000s, the mortgage market had played an important role in aggregate financial stability. Unfortunately, we are not able to control for the sub-components of bank lending due to data limitations. However, we can indirectly account for

[19] Some differences emerge in the response of real GDP and inflation, with the second being positive before the crisis (Fig. A2) and the first being negative after the crisis (Fig. A3). However, one should be wary in interpreting the results of the split samples since, especially for the second period, the sample size is rather small.

the role of the mortgage market by including the growth of real house prices as an additional control variable.[20] We, therefore, estimate a six-variable PVAR model by including the growth of real house prices, and by placing such series as last in the Cholesky ordering to allow for lagged impacts originating from the remaining variables of the specification, including a dummy variable from 2008 onwards.[21] Fig. A4 in the Appendix illustrates the responses of the gap to the other variables when house prices are included in our setting. The baseline result of a positive response of the gap to a shock in the banking shocks variable holds, again, with some differences in the responses to the other variables. In particular, we find a different response to real GDP and inflation rate shocks compared to Fig. 3 with real GDP and inflation having a negative and positive response, respectively. The response to a shock in the spread has the same initial negative reaction, later followed by a positive one.

Fig. A5 shows that house prices respond positively and significantly to a positive shock in banking shocks for up to two years, with a small negative correction taking place at year three. Interestingly, banking shocks also respond positively and significantly to a shock in house prices up to two years. This result signals the importance of banks in the transmission of shocks to the real economy. A positive banking shock, which indicates an increase in bank lending, raises house prices via housing wealth and collateral effects. In parallel, credit supply depends on house prices, as homes are commonly used as collateral for loans. This last result, and in particular the endogenous response between banking shocks and house prices, is in line with the literature on the interplay between the credit and housing markets, and the macroeconomy (see, e.g., Favara and Imbs (2015); Goodhart and Hofmann (2008)).

Finally, we perform a number of robustness checks by using slightly different specifications of the variables in use. More specifically, we re-estimate our baseline PVAR by using modified series for bank loan growth and banking shocks. We do so by calculating the former without taking the logarithm, and the latter by setting negative values for operating income equal to zero, we then use the growth rate of real GDP per capita instead of real GDP growth, and the Baxter and King (1999) band-pass filter to compute an alternative measure for the credit-to-GDP gap. In all these cases, the modified specifications have a minimal impact on the series in use and do not alter our findings.

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[20] We would like to thank an anonymous Reviewer for pointing us to this direction of this robustness analysis. Indeed, mortgage lending in relation to other loans supplied by large banks has increased substantially in the last decades. The literature highlights the importance of such type of lending for macroeconomic aggregates, and the risk that it poses to aggregate economic stability (Jordà et al., 2016).

[21] As before, we follow a similar order to Goodhart and Hofmann (2008) by placing the real variables first, followed by the financial variables (i.e., real GDP, inflation, spread, house prices), and by adding credit-to-GDP gap and banking shocks at the bottom end of the Cholesky ordering. Again, we also compute the IRFs with alternative orderings to check the robustness of the PVAR results with house prices. We confirm that this does not alter the findings.

6. Conclusion

In this paper, we build on Gabaix's granularity hypothesis and investigate how banking granular shocks impact on the aggregate leverage of the economy, as measured by the credit-to-GDP gap. We construct a measure of banking shocks derived from the balance sheet data of large banks for 15 developed countries over the period 1989-2016 and study the link between the two while controlling for GDP growth, inflation and the interest rate spread in a PVAR setting that accounts for possible endogeneity among the variables of interest. Allowing for endogeneity can be important, as macroeconomic factors could affect the modus operandi of banks, their way of dealing with shocks, and their lending policy. While the role of banking granular shocks has been considered in recent studies, to the best of our knowledge, we are the first to uncover their impact on the credit-to-GDP gap, a measure of leverage risk often considered as an early warning indicator of crises.

Our empirical results show that large and positive banking shocks are associated with substantial increases in the levels of credit-to-GDP gap. A sizeable deviation of the credit-to-GDP ratio from its long-term trend indicates that the private sector is borrowing at levels not consistent with the level of economic activity. In such a scenario, the banking system becomes vulnerable and exposed to substantial rates of loan defaults, potentially leading to an economic slowdown, banking disintermediation and crises.

Macroprudential policies such as borrower-based tools (i.e., loan-to-value and loan-to-income) besides lender-based tools (i.e., countercyclical capital buffer) are often believed to reduce the risk of default. These tools would eventually curb the magnitude of banking shocks that emerge from large banks and prepare the system to absorb losses should such banks fall into financial distress. Such positive link between credit-to-GDP gap and lending by large banks is important for regulators, as it conveys the idea that a high degree of concentration is the foundation whereby banking shocks do not cancel out and therefore matter for macroeconomic outcomes. Based on this evidence, policies that may increase market concentration should be considered carefully in the context of banking resilience. Similarly, an outlook to monitor banking shocks is not only wise, but a realistic strategy to reinforce the stability of the banking system.

Future work could expand our analysis in different directions. One possibility could be to examine the micro and macro determinants of banking granular shocks. Also, our analysis recommends further inspection of the responses of the credit-to-GDP gap to shocks other than the banking granular shocks. Additionally, from the macroprudential standpoint, it would be relevent to study the role of banking granular shocks alongside other indicators considered in the early warning indicators literature, such as global liquidity and risk measures. Finally, it would also be interesting to examine the sub-components of the credit-to-GDP ratio and test the nexus between different types of credit and banking shocks. Research in these directions could complement the literature on banking and financial crises and help identify appropriate policy responses.

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Appendix

Table A1. Granger-causality tests

Null hypothesis	χ^2	p-value
GDP growth does not Granger-cause banking shock	8.628***	0.003
Inflation rate does not Granger-cause banking shock	12.85***	0.000
Interest rate spread does not Granger-cause banking shock	3.068***	0.000
Banking shock does not Granger-cause GDP growth	17.53***	0.000
Inflation rate does not Granger-cause GDP growth	13.65***	0.000
Credit-to-GDP gap does not Granger-cause GDP growth	1.790	0.181
Interest rate spread does not Granger-cause GDP growth	65.68***	0.000
Banking shock does not Granger-cause inflation rate	7.838***	0.005
GDP growth does not Granger-cause inflation rate	14.93***	0.000
Credit-to-GDP gap does not Granger-cause inflation rate	5.129**	0.024
Interest rate spread does not Granger-cause inflation rate	1.739	0.187
Banking shock does not Granger-cause interest rate spread	76.65***	0.000
GDP growth does not Granger-cause interest rate spread	0.059	0.808
Credit-to-GDP gap does not Granger-cause interest rate spread	2.353	0.125
Inflation rate does not Granger-cause interest rate spread	0..525	0.469

Notes: Sample period 1989-2016 for 15 countries (N=15, T=28). **,*** indicates rejection of the null hypothesis at 5% and 1% significance levels respectively. Lag length = 1 and is selected based on the minimum of AIC. Granger-causality test are based on a likelihood ratio statistic that follows a χ^2 distribution with one degree of freedom.

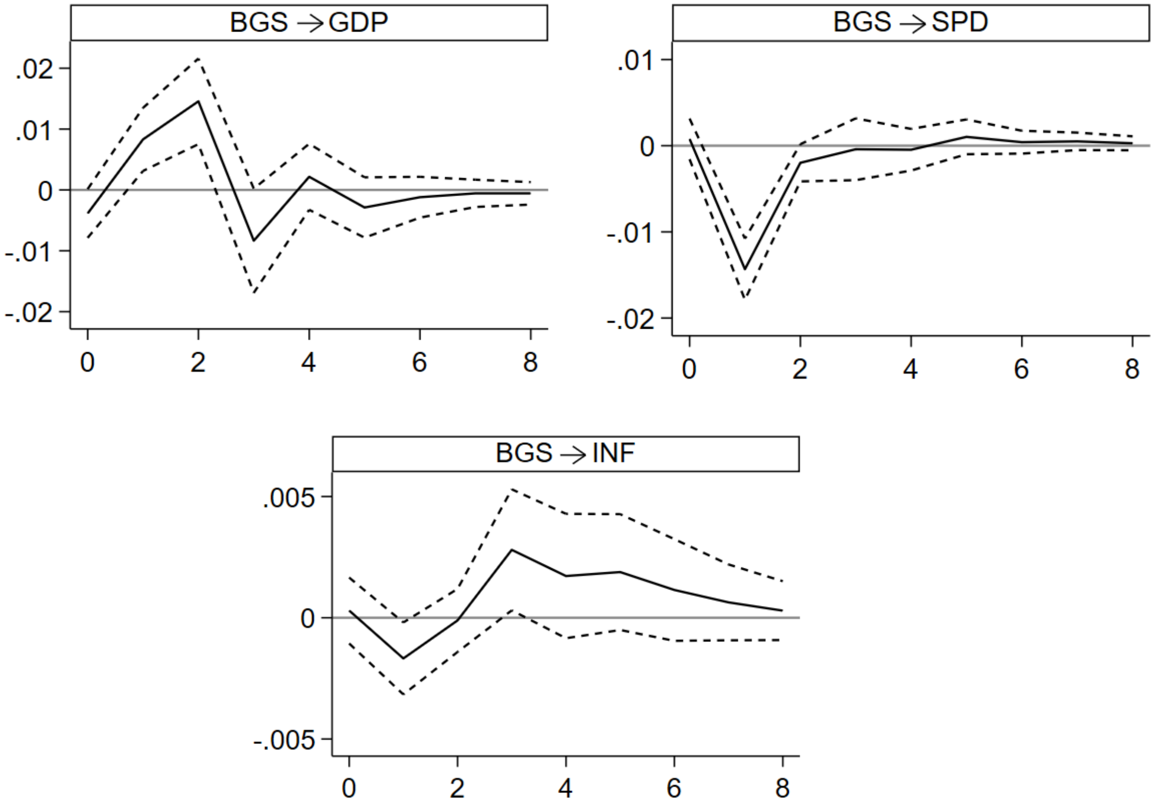

Fig. A1. IRFs of real output, interest rate spread and inflation rate variables (solid lines) following a one-standard-deviation shock in the banking shocks variable. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. IRFs obtained from PVAR model estimated on the panel data of 15 countries over the period 1989-2016 (*N*=15, *T*=28).

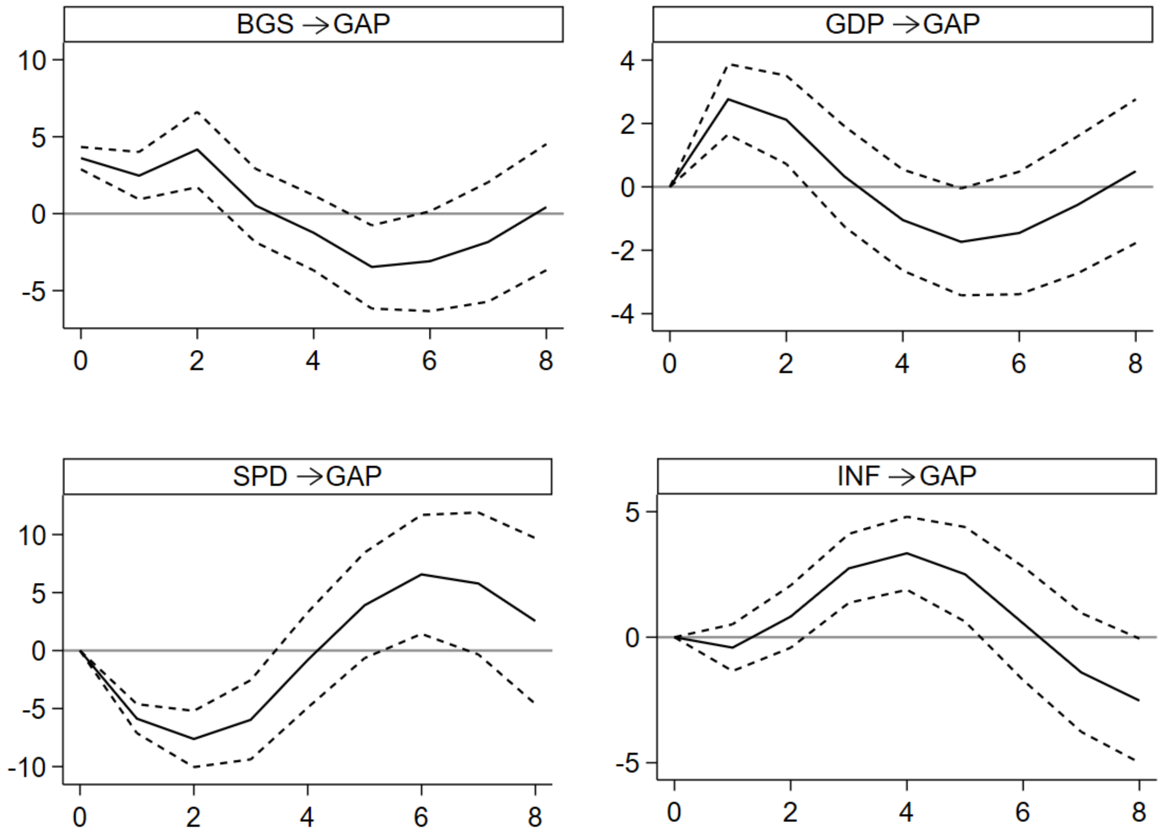

Fig. A2. Credit-to-GDP gap IRFs (solid lines) following a one-standard-deviation shock in the banking shocks, real output, interest rate spread, and inflation rate variables for the pre-crisis period. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. IRFs obtained from PVAR model estimated on the panel data of 15 countries over the period 1989-2006 (N=15, T=18).

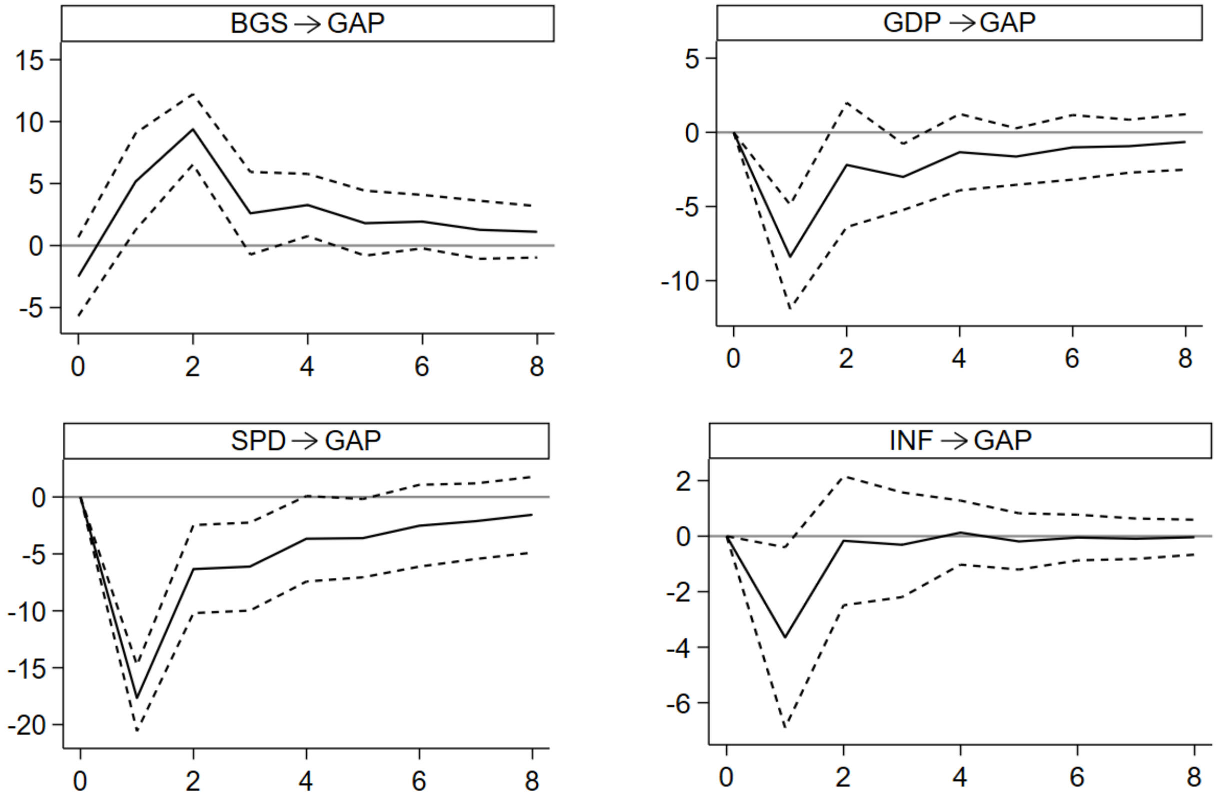

Fig. A3. Credit-to-GDP gap IRFs (solid lines) following a one-standard-deviation shock in the banking shocks, real output, interest rate spread, and inflation rate variables for the post-crisis period. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. IRFs obtained from PVAR model estimated on the panel data of 15 countries over the period 2007-2016 (*N*=15, *T*=10).

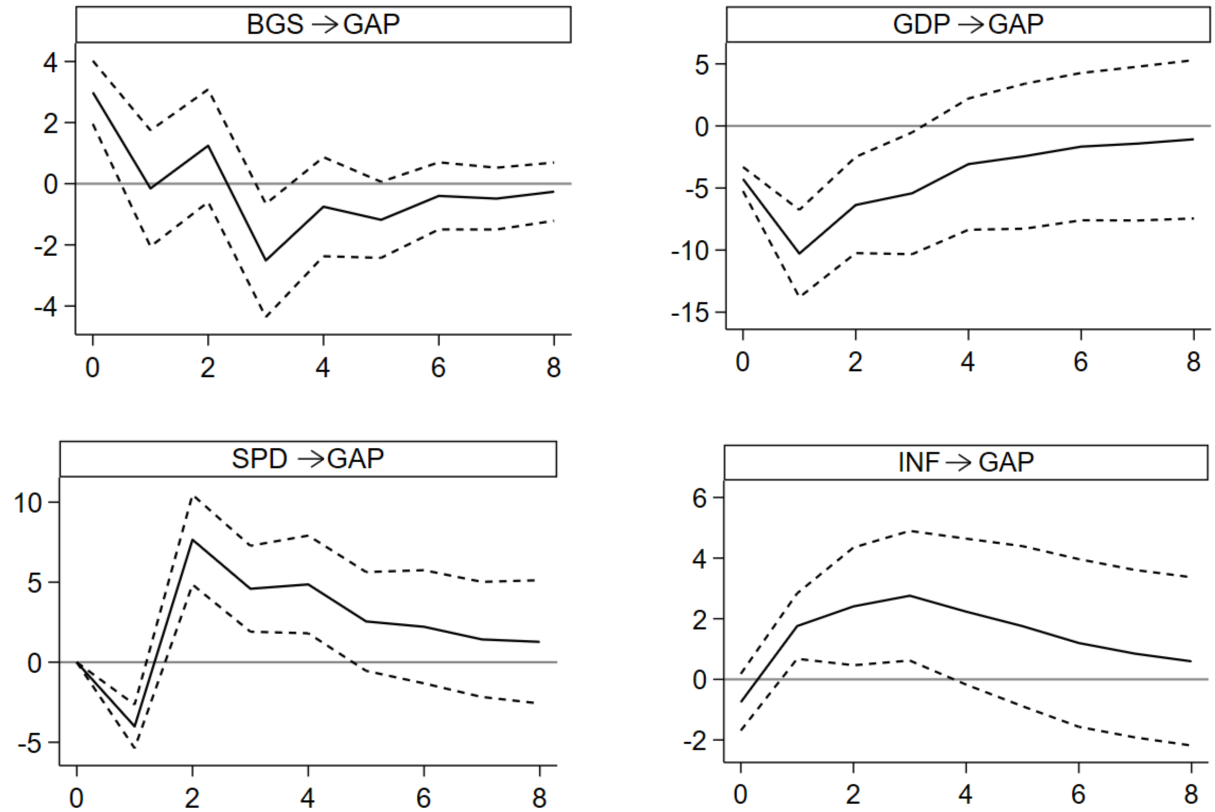

Fig. A4. IRFs of all macro-variables, including credit-to-GDP gap, real output, interest rate spread and inflation rate (solid lines) following a one-standard-deviation shock in the banking shocks variable after controlling for house prices. The dashed lines denote the upper and lower bounds of the 95% confidence intervals. IRFs obtained from PVAR model estimated on the panel data of 15 countries over the period 1989-2016 (N=15, T=28).

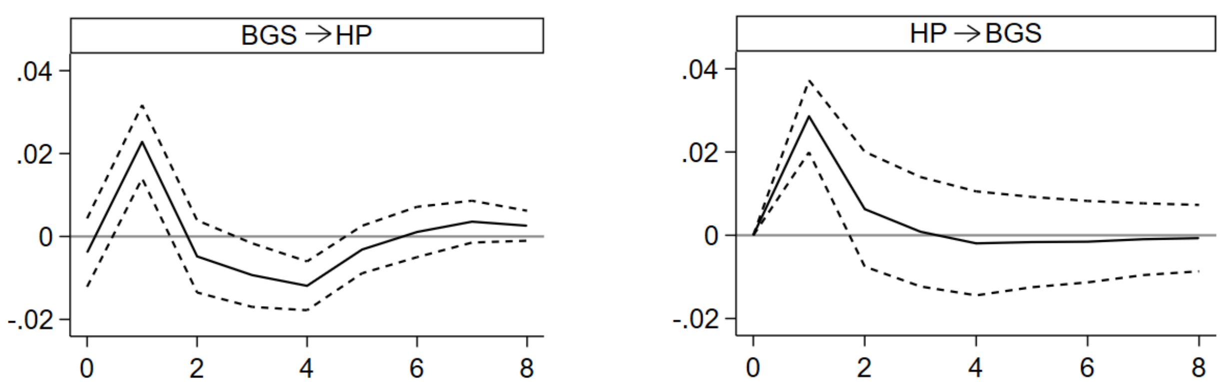

Fig. A5. IRFs for banking shocks and house prices variables. The left panel displays the house prices response function (solid line) to a one-standard-deviation shock in banking shocks. The right panel displays banking shocks response function (solid line) to a one-standard-deviation shock in house prices. The dashed lines denote upper and lower bounds of the 95% confidence intervals. IRFs obtained from the PVAR model with six variables estimated on the panel data of 15 countries over the period 1989-2016 (N=15, T=28).