

# Competition and credit procyclicality in European banking

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February 19, 2017

## Abstract

This paper empirically assesses the effects of competition in the financial sector on credit procyclicality by estimating both an interacted panel VAR (IPVAR) model using macroeconomic data and a single-equation model with bank-level European banking data. The findings of these two empirical approaches highlight that an exogenous deviation of actual GDP from potential GDP leads to greater credit fluctuation in economies where (i) competition among banks and (ii) competition from non-bank financial institutions or direct finance (proxied by the financial structure) are weak. According to the financial accelerator theory, whether lower competition strengthens the cyclical behavior of financial intermediaries, it follows that these "endogenous developments in credit markets work to amplify and propagate shocks to the macroeconomy" (Bernanke et al., 1999). Furthermore, since credit booms are closely associated with future financial crises (Valencia and Laeven, 2012), our results can also be read as evidence that greater competition in the financial sphere reduces financial instability, which is in line with the competition-stability view denying the existence of a trade-off between competition and stability.

**Keywords:** Credit Cycle; Business Cycle; Bank Competition; Interacted Panel VAR

**JEL Codes:** E32, E51, G20, D40, C33

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This study was supported by the Chair of Finance of the University of Nantes Research Foundation. We thank Leonardo Gambacorta, Federico Maria Signoretti and other participants at the 4th Bordeaux Workshop in International Economics and Finance for insightful comments.

# 1 Introduction

There is a long-standing debate among economists about whether more intense competition among financial intermediaries improves economic outcomes. However, this debate greatly intensified with the onset of the global financial crisis. First, academics and policy makers have wondered whether excessive competition was responsible for the crisis. Second, the banking sector has experienced numerous structural changes (e.g., the beginning of consolidation, the strengthening of banking regulation, the willingness of European policy makers to deepen financial integration and develop capital markets, the low interest environment) that may change the level of competition in the financial sphere in the future.

Most empirical studies on the nexus between bank competition and economic outcomes have focused on the link between bank competition and financial instability. This has led to mixed empirical results. While a strand of this literature (the competition-fragility view) argues that bank competition is detrimental to financial stability (Berger et al., 2009; Ariss, 2010; Jiménez et al., 2013), another strand (the competition-stability view) provides diametrically opposed evidence (Boyd et al., 2006; Schaeck et al., 2009; Schaeck and Cihák, 2014; Anginer et al., 2014; Akins et al., 2016). Although financial crises lead to economic dislocation, which both decreases economic growth and increases macroeconomic volatility, bank competition may also affect the real sphere by making the system more efficient both in normal time and in response to a crisis. As a result, some contributions have directly focused on the effects of bank competition on economic growth in the medium run (Cetorelli and Gambera, 2001; Claessens and Laeven, 2005; de Guevara and Maudos, 2011). Similarly, the effects of bank competition on stability should be considered not only through the financial stability dimension but also through the global effects on macroeconomic volatility (the occurrence and intensity of economic booms and busts), which has not attracted a lot of interest in the literature.

The purpose of this paper is to address this shortfall by examining the relationship between competition among financial intermediaries and credit procyclicality, which is a factor that amplifies business cycle fluctuations and, therefore, macroeconomic volatility. The fact that financial systems are not just passive reflections of the real sector but sources of real economic activity fluctuations is at the heart of financial accelerator theory (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Bernanke et al., 1999). Loosely speaking, financial accelerator theory states that shocks (real, monetary or financial) that decrease (increase) borrowers' net worth (by altering the revenue and collateral values of non-financial agents) have an additional effect, in more of the wealth effect, by decreasing (increasing) borrower credit worthiness due to asymmetric information. As a result, credit becomes more (less) expensive and its availability is reduced (increased) during recessions (expansions). The procyclicality of credit tends to amplify the real economic cycle due to the weakening (expanding) of investment, for instance. Thus, relatively small economic shocks can be amplified and propagated by endogenous procyclical changes in the credit market. Another insight into the linkages between credit and economic fluctuations is provided by Minsky's financial instability hypothesis. In this conceptual framework, the deterioration of lenders' credit conditions, as well as reduced monitoring and regulation of banks, dur-

ing periods of stability lead to speculative borrowing (by so-called "Ponzi borrowers") and, therefore, excessive lending, increasing aggregate demand. It follows that this supports the "exuberance" of a boom with excessive credit, which suddenly stop when a negative shock makes Ponzi borrowers unable to pay their loans. Thus, unlike the financial accelerator theory, the works of Minsky (1982) and Kindleberger (2000) note that the peak of a credit cycle (which is driven by the procyclicality of credit) is associated with financial crisis. That being said, credit procyclicality enhances both the persistence of economic shocks and the probability of financial crisis, which in turn reinforce the volatility of the economy.

A large empirical literature has explored several aspects of procyclicality in the banking sector. In particular, two different approaches have been taken in the existing literature. The first analyzes the consequences of procyclicality not only on the real economy but also on the banking sector itself. For example, some studies analyze the behavior of demand and supply of loans, their roles in economic fluctuations (see, e.g., Lown and Morgan (2006); Bassett et al. (2014)), and the procyclical behavior of bank profitability (see, e.g., Albertazzi and Gambacorta (2009)). The second tries to identify the factors that help strengthen or mitigate the procyclicality of the banking industry. As discussed by Athanasoglou et al. (2014), these factors include asymmetric information, the regulatory and supervisory framework, monetary policy, the practices of financial firms, such as leverage and remuneration policies, and some other factors, such as credit rating agency reports or the use of automated risk management systems. More generally, cross-country differences in bank procyclicality are related to cross-country financial structure differences (Albertazzi and Gambacorta, 2009).

Our paper contributes to this second strand of the literature. Indeed, we assess whether the level of bank competition constitutes a driving force of credit procyclicality in European banking. Economic theory makes conflicting predictions on this subject. IN fact, we can isolate two channels by which bank competition may impact credit procyclicality.

The first channel is related to the ability of the banking system to mitigate information asymmetries and reduce the associated agency costs. Theory shows that bank competition can play a key role in this area. On the one hand, low competition can lead to a "quiet life" for banks, reducing their efficiency and therefore increasing the cost of gathering the information necessary to mitigate lender-borrower problems. Berger and Hannan (1998) argue that this quiet life effect is due to the decrease in managers' incentives to maximize operating efficiency, since market power ensures that prices will be above their marginal costs. On the other hand, bank competition can play on banks' incentives to build long-run relationship with borrowers, which is a means to gathering information and reducing principal-agent problems. However, there is no academic consensus on whether lower bank competition is favorable. While some contributions note that market power is critical to providing incentives to collect private information (Petersen and Rajan, 1995), others suggest that high competition creates incentives for relationship banking that help "to partially isolate the bank from pure-price competition" (Boot and Thakor, 2000).

The second channel focuses on the effects of bank competition on risk taking and

risk management. On the one hand, the competition-fragility view claims that an increase in bank competition erodes their franchise value (the present value of future rents) and, therefore, induces banks to gamble, i.e., to behave less prudently, since the opportunity costs of bankruptcy are lower (Keeley, 1990; Hellmann et al., 2000). As a result, higher competition should reduce procyclicality in this view. On the other hand, another strand of the literature argues that an increase in bank competition, by reducing loan rates, reduces bank risks, as moral hazard incentives to shift to riskier projects decrease (Boyd and De Nicolo, 2005). Furthermore, a decrease in loan rates should also restrain adverse selection problems and improve the quality of borrowers' portfolios. Finally, competition could act on the efficiency of risk-management practices (Allen and Santomero, 2001).

In order to clarify these theoretical discrepancies, we empirically test the relationship between bank competition and procyclicality in European banking. To the best of our knowledge, only Bouvatier et al. (2012) have previously investigated a similar issue. Considering a sample of OECD countries, they assess the relationship between banking sector structure and credit procyclicality, i.e., whether banking sector structure affects how credit responds to business cycles. To this end, they proceed in two steps. First, they perform a cluster analysis to evaluate the degree of similarity in banking industry structures, and then, they split their sample of countries into different clusters.<sup>1</sup> Second, they estimate a panel VAR (PVAR) on cyclical components for each of the clusters and compare the impulse response functions of credit to a shock in GDP. Results that they obtain suggest that credit significantly responds to shocks to GDP, but they do not find that banking sectors with various characteristics exhibit differences in terms of credit procyclicality. Therefore, the authors conclude that the banking sector structure is not an important cause of credit procyclicality.

In comparison to Bouvatier et al. (2012), our analysis goes a step further by proposing both a macro- and micro-level assessment of the relationship between bank competition and credit procyclicality. Our macro-level analysis relies on a VAR framework and follows Bouvatier et al. (2012) by defining credit procyclicality as the orthogonalized impulse response function of the credit cycle to a business cycle shock. However, contrary to Bouvatier et al. (2012), we not only assess cross-country heterogeneity in credit procyclicality and relate it to differences in terms of bank competition but also formally investigate whether credit procyclicality is conditional on bank competition. To this end, we estimate an interacted panel VAR (IPVAR) model recently developed by Towbin and Weber (2013). The model is estimated using quarterly HP-filtered data over the period 1997Q1–2014Q4 for 16 European economies. The main feature of the IPVAR is that it models the autoregressive coefficients as a function of an exogenous variable, bank competition in our case, and then allows the relationship between credit and business cycles to vary with the level of bank competition. As a result, in this framework, the impulse responses of credit to a shock in GDP (i.e., the propagation mechanism in the financial accelerator view) are conditioned by the level of

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<sup>1</sup>Bouvatier et al. (2012) consider seven variables to provide a classification of banking system structures. These variables aim to capture the degree of concentration in the banking sector, the size of the banking sector, the financial structure (i.e., bank based vs. market based) of an economy, the ownership structure of the banking sector, and restrictions in banking activities. Using a hierarchical clustering methodology, they obtain four different clusters for a sample of 17 OECD countries.

bank competition, which are proxied in this paper by the commonly used Lerner index.

The micro-level analysis aims to give a more granular view of the link between bank competition and credit procyclicality by analyzing whether banking sector competition and bank market power play a role in the procyclical behavior of bank credit activity. It also aims to address some important econometric issues with the VAR framework, such as identification and endogeneity issues. Moreover, one major advantage of such an approach is to control for some individual bank characteristics that could explain their credit policies. Indeed, one can argue that the fact that banks are more willing to grant loans during the upward phase of the business cycle and more reluctant to do so during the downward phase is due not only to bank competition but also to bank specificities, such as their size or the diversification of their activities. Our analysis relies on balance sheet data and analyzes whether the change in the bank loan supply in response to an output gap depends on the level of bank competition. More precisely, we estimate a fixed effects model using panel data from 2005 to 2014 for a large sample of European banks, in which we introduce an interaction term between the output gap and the Lerner index. In this way, we examine whether the link between the output gap and credit dynamics is affected by the competitive environment and the market power of banks.

The results that we obtain suggest that bank competition reduces credit procyclicality. Indeed, the structural analysis of the IPVAR model shows that an exogenous one-percent deviation of GDP from its trend induces a significant and more-severe credit response in economies where bank competition is low. Therefore, these results, which are robust to a battery of robustness checks, suggest that bank competition reduces macroeconomic volatility by limiting the amplification mechanism of the financial sphere to the real sphere. The results of the micro-level empirical analysis corroborate these findings. We find that the bank loan supply is significantly less sensitive to the output gap when the competitive environment is fierce and the individual market power of banks is weak.

Finally, one important contribution of our analysis to the existing literature is that we do not just focus on competition among banks but also consider competition from direct finance as a potential driver of credit procyclicality. Indeed, all financial systems combine bank-based and market-based intermediation. However, the financial structure, i.e., the particular blend of intermediation channels, varies across countries. In line with previous results and the recent contributions of Langfield and Pagano (2016), Adrian et al. (2013) and Grjebine et al. (2014), one can expect that countries characterized by a relatively high degree of competition between banks and financial markets (market-based economies) exhibit lower credit procyclicality than bank-based economies. The results of our analysis confirm this expectation.

The remainder of this paper is structured as follows. Section 2 assesses the impact of bank competition on credit procyclicality using country-level data. This section is divided into two parts. First, we discuss the data, the identification strategy and the estimation methodology (section 2.1). Second, we present the empirical results (section 2.2). Section 3 presents the results of the analysis with granular data, i.e., bank-level data. Section 3.1 describes the data and the empirical model, and section

3.2 provides the empirical results. In section 4, we discuss the effects of the financial structure of an economy on credit procyclicality. We conclude in section 5.

## 2 Bank Competition and Credit Procyclicality at the Aggregate Level

### 2.1 Data and Methodology

#### 2.1.1 Data

Our macro-level empirical analysis covers the period 1997Q1–2014Q4. It includes 16 European economies: the old member states of the EU-15, with the exception of Luxembourg, Norway and Switzerland.<sup>2</sup> Therefore, the time dimension of our panel is relatively large, including 72 quarterly observations, and the cross-section dimension relatively tightened, comprising only countries at similar stages of growth.

In order to analyze the cyclical behavior of credit in European banking, our baseline econometric specification, described below, is parsimonious and comprises 4 main quarterly macroeconomic variables: real GDP, the consumer price index (CPI), the real outstanding amount of credit to the private non-financial sector and the nominal short-term interest rate.<sup>3</sup> Alternative specifications of our baseline model include a residential property price index, a stock price index and the real outstanding amount of bank credit to the private non-financial sector instead of the total amount of credit. Except for the interest rate, all the series are initially seasonally adjusted and log-transformed. Since we are interested in economic fluctuations, we do not consider these adjusted series in level or first-difference terms but consider their HP-filtered versions. In this way, we statistically remove the trend and isolate the cyclical component of the series, which ensures that the series are  $I(0)$ .<sup>4</sup> Essentially, this means that the log-transformed variables in our model are defined as the percentage gaps between the trend values and the observed values of the macroeconomic indicators.

In addition to macroeconomic variables, our empirical analysis requires the assessment of the degree of monopolistic competition. In line with related empirical work on the relationship between banking competition and stability (see Berger et al. (2009); Beck et al. (2013); Anginer et al. (2014)), we use a non-structural measure of bank competition: the Lerner index. This index represents the mark-up of prices over marginal costs and is a country-level indicator of the degree of market power, i.e., higher values indicate lower competition. Further details on the index construction are provided in Section 3, where we compute a bank-level measure of the Lerner index.

Turning to the data sources, GDP values, CPI values, short-term interest rates

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<sup>2</sup>Our data set comprises 16 countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

<sup>3</sup>Real credit series are constructed by deflating nominal credit by the CPI.

<sup>4</sup>Formally, the HP-filter decomposition consists of determining the trend component ( $\tau_t$ ) of a time series ( $y_t$ ) from the following minimization problem:  $\min_{\tau_t} = \sum_{t=1}^T ((y_t - \tau_t)^2 + \lambda((\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1}))^2)$ . A higher value of  $\lambda$  implies a higher degree of smoothing. In our study, we follow Ravn and Uhlig (2002) in initially setting a value of  $\lambda$ , the smoothing parameter, of 1600.

and two asset price indices (residential property and share prices) are drawn from the OECD database. The two credit series for the private non-financial sector are from the BIS database.<sup>5</sup> Finally, our measure of bank competition, the Lerner index, is from the Global Financial Development database of the World Bank. Unlike the other series, bank competition is computed annually. Therefore, to match the variable to the quarterly frequency of our study, we use a linear interpolation procedure.<sup>6</sup> All series included in the analysis are reported in Figure A2 and Figure A3.

### 2.1.2 Empirical Methodology

To test whether bank competition affects credit procyclicality, we use a two-step approach: (i) we check that credit procyclicality is heterogeneous in the European banking sector, and (ii) we test whether the differences in terms of procyclicality across economies might be explained by differences in bank competition.

These two steps require first and foremost that we define how we measure credit procyclicality. Roughly speaking, credit procyclicality corresponds to a positive reaction of credit to a change in GDP.<sup>7</sup> Therefore, it is necessary to use an econometric framework that (i) allows measuring the effects of GDP on credit, (ii) takes into account the fact that the GDP cycle is a process that is not independent from the credit cycle, i.e., the existence of feedback between the banking system and the real economy (see, among others, Bernanke and Blinder (1988), Kiyotaki and Moore (1997); Kindleberger (2000), Lowe et al. (2002), Borio (2014)) and (iii) imposes few theoretical restrictions, since the interactions between financial and macro variables have not been perfectly theoretically identified. Unlike a single-equation framework, a VAR approach fulfills these three criteria. Thus, we opt for a multivariate framework and follow Bouvatier et al. (2012) in defining credit procyclicality as the orthogonalized impulse response function of the credit cycle to a GDP cycle shock.<sup>8</sup>

Our exploratory phase consists of assessing whether credit procyclicality, defined as the credit effect of an unexpected change in the output gap, differs from country to country. Therefore, we start by considering country-specific VARs. The reduced-form of the model is given by:

$$Y_{i,t} = c_i + A_i(L_i)Y_{i,t-1} + \varepsilon_{i,t} \quad \varepsilon_{i,t} \hookrightarrow N(0, \Sigma) \quad (1)$$

where  $i$  and  $t$  are indexes of country and time, respectively,  $Y_{i,t}$  is a  $(4 \times 1)$  vector of endogenous variables ( $CPI, GDP, CRED, r$ ),  $A(L)_i$  is a matrix polynomial in the lag operator specific to each country,  $c_i$  is a country-specific intercept, and  $\varepsilon_{i,t}$  is a vector of errors.<sup>9</sup>

<sup>5</sup>Compared with time series from the International Financial Statistics (IFS) database of the IMF, the BIS series have the advantage of being adjusted for the existence of breaks due to changes in classifications or variable definitions.

<sup>6</sup>Bank competition data are available from 1996, so our study period begins in 1997Q1.

<sup>7</sup>Credit is a component of aggregate demand. As a result, the positive reaction of credit to a GDP shock naturally increases the persistence and amplitude of the business cycle.

<sup>8</sup>This is based on the common result that output causes credit (in the VAR sense) (Lown and Morgan, 2006). Recently, Peia and Roszbach (2015) confirm this idea, finding significant evidence of causality from GDP to credit, with no systematic reverse causality going from credit to GDP.

<sup>9</sup>Note that the order of the matrix polynomial is determined by the Akaike Information Criterion (AIC), where the maximum lag length has been fixed to 4.  $CPI$ ,  $GDP$ ,  $CRED$  and  $r$  refer to the

The country-specific VAR systems are estimated by OLS, and shocks are identified based on a recursive identification scheme by applying a Cholesky decomposition of the residuals with the variables ordered as follows: *CPI*, *GDP*, *CRED* and *r*. Hence, the GDP cycle only responds to shocks in the credit cycle with a lag, and the contemporaneous response remains zero. The ordering of inflation and GDP in a first block and financial variables in a second block is fairly standard in the macroeconomic literature using VAR. This implies that financial variables may respond immediately to real shocks. By contrast, the relative ordering of financial variables is subject to some discussion. In our baseline model, we follow Assenmacher-Wesche and Gerlach (2008) by ordering credit before the short-term interest rate. Thus, our triangular identification structure imposes that the credit cycle react with a lag to the short-term interest cycle. In other words, the contemporaneous impact on credit is restricted to zero. As shown by Leroy and Lucotte (2015), among others, bank interest rate pass-through is sluggish in the short term, justifying the fact that credit does not respond immediately to a policy rate shock.

Then, to test the implication of bank competition on credit procyclicality, we have two possibilities. The first is to compare the average impulse response of countries characterized by low and high levels of bank competition. This involves dividing the sample into two groups of countries according to their level of banking sector competition. Within this approach, we have to estimate a two-panel VAR and compare whether the orthogonalized impulse responses of credit to a one-percent output-gap shock (to ensure comparability) are significantly different between the two groups of countries. Although this approach is tractable, it has two shortcomings: (i) it prevents the consideration of a varying degree of competition over time, and (ii) it does not allow us to control for other sources of heterogeneity, which could explain the difference between the two groups of countries. Therefore, this calls for an alternative specification of the VAR model that allows us to explicitly take into account the time-varying level of bank competition as an exogenous factor acting on the credit response to a GDP shock and to control for potentially correlated variables. For this purpose, we use a panel VAR framework, where the autoregressive coefficients of the endogenous variables are functions of the cross-time-varying level of bank competition. Such frameworks have recently been developed by Loayza and Raddatz (2007), Tobin and Weber (2013), Sá et al. (2014) and Georgiadis (2014) and allow us to assess the impact of exogenous structural characteristics on the response of macroeconomic variables to macroeconomic shocks. Specifically, our econometric approach is based on the interacted panel VAR framework (IPVAR) of Tobin and Weber (2013).<sup>10</sup>

The structural form of the IPVAR that we estimate is given by:

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consumer price index, real GDP, the real outstanding amount of credit to the private non-financial sector and the nominal short-term interest rate, respectively.

<sup>10</sup>We thank Sebastian Weber and Pascal Tobin for providing their MATLAB code for the interacted panel VAR procedure.



$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ \alpha_{0,it}^{21} & 1 & 0 & 0 \\ \alpha_{0,it}^{31} & \alpha_{0,it}^{32} & 1 & 0 \\ \alpha_{0,it}^{41} & \alpha_{0,it}^{42} & \alpha_{0,it}^{43} & 1 \end{pmatrix} \begin{pmatrix} CPI_{i,t} \\ GDP_{i,t} \\ Cred_{i,t} \\ r_{i,t} \end{pmatrix} = \sum_{l=1}^L \begin{pmatrix} \alpha_{l,it}^{11} & \alpha_{l,it}^{12} & \alpha_{l,it}^{13} & \alpha_{l,it}^{14} \\ \alpha_{l,it}^{21} & \alpha_{l,it}^{22} & \alpha_{l,it}^{23} & \alpha_{l,it}^{24} \\ \alpha_{l,it}^{31} & \alpha_{l,it}^{32} & \alpha_{l,it}^{33} & \alpha_{l,it}^{34} \\ \alpha_{l,it}^{41} & \alpha_{l,it}^{42} & \alpha_{l,it}^{43} & \alpha_{l,it}^{44} \end{pmatrix} \begin{pmatrix} CPI_{i,t-1} \\ GDP_{i,t-1} \\ Cred_{i,t-1} \\ r_{i,t-1} \end{pmatrix} + \begin{pmatrix} \delta^{11} \delta^{12} \\ \delta^{11} \delta^{12} \\ \delta^{11} \delta^{12} \\ \delta^{11} \delta^{12} \end{pmatrix} \begin{pmatrix} I_i \\ Z_{i,t-4} \end{pmatrix} + \varepsilon_{i,t} \quad (2)$$

where  $C$  is a constant,  $Z_{i,t-4}$  is a cross-time-varying measure of bank competition, and  $\varepsilon_{i,t}$  is a vector of uncorrelated iid shocks.<sup>11,12</sup> The indices  $t$  and  $i$  refer to quarters and countries, respectively. Furthermore,  $L$  refers to the number of lags.<sup>13</sup>

The structural parameters  $\alpha_{l,it}$  distinguish the traditional panel VAR from our framework and allow us to analyze whether the bank credit cycle response to a business cycle shock varies with the degree of bank competition. For this purpose, the coefficients  $\alpha_{l,it}$  have the following form:

$$\alpha_{l,it} = \beta_{l,it} + \eta_l Z_{i,t-4} \quad (3)$$

where  $\beta_{l,it}$  and  $\eta_l$  are two vectors of coefficients, and  $Z_{i,t-4}$  is a cross-time-varying measure of bank competition. Therefore, the structural parameters  $\alpha_{l,it}$  vary over time and across countries with the level of bank competition. However, the coefficients are not country specific. As noted by Georgiadis (2014), the coefficients remain "conditionally homogeneous". Indeed, if the structural characteristics of countries are the same, the slope coefficients will be also the same. In our baseline specification, all the autoregressive coefficients of the VAR system are allowed to be dependent on the level of bank competition, i.e., all the variable dynamics are allowed to be conditional on the degree of bank competition. However, for robustness purposes, we also set more restrictions to our model by considering a parameter matrix where only the autoregressive coefficients of the credit and output equations are interacted with our measure of competition, which leads to similar results.

The fact that we require that the impact matrix be lower triangular induces that the error terms are, by construction, uncorrelated across the equations. This allows us to estimate the system equations sequentially using OLS. It can be noted that the zero-restrictions imposed on the impact matrix correspond to the same identification scheme as in the country-specific VAR model. Thus, the variables remain in the following ordering:  $CPI$ ,  $GDP$ ,  $CRED$  and  $r$ .

<sup>11</sup>To account for potential endogeneity, the variable measuring the bank competition has been lagged by 4 quarters.

<sup>12</sup>Furthermore, we draw attention to the fact that our model assumes that there are no dynamic cross-unit interdependencies, i.e., that residuals are uncorrelated across countries, which is certainly a restrictive assumption (see Canova and Ciccarelli, 2013). To address cross-section dependence, we have checked whether we obtain similar results when we include a common factor, such as the oil price, or an indicator of systemic risk as an exogenous variable in our model.

<sup>13</sup>The lag length is fixed to 2 based on the average optimal lag orders of the country-specific VAR.

One important aspect of our baseline panel VAR is that it includes country fixed effects. This may appear unnecessary since the endogenous variables included in the VAR are in their HP-filtered forms. Indeed, this purges unobserved unit-specific fixed effects by removing the country-specific trend from the series and implies zero-means.<sup>14</sup> Nevertheless, the structural characteristics present potential timeless specificities. Therefore, we need to control for unobserved unit-specific factors, which could be sources of heterogeneity, by demeaning the data (which is equivalent to allowing intercept heterogeneity). In this case, it is well known that estimations can be biased because demeaning in a dynamic model leads to correlated error terms and regressors. However, as shown by Nickell (1981), the size of the fixed effect bias decreases as the length of the sample increases, which reduces the importance of this bias in our analysis given that the time dimension of the panel is relatively long (72 observations per country).<sup>15</sup>

Another important feature of our empirical model is that it allows dynamic heterogeneity by making the slopes conditional on cross-time-varying measure of competition. However, dynamic credit heterogeneity could be related to factors other than competition, which are potentially correlated with competition. In this case, the issue is that allowing for heterogeneous intercepts, as in the previous estimation method, controls for unobserved level heterogeneity but not unobserved dynamic heterogeneity, which can lead to inconsistent estimates (Pesaran and Smith, 1995) and misleading conclusions. To model this type of cross-sectional heterogeneity, Pesaran and Smith (1995) propose the mean group estimator, which consists of estimating country-specific VARs and then computing the average of the unit-specific slope parameters. Nevertheless, this approach is not suited to our analysis, since it conceals the underlying sources of cross-country dynamic heterogeneity. To capture both unobserved country-specific variations and variations conditional on specific structural characteristics, Sá et al. (2014) implement a mean group-type estimator. In practice, the authors augment the baseline IPVAR model by interacting all endogenous variables with country dummies. In this way, we can disentangle the coefficient heterogeneity due to country-specific effects from that due to banking competition effects.<sup>16</sup>

After the estimation of the IPVAR, a structural analysis comparing the impulse responses to a GDP shock for "high" and "low" levels of bank competition is conducted. To obtain this type of impulse response, we first use our IPVAR estimates and replace the structural characteristic ( $Z_{i,t}$ ) with the first and fourth quintiles of the sample distribution. Thus, we obtain two different coefficient matrices, i.e., two different sets of interactions and feedback between the variables. As a result, the computed impulse responses to a common change vary according to the value of the structural characteristic, for example, "high" and "low" levels of bank competition. In this way, we

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<sup>14</sup>In fact, the endogenous variables are not perfectly zero-centering. The reason is that we use a longer sample period to apply the HP filtering method than to estimate our model.

<sup>15</sup>Monte Carlo evidence in Judson and Owen (1999) suggests that the magnitude of this bias is small in a sample of our size (72 observations per country). Moreover, other studies, such as Goodhart and Hofmann (2008), using a panel VAR methodology and time series of similar length also employ a fixed effects OLS estimator.

<sup>16</sup>Obviously, this procedure considerably increases the number of parameters to be estimated, since each endogenous variable is interacted with 15+1 exogenous variables (the number of country dummies + the indicators of bank competition), which could decrease the precision of the estimated impulse responses.

address our research question of how credit procyclicality changes when bank competition moves from a low to a high level.

Finally, a bootstrap procedure is used for inference of the impulse responses.<sup>17</sup> In the figures below, we report the mean of 1000 bootstrapped impulse responses with a 95% confidence band, i.e., the lower bound of the band is the 2.5th percentile and the upper bound is the 97.5th percentile. In order to assess whether the impulse responses are significantly different, we consider the difference between two impulse responses computed at each draw and display the mean of this difference with a 95% confidence band in the figures.

## 2.2 Results

We present the cross-country asymmetries in credit procyclicality in Section 2.2.1 and the main results of our empirical analysis in Section 2.2.2. The robustness of our findings is examined in Section 2.2.3.

### 2.2.1 Preliminary Analysis

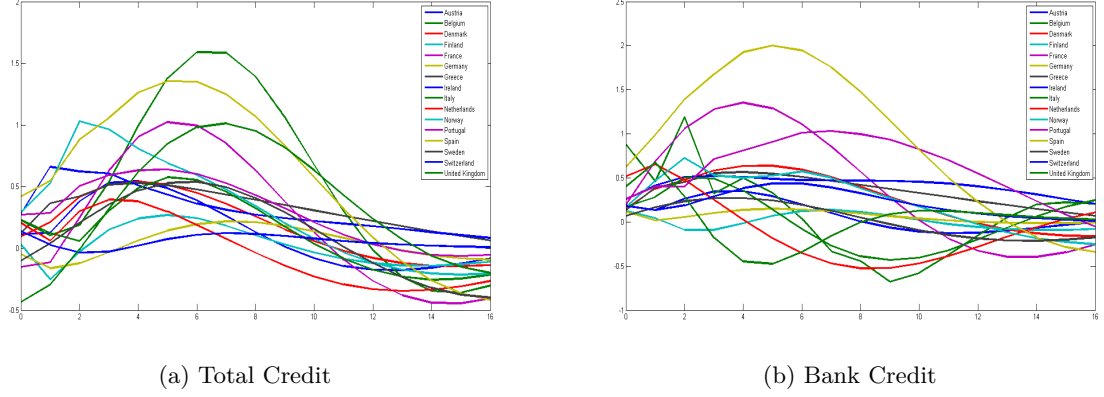
The first step of our empirical analysis is to assess cross-country heterogeneity in credit procyclicality. Figure 1 displays the impulse responses of *Credit* or *Bank Credit* to a business cycle shock based on the country-specific VAR model in equation (1).<sup>18</sup> At first sight, the choice to examine the responses of both total credit and bank credit cycles may appear irrelevant. First, the total credit cycle comprises the bank credit cycle, so the analysis might be redundant. Second, bank competition should primarily impact the bank credit cycle. However, in our view, focusing exclusively on the bank credit cycle responses would be damaging. Indeed, since bank credit series do not include the securitized credit, the fact that banks not only originate and hold credit but also distribute credit to the non-bank financial sector is not considered. Furthermore, as a result of wide differences in the weight of the "originate-to-distribute" model and in the financial structure across European economies, bank credit cycle responses might suffer from a lack of comparability.

The chart on the left in Figure 1 depicts the orthogonalized country-specific responses of total credit to the non-financial sector to a shock in GDP, normalized to unity (i.e., a shock of one percent in the output gap) with a simulation horizon of 16 quarters. As can be seen, in most cases, a GDP cycle shock contemporaneously and positively affects the credit cycle. The only four exceptions are for France, Germany, Sweden and the UK, where the initial responses are negative and become positive only after a few quarters. Furthermore, with the exception of Switzerland, the IRFs suggest that the credit gap after a shock to the output gap remains above the baseline value for at least 7 quarters. The results for Germany are singular, since they highlight a very low and non-persistent impact of GDP on credit, i.e., low procyclical behavior of

<sup>17</sup>See Towbin and Weber (2013) for the details of the bootstrap procedure.

<sup>18</sup>Prior to computing the IRFs, standard tests have been applied to check for residual autocorrelation and that the moduli of the eigenvalues of matrix  $A$  are less than one. In addition to checking that the VAR models adequately represent the DGP of the macroeconomic variables, the inter-relations among these variables have been investigated. As expected, in almost all cases, we find Granger causality from GDP to credit and, quite often, reverse causality.

Figure 1: Country-specific impulse response functions of Credit to a GDP shock



Note: The figures display country-specific impulse response functions of total credit and bank credit cycles to a one-percentage-point shock to the GDP cycle.

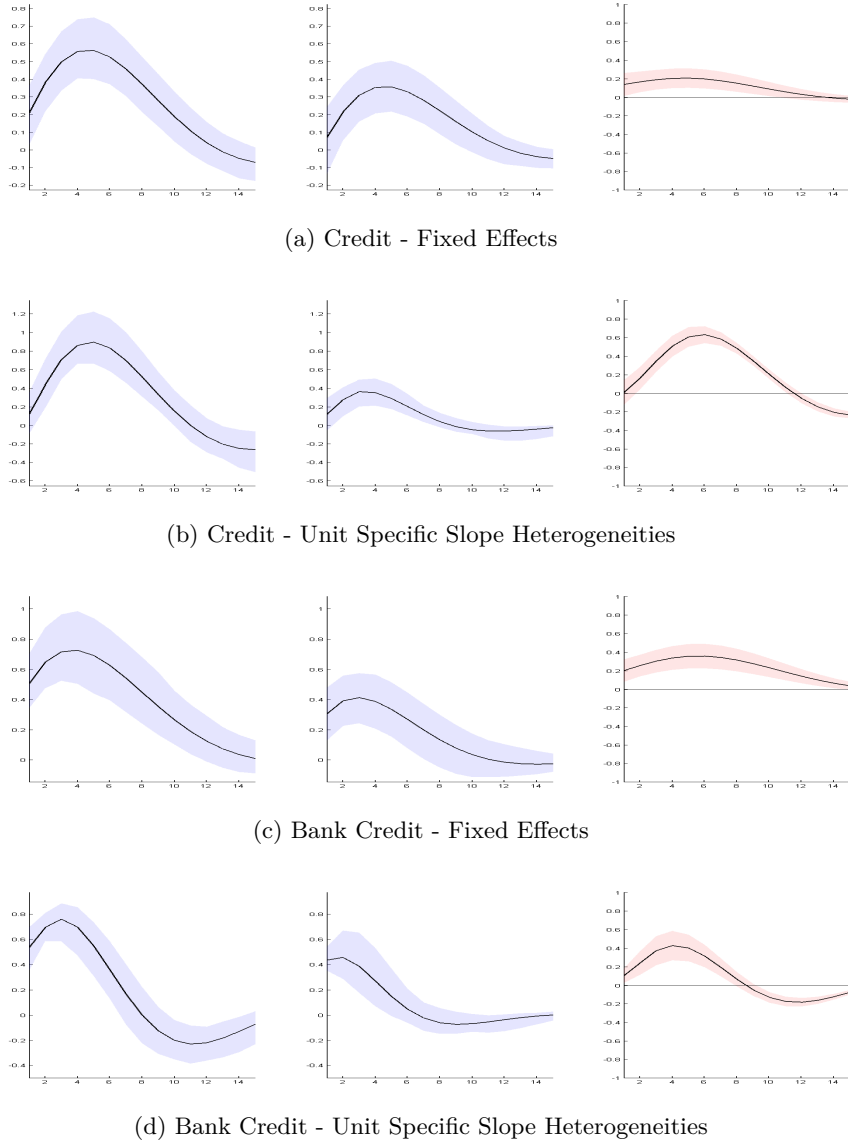
credit. As a result, we should check in the next step – in which we test the effects of bank competition on procyclicality – that our panel data results are not driven by the behavior of some countries. Overall, chart (a) clearly shows the existence of major asymmetries in terms of credit procyclicality within European economies. For instance, in Spain, the maximum response of the credit gap to a 1% shock to the output gap is 1.35%, whereas in Germany, the maximum response of credit to a shock of the same magnitude is 0.21%. Similar comments can be made based on the chart on the right of Figure 1, which displays the heterogeneous responses of the bank credit cycle to a one-unit shock in the output gap.

## 2.2.2 Main Results

Figure 2 displays the impulse responses of the credit and bank credit cycles to a one-unit GDP cycle shock. The orthogonalized responses are generated from the estimation of the panel VAR model in Equation 2 with fixed effects and mean-group type estimators, where the exogenous variable ( $Z_{i,t-4}$ ) corresponds to the Lerner index. The charts on the left of the figure present the impulse response functions generated by setting the Lerner index to the 80<sup>th</sup> percentile of its sample distribution. Therefore, these charts illustrate the average responses of credit in countries with less competitive banking markets. The charts in the center show the impulse response functions evaluated at the 20<sup>th</sup> percentile of the Lerner index sample distribution, i.e., for the case where bank competition is fierce. In both cases, the solid lines correspond to the mean impulse responses in a two-standard-error band, which is computed by bootstrapping (1000 draws). Finally, the charts on the right display the differences between the mean impulse response functions for low and high levels of bank competition with a 95% confidence band.

Before presenting our main results, a few preliminary comments about Figure 2 can be made. First, counter to our expectations, the estimation of the model allowing unit-specific slope heterogeneity reduces the confidence interval of the impulse response

Figure 2: Impulse Response Functions of Credit to a GDP shock: Baseline model



Note: The figure shows the impulse responses of credit and bank credit to a one-percentage-point shock to the output cycle evaluated (from left to right) at the 80<sup>th</sup> (high level) and 20<sup>th</sup> (low level) percentiles of the Lerner index sample distribution. The charts on the right represent the differences between the two. The colored bands represent 5% error bands (two standard deviations) generated by bootstrapping (1000 draws).

functions.<sup>19</sup> Despite this difference in terms of precision, the two estimators lead to broadly similar results. The only noticeable difference is in the persistence of the

<sup>19</sup>This indicates that the estimates with interacted country dummies have smaller standard errors than the fixed effects estimates. One explanation is that the proposal of Sá et al. (2014) leads to the use of the same sample, i.e., the same number of observations for the estimation of the model with both types of estimators, which differs from the mean group estimator wherein coefficients and standard errors are calculated from each country sample. A second explanation is that the model presents strong dynamic heterogeneity, which leads the estimator with interacted country dummies to increase the quality of the estimates.

output-gap shocks, which are longer in the case of fixed effects estimates. Regarding the comparison of the responses of total credit and bank credit, we observe that bank credit has an immediate, very significant response to an exogenous change in the output gap, while the effects on total credit become significantly positive progressively. In our view, this is not puzzling, since firms that issue bonds (i.e., the difference between total and bank credit) are, on average, less opaque, more creditworthy, more geographically diversified and, therefore, less sensitive to national business cycles. However, apart from the initial impact, the results do not suggest that bank credit and total credit behave differently.

Turning to the difference of impulse responses, there is clear evidence that bank competition affects credit procyclicality. Indeed, the reaction of credit dynamics to GDP cycle shocks varies according to the degree of bank competition. Specifically, the results suggest that a shock of one percent to the output gap causes a greater response in credit in a less competitive banking market. As shown in the charts on the right, the differences between high and low levels of competition are significantly different from zero at the 5% level. This means that credit booms and busts are less pronounced when bank competition is fiercer. This indicates that more competitive banking markets can better absorb shocks.<sup>20</sup>

There are several possible explanations, which are not necessarily in opposition but rather complementary, for the positive association between greater bank competition and lower credit fluctuation.

First, bank competition could allow asymmetric information problems between borrowers and lenders to be solved more easily, reducing market imperfections. On the one hand, as stated by the quiet life theory (Hicks, 1935; Berger and Hannan, 1998), bank competition may lead banks to operate in a more efficient way. Specifically, bank competition could improve the screening and monitoring of borrowers. In this way, asymmetric information would be reduced, weakening the repercussions of a real shock on financial conditions. On the other hand, a strand of the literature on relationship banking argues that an increase in bank competition can encourage some banks to foster long-term relationships with borrowers (Boot and Thakor, 2000). Since a long-term relationship is one way to overcome asymmetric information, banks would, for example, be more inclined to smooth a real shock by offering credit during a slowdown. Second, our results are related to the literature on bank competition and stability. Indeed, theoretical (Boyd and De Nicolo, 2005; Allen et al., 2011) and empirical works (Uhde and Heimeshoff, 2009; Schaeck and Cihak, 2012; Anginer et al., 2014; Akins et al., 2016) show that an increase in bank competition may lead banks to hold more capital and/or engage in less risky activities. Taking less risk implies that credit booms are less important in the upward phase of the cycle and, therefore, that banks experience less financial losses on their loans and other activities in the downward phase,

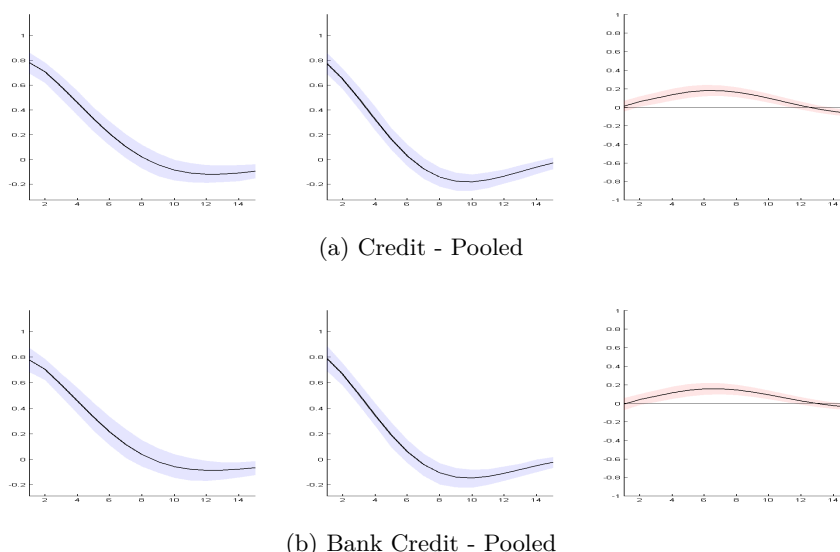
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<sup>20</sup>To corroborate our findings, we present in Table A1 of the Appendix the responses of credit to a GDP shock based on the estimations of two panel VARs for two groups of economies. To split our panel into two sub-panels, we group the countries according to whether they are above or below the median value of the average Lerner index. Although this framework is less efficient than the previous one, overall, it confirms that bank competition reduces credit procyclicality. As a matter of fact, the average credit responses in countries where bank competition is, on average, lower are significantly greater than the credit responses in countries characterized by relatively high levels of bank competition.

which tends to preserve bank equity capital and the ability of banks to take new risks and supply new credit during a recession. This would be also be strengthened by the positive influence of bank competition on risk-management practices.

Third, in a broader context, our results could be simply explained by firm profit maximization behavior. Indeed, a general result of the theory of the firm is that the optimal behavior of a firm with market power is to adjust the equilibrium quantity rather than the equilibrium price following a change in demand.<sup>21</sup>

Figure 3: Impulse Response Functions of GDP to a shock of GDP



Note: The figure shows the impulse responses of the GDP cycle to a one-percentage-point shock to the output cycle evaluated (from left to right) at the 80<sup>th</sup> (high level) and 20<sup>th</sup> (low level) percentiles of the Lerner index sample distribution. The charts on the right represent the differences between the two. The colored bands represent the 5% error bands (two standard deviations) generated by bootstrapping (1000 draws).

Our previous findings suggest that imperfect bank competition acts as a financial accelerator by intensifying the propagation of an output-gap shock to the credit market. According to financial accelerator theory, that should amplify the business cycle. Indeed, this theory states that the persistence of economic fluctuations depends on the amplitude of the effects on financial conditions and, therefore, on the credit dynamics of an initial non-persistent exogenous real shock. As a consequence, we expect that the responses of the GDP cycle to an exogenous GDP cycle shock will be greater in economies where bank competition is weaker because this leads to more credit fluctuations. Figure 3 presents the GDP cycle impulse responses to an exogenous GDP cycle shock. The charts confirm our expectations: a GDP cycle shock has a smaller effect on output in competitive banking markets. Indeed, it appears that the GDP cycle returns to baseline at a faster pace under these conditions.

<sup>21</sup>Within this framework, market power would imply simultaneously higher credit fluctuations and higher bank interest rate stickiness. The latter point is made in Leroy and Lucotte (2015).

### 2.2.3 Sensitivity Analysis

We perform a broad set of robustness checks, which may be grouped into three categories: (i) testing alternative specifications, (ii) changing the data definition and (iii) disentangling the effects of bank competition from other potential determinants causing procyclicality asymmetry.

In order to assess the robustness of the results presented above, we start by estimating different specifications of the interacted panel VAR (equation (2)). First, we extend the vector of endogenous variables by including a variable reflecting the dynamics of asset prices. This provides a more complete representation of the macro-level dynamics in response to several studies showing that there are linkages among credit, economic activity and asset prices (see Annett, 2005; Goodhart and Hofmann, 2008; Assenmacher-Wesche and Gerlach, 2008; Muellbauer and Murphy, 2008; Beltratti and Morana, 2010). In practice, we estimate two 5-dimensional interacted panel VAR models: one incorporating a measure of the house price cycle; the other, a measure of the stock price cycle. In both cases, the asset price series are last, meaning that credit is restricted from reacting immediately to asset prices.<sup>22</sup> Figure 4 depicts the results. As one would expect, the credit responses are not fundamentally different, and the difference in procyclicality between low and high competition environments remains significant.

Second, as is common in VAR models, we check the robustness of our findings by ordering the variables differently. In our baseline model, our recursive identification scheme places bank credit before the short-term rate. Our theoretical justification is that interest rate pass-through is sluggish, justifying the fact that the supply and demand of credit react with a lag to changes in the short-term rate. Although our choice is in line with several previous empirical works (see, for instance, Assenmacher-Wesche and Gerlach (2008) and Bouvatier et al. (2012)), it remains arbitrary. It is theoretically not unlikely that credit reacts to the current monetary policy stance, since changes in the interest rate immediately affect borrowers' net worth. Therefore, to take into account this possibility, we switch the ordering of credit and policy rate in our VAR system as in Goodhart and Hofmann (2008). Figure 5 displays the new IRFs and confirms our previous results.<sup>23</sup>

Third, we check that our conclusions remain identical when we consider a longer lag (3 lags) for the autoregressive terms (see Figure 5) and when we marginally change our sample. To carry out the latter robustness test, we re-estimate our canonical econometric model dropping one country at a time. In this way, we can be sure that our results are not driven by the inclusion of a particular country, which is important since Section 2.2.1 noted that some countries behave atypically.

Our second set of robustness checks considers data processing. It is well-known that the HP filter has some drawbacks.<sup>24</sup> One is that it implies an a priori definition

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<sup>22</sup>This ordering choice is questionable. For instance, it implies that policy makers do not use current asset prices to implement monetary policy. This also implicitly implies that house prices are characterized by a low degree of stickiness, since they immediately respond to credit innovations. As a result, we also test for the possibility that credit immediately responds to asset prices by considering the latter variable before credit. The results are not affected by this change.

<sup>23</sup>This means that the correlation between credit and policy rate changes is small. The other ordering choices appear standard in the literature (see Christiano et al., 1999).

<sup>24</sup>Note that the typical issue of the end-point problem has been addressed by estimating the model



of the cycle frequency of the time series, i.e., setting an arbitrary value of the smoothing parameter. In our benchmark model, we have chosen to estimate the cycles at the business cycle frequency for all the macroeconomic series. Indeed, we have set the smoothing parameter to 1600, corresponding to cycles that last between 1 and 8 years. However, as argued by Drehmann et al. (2012) and Borio (2014), one of the features of the financial cycle is that it "has a much lower frequency than the traditional business cycle". In order to address this caveat, we assume that credit cycles are twice as long as the usual business cycle. In order to obtain the corresponding value of the smoothing parameter, we follow the approach of Ravn and Uhlig (2002). The authors show that it is optimal to set  $\lambda$  to 1600 multiplied by the fourth power of the observation frequency ratio (here, 2). Thus, we set the  $\lambda$  of the credit series to 25600 to obtain a cycle lasting twice as long as the business cycle.<sup>25</sup> As an alternative to the HP filter, we employ the Baxter and King (BK) filter (Baxter and King, 1999) to test for robustness. The BK filter is based on the approximation of the ideal band-pass in the frequency domain to estimate the cyclical behavior of the series.<sup>26</sup> On the whole, the graphs displayed in Figure 6 indicate that our results are robust to the filtering method.<sup>27,28</sup>

The extent to which credit dynamics are affected by a GDP shock may not depend exclusively on the degree of banking competition. Credit responses may also be related to other financial characteristics, such as the capitalization of the banking system, its soundness or the financial structure. Since these characteristics are potentially correlated with bank competition, it is important to control for their effects on our results. Therefore, we extend our baseline model by including three additional interaction variables at the same time. Thus,  $Z_{i,t}$  is now a  $(4 \times 1)$  vector. To evaluate the effects of bank competition, the impulse response functions continue to be evaluated at the 20th and 80th percentiles of the distributions of the Lerner index, while the three other variables are set to their medians.<sup>29</sup> Analyzing the results in Figure 7, we observe that controlling for the correlations between bank competition and other structural

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over the period 1997Q1–2014Q4 using data through 2015Q4. The starting point also presents some statistical problems (Drehmann and Tsatsaronis, 2014). Therefore, we estimate cycles from 1997Q1 using data starting in 1990Q1.

<sup>25</sup>Lowe et al. (2002) suggest setting  $\lambda$  to 400000 to isolate medium-term frequencies of the credit series. In this way, cycles ranging from 8–30 years would be obtained, which is consistent with statistical observations of the average length of the financial cycle. However, the moderate length of our panel forces us to focus more on medium-term frequencies of the credit series. Furthermore, this choice is in line with financial accelerator theory, which focuses on short-term frequencies of the credit cycle. Another issue is related to the fact that our statistical approach supposes that the credit cycle is a regular and stationary process by definition, which is criticized by Borio (2014).

<sup>26</sup>Despite some statistically distinctive features, the BK filter is in line with the Christiano and Fitzgerald (2003) filter.

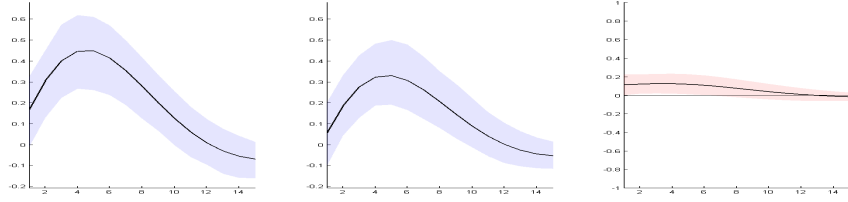
<sup>27</sup>The only slight difference is for the responses of credit when the Baxter and King filter is used. Indeed, the difference in the reaction according to the level of bank competition appears to have a shorter duration.

<sup>28</sup>We also run robustness checks regarding the transformation of the Lerner index (not reported in this draft). We consider two other versions of the Lerner index: one without quarterly interpolation and another with interpolation and smoothing with the HP filter, as in Georgiadis (2014). These amendments do not affect our findings.

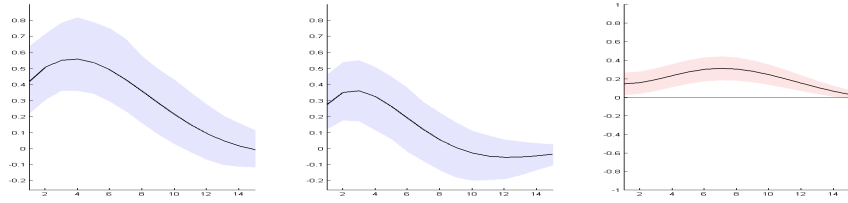
<sup>29</sup>These three variables are extracted from the Global Financial Development database of the World Bank. Bank capitalization, bank soundness and financial structure are proxied by the ratio of bank regulatory capital to risk-weighted assets, the bank Z-score index and the financial structure ratio defined in the section 4, respectively.

characteristics does not change our previous findings. However, this additional analysis might refine our explanations regarding imperfect competition as a propagation mechanism of an output-gap shock. Two explanations have previously been given: (i) imperfect competition increases friction, and (ii) imperfect competition exacerbates risk-taking behavior. Because we control for disturbances in the banking system using the Z-score and for bank riskiness using the capital requirement ratio, we confirm that the first effect (that imperfect competition increases friction) plays a very significant role. However, this does not imply that the second effect (that imperfect competition exacerbates risk-taking behavior) is irrelevant.

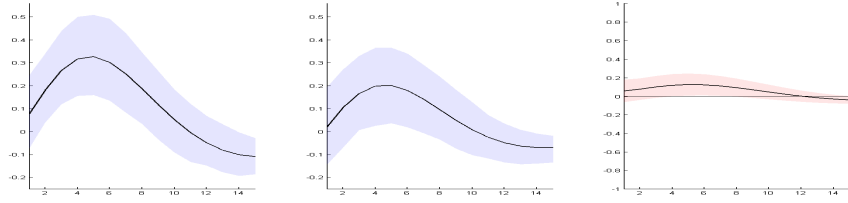
Figure 4: Impulse Response Functions of Credit to a GDP shock: 5-dimensional VAR  
- Asset prices



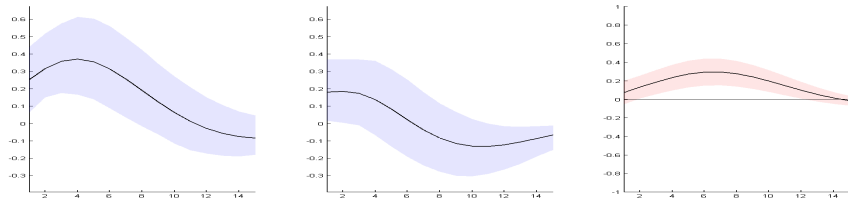
(a) Credit - House prices



(b) Bank Credit - House prices



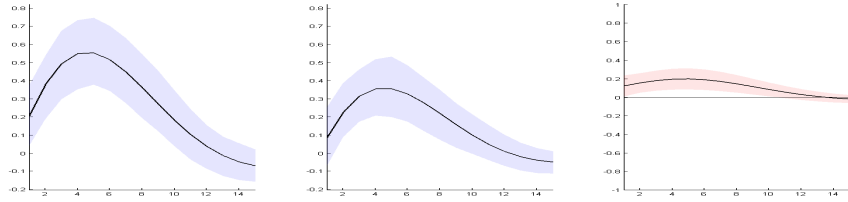
(c) Credit - Stock prices



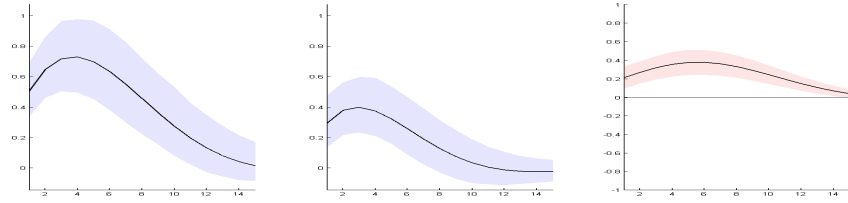
(d) Bank Credit - Stock prices

Note: The figure shows the impulse responses of credit and bank credit to a one-percentage-point shock in the output cycle evaluated (from left to right) at the 80<sup>th</sup> (high level) and 20<sup>th</sup> (low level) percentiles of the Lerner index sample distribution. The charts on the right represent the difference between the two. The colored bands represent the 5% error band (two standard deviations) generated by bootstrapping (1000 draws).

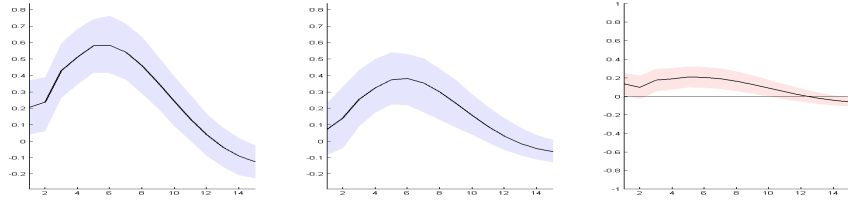
Figure 5: Impulse Response Functions of Credit to a GDP shock: Different ordering of the variables and IPVAR(3)



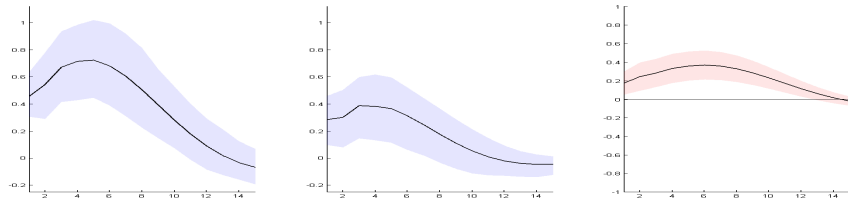
(a) Credit - Different ordering



(b) Bank Credit - Different ordering



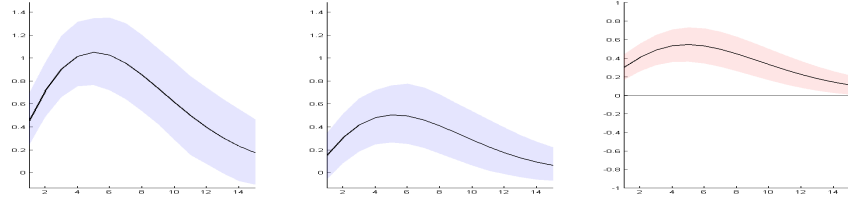
(c) Credit - IPVAR(3)



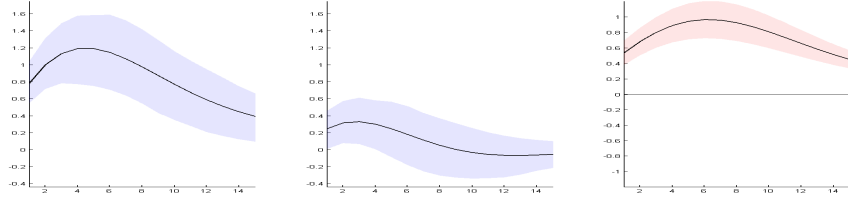
(d) Bank Credit - IPVAR(3)

Note: The figure shows impulse responses of credit and bank credit to a one percentage point shock in output cycle evaluated (from the left to the right) at the 80<sup>th</sup> (high level) and 20<sup>th</sup> (low level) percentiles of the Lerner index sample distribution. The charts on the right represent the difference between the two. The colored bands represent the 5% error band (two standard deviations) generated by bootstrapping (1000 draws).

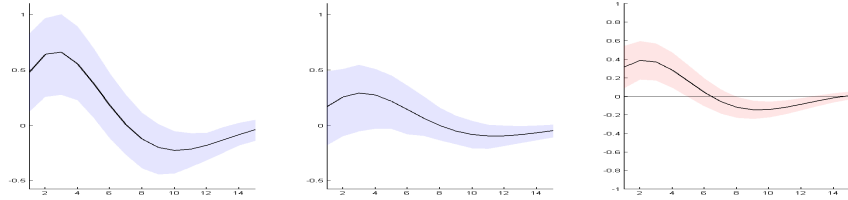
Figure 6: Impulse Response Functions of Credit to a GDP shock: HP filter with  $\lambda$  equal to 25600 and Baxter-King Filter



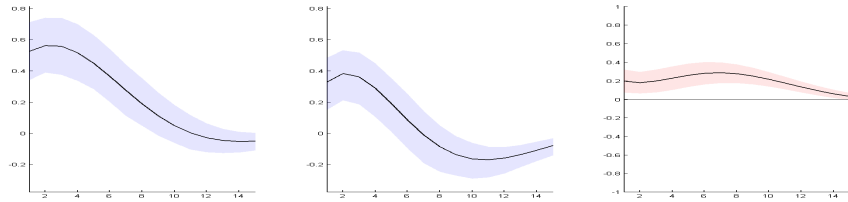
(a) Credit - HP filter



(b) Bank Credit - HP filter



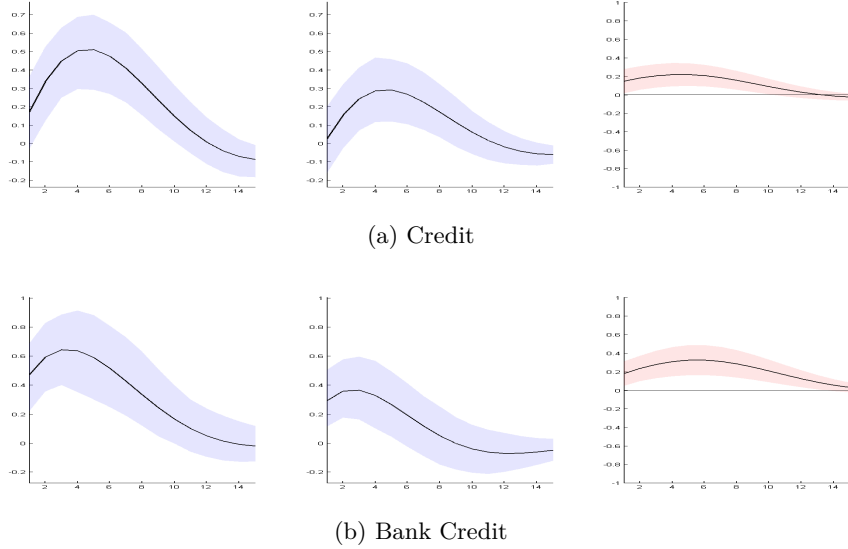
(c) Credit - BK Filter



(d) Bank Credit - BK Filter

Note: The figure shows impulse responses of credit and bank credit to a one-percentage-point shock in the output cycle evaluated (from left to right) at the 80<sup>th</sup> (high level) and 20<sup>th</sup> (low level) percentiles of the Lerner index sample distribution. The charts on the right represent the differences between the two. The colored bands represent the 5% error band (two standard deviations) generated by bootstrapping (1000 draws).

Figure 7: Impulse Response Functions of Credit to a GDP shock: Controlling for correlation with other structural characteristics



Note: The figure shows impulse responses of credit and bank credit to a one-percentage-point shock in the output cycle evaluated (from left to right) at the 80<sup>th</sup> (high level) and 20<sup>th</sup> (low level) percentiles of the Lerner Index sample distribution. The charts on the right represent the difference between the two. The colored bands represent the 5% error band (two standard deviations) generated by bootstrapping (1000 draws).

### 3 Bank Competition and Credit Procyclicality at the institution level

In this section, we examine whether more granular data support our previous findings. Specifically, we aim to highlight whether the bank response to an output shock varies with the degree of bank competition.

#### 3.1 Data and Methodology

##### 3.1.1 Data

We start with a presentation of the data used in our analysis. The required data are a mix of bank-level and country-level data. We obtain bank balance sheet and income statement information from the Bankscope database published by the Bureau Van Dijk. This database provides comprehensive detailed information regarding European banking. Our sample comprises more than 3,600 banks operating in the 16 previously analyzed economies.<sup>30</sup> Thus, the geographical coverage is identical in both sections. By contrast, the time dimension differs since the bank-level data are only available for the period 2005–2014. We apply some selection criteria to build our sample. First, we select unconsolidated statement to avoid double counting of commercial, cooperative and saving banks. Then, we exclude banks for which financial statements are available for less than 5 consecutive years to capture the benefits of the panel dimension of our

<sup>30</sup>Since not all variables are available for all bank-year observations, the sample size differs from one regression to another.

sample, and we drop banks for which the loan-to-asset ratio are missing for any one of these 5 years of observation. Some basic information about the sample is provided in Table A1.

The bank-level data are employed to measure the growth rate of loans on banks' balance sheets (which is our dependent variable), as well as to build a set of control variables and an indicator of bank market power, which varies across banks and over time. With regard to the latter point, we measure market power using the Lerner index, which is the only indicator that complies with those two conditions.

Formally, the Lerner index is defined as the difference between price and marginal cost divided by price:

$$Lerner_{it} = \frac{p_{it} - mc_{it}}{p_{it}} \quad (4)$$

where  $p$  the price and  $mc$  the marginal cost for the bank  $i$  in year  $t$ . In our case,  $p$  is the price of assets and is equal to the ratio of total revenue (the sum of interest and non-interest income) to total assets. To obtain the marginal cost, we also employ a conventional approach in the literature that consists of estimating a translog cost function and deriving it. Consistent with most banking studies, we consider a production technology with three inputs and one output (see, e.g., Berger et al., 2009, Ariss, 2010, Anginer et al., 2014). Thus, we estimate the following translog cost function:

$$\begin{aligned} \ln TC_{it} = & \beta_0 + \beta_1 \ln TA_{it} + \frac{\beta_2}{2} \ln TA_{it}^2 + \sum_{k=1}^3 \gamma_k \ln W_{k,it} + \sum_{k=1}^3 \phi_k \ln TA_{it} \ln W_{k,it} \\ & + \sum_{k=1}^3 \sum_{j=1}^3 \frac{\rho_{kj}}{2} \ln W_{k,it} \ln W_{j,it} + \delta_1 T + \frac{\delta_2}{2} T^2 + \delta_3 T \ln TA_{it} + \sum_{k=4}^6 \delta_k T \ln W_{k,it} + \varepsilon_{it} \end{aligned} \quad (5)$$

where  $C_{it}$  corresponds to the total costs of bank  $i$  in year  $t$  and is equal to the sum of interest expenses, commission and fee expenses, trading expenses, personnel expenses, administrative expenses, and other operating expenses measured in millions of dollars.  $TA_{it}$  is the quantity of output and is measured as total assets in millions of dollars.  $W_{1,it}$ ,  $W_{2,it}$  and  $W_{3,it}$  are input prices.  $W_{1,it}$  is the ratio of interest expenses to total assets.  $W_{2,it}$  is the ratio of personnel expenses to total assets.  $W_{3,it}$  is the ratio of administrative and other operating expenses to total assets.  $T$  is a trend. Furthermore, to reduce the influence of outliers, all variables are winsorized at the 1st and 99th percentiles (see, e.g., Berger et al., 2009; Anginer et al., 2014). We further impose the following restrictions on the regression coefficients to ensure homogeneity of degree one in input prices:  $\sum_{k=1}^3 \gamma_{k,t} = 1$ ,  $\sum_{k=1}^3 \phi_k = 0$  and  $\sum_{k=1}^3 \sum_{j=1}^3 \rho_{kj} = 0$ . Under these conditions, we can use the coefficient estimates from the translog cost function to estimate the marginal cost for each bank  $i$  in year  $t$ :

$$mc_{it} = \frac{TC_{it}}{TA_{it}} [\beta_1 + \beta_2 TA_{it} + \sum_{k=1}^3 \phi_k \ln W_{k,it} + \delta_3 T] \quad (6)$$

The translog cost function is estimated using pooled ordinary least squares (OLS) for each country separately to reflect differences in technology across European banking markets. We also include in the regression a trend ( $T$ ) to control for the evolution of

the translog function over time.

Recently, Koetter et al. (2012) note that the estimation approach discussed above might lead to biased Lerner indices. The rationale is that this approach is based on the implicit assumption that banks are fully efficient. In order to correct this potential bias, the authors propose an efficiency-adjusted estimate of the conventional Lerner index:

$$adjusted - Lerner_{it} = \frac{(\hat{\pi}_{it} + \hat{TC}_{it}) - \hat{mc}_{it}}{(\hat{\pi}_{it} + \hat{TC}_{it})} \quad (7)$$

where  $\hat{\pi}_{it}$  is the estimated profit,  $\hat{TC}_{it}$  is the estimated total cost, and  $\hat{mc}_{it}$  is the marginal cost.

To estimate this adjusted Lerner index, we follow Koetter et al. (2012) and first conduct a stochastic frontier analysis (SFA) to estimate the translog cost function. We then obtain  $\hat{TC}_{it}$  and  $\hat{mc}_{it}$ . Such an approach has the advantage of taking into account banks' cost inefficiency, defined as the distance of a bank from the cost frontier accepted as the benchmark.<sup>31</sup> Second, we specify an alternative profit function (Berger and Mester, 1997), which we estimate using SFA to obtain  $\hat{\pi}_{it}$ .

In addition to bank-level variables, we collect or build country-level variables. First, we consider three country-level measures of the Lerner index. The first is the same as that used in the previous section and is drawn from the Global Financial Development Database (GFDD). In this way, we effectively examine whether granular data on credit support our cross-country analysis. The two other Lerner indices are built by taking the median value by country and year of our own individual estimates of the conventional and efficiency-adjusted Lerner indices. Finally, our analysis also requires a yearly measure of business cycle fluctuation. For that, we use the output-gap measure from the OECD Economic Outlook database. The latter is defined as the deviation (in %) of actual GDP from the potential GDP obtained from a production function framework.<sup>32</sup> Summary statistics for the variables used in this section can be found in Table A2.

### 3.1.2 Methodology

Our empirical specification is designed to test whether the degree of bank competition impacts the reaction of banks – in terms of the supply of loans – to an output-gap shock. Thus, the model that we estimate has the following form:

$$\Delta \ln(loans_{it}) = \beta_1 OG_{ct} + \beta_2 OG_{ct} * Lerner_{i,t-1/c,t-1} + \beta_3 Lerner_{i,t-1/c,t-1} + \sum_{j=4}^n \beta_j X_{j,i,t-1} + \mu_{i/c} + \lambda_t + \varepsilon_{it} \quad (8)$$

with  $i = 1, \dots, N$ ,  $c = 1, \dots, 16$ , and  $t = 1, \dots, T$ .  $N$  denotes the number of banks,  $c$  the country and  $T$  the total number of years. In our model, the growth rate of loans

<sup>31</sup>Formally, the SFA consists of decomposing the error term of the translog cost function into two components, such as  $\varepsilon_{it} = v_{it} + \mu_{it}$ . The random error term  $v_{it}$  is assumed to be iid with  $v_{it} \sim N(0, \sigma_v^2)$  and independent of the explanatory variables. The inefficiency term  $\mu_{it}$  is iid with  $\mu_{it} \sim N(0, \sigma_\mu^2)$  and independent of the error term  $v_{it}$ . It is drawn from a non-negative distribution truncated at zero.

<sup>32</sup>The potential GDP required to compute the output gap is obtained from a production function framework.



( $\Delta \ln(\text{loans}_{it})$ ) is regressed on the output gap ( $OG_{ct}$ ), the Lerner index ( $Lerner_{i,t-1/c,t-1}$ ),<sup>33</sup> their product term ( $OG_{ct} * Lerner_{i,t-1/c,t-1}$ ), which constitutes our main variable of interest, and some bank-specific control variables ( $X_{j,i,t-1}$ ). The vector of control variables includes the log of total assets, the ratio of loans to total assets, the ratio of equity to total assets and, in some specifications, the product term between our measure of bank competition and a monetary policy shock. In order to avoid endogeneity bias, all bank-specific variables have been lagged. We further note that we include bank fixed effects ( $\mu_i$ ) (or country fixed effects ( $\mu_c$ ) in some specifications) and year fixed effects ( $\lambda_t$ ) to capture bank specificities and time-varying common shocks.<sup>34</sup>

Unlike in the cross-country analysis, here, the single equation modeling is perfectly appropriated. Indeed, the possibility that the output gap of country  $i$  responds to the loan growth of a particular bank is limited because, in most cases, the weight of a random bank is small compared to that of the overall economy. Therefore, this makes us relatively confident that the output gap is exogenous and that our regression results capture a causal link from the output gap to bank credit growth. However, to address remaining concerns about endogeneity – due to the fact that banking markets are not atomistic and that some banks are large enough to have a notable impact on the overall economy – we conduct some robustness checks excluding banks with very significant market shares.

### 3.2 Results

The estimation results for equation (8) are shown in Table 1 and Table 2. Table 1 reports the estimation results obtained from three country-level measures of bank competition: the Lerner index from the GFDD (columns (1) to (4)), our own estimates of the cross-country conventional Lerner index (columns (5) to (8)) and our own estimates of the cross-country efficiency-adjusted Lerner index (columns (9) to (12)). Regressions (1), (5) and (9) include the *output gap*, the *Lerner index*, and their product term as explanatory variables. To ensure that these estimates do not capture the effects of other variables, the regressions that follow include conventional control variables, while regressions (3), (7) and (11) control for the existence of a bank-lending channel effect. Finally, in regressions (4), (8) and (12), we replace bank fixed effects with country fixed effects.<sup>35</sup>

From these estimates, the first step consists of checking that credit is, on average, procyclical, i.e., changes in the business cycle positively impact the growth of credit. Since our regressions include the interaction of the *output gap* and the *Lerner index*, the coefficient estimates of *output gap* cannot be read as an average effect but as the effect of the output gap on credit when the banking market is perfectly competitive, i.e., when the Lerner index is equal to 0. The estimates of procyclicality for an average level of bank competition are displayed at the bottom of the table. The estimated

<sup>33</sup>In some specifications, we consider an aggregate measure of the Lerner index ( $Lerner_{ct}$ ), as in previous section, while in other specifications, we take advantage of the granularity of the data and use bank-level estimates of the Lerner index ( $Lerner_{ct}$ ).

<sup>34</sup>Initially, we specify a dynamic model estimated using both difference and system GMM. However, the results, in both cases, indicate that the lagged dependent variable is not significant. Note that our findings and specification choice are in line with Fungáčová et al. (2014).

<sup>35</sup>All specifications include year fixed effects.

coefficients vary between 1.442 and 1.677 and are very statistically significant. These results imply that GDP growth of 1 percentage point under its potential is associated with an approximately 1.5 percentage-point decline in loan growth.

The second step is to check whether the level of procyclicality varies with the level of bank competition. Across all specifications, the interaction of *Lerner index* and *output gap* enters with a positive coefficient that is significant at the 1% level. This suggests that lower country-level bank competition significantly increases the reaction of the loan supply to a change in the output gap. Apart from statistical significance, we also check the economic significance of the relationship. To do so, as in previous section, we compute and compare procyclicality at the first and fourth quintiles of the empirical distribution of the Lerner indices. In Table 1, we show that the economic effect is sizable. For instance, in specification (1), the estimated procyclicality is 1.443 and 1.896 for a low and high level of the Lerner index, respectively. In summary, the estimations with granular data corroborate the findings of the previous section: bank competition reduces credit procyclicality.

Our estimations also highlight other results. Briefly, we find that the main effect of the Lerner index is significantly negative in all specifications.<sup>36</sup> The more competitive the market, more important the growth of loans, which is consistent with the traditional microeconomic view. Furthermore, bank size (the log of total assets) and the loan ratio are negatively associated with loan growth. Finally, in regressions (4), (8) and (12), we have some interesting results regarding the existence of a bank-lending channel in Europe. First, it appears that the response of bank lending to a change in the monetary policy rate ( $\Delta MP$ ) has the expected negative sign. If we consider regression (4), an increase of 1 point in the monetary policy rate leads to a decline of 1.14 percentage points in loan growth. Second, in line with Fungáčová et al. (2014) and Leroy (2014), we find for two of the three macro-level measures of bank competition, the interaction terms of  $\Delta MP$  and *Lernerindex* are significantly positive. This indicates that lower bank competition strengthens the bank-lending channel, i.e., monetary policy transmission.

We now focus on the estimation results reported in Table 2. In these regressions, *Lerner index* is a bank-level measure of market power. It corresponds to the detailed data used to build our own country-level measures of bank competition. Using bank-specific estimations of bank market power is of great interest because it is a convenient way to disentangle demand from supply credit movements. This relies on the hypothesis that bank-specific market power influences the loan supply, while loan demand is independent of changes in bank market power.<sup>37</sup> Regressions (1)-(4) present estimates with the conventional Lerner index; regressions (5)-(8), those with the efficiency-adjusted Lerner index. Apart from the different level of observation of market power, the regressions are identical to those presented previously. Thus, regressions (1) and (5) only include the *output gap*, the *Lerner index* and their product as explanatory variables. Regressions (2) and (4) include more control variables, regres-

<sup>36</sup>The average output gap is equal to  $-0.506$ .

<sup>37</sup>By contrast, it is less certain that loan demand is independent of the aggregate level of bank competition, since the latter could impact the cost of credit, i.e., be correlated with macroeconomic factors affecting credit demand.

sions (3) and (7) control for the existence of a bank-lending channel, and regressions (4) and (8) control for the existence of country fixed effects.

Overall, the results obtained from the individual market power estimates are similar to those obtained with the aggregate-level estimates: (i) credit is procyclical, and (ii) the coefficients of the *Lerner index* and *output gap* product terms are positive and highly significant for both the conventional and efficiency-adjusted Lerner indices. Interestingly, we also observe that the economic impact of bank market power on credit procyclicality remains sizable and comparable to the previous estimates. For instance, moving from the 20<sup>th</sup> percentile of the conventional Lerner Index to the 80<sup>th</sup> percentiles increases the sensitivity of bank-lending growth to change of business cycle by 0.453 point (for regression (1)). The effects are slightly less important when we consider the efficiency-adjusted Lerner index since the interquintile values of 0.366 in regression (5) and 0.262 in regression (6).

Table 1: Credit procyclicality and bank competition: Aggregate measures of bank competition

	Lerner index from the GFD data set				Conventional Lerner index (own estimates)				Efficiency-adjusted Lerner index (own estimates)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Output Gap	1.064*** (0.095)	1.082*** (0.100)	1.094*** (0.098)	1.086*** (0.097)	-0.801*** (0.261)	-0.464* (0.245)	-0.832*** (0.233)	-0.996*** (0.271)	-0.455*** (0.156)	-0.247 (0.161)	-0.299* (0.160)	-0.346** (0.159)
Lerner index	-19.619*** (1.995)	-21.031*** (2.091)	-18.394*** (2.046)	-16.331*** (2.231)	15.567*** (5.326)	-2.525 (5.826)	-1.060 (5.996)	9.931** (4.609)	17.100*** (1.888)	13.573*** (1.976)	14.680*** (2.040)	18.468*** (1.776)
Output Gap*Lerner index	3.713*** (0.487)	3.079*** (0.503)	2.908*** (0.501)	3.185*** (0.530)	10.895*** (1.113)	9.712*** (1.071)	11.082*** (1.007)	11.491*** (1.129)	8.256*** (0.674)	7.362*** (0.724)	7.433*** (0.725)	7.363*** (0.621)
Total assets		-13.416*** (1.493)	-13.496*** (1.489)	-0.502*** (0.070)		-13.025*** (1.500)	-13.073*** (1.493)	-0.508*** (0.070)		-12.154*** (1.391)	-12.256*** (1.392)	-0.494*** (0.070)
Loans / Total assets		-28.359*** (2.472)	-26.845*** (2.489)	-6.142*** (0.731)		-30.735*** (2.555)	-29.647*** (2.569)	-6.859*** (0.739)		-28.272*** (2.345)	-27.610*** (2.363)	-6.801*** (0.740)
Equity / Total assets		-13.108 (9.337)	-13.882 (9.353)	-0.783 (2.586)		-20.004** (8.901)	-21.966** (8.909)	-2.771 (2.604)		-20.673** (8.925)	-21.801** (8.936)	-2.869 (2.604)
$\Delta$ MP			-2.194*** (0.233)	-2.574*** (0.255)			-2.148*** (0.805)	-1.896** (0.774)			-1.730*** (0.523)	-1.840*** (0.457)
$\Delta$ MP * Lerner index			8.220*** (1.301)	8.902*** (1.741)			3.789 (3.380)	1.486 (3.338)			4.690*** (1.774)	4.257** (1.683)
Constant	17.930*** (0.378)	214.188*** (20.894)	213.475*** (20.828)	28.501*** (1.260)	11.868*** (1.049)	208.321*** (21.232)	207.302*** (21.137)	22.319*** (1.503)	9.464*** (0.562)	190.398*** (19.607)	190.884*** (19.641)	19.324*** (1.233)
Average Lerner index	0.119	0.119	0.119	0.119	0.22	0.22	0.22	0.22	0.243	0.243	0.243	0.243
Low Lerner index	0.069	0.069	0.069	0.069	0.174	0.174	0.174	0.174	0.2	0.2	0.2	0.2
High Lerner index	0.181	0.181	0.181	0.181	0.239	0.239	0.239	0.239	0.268	0.268	0.268	0.268
Procyclicality: Average	1.508	1.45	1.442	1.467	1.6	1.677	1.611	1.537	1.551	1.542	1.507	1.443
Procyclicality: Low Lerner index	1.322	1.296	1.296	1.307	1.097	1.228	1.099	1.006	1.196	1.225	1.188	1.127
Procyclicality: High Lerner index	1.737	1.64	1.621	1.663	1.808	1.862	1.822	1.756	1.763	1.731	1.698	1.632
Difference between High and low	0.415	0.344	0.325	0.356	0.711	0.633	0.723	0.749	0.566	0.505	0.51	0.505
Observations	24,719	24,719	24,719	24,719	24,771	24,771	24,771	24,771	24,771	24,771	24,771	24,771
R-squared	0.529	0.558	0.560		0.528	0.556	0.558		0.539	0.563	0.565	
Number of banks	3,736	3,736	3,736	3,736	3,736	3,736	3,736	3,736	3,736	3,736	3,736	3,736
F	1816	1470	1304	.	1711	1408	1295	.	1724	1408	1282	.

Note: "Low" and "High" Lerner index refer to the 20<sup>th</sup> and the 80<sup>th</sup> percentiles of the sample distribution of the Lerner index, respectively. Robust standard errors are reported below their coefficient estimates. \*, \*\* and \*\*\* indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 2: Credit procyclicality and bank competition: Bank-level measures of bank competition

	Conventional Lerner Index (bank level)				Efficiency-adjusted Lerner index (bank level)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Output Gap	0.933*** (0.128)	0.866*** (0.141)	0.807*** (0.138)	0.959*** (0.112)	1.054*** (0.110)	1.174*** (0.114)	1.100*** (0.118)	1.053*** (0.107)
Lerner index	5.592*** (1.681)	6.400*** (1.778)	5.914*** (1.809)	3.751*** (1.281)	8.777*** (0.975)	7.951*** (1.037)	7.874*** (1.079)	5.941*** (0.904)
Output Gap*Lerner index	3.493*** (0.440)	3.527*** (0.483)	3.589*** (0.481)	3.074*** (0.385)	2.440*** (0.325)	1.746*** (0.308)	1.857*** (0.325)	2.204*** (0.307)
Total assets		-13.660*** (1.527)	-13.736*** (1.516)	-0.439*** (0.059)		-14.299*** (1.682)	-14.369*** (1.671)	-0.250*** (0.065)
Loans / Total assets		-29.748*** (2.508)	-28.617*** (2.521)	-6.279*** (0.664)		-28.942*** (2.649)	-27.817*** (2.660)	-5.785*** (0.679)
Equity / Total assets		-19.345** (9.328)	-20.078** (9.336)	-1.606 (2.609)		-21.327** (10.257)	-22.413** (10.249)	-0.085 (3.019)
$\Delta$ MP			-0.618** (0.292)	-0.898** (0.352)			-0.931*** (0.350)	-1.217*** (0.400)
$\Delta$ MP * Lerner index			-2.247** (0.923)	-1.902* (1.062)			-0.511 (0.909)	-0.213 (0.959)
Constant	13.824*** (0.354)	213.870*** (21.281)	213.664*** (21.135)	22.637*** (1.042)	12.159*** (0.357)	221.074*** (23.646)	220.733*** (23.501)	18.741*** (1.216)
Average Lerner index	0.209	0.209	0.209	0.209	0.241	0.241	0.241	0.241
Low Lerner index	0.146	0.146	0.146	0.146	0.163	0.163	0.163	0.163
High Lerner index	0.275	0.275	0.275	0.275	0.313	0.313	0.313	0.313
Procyclicality: Average	1.663	1.604	1.558	1.602	1.643	1.596	1.548	1.585
Procyclicality: Low Lerner index	1.443	1.381	1.331	1.408	1.453	1.459	1.403	1.413
Procyclicality: High Lerner index	1.896	1.838	1.797	1.807	1.819	1.721	1.682	1.744
Difference between High and Low	0.453	0.457	0.465	0.399	0.366	0.262	0.278	0.3308
Observations	24,194	24,194	24,194	24,194	23,765	23,765	23,765	23,765
R-squared	0.529	0.559	0.561		0.538	0.568	0.569	
Number of banks	3,661	3,661	3,661	3,661	3,622	3,622	3,622	3,622
F	1721	1404	1256	.	1722	1416	1284	.

Note: "Low" and "High" Lerner index refer to the 20<sup>th</sup> and the 80<sup>th</sup> percentiles of the sample distribution of the Lerner index, respectively. Robust standard errors are reported below their coefficient estimates. \*, \*\* and \*\*\* indicate statistical significance at the 10%, 5% and 1% levels, respectively.

## 4 Financial Structure and Credit Procyclicality

Finally, we extend our previous analysis by investigating whether the financial structure of an economy drives credit procyclicality. Following Levine (2002), financial structure refers to the importance in an economy of bank-based intermediation relative to market-based intermediation. All financial systems combine these two intermediation channels, but the financial structure varies across countries. Indeed, even if the European banking sector is heavily bank-based (see, e.g., (Langfield and Pagano, 2016)), significant cross-country differences exist. For example, Gambacorta et al. (2014) show that peripheral euro area countries (Italy, Portugal, Spain) exhibit financial structures that are more bank-based than those of core euro area countries (Belgium, France, Germany, Netherlands). Therefore, this implies that the nature of relationships between lenders and borrowers differ across Europe. Indeed, bank-based systems are characterized by more reliance on relationship banking, while market-based systems are associated with more arm's-length relationships (Rajan and Zingales, 2001). These two kinds of relationships matter for competition: the first, which implies opacity and implicit contracts, limits it, whereas the second, characterized by transparency and explicit contracts, favors it. As a result, the financial structures of economies are not orthogonal to their competitive environments, which justifies the focus of this section.

The theoretical literature has long debated the relative merits of bank-based (or relationship-banking) and market-based (or arm's length) systems in terms of economic performance (Allen and Gale, 2000). However, since the pioneering paper of Levine (2002), no clear empirical evidence has emerged regarding the superiority of bank-based or market-based systems in promoting economic growth. Most studies do not find that financial structure *per se* matters, suggesting that banks and financial markets are complementary and that it is the overall provision of financial services that is important for growth. However, as argued by Langfield and Pagano (2016), the effect of the financial structure on economic growth is not the only dimension along which one can assess the relative advantages and disadvantages of these two financial systems. Another key dimension is the extent to which banks and markets differ in their moderating effects on business cycle fluctuations and, thus, whether the financial structure is likely to explain cross-country differences in economic recovery paths. Indeed, the role of bank financing in economic recovery has been a controversial issue since Calvo et al. (2006) noted "phoenix miracles", i.e., the fact that output recovery occurs with virtually no recovery of private sector credit.

For the proponents of the bank-based system, the comparative advantage of banks vis-à-vis markets is their ability to collect private information through long-term relationships with borrowers. As argued above, such information implies that banks are more likely to supply loans during economic downturns because they are able to identify solvent borrowers facing temporary liquidity shocks (see, e.g., Bolton et al., 2016, thus smoothing the impact of a recession. Despite the informational superiority of such a banking sector, Langfield and Pagano (2016) do not find low sensitivity of bank lending to economic activity. On the contrary, they find for a large sample of European countries that bank lending is more volatile and pro-cyclical than bond financing, especially during financial crises. More precisely, in line with Adrian et al. (2013) and Grjebine et al. (2014), the findings obtained by Langfield and Pagano (2016) suggest

that the two types of financing are partial substitutes. Indeed, they observe substitution between loan and bond financing in the aftermath of the subprime loan crisis. This means that firms located in countries with well-developed corporate debt markets were able to respond to the contraction in bank lending by issuing more debt securities. Consequently, according to this result, it is expected that market-based economies would be more resilient to macroeconomic shocks than bank-based economies.

Two recent empirical studies (Allard and Blavy, 2011; Gambacorta et al., 2014) try to clarify this issue. To this end, they cluster their sample as bank-oriented or market-oriented countries and assess whether the speed of economic recovery after a crisis is significantly different in bank-based and market-based economies. The results obtained by Allard and Blavy (2011) suggest that market-based economies recover faster than bank-based economies. The gap in terms of cumulative growth ranges between 0.8 and 1.4 percentage points two years into the recovery. This gap increases to 2.7 percentage points when they compare strongly market-based economies to strongly bank-based economies. More importantly, Allard and Blavy (2011) show that the nature of the crisis matters. They find that financial crises negatively impact the ability of market-based economies to recover compared to bank-based economies. The opposite result is obtained by Gambacorta et al. (2014). Indeed, they show that when recessions coincide with financial crises, bank-based economies tend to be more severely affected than market-based economies, since the ability of banks to supply credit tends to be damaged. The total real GDP losses in countries with bank-oriented system is three times more severe than in those with a market-oriented financial structure, while the inverse trend is observed during a "normal" recession.

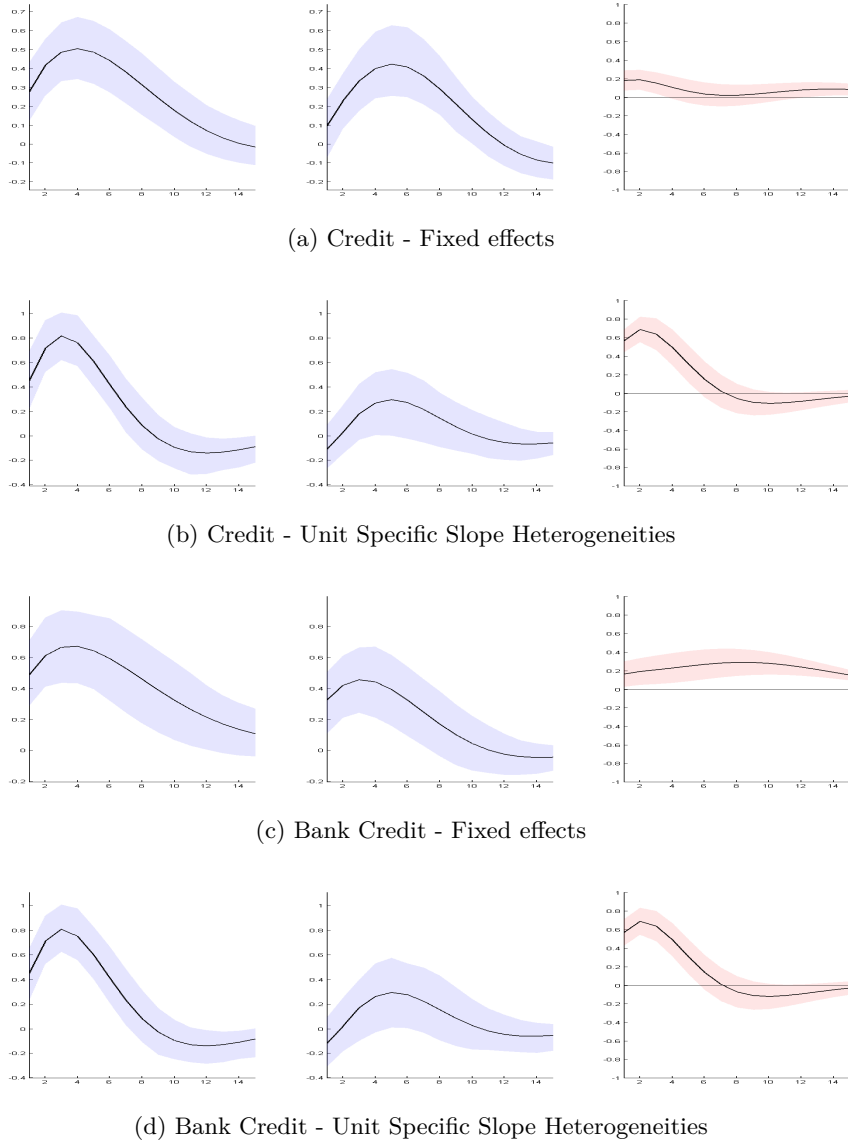
In light of these conflicting results, one of the contributions of this paper is to extend this emerging literature by estimating whether differences in financial structure in Europe explain cross-country heterogeneity in credit procyclicality. Contrary to Allard and Blavy (2011) and Gambacorta et al. (2014), we do not split our sample of countries in two sub-samples, but we consider a time-varying aggregate indicator of financial structure. Because there is no direct measure of the intermediation services that banks and markets provide, we use a bank-market ratio as a proxy for financial structure. In line with Levine (2002) and Langfield and Pagano (2016), this ratio is defined as bank credit divided by stock and private bond market capitalization. Larger values of the ratio indicate a more bank-based financial system. Moreover, to control for the fact that the financial structure can vary over the business cycle (see Grjebine et al., 2014; Langfield and Pagano, 2016), we consider the trend in the bank-market ratio by applying an HP filter.

Due to the nature of our financial structure measure, we rely on our macroeconomic framework to assess the conditional effect of the financial structure on credit procyclicality. We re-estimate our baseline IPVAR model replacing the Lerner index with the bank-market ratio. The results are reported in Figure 8. As before, we consider bank credit and total credit as endogenous variables and estimate the IPVAR model by considering both the OLS fixed effects and the mean group estimators. We can see that more bank-based financial structures are conditionally associated with a higher credit procyclicality. Following Langfield and Pagano (2016), this result can be explained by a procyclical deleveraging process in the banking sector, which makes

the credit supply more sensitive to economic activity fluctuations in bank-based structures than in market-based structures. Furthermore, according to Adrian et al. (2013), this deleveraging process can be exacerbated by regulatory requirements. Indeed, they argue that the credit supply decreases during recessions because banks are forced to reduce their exposure to rising default risk in order to satisfy a value-at-risk constraint. Moreover, competition from direct finance may also matter. Indeed, beyond the fact that higher competition from non-bank financial intermediaries puts pressure on banks to price their lending and deposit rates more competitively (see, e.g., Mojon, 2000; Gropp et al., 2014), we also expect that easier access to direct debt financing puts pressure on banks to reduce their procyclical behavior, since it decreases the dependency of some borrowers on intermediaries for financing. Finally, our findings confirm the fact that the financial structure of an economy and the degree of banking competition are linked. Indeed, as we argue above, a more market-based financial structure is expected to foster competition within the banking industry, inducing lower credit procyclicality, as our previous results suggest.



Figure 8: Impulse Response Functions of Credit to a GDP shock: Financial structure



Note: The figure shows impulse responses of credit and bank credit to a one-percentage-point shock in the output cycle evaluated (from left to right) at the 80<sup>th</sup> (high level) and 20<sup>th</sup> (low level) percentiles of the indicator of financial structure. The charts on the right represent the differences between the two. The colored bands represent the 5% error band (two standard deviations) generated by bootstrapping (1000 draws).

## 5 Conclusion

This paper is the first to empirically assess whether the degree of competition in the financial system constitutes a driving force of credit procyclicality. More precisely, the main objective of this paper is to gauge whether the sensitivity of credit to the business cycle is conditional on the level of competition. To this end, we consider a large sample of European economies and use two complementary panel data approaches. The first relies on macroeconomic data and consists of estimating an interacted panel

VAR framework (IPVAR), recently developed by Towbin and Weber (2013), in which credit procyclicality is defined as the orthogonalized impulse response function of the credit cycle to a GDP cycle shock. The main advantage of such an approach is that we can explicitly assess whether the time-varying level of competition as an exogenous factor affects the credit response to a GDP shock. Indeed, we can compute and compare impulse response functions according to the level of competition. We then rely on bank-level data by estimating a single-equation model in which we control for some individual characteristics of banks that could explain their credit policy. Considering more than 3,600 banks located in Europe, we analyze whether the market power of each bank affects the link between the output gap and the annual growth rate of loans.

Moreover, contrary to most of the studies in the banking literature, we not only focus on competition within the banking sector but also consider competition from financial markets. Following the existing literature, the level of competition within the banking industry is proxied by the Lerner index. This index measures the degree to which firms can markup price above marginal cost, which is an indicator of the degree of market power. A country-level Lerner index is considered within the IPVAR framework, and we use balance sheet data to compute individual Lerner indices in our micro-level analysis. The level of competition from direct finance is proxied by an aggregate measure of the financial structure of an economy. This measure is defined as the ratio of bank credit divided by stock and private bond market capitalization. Lower values of the ratio indicates a more market-based financial system and, thus, higher competition from non-bank financial institutions.

The results that we obtain at the macro- and micro-level suggest that the procyclicality of credit is higher in economies where competition among banks is relatively low. This means that the lack of competition within the banking industry tends to exacerbate the sensitivity of loans to the business cycle and then amplify and propagate shocks to the macroeconomy. As we explain in this paper, there are two possible reasons for this result. First, competition may lead banks to operate in a more efficient way, in particular, by improving the screening and monitoring of borrowers. This leads to reduced asymmetric information, weakening the repercussions of real shocks for financial conditions. The second possible explanation relates to the literature on bank competition and financial stability. Indeed, a large theoretical and empirical literature supports the fact that banks hold more capital and engage in less risky activities when competition increases. This reduced risk-taking behavior of banks implies that credit booms are less important in the upward phase of the cycle and, consequently, that banks experience smaller financial losses in the downward phase, preserving the ability of banks to supply new loans during recessions.

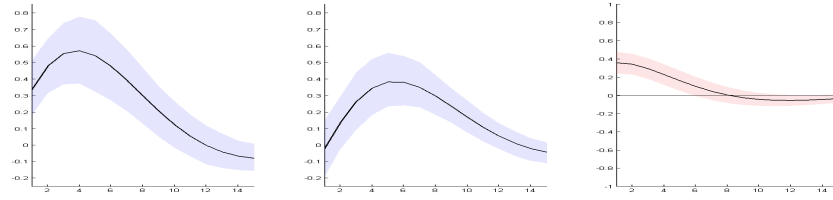
If we now turn to the relationship between the financial structure of an economy and credit procyclicality, we find that more bank-based economies are characterized by higher credit procyclicality. Beyond the fact that this result could be explained by a relatively pronounced deleveraging process in the European banking sector (Langfield and Pagano, 2016) and competition from direct finance, we can also relate it to our previous findings. It confirms the link between the financial structure of an economy and the level of competition within the banking industry. Due to their arm's-length relationships and higher transparency, market-based systems are expected to foster

competition within the banking sector and, thus, to reduce the procyclicality of credit.

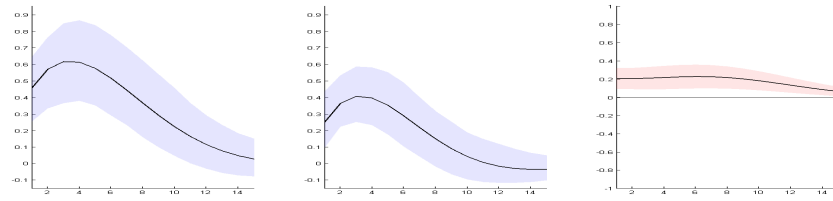
In terms of policy implications, our findings first suggest that promoting competition within the European banking sector should ensure lower procyclicality of credit and, thus, investment and consumption that are relatively less sensitive to the business cycle. Consequently, by limiting the amplification mechanism of the financial sphere to the real sphere, such a pro-competitive policy is expected to reduce macroeconomic volatility. Furthermore, lower credit procyclicality should limit credit booms and excessive accumulation of risks during the upward phase of the business cycle. Since credit booms usually precede financial crises (see, e.g., Schularick and Taylor, 2012), our results can also be read as evidence that greater bank competition reduces financial instability, supporting the competition-stability view advocated by Boyd and De Nicolo (2005), which rejects the existence of a trade-off between competition and stability. Finally, in line with an emerging empirical literature, our results confirm the fact that the financial structure of an economy and the development of financial markets can help to mitigate the contraction of the supply of loans during a recession and, thus, to reduce recession costs. These findings support recent initiatives by the European Commission to implement policies to develop markets for corporate debt securities.

## Appendix

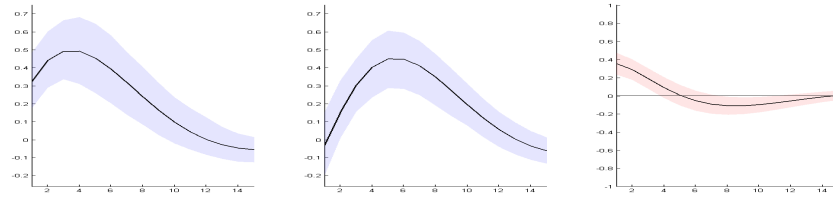
Figure A1: Impulse Response Functions of Credit to a GDP shock: Sample split



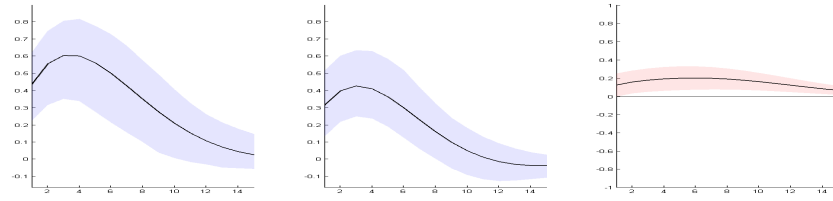
(a) Total Credit - Bank competition



(b) Bank Credit - Bank competition



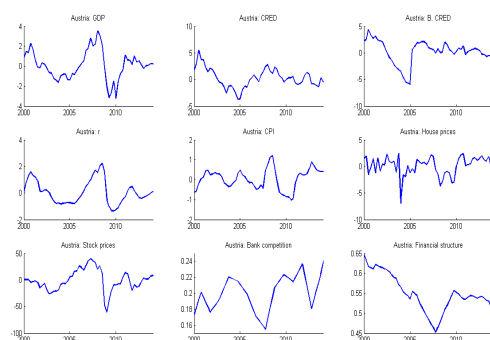
(c) Total Credit - Financial structure (Global structure)



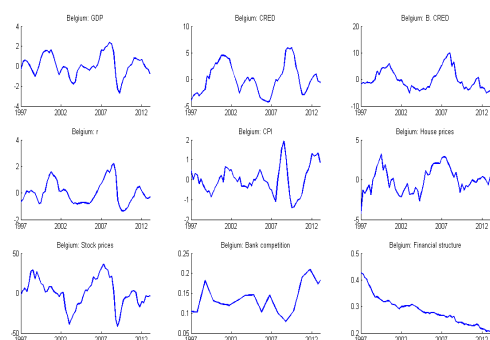
(d) Bank Credit - Financial structure (Global structure)

Note: This figure compares the impulse response functions of credit/bank credit to a one-unit shock in GDP for economies characterized by a low and a high level of competition in the financial sphere. Competition refers to both competition among banks and competition from financial markets. In order to split our initial sample into two groups, we rank the countries according to the country average Lerner index value and our measure of financial structure. The credit responses depicted on the left correspond to economies where competition in the financial system is weaker, i.e., characterized by low bank competition or bank-based financial intermediation. The low bank competition sub-sample comprises Austria, Denmark, Greece, Ireland, Norway, Spain, Sweden and the United Kingdom, while the bank-based sub-sample includes Austria, Denmark, Germany, Greece, Ireland, Italy, Portugal and Spain. Obviously, the credit responses depicted in the center correspond to the average reaction of countries where banking markets are more competitive (Belgium, Finland, France, Germany, the Netherlands, Portugal, Sweden and Switzerland) and where the market-based intermediation is more developed (Belgium, Finland, France, the Netherlands, Norway, Sweden, Switzerland and the United Kingdom).

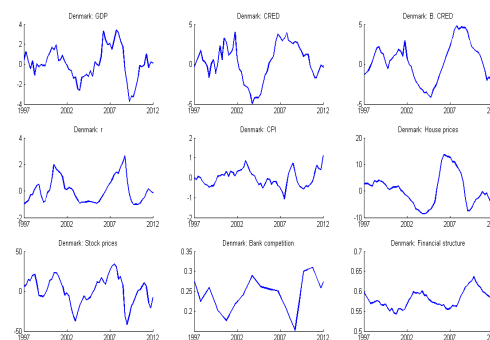
Figure A2: Time series by country



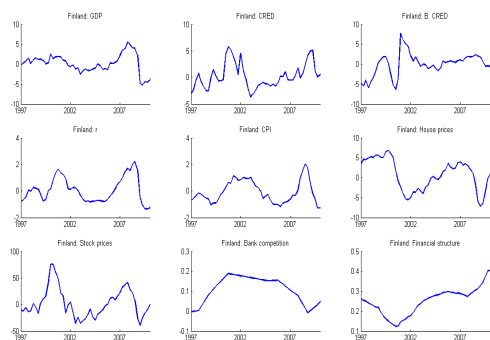
(a) Austria



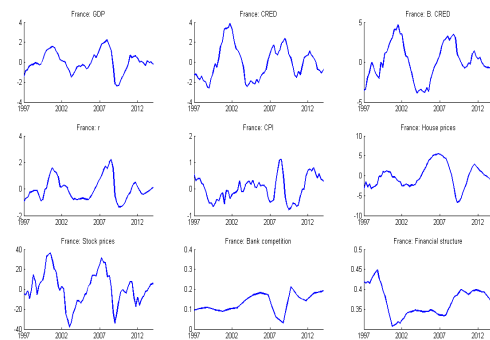
(b) Belgium



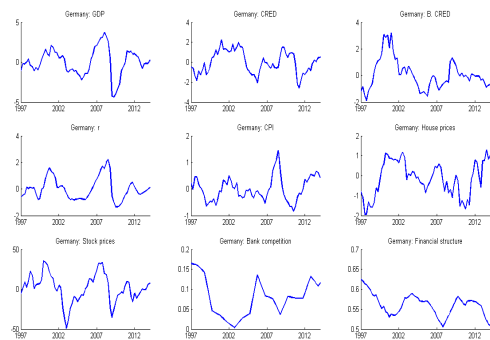
(c) Denmark



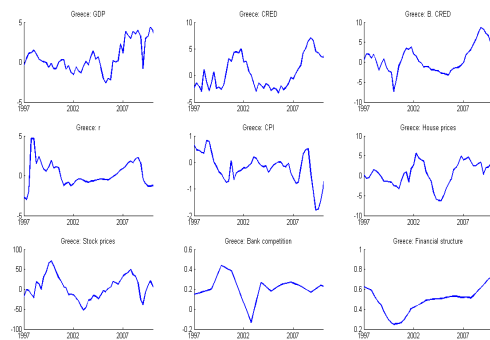
(d) Finland



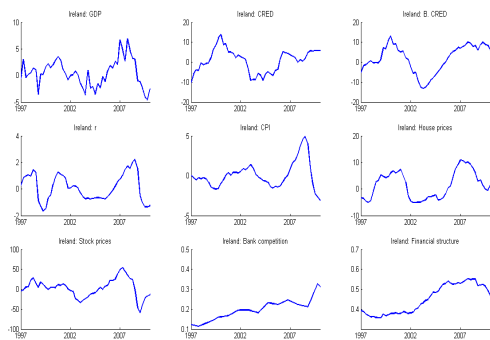
(e) France



(f) Germany

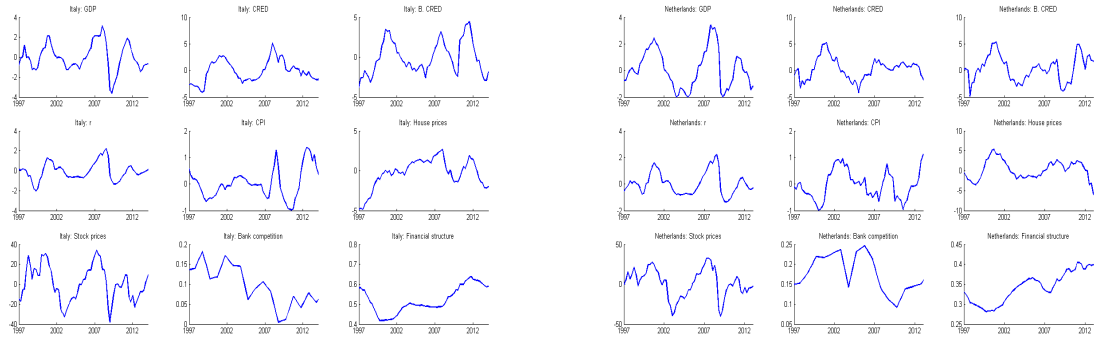


(g) Greece



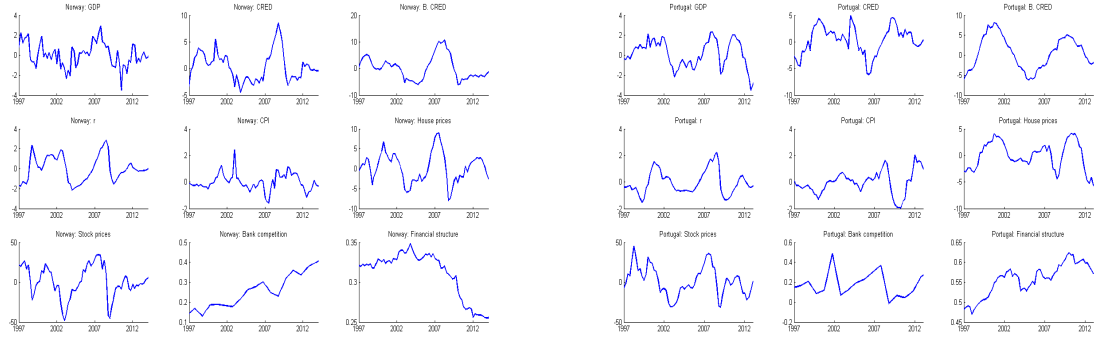
(h) Ireland

Figure A3: Time series by country



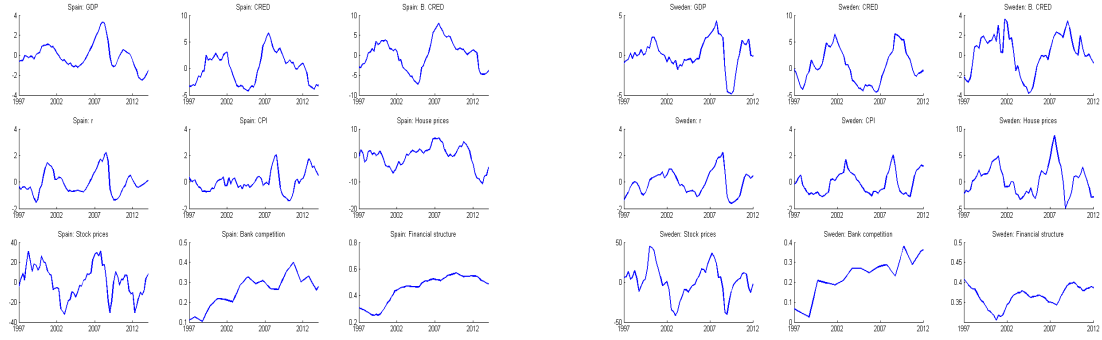
(i) Italy

(j) the Netherlands



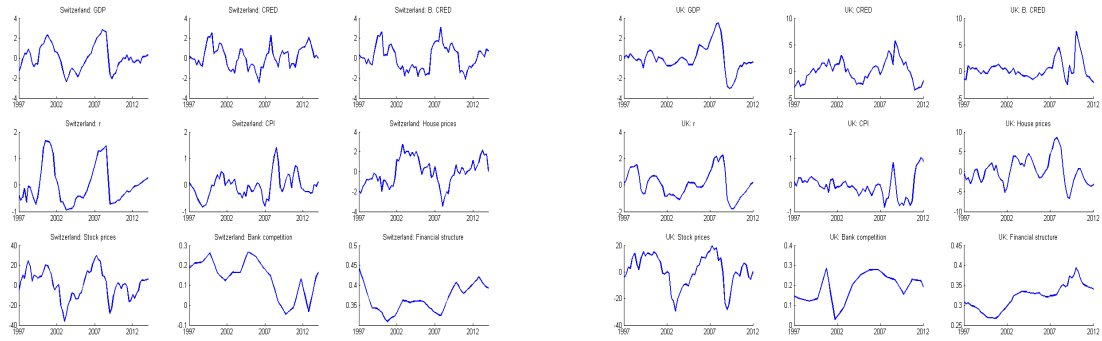
(k) Norway

(l) Portugal



(m) Spain

(n) Sweden



(o) Switzerland

(p) UK

Table A1: Number of banks by country

Austria	233	France	211	Italy	577	Sweden	89
Belgium	34	Germany	1711	Norway	128	Switzerland	356
Denmark	98	Greece	16	Portugal	21	the Netherlands	23
Finland	13	Ireland	10	Spain	126	United Kingdom	90

Table A2: Summary statistics: Bank-level data analysis

Variable	Mean	Median	SD	Min	Max
Loan growth	5.61	4.49	13.3	-17.5	55
Output-Gap	-0.695	-0.527	2.4	-14.2	9.42
Lerner index (GFDD)	0.12	0.083	0.086	-0.045	0.428
Conventional Lerner index	0.209	0.209	0.0956	-0.253	0.504
Efficiency-adjusted Lerner index	0.242	0.222	0.121	-0.005	0.689
ln(Total assets)	13.5	13.3	1.65	7.17	21.9
Loans / Total assets	0.619	0.629	0.179	0.161	1
Equity / Total assets	0.083	0.072	0.060	-0.458	1
$\Delta$ MP	-0.181	-0.233	0.598	-1.33	6.75
W1	0.012	0.012	0.006	0.001	0.052
W2	0.022	0.020	0.011	0.002	0.076
W3	0.009	0.008	0.006	0.001	0.057
TC	233390	23314	1955348	89.5	9.40E+07
P	0.050	0.050	0.015	0.02	0.156

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