Competition and credit procyclicality in European banking

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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 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 competition among banks is weak. According to the financial accelerator theory, if 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 (Reinhart and Rogoff, 2009; Schularick and Taylor, 2012; Gourinchas and Obstfeld, 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.

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

Keywords: credit cycle; business cycle; bank competition; interacted panel VAR

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1 Introduction

There is a long-standing debate among economists about whether more intense competition between financial intermediaries improves economic outcomes. This debate greatly intensified with the onset of the global financial crisis. First, academics and policy makers wondered whether excessive competition was partly responsible for the crisis. Second, the banking sector experienced numerous structural changes (for instance, 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, known as the competition-fragility view, argues that competition between banks is detrimental to financial stability (Berger et al., 2009; Turk Ariss, 2010; Jiménez et al., 2013), another strand, known as the competition-stability view, provides diametrically opposed evidence (Boyd et al., 2006; Schaeck et al., 2009; Schaeck and Cihák, 2014; Anginer et al., 2014; Atkins 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 times and in response to a crisis. As a result, some contributions have focused directly on the effects that bank competition has 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 impact on macroeconomic volatility (the occurrence and intensity of economic booms and busts), which has not attracted a lot of interest in the literature.

This paper addresses 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 are sources of fluctuations in real economic activity is at the heart of the financial accelerator theory (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Bernanke et al., 1999). Loosely speaking, the financial accelerator theory states that shocks, whether real, monetary or financial, that increase or decrease the net worth of borrowers by altering the revenue and collateral values of non-financial agents have in addition of the wealth effect an additional effect, by increasing or reducing the credit worthiness of the borrowers through asymmetric information. As a result, credit becomes more expensive and less available during recessions, while the opposite happens during expansions. The procyclicality of credit tends to amplify the real economic cycle by expanding or shrinking investment, for instance. In this way, 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 given 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, during periods of stability lead to speculative borrowing (by so-called "Ponzi borrowers") and, therefore, excessive lending and increasing aggregate demand. It follows that this fuels the "exuberance" of the boom and the bubble that suddenly stop when a negative shock makes Ponzi borrowers unable to pay their loans. 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 a financial crisis. Therefore, credit procyclicality enhances both the persistence of economic shocks and the probability of a financial crisis arising, and these in turn amplify the volatility of the economy (Schularick and Taylor, 2012; Gourinchas and Obstfeld, 2012).

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 analyses the consequences of procyclicality not only for the real economy but also for the banking sector itself. For example, some studies analyse the behaviour 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 approach tries to identify the factors that 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 their leverage and remuneration policies, and some other factors, like credit rating agency reports or the use of automated risk management systems. More generally, cross-country differences in bank procyclicality are related to differences in cross-country financial structures (Albertazzi and Gambacorta, 2009).

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

The first channel is related to the rate setting strategies of the financial institutions. As shown by the Monti-Klein model, by reducing interest rate elasticity, a decrease of bank competition allows banks to charge a higher markup (markdown) in bank loans (deposits), increasing the spreads between the policy interest rate and the loan (deposit) rates and, therefore, the cost of credit. The empirical evidence reported in the surveys of Berger et al. (2004) and Degryse and Ongena (2008) confirm this result. Further to matter for interest rate spread, bank competition does impact the degree of interest rate stickiness, i.e. the speed of adjustment of the retail interest rate to a change of monetary policy rate. From a theoretical point of view, the degree of price stickiness can be explained by the existence of switching costs that reduce the interest rate elasticity (Calem et al., 2006). Several recent empirical findings also confirm the link between the degree of competition and stickiness (see, Sørensen and Werner, 2006 ; Van Leuvensteijn et al., 2013 ; Leroy and Lucotte, 2015). The inclusions of markups and rigidities are now common in neo-keynesian macro-models, but generally limited to the goods and wage markets (Woodford, 2003). As regard the banking market, few studies have considered imperfect competition, i.e. embeded microfoundation of the supply side of the banking market. Indeed, the most of the DSGE models including a banking sector only focuses on the demand side of the market (the external finance premium related to the riskiness of the borrowers). Aliaga-Díaz and Olivero (2010) is one of the first contribution analysing the effect of bank competition on business cycle. In their model, bank market power arises from switching costs and generates a countercyclical price-cost margin, i.e the cost of credit increases during recession. Thus, this countercyclical margin acts as a financial accelerator, amplifying the initial macroeconomic shock. The reason why bank market power increases fluctuations is explained by the fact that switching costs lock-in borrowers. In case of "deep habit" effects, the bank faces a trade-off between current profit and potential future profit. If a bank has good expectations over future economic activity, its optimal strategy is to reduce the current margin and, therefore, its current profit. This will attract more new customers (more credit supplied), which will be locked-in in the future and profitable because the good economic environment. Opposite effects are expected following a negative shock on economic activity. Mandelman (2011) provides same conclusions but explains the countercyclical margin differently. The banking industry is modelled as a set of different segments. Each segment is characterized by free entry but sunk cost. This implies that the entry of new banks in each segment depends on the size of investment. Indeed, banks need a minimal scale to amortize sunk cost and be profitable. In this scenario, an increase of macroeconomic investment in the economy during expansion phase is like a reduction of the barrier of entry, forcing incumbent banks to reduce their margin. More important is the degree of competition, less important this effect. The DSGE of Gerali et al. (2010) enriches the previous models by different aspects (banks setting different rates for households and firms, sticky interest rates, capital requirements, collateral constraints, etc.) but broadly leads to similar general conclusions. Indeed, the model shows that market power amplifies the financial accelerator mechanism initiated by a positive technology shock by leading to a more severe contraction of interest rates and an increase of credit demand following a such initial shock. However, sticky rates, possibly related to the level of competition, have an opposite effect, but act only marginally. Andrés and Arce (2012) provide a different picture of the effect of banking competition on short-run dynamic. They show that the effects of competition depend crucially on the nature of the shock hitting the economy. Following a monetary policy tightening shock, output exhibits a larger and more persistent fall as banking competition increases. By contrast in face of a credit crunch shock, an enhanced competition allows quicker adjustment of the economy. While the above general equilibrium models study competition on interest rate, Ravn (2016) considers in addition the effects of competition on collateral. In the wake of Ruckes (2004) and Dell'Ariccia and Marquez (2006), he shows that imperfect competition on collateral requirements creates countercyclical credit standards that also amplify business cycle fluctuations.

Further countercyclical margins (and credit standards), competition may also distort bank risk-taking behaviour, which could indirectly affect the strength of the financial accelerator effect and the financial cycle. Indeed, excess risk-taking will foster the boom of credit, pushing the economy toward financial crisis, and make the trend reversal more violent and persistent because banks will be forced to clean up their bad assets. The issue is that no clear consensus has emerged in the literature on the relationship between competition and stability. One stand, the competition-fragility view, claims that an increase in bank competition erodes the banks' franchise values (i.e. the present value of future rents) and, therefore, induces banks to gamble by behaving less prudently, since the opportunity costs of bankruptcy are lower (Keeley, 1990; Hellmann et al., 2000). However, another strand argues that because an increase in bank competition reduces loan rates, it also reduces bank risks, as the moral hazard incentives to shift to riskier projects decrease (Boyd and De Nicolo, 2005).

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, or whether the structure of the banking sector affects how credit responds to business cycles. They do this 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.[1] 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. The results that they obtain suggest that credit responds significantly to shocks to GDP, but they do not find that banking sectors with different characteristics exhibit differences in their credit procyclicality. Therefore the authors conclude that the structure of the banking sector is not an important cause of credit procyclicality.

Our analysis goes a step further than Bouvatier et al. (2012) by proposing both macro-level and micro-level assessment of the relationship between bank competition and credit procyclicality. Our macro-level analysis uses a VAR framework and follows Bouvatier et al. (2012) by defining credit procyclicality as the orthogonalised impulse response function of the credit cycle to a business cycle shock. Unlike Bouvatier et al. (2012), however, 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 do this, 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. The result is that in this framework the impulse responses of credit to a shock in GDP, which is the propagation mechanism in the financial accelerator view, are conditioned by the level of bank competition, which is 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 analysing whether banking sector competition and bank market power play a role in the procyclical behaviour of bank credit activity. It also aims to address some important econometric issues with the VAR framework,

[1] Bouvatier et al. (2012) consider seven variables to provide a classification of banking system structures. These variables are intended 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.

such as identification and endogeneity issues. One major advantage of such an approach is that it can control for some characteristics of individual banks that could explain their credit policies. It can be argued indeed, that the fact that banks being more willing to grant loans during the upward phase of the business cycle and more reluctant to do so during the downward phase is a consequence not only of bank competition but also of bank specificities, such as their size or the diversification of their activities. Our analysis uses balance sheet data and analyses 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 competition is fierce and the individual market power of banks is weak.

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 in Section 2.1. Second, we present and discuss the empirical results in Section 2.2. Section 3 presents the results of the analysis with bank-level data. Section 3.1 describes the data and the empirical model, and Section 3.2 provides the empirical results. We conclude in Section 4.

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 and takes in 16 European economies. These are Norway, Switzerland, and the member states of the EU-15 prior to 2004 with the exception of Luxembourg.[2] This means that the time dimension of our panel is relatively large, with 72 quarterly observations, and the cross-section dimension is relatively tight, covering only countries at similar stages of growth.

[2]Our data set comprises the following countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and the United Kingdom.

Our baseline econometric specification that we use in analysing the cyclical behavior of credit in European banking, as described below, is parsimonious and comprises four main quarterly macroeconomic variables: real GDP (GDP), the consumer price index (CPI), the real outstanding amount of credit to the private non-financial sector (CRED), and the nominal short-term interest rate (r).[3] 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. All the series except for the interest rate 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 instead 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).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 degree of monopolistic competition to be assessed. 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 the Lerner index, which is a non-structural measure of bank competition. This index represents the mark-up of prices over marginal costs and is a country-level indicator of the degree of market power, where higher values indicate lower competition. Further details on the construction of the index are provided in Section 3, where we compute a bank-level measure of the Lerner index.

The data source for GDP values, CPI values, short-term interest rates and the two asset price indexes for residential property and share prices is the OECD database. The two credit series for the private non-financial sector are from the BIS database. Finally, our measure of bank competition, the Lerner index, is taken from the Global Financial Development database of the World Bank. Unlike the other series, bank competition is computed annually. So to match the variable to the quarterly frequency of our study, we use a linear interpolation procedure.[4] All the 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, where first we check that credit procyclicality is heterogeneous in the European banking sector, and then we test whether the differences in procyclicality across economies might be explained by differences in bank competition.

These two steps require us first of all to define how we measure credit procyclicality. Roughly speaking, credit procyclicality corresponds to a positive reaction of credit to a change in GDP. This makes it necessary to use an econometric framework that firstly

[3]Real credit series are constructed by deflating nominal credit by the CPI.

[4]Bank competition data are available from 1996, so our study period begins in 1997Q1.

allows the effects of GDP on credit to be measured, secondly takes account of the GDP cycle being a process that is not independent of the credit cycle, as there is 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 thirdly 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 meets these three criteria. So we opt for a multivariate framework and follow Bouvatier et al. (2012) in defining credit procyclicality as the orthogonalised impulse response function of the credit cycle to a GDP cycle shock.[5]

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:

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

where i and t are indexes of country and time, respectively, $Y_{i,t}$ is a 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.[6]

The country-specific VAR systems are estimated by OLS, and shocks are identified using a recursive identification scheme by applying a Cholesky decomposition of the residuals with the variables ordered as follows: CPI, GDP, $CRED$ and r. From this, 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 and it implies that financial variables may respond immediately to real shocks. By contrast, there is some discussion about the relative ordering of financial variables. 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 reacts 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.

We then have two options for testing the implication of bank competition for credit procyclicality. The first is to compare the average impulse response of countries with low and high levels of bank competition. This involves dividing the sample into two

[5] 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.

[6] Note that the order of the matrix polynomial is determined by the Akaike Information Criterion (AIC), where the maximum lag length has been fixed at four. CPI, GDP, $CRED$ and r refer to the 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.

groups of countries by their level of banking sector competition. To ensure comparability within this approach, we have to estimate a two-panel VAR and compare whether the orthogonalised impulse responses of credit to an output gap shock of one per cent are significantly different between the two groups of countries. Although this approach is tractable, it has two shortcomings; one is that it prevents variation in the degree of competition over time being considered, and the second is that it does not allow us to control for other sources of heterogeneity that could explain the difference between the two groups of countries. Therefore, an alternative specification of the VAR model is called for that would allow us to take account of the time-varying level of bank competition explicitly 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), Towbin 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 Towbin and Weber (2013).[7]

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

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

where $Z_{i,t-4}$ is a cross-time-varying measure of bank competition, I_i a set of country fixed effects and $\varepsilon_{i,t}$ is a vector of uncorrelated iid shocks.[8] The indices t and i relate to quarters and countries, respectively, while L is the number of lags.[9]

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

[7]We thank Sebastian Weber and Pascal Towbin for providing their MATLAB code for the interacted panel VAR procedure.

[8]To account for potential endogeneity, the variable measuring the bank competition is lagged by four quarters.
Furthermore, we should note that our model assumes that there are no dynamic cross-unit interdependencies, meaning 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.

[9]The lag length is fixed at two, based on the average optimal lag orders of the country-specific VAR.

coefficients $\alpha_{l,it}$ have the following form:

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

where β_l and η_l are two vectors of coefficients, and $Z_{i,t-4}$ is a cross-time-varying measure of bank competition. Therefore, all the structural parameters $\alpha_{l,it}$ are allowed to vary over time and across countries with the level of bank competition.

The fact that we require the impact matrix to 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 that in the country-specific VAR model, so the variables remain in the order CPI, GDP, $CRED$ and r.

One important aspect of our baseline panel VAR is that it includes country fixed effects. This may appear unnecessary since the endogenous variables in the VAR are in their HP-filtered forms since it purges unobserved unit-specific fixed effects by removing the country-specific trend from the series and implies zero-means.[10] Nevertheless, the structural characteristics present potential timeless specificities, and therefore we need to control for unobserved unit-specific factors, which could be sources of heterogeneity, by demeaning the data, which is the equivalent of 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).[11]

Another important feature of our empirical model is that it allows dynamic heterogeneity by making the slopes conditional on a cross-time-varying measure of competition. However, dynamic credit heterogeneity could be related to factors other than competition that could be 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 estimates to be inconsistent (Pesaran and Smith, 1995) and conclusions to be misleading. 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. The authors augment the baseline IPVAR model by interacting all the endogenous variables with country dummies. In

[10] In fact, the endogenous variables are not perfectly zero-centering. The reason is that we use a longer sample period in applying the HP filtering method than in estimating our model.

[11] 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.

this way, we can disentangle the coefficient heterogeneity caused by country-specific effects from that due to banking competition effects.[12]

After the IPVAR is estimated, 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. This gives us two different coefficient matrices with 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 address our research question of how credit procyclicality changes when bank competition moves from a low level to a high level.

Finally, a bootstrap procedure is used for inference of the impulse responses.[13] In the figures below, we report the mean of 1000 bootstrapped impulse responses with a 90% confidence band, meaning the lower bound of the band is the 5th percentile and the upper bound is the 95th 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 90% 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 in our empirical analysis is to assess cross-country heterogeneity in credit procyclicality by estimating a country-specific VAR model (Equation (1)) for each economy in our sample. Figure 1 displays the impulse responses of *Credit* or *Bank Credit* to a business cycle shock.[14] At first sight, the decision to examine the

[12]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 indicator of bank competition). Obviously, the model does not include fixed effects when we allow for unit specific slope heterogeneities.

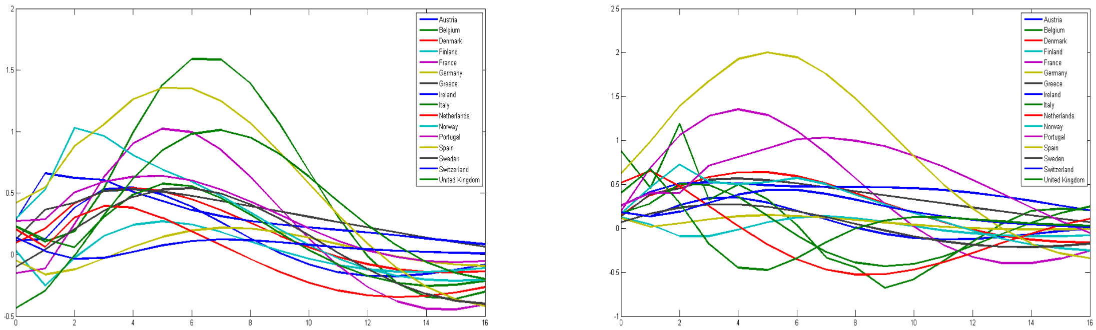
[13]The bootstrap procedure has the following steps. 1/Estimate the model by OLS on the original data. 2/ Draw an artificial vector of innovation from a normal distribution centred on zero and with a variance equal to the OLS estimated variance. 3/ Create artificial endogenous variables with the randomly resampled residuals, the original data and the structural coefficient OLS estimates. 4/ Interact the simulated endogenous variables with the interaction terms. 5/ Use the artificial endogenous and interaction variables to re-estimate the model by OLS. 6/ Compute the IRF for a high level and a low level of the interaction variable. 7/ Calculate the difference between the two IRF estimates. 8/Repeat the procedure 1000 times. 9/ Compute the mean, the 20th and 80th percentiles of the two types of IRF and of the IRF difference. See Towbin and Weber (2013) for more details about the bootstrap procedure.

[14]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 data generation process (DGP) of the macroeconomic variables,

responses of both total credit and bank credit cycles may appear irrelevant. Indeed, as the total credit cycle contains the bank credit cycle, the analysis might be redundant. Moreover, bank competition should primarily impact the bank credit cycle. However, in our view, it would be damaging to focus exclusively on the bank credit cycle responses. Indeed, since bank credit series do not include the securitised 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, wide differences in the weight of the "originate-to-distribute" model and in the financial structure across European economies mean that bank credit cycle responses might suffer from a lack of comparability.

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

(a) Total Credit (b) Bank Credit



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.

The chart on the left in Figure 1 depicts the orthogonalised country-specific responses of total credit to the non-financial sector to a shock in GDP, normalised to unity as a shock of one per cent in the output gap, with a simulation horizon of 16 quarters. As we can see, 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 responses are initially negative and become positive only after a few quarters. Furthermore, the IRFs other than that for Switzerland suggest that after a shock to the output gap the credit gap remains above the baseline value for at least seven quarters. The results for Germany are different from the others, since they highlight a very low and non-persistent impact from GDP on credit, meaning the behaviour of credit has low procyclicality. As a result, the next step, in which we test the effects of bank competition on procyclicality, should check that our panel data results are not driven by the behaviour of only some of the countries. Overall, chart (a) clearly shows the existence of major asymmetries in 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

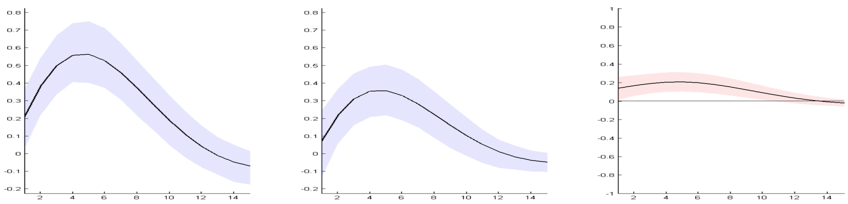
the inter-relations among these variables have been investigated. As expected, in almost all cases, we find Granger causality from GDP to credit and, quite often, reverse causality.

about the chart (b), which displays the heterogeneous responses of the bank credit cycle to a one-unit shock in the output gap.

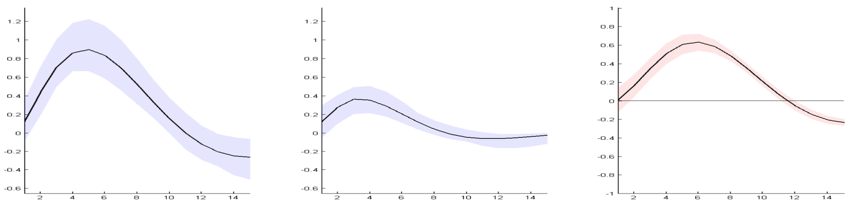
2.2.2 Main Results

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

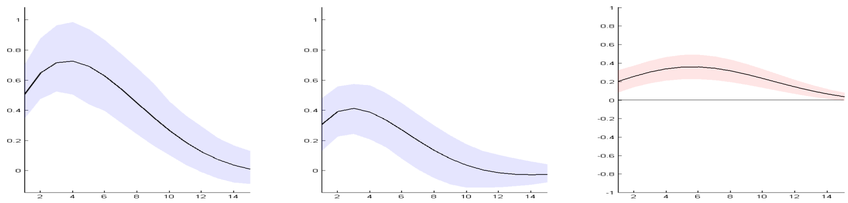
(a) Credit - Fixed Effects



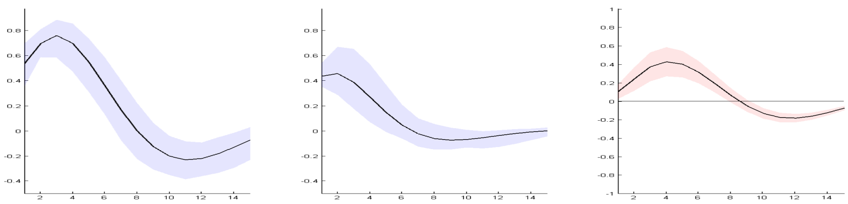
(b) Credit - Unit Specific Slope Heterogeneities



(c) Bank Credit - Fixed Effects



(d) Bank Credit - Unit Specific Slope Heterogeneities



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^{th} (high level) and 20^{th} (low level) percentiles of the Lerner index sample distribution. The charts on the right represent the differences between the two. The coloured bands represent 90% confidence bands generated by bootstrapping (1000 draws).

Figure 2 displays the impulse responses of the credit and bank credit cycles to a one-unit GDP cycle shock. The orthogonalised 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^{th} 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 centre show the impulse response functions evaluated at the 20^{th} percentile of the Lerner index sample distribution, where competition between banks is fierce. In both cases, the solid lines correspond to the mean impulse responses in a 90% band, which is computed by bootstrapping with 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 90% confidence band.

Before we present our main results, a few preliminary comments can be made about Figure 2. First, contrary to our expectations, the estimation of the model allowing unit-specific slope heterogeneity reduces the confidence interval of the impulse response functions.[15] Despite this difference in precision, the two estimators give broadly similar results. The only notable difference is in the persistence of the output-gap shocks, which are longer for fixed effects estimates. Comparing the responses of total credit and bank credit, we observe that bank credit has an immediate and very significant response to an exogenous change in the output gap, while the effects on total credit progressively become significantly positive. This is not puzzling in our view, 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. Apart from the initial impact however, the results do not suggest that bank credit and total credit behave differently.

There is clear evidence in the difference in the impulse responses that bank competition affects credit procyclicality. Indeed, the reaction of credit dynamics to GDP cycle shocks varies with the degree of bank competition. Specifically, the results suggest that a shock of one per cent to the output gap causes a greater response in credit in a less competitive banking market. As the charts on the right show, the differences between high and low levels of competition are significantly different from zero at the 10% 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.[16]

There are several possible explanations, which are not necessarily in opposition but

[15] 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.

[16] To corroborate our findings, we present the responses of credit to a GDP shock based on the estimations of two panel VARs for two groups of economies in Figure A1 of the Appendix. To split our panel into two sub-panels, we group the countries by 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. In fact, the average credit responses in countries where bank competition is lower on average are significantly greater than the credit responses in countries with relatively high levels of bank competition.

rather are complementary, for the positive association between greater bank competition and lower credit fluctuation.

The first one relies on the effects of competition on the bank rate setting strategy. The DSGE model of Aliaga-Díaz and Olivero (2010) or Gerali et al. (2010) show that market power increases the countercyclicality of the interest rate margin, which acts as a financial accelerator effect. In this view, face a positive (negative) economic activity shock, banking markets where competition is weaker decreases (increase) more strongly their margin. This naturally implies a stronger expand (shrink) of credit in such banking system as our empirical work shows.

The second one is more indirect and is based on risk-taking behaviour. It appears that our results could be related to the literature on bank competition and stability. 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; Atkins et al., 2016; Leroy and Lucotte, 2017) show that an increase in bank competition may lead banks to hold more capital, to engage in less risky activities or contribute less to systemic risk. Taking less risk implies that credit booms are less pronounced in the upward phase of the cycle, so banks experience smaller financial losses on their loans and other activities in the downward phase, which tends to preserve bank equity capital and the ability of banks to take new risks and supply new credit during a recession.

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. The financial accelerator theory posits that this 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 expectation that a GDP cycle shock has a smaller effect on output in competitive banking markets. Indeed, it appears that the GDP cycle returns to its baseline at a faster pace under these conditions.

2.2.3 Sensitivity Analysis

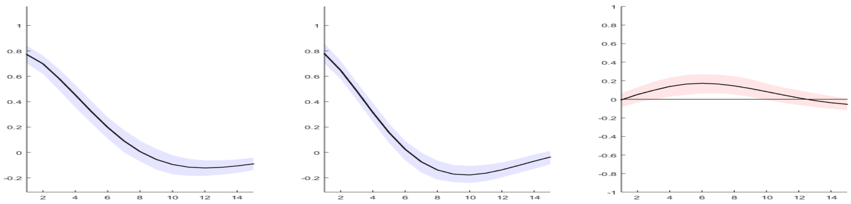
We perform a broad set of robustness checks, which may be grouped into four categories: (i) testing alternative specifications, (ii) changing the data definition and (iii) disentangling the effects of bank competition from other potential determinants that cause asymmetry in procyclicality.[17]

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 to reflect the dynamics of asset prices. This provides a more complete representation of the macro-level dynamics in response to several studies that show there to be linkages between credit, economic activity and asset prices (see Annett, 2005; Goodhart and Hofmann, 2008;

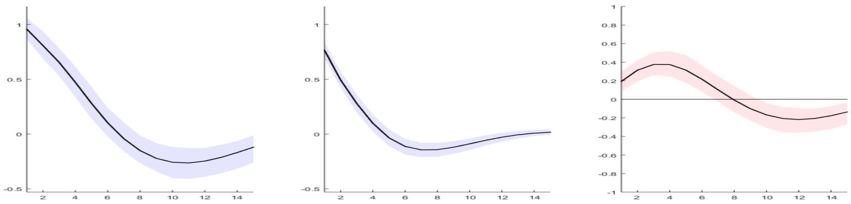
[17]The robustness tests will be based on the specification with fixed effects of our model.

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

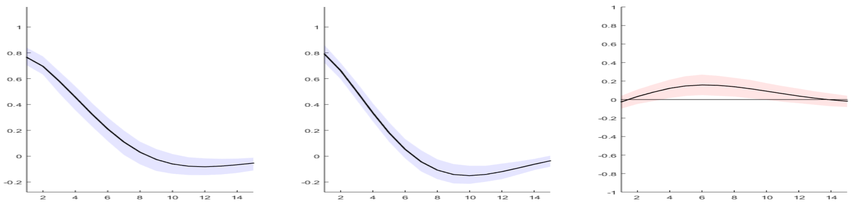
(a) Credit - Fixed Effects



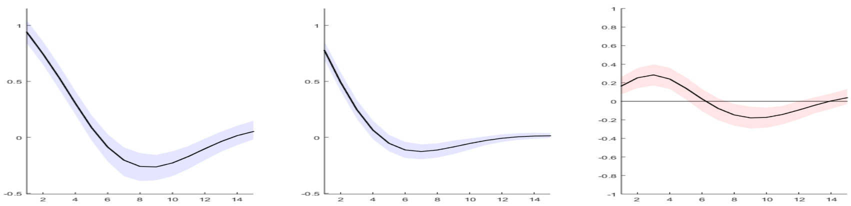
(b) Credit - Unit Specific Slope Heterogeneities



(c) Bank Credit - Fixed Effects



(d) Bank Credit - Unit Specific Slope Heterogeneities



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^{th} (high level) and 20^{th} (low level) percentiles of the Lerner index sample distribution. The charts on the right represent the differences between the two. The coloured bands represent the 90% error bands generated by bootstrapping (1000 draws).

Assenmacher-Wesche and Gerlach, 2008; Muellbauer and Murphy, 2008; Beltratti and Morana, 2010). In practice, we estimate a 6-dimensional interacted panel VAR models that enriches our baseline VAR with a measure of the house price and stock price cycle. The asset price series come last with house prices before sotck prices as in Assenmacher-Wesche and Gerlach (2008), meaning that credit is restricted from reacting immediately to asset prices.[18] Figure 4 depicts the results. As would be expected,

[18] This ordering choice is questionable as it implies for instance that policy makers do not use current asset prices when setting monetary policy. It also implicitly implies that house prices have a low degree of stickiness, since they respond immediately to credit innovations. As a result, we also test for the

the credit responses are not fundamentally different, and the differences in procyclicality between low and high competition environments remain significant.
Second, as is common in VAR models, we check the robustness of our findings by ordering the variables differently. Our recursive identification scheme in our baseline model places output gap before credit gap. For robustness, we now consider credit credit as the first variable in the ordering. By this way, the credit is not contemporaneously affected by shocks to the remaining variables, while shocks to the first variable do affect the other variables in the system. Specifically this alternative ordering means that credit is not contemporaneously affected by shocks to GDP, and it is considered to be more exogenous than in our baseline specification. Figure 4 displays the IRFs obtained with this alternative ordering and confirms our previous results.
Third, we check that our conclusions remain identical when we consider a longer lag of three lags for the autoregressive terms and when we marginally change our sample. For this robustness test, we re-estimate our canonical econometric model by dropping one country at a time.[19] In this way, we can be sure that our results are not driven by the inclusion of any one 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.[20] One is that it implies an a priori definition of the cycle frequency of the time series, meaning an arbitrary value is set for the smoothing parameter. In our benchmark model, we have chosen to estimate the cycles at the business cycle frequency for all the macroeconomic series, and we have set the smoothing parameter to 1600, corresponding to cycles that last between one and eight 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. To address this caveat, we assume that credit cycles are twice as long as the usual business cycle and we follow the approach of Ravn and Uhlig (2002) to obtain the corresponding value of the smoothing parameter. These authors show that it is optimal to set lambda to 1600 multiplied by the fourth power of the observation frequency ratio, which here is two. Thus we set the lambda of the credit series to 25,600 to obtain a cycle that lasts twice as long as the business cycle.[21] 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 behaviour of the series. On the whole, the graphs displayed in Figure 5 indicate that our results are

possibility that credit responds immediately to asset prices by considering the asset price variable before credit. The results are not affected by this change.

[19] These results are not reported but available upon request.

[20] Note that the typical issue of the end-point problem has been addressed by estimating the model over the period 1997Q1–2014Q4 using data through to 2015Q4. The starting point also presents some statistical problems (Drehmann and Tsatsaronis, 2014). Therefore, we estimate cycles from 1997Q1 using data starting in 1990Q1.

[21] Lowe et al. (2002) suggest setting lambda to 400,000 to isolate the 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 the medium-term frequencies of the credit series. Furthermore, this choice is in line with the financial accelerator theory, which focuses on the 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 criticised by Borio (2014).

robust to the filtering method.[22]

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 capitalisation 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 how they affect our results. Therefore we extend our baseline model by including three additional interaction variables at the same time, so that $Z_{i,t}$ is now a $(4 * 1)$ 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.[23] Analysing the results in Figure 6, we observe that controlling for the correlations between bank competition and other structural characteristics does not change our previous findings.[24]
Finally, we test whether conditionally to the degree of competition output and credit are differently linked in the upward and downward phases of the business cycle. According to our theoretical arguments the procyclical effect of bank competition should act in similar fashion in the two phases. Interest rate margins and risk-taking would decrease and increase, respectively, in the upward phase of the cycle and would have opposite behaviour after the peak of the cycle. In practice, we extend our IPVAR model by including a dummy variable in interaction, set equal to one when there is a positive output gap in period t in country i and equal to zero otherwise. In order to compare asymmetry, we represent IRFs conditionally to the position in the business cycle (upward or downward phases) for a median level of competition. The results in Figure 6 reveal that the dynamic response of credit to output, conditional to the degree of competition, is not significantly different from zero between the two phases of the business cycle. This supports our view that competition has an effect in the upward as well as downward phases of the cycle.

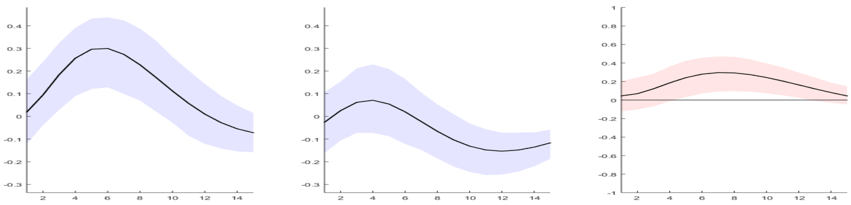
[22]We also run robustness checks for the transformation of the Lerner index (not reported in this paper). We consider two other versions of the Lerner index: one without quarterly interpolation and another with interpolation and smoothing with the HP filter, as in Georgiadis (2014). These amendments do not affect our findings.

[23]These three variables are extracted or built 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 bank credit over stock market capitalization ratio, respectively.

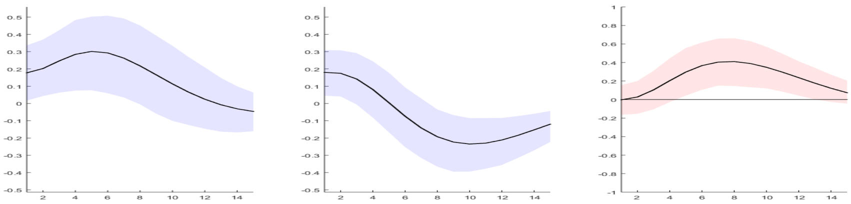
[24]This additional analysis might refine our explanations for imperfect competition as a propagation mechanism of an output-gap shock. Two explanations have previously been given, which are that imperfect competition increases the interest rate counter-cyclicality, and that imperfect competition exacerbates risk-taking behaviour. 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 plays a very significant role. However, this does not imply that the second effect (that imperfect competition exacerbates risk-taking behaviour) is irrelevant.

Figure 4: Impulse Response Functions of Credit to a GDP shock: 6-dimensional VAR - Different ordering of the variables

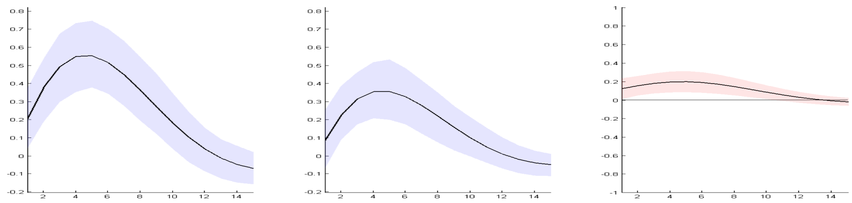
(a) Credit - Assets prices



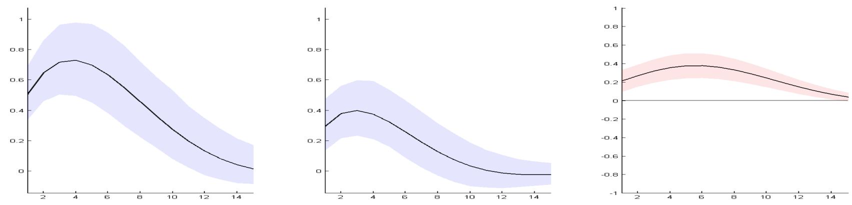
(b) Bank Credit - Assets prices



(c) Credit - Different ordering



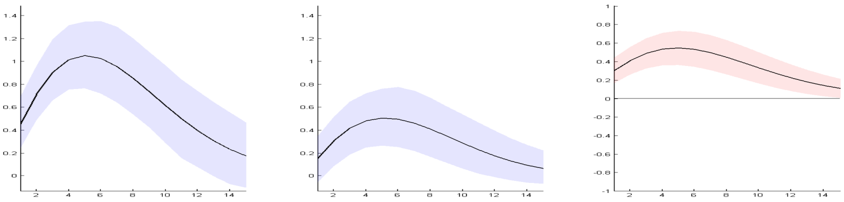
(d) Bank Credit - Different ordering



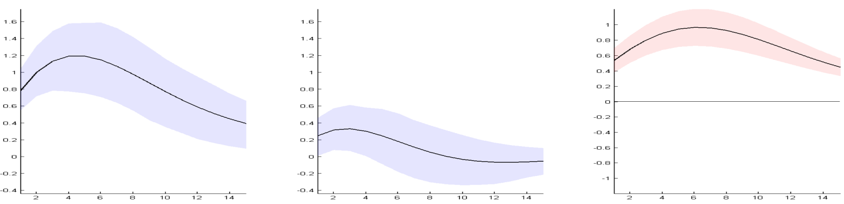
Note: The figure shows the impulse responses of credit and bank credit to a one-percentage-point shock in the output cycle evaluated (from left to right) at the 80^{th} (high level) and 20^{th} (low level) percentiles of the Lerner index sample distribution. The charts on the right represent the difference between the two. The coloured bands represent the 90% confidence bands generated by bootstrapping (1000 draws).

Figure 5: Impulse Response Functions of Credit to a GDP shock: HP filter with λ equal to 25600 and Baxter-King Filter

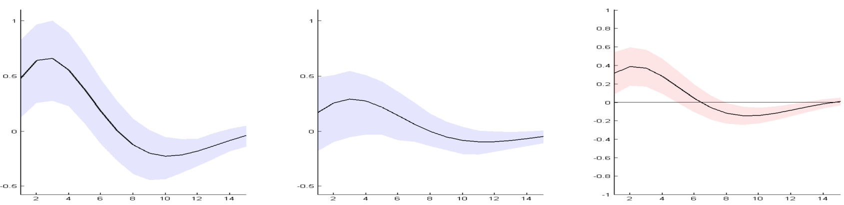
(a) Credit - HP filter



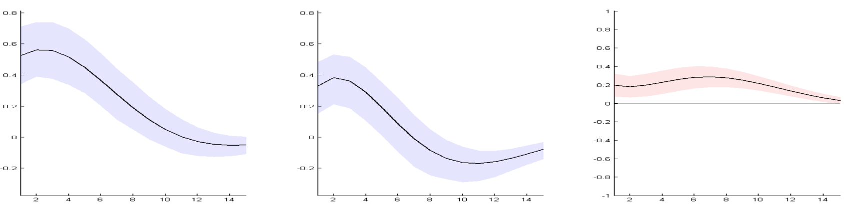
(b) Bank Credit - HP filter



(c) Credit - BK Filter



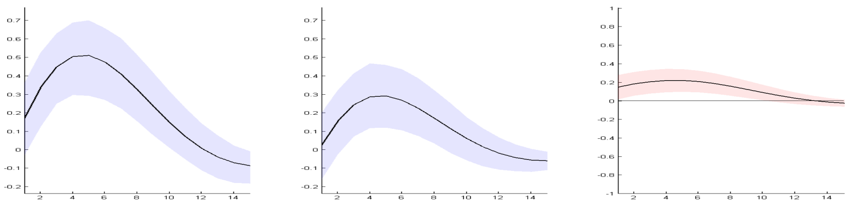
(d) Bank Credit - BK Filter



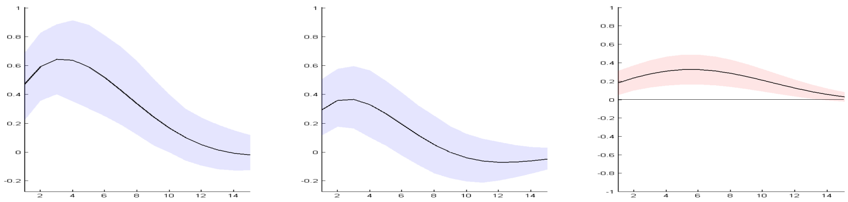
Note: The figure shows impulse responses of credit and bank credit to a one-percentage-point shock in the output cycle evaluated (from left to right) at the 80^{th} (high level) and 20^{th} (low level) percentiles of the Lerner index sample distribution. The charts on the right represent the differences between the two. The colored bands represent the 90% confidence bands generated by bootstrapping (1000 draws).

Figure 6: Impulse Response Functions of Credit to a GDP shock: Controlling for correlation with other structural characteristics - Asymmetry

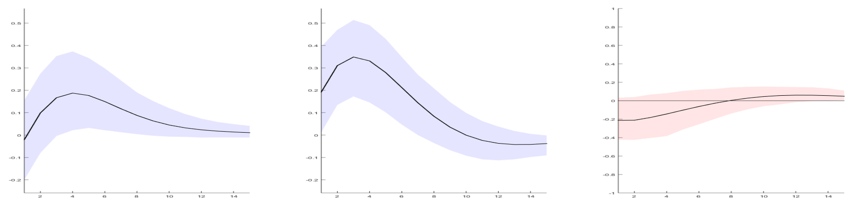
(a) Credit - Control variables



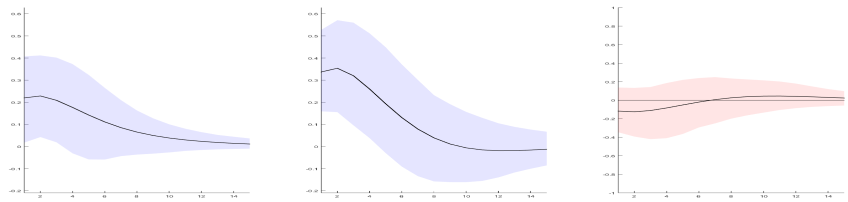
(b) Bank Credit - Control variables



(c) Credit - Asymmetry



(d) Bank Credit - Asymmetry



Note: The charts (a) and (b) show 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^{th} (high level) and 20^{th} (low level) percentiles of the Lerner Index sample distribution and the median of three control variables. The charts (c) and (d) show impulse responses of credit and bank credit to a one-percentage-point shock in the output cycle evaluated at the median of the Lerner Index sample distribution for the case where the output gap is negative (in the left) and the case where the output gap is positive (in the center). The charts on the right represent the difference between the two. The coloured bands represent the 90% confidence bands 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. Those required are a mix of bank-level and country-level data. We take bank balance sheet and income statement information from the Bankscope database published by the Bureau Van Dijk, which provides comprehensive detailed information on European banking. Our sample comprises more than 3,600 banks operating in the 16 previously analysed economies.[25] This means the geographical coverage is identical in both sections. The time dimension differs between the two however, 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 statements to avoid any double counting of commercial, cooperative and saving banks. Then we exclude banks for which financial statements are available for less than five consecutive years to preserve the benefits of the panel dimension of our sample, and we drop banks for which the loan-to-asset ratio is missing for any one of these five minimal 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 the banks' balance sheets as this is our dependent variable, and to build a set of control variables and an indicator of bank market power, which varies across banks and over time. We measure the 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:

$$Lerner_{it} = \frac{p_{it} - mc_{it}}{p_{it}} \tag{4}$$

where p is the price and mc is the marginal cost for 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. We obtain the marginal cost by employing 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, for instance, Berger et al., 2009, Turk Ariss, 2010, Anginer et al., 2014). Thus, we estimate the following translog cost function:

$$\begin{aligned} lnTC_{it} = {} & \beta_0 + \beta_1 lnTA_{it} + \frac{\beta_2}{2} lnTA_{it}^2 + \sum_{k=1}^{3} \gamma_k lnW_{k,it} + \sum_{k=1}^{3} \phi_k lnTA_{it} lnW_{k,it} \\ & + \sum_{k=1}^{3}\sum_{j=1}^{3} \frac{\rho_{kj}}{2} lnW_{k,it} lnW_{j,it} + \delta_1 T + \frac{\delta_2}{2} T^2 + \delta_3 T lnTA_{it} + \sum_{k=4}^{6} \delta_k T lnW_{k,it} + \varepsilon_{it} \end{aligned} \tag{5}$$

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,

[25] Since not all variables are available for all bank-year observations, the sample size differs from one regression to another.

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, and $W_{3,it}$ 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 winsorised at the 1st and 99th percentiles (see, for instance, 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 $\sum_{k=1}^{3} \sum_{j=1}^{3} \rho_k = 0$. 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:

$$mc_{it} = \frac{TC_{it}}{TA_{it}}[\beta_1 + \beta_2 TA_{it} + \sum_{k=1}^{3} \phi_k lnW_{k,it} + \delta_3 T] \tag{6}$$

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 indexes. The rationale is that this approach is based on the implicit assumption that banks are fully efficient. To correct this potential bias, the authors propose an efficiency-adjusted estimate of the conventional Lerner index:

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

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 $\hat{mc}_{it}$. This approach has the advantage of taking account of the banks' cost inefficiency, which is defined as the distance of a bank from the cost frontier accepted as the benchmark.[26] 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 indexes are built by taking the median value by country and year of our own individual estimates of the conventional and efficiency-adjusted Lerner indexes. Finally, our analysis also requires a yearly measure of business cycle fluctuation. For that, we use the output-gap measure

[26]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 μ_{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.

from the OECD Economic Outlook database, which is defined as the deviation in % of actual GDP from the potential GDP obtained from a production function framework. 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 how banks react in their supply of loans to an output-gap shock. 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 $i = 1, ..., N$, $c = 1, ..., 16$, and $t = 1, ..., T$. N denotes the number of banks, c the country and T the total number of years. In our model, the growth rate of loans ($\Delta ln(loans_{it})$) is regressed on the output gap (OG_{ct}), the Lerner index ($Lerner_{i,t-1/c,t-1}$),[27] their product term ($OG_{ct} * Lerner_{i,t-1/c,t-1}$), which is 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 (μ_i) (or country fixed effects (μ_c) in some specifications) and year fixed effects (λ_t) to capture bank specificities and time-varying common shocks.[28]

Unlike in the cross-country analysis, the single equation modelling is perfectly appropriate here. Indeed, the possibility of the output gap of country i responding 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. 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 the remaining concerns about endogeneity that arise because banking markets are not atomistic and 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

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

[28] 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).

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.[29]

From these estimates, the first step is to check that credit is procyclical on average, so that 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, meaning 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 coefficients vary between 1.442 and 1.677 and are statistically very significant. These results imply that GDP growth of one percentage point below its potential is associated with a decline in loan growth of approximately 1.5 percentage points.

The second step is to check whether the level of procyclicality varies with the level of bank competition. Across all specifications, the interaction of the *Lerner index* and the *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. As well as statistical significance, we also check the economic significance of the relationship. To do so, as in the 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 sizeable. For instance, in specification (1), the estimated procyclicality is 1.443 for a low level of the Lerner index and 1.896 for a high level. In summary, the estimations with granular data corroborate the findings of the previous section that 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.[30] The more competitive the market, more important the growth of loans, which is consistent with the traditional microeconomic view. Furthermore, bank size, taken as the log of total assets, and the loan ratio are negatively associated with loan growth. Finally, regressions (4), (8) and (12) give us some interesting results about 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 (ΔMP) has the expected negative sign. In regression (4), an increase of one 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 that the interaction terms of ΔMP and *Lerner index* are significantly positive. This indicates that lower bank competition strengthens the bank-lending channel through monetary policy transmission.

[29] All specifications include year fixed effects.

[30] The average output gap is equal to -0.506.

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 movements in the demand for credit from those in the supply of it. This follows the hypothesis that bank-specific market power influences the loan supply, while loan demand is independent of changes in the market power of banks.[31] Regressions (1)-(5) present estimates with the conventional Lerner index, and regressions (5)-(10) present those with the efficiency-adjusted Lerner index. Regressions (1) and (6) only include the *output gap*, the *Lerner index* and their product as explanatory variables. Regressions (2) and (7) include more control variables, regressions (3) and (8) control for the existence of a bank-lending channel, regressions (4) and (9) control for the existence of country fixed effects, while regressions (5) and (10) control for time-varying country-specific characteristics.

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 the efficiency-adjusted Lerner indexes. Interestingly, we also observe that the economic impact of bank market power on credit procyclicality remains sizeable and comparable to the previous estimates. For instance, moving from the 20^{th} percentile of the conventional Lerner Index to the 80^{th} percentile increases the sensitivity of bank-lending growth to the change of the business cycle by 0.453 point for regression (1). The effects are slightly less important with the efficiency-adjusted Lerner index since the interquintile values are 0.366 in regression (5) and 0.262 in regression (6).

[31]By contrast, it is less certain that loan demand is independent of the aggregate level of bank competition, since that level could impact the cost of credit, and be correlated with macroeconomic factors affecting credit demand.

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)			
Dependent variable: Δln(Loans)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Output Gap	1.064***	1.082***	1.094***	1.086***	-0.801***	-0.464*	-0.832***	-0.996***	-0.455***	-0.247	-0.299*	-0.346**
	(0.095)	(0.100)	(0.098)	(0.097)	(0.261)	(0.245)	(0.233)	(0.271)	(0.156)	(0.161)	(0.160)	(0.159)
Lerner index	-19.619***	-21.031***	-18.394***	-16.331***	15.567***	-2.525	-1.060	9.931**	17.100***	13.573***	14.680***	18.468***
	(1.995)	(2.091)	(2.046)	(2.231)	(5.326)	(5.826)	(5.996)	(4.609)	(1.888)	(1.976)	(2.040)	(1.776)
Output Gap*Lerner index	3.713***	3.079***	2.908***	3.185***	10.895***	9.712***	11.082***	11.491***	8.256***	7.362***	7.433***	7.363***
	(0.487)	(0.503)	(0.501)	(0.530)	(1.113)	(1.071)	(1.007)	(1.129)	(0.674)	(0.724)	(0.725)	(0.621)
Total assets		-13.416***	-13.496***	-0.502***		-13.025***	-13.073***	-0.508***		-12.154***	-12.256***	-0.494***
		(1.493)	(1.489)	(0.070)		(1.500)	(1.493)	(0.070)		(1.391)	(1.392)	(0.070)
Loans / Total assets		-28.359***	-26.845***	-6.142***		-30.735***	-29.647***	-6.859***		-28.272***	-27.610***	-6.801***
		(2.472)	(2.489)	(0.731)		(2.555)	(2.569)	(0.739)		(2.345)	(2.363)	(0.740)
Equity / Total assets		-13.108	-13.882	-0.783		-20.004**	-21.966**	-2.771		-20.673**	-21.801**	-2.869
		(9.337)	(9.353)	(2.586)		(8.901)	(8.909)	(2.604)		(8.925)	(8.936)	(2.604)
Δ MP			-2.194***	-2.574***			-2.148***	-1.896**			-1.730***	-1.840***
			(0.233)	(0.255)			(0.805)	(0.774)			(0.523)	(0.457)
Δ MP * Lerner index			8.220***	8.902***			3.789	1.486			4.690***	4.257**
			(1.301)	(1.741)			(3.380)	(3.338)			(1.774)	(1.683)
Constant	17.930***	214.188***	213.475***	28.501***	11.868***	208.321***	207.302***	22.319***	9.464***	190.398***	190.884***	19.324***
	(0.378)	(20.894)	(20.828)	(1.260)	(1.049)	(21.232)	(21.137)	(1.503)	(0.562)	(19.607)	(19.641)	(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^{th} and the 80^{th} 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)				
Dependent variable: Δln(Loans)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Output Gap	0.933***	0.866***	0.807***	0.959***	3.341***	1.054***	1.174***	1.100***	1.053***	3.811***
	(0.128)	(0.141)	(0.138)	(0.112)	(0.274)	(0.110)	(0.114)	(0.118)	(0.107)	(0.268)
Lerner index	5.592***	6.400***	5.914***	3.751***	2.719	8.777***	7.951***	7.874***	5.941***	0.370
	(1.681)	(1.778)	(1.809)	(1.281)	(1.738)	(0.975)	(1.037)	(1.079)	(0.904)	
Output Gap*Lerner index	3.493***	3.527***	3.589***	3.074***	0.938**	2.440***	1.746***	1.857***	2.204***	
	(0.440)	(0.483)	(0.481)	(0.385)		(0.325)	(0.308)	(0.325)	(0.307)	
Total assets		-13.660***	-13.736***	-0.439***	-6.392***		-14.299***	-14.369***	-0.250***	
		(1.527)	(1.516)	(0.059)	(1.162)		(1.682)	(1.671)	(0.065)	
Loans / Total assets		-29.748***	-28.617***	-6.279***	-28.389***		-28.942***	-27.817***	-5.785***	
		(2.508)	(2.521)	(0.664)	(2.266)		(2.649)	(2.660)	(0.679)	
Equity / Total assets		-19.345**	-20.078**	-1.606	-4.142***		-21.327**	-22.413**	-0.085	
		(9.328)	(9.336)	(2.609)	(8.397)		(10.257)	(10.249)	(3.019)	
Δ MP			-0.618**	-0.898**	-11.987***			-0.931***	-1.217***	
			(0.292)	(0.352)	(0.752)			(0.350)	(0.400)	
Δ MP * Lerner index			-2.247**	-1.902*	-2.152*			-0.511	-0.213	
			(0.923)	(1.062)	(1.120)			(0.909)	(0.959)	
Constant	13.824***	213.870***	213.664***	22.637***	99.569***	12.159***	221.074***	220.733***	18.741***	
	(0.354)	(21.281)	(21.135)	(1.042)	(15.988)	(0.357)	(23.646)	(23.501)	(1.216)	
Average Lerner index	0.209	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	0.146	0.163	0.163	0.163	0.163	
High Lerner index	0.275	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^{th} and the 80^{th} 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 Conclusion

This paper is the first to assess empirically whether the degree of competition in the financial system constitutes a driving force for credit procyclicality. More specifically, 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 uses 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 orthogonalised 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. It lets us compute and compare impulse response functions according to the level of competition. The second approach uses bank-level data to estimate 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 in Europe, we analyse whether the market power of each bank affects the link between the output gap and the annual growth rate of loans. Following the existing literature, the level of competition within the banking industry is proxied by the Lerner index, which measures how far firms can mark price up above marginal cost, and 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 indexes in our micro-level analysis.

The results at the macro-level and the micro-level suggest that the procyclicality of credit is higher in economies where competition among banks is relatively weak. 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. There are two possible reasons for this result. The first is that market power can incite banks to set countercyclical margins as theoretically shown by Aliaga-Díaz and Olivero (2010) and Mandelman (2011). The second possible explanation is more indirect and comes from the literature on the nexus between bank competition and financial stability as well as between bank competition and information asymmetries. On the first point, a large theoretical and empirical literature supports the fact that banks hold more capital and engage in less risky activities when competition increases. This reduction in the risk-taking behaviour of banks can imply 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. On the second point, competition may lead banks to operate in a more efficient way, notably by improving the screening and monitoring of borrowers. Asymmetric information would be reduced, which would reduce the amplification mechanism of the financial accelerator.

The policy implications of our findings are that promoting competition within the European banking sector should ensure lower procyclicality of credit, making investment and consumption less sensitive to the business cycle. Such a pro-competitive policy would be expected to reduce macroeconomic volatility by limiting the amplification mechanism from the financial sphere to the real sphere. Furthermore, lower credit procyclicality should limit credit booms and the 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; Gourinchas and Obstfeld, 2012), our results can also be read as evidence that greater bank competition contribute to reduce systemic risk. As a result, there is a priori no tensions between the objectives of competition and macroprudential authorities. Conversely, there are strong complementarities between the two policies (IMF, 2013). Macroprudential policy makers, especially if they have the objective to act pro-actively to contain the build-up of systemic vulnerability over the time, have an interest that the financial system be competitive. At the top of their agenda, the TBTF problem could be address with competition policies, especially in Europe where the competition authority monitors the state aids - that distorts in the case of TBTF entities fair competition. Improving banking integration, via an increase of cross-border banking competition, could also be complementary to the objective of the macroprudential authority since it will ensure a better diversity of the national banking markets.

References

Albertazzi, U. and Gambacorta, L. (2009). Bank profitability and the business cycle. *Journal of Financial Stability*, 5(4):393–409.

Aliaga-Díaz, R. and Olivero, M. P. (2010). Macroeconomic implications of “deep habits” in banking. *Journal of Money, Credit and Banking*, 42(8):1495–1521.

Allen, F., Carletti, E., and Marquez, R. (2011). Credit market competition and capital regulation. *Review of Financial Studies*, 24(4):983–1018.

Andrés, J. and Arce, O. (2012). Banking competition, housing prices and macroeconomic stability. *The Economic Journal*, 122(565):1346–1372.

Anginer, D., Demirguc-Kunt, A., and Zhu, M. (2014). How does competition affect bank systemic risk? *Journal of Financial Intermediation*, 23(1):1–26.

Annett, A. (2005). *Assessing the Determinants of Interest Rate Transmission Through Conditional Impulse Response Functions*, volume 05/266. IMF Country Report.

Assenmacher-Wesche, K. and Gerlach, S. (2008). *Monetary policy, asset prices and macroeconomic conditions: a panel-VAR study.* National Bank of Belgium Working Papers.

Athanasoglou, P. P., Daniilidis, I., and Delis, M. D. (2014). Bank procyclicality and output: Issues and policies. *Journal of Economics and Business*, 72:58–83.

Atkins, B., Li, L., Ng, J., and Rusticus, T. O. (2016). Bank competition and financial stability: evidence from the financial crisis. *Journal of Financial and Quantitative Analysis*, 51(01):1–28.

Bassett, W. F., Chosak, M. B., Driscoll, J. C., and Zakrajšek, E. (2014). Changes in bank lending standards and the macroeconomy. *Journal of Monetary Economics*, 62:23–40.

Baxter, M. and King, R. G. (1999). Measuring business cycles: approximate band-pass filters for economic time series. *Review of economics and statistics*, 81(4):575–593.

Beck, T., De Jonghe, O., and Schepens, G. (2013). Bank competition and stability: cross-country heterogeneity. *Journal of financial Intermediation*, 22(2):218–244.

Beltratti, A. and Morana, C. (2010). International house prices and macroeconomic fluctuations. *Journal of Banking & Finance*, 34(3):533–545.

Berger, A. N., Demirguc-Kunt, A., Levine, R., and Haubrich, J. G. (2004). Bank concentration and competition: An evolution in the making. *Journal of Money, Credit, and Banking*, 36(3):433–451.

Berger, A. N., Klapper, L. F., and Turk-Ariss, R. (2009). Bank competition and financial stability. *Journal of Financial Services Research*, 35(2):99–118.

Berger, A. N. and Mester, L. J. (1997). Inside the black box: What explains differences in the efficiencies of financial institutions? *Journal of banking & finance*, 21(7):895–947.

Bernanke, B. and Gertler, M. (1989). Agency costs, net worth, and business fluctuations. *The American Economic Review*, pages 14–31.

Bernanke, B. S. and Blinder, A. S. (1988). Credit, money, and aggregate demand. *The American Economic Review*, 78(2):435–439.

Bernanke, B. S., Gertler, M., and Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. In Taylor, J. B. and Woodford, M., editors, *Handbook of macroeconomics*, volume 1, chapter 21, pages 1341–1393. Elsevier.

Borio, C. (2014). The financial cycle and macroeconomics: What have we learnt? *Journal of Banking & Finance*, 45:182–198.

Bouvatier, V., López-Villavicencio, A., and Mignon, V. (2012). Does the banking sector structure matter for credit procyclicality? *Economic Modelling*, 29(4):1035–1044.

Boyd, J. H. and De Nicolo, G. (2005). The theory of bank risk taking and competition revisited. *The Journal of Finance*, 60(3):1329–1343.

Boyd, J. H., De Nicolò, G., and Jalal, A. M. (2006). *Bank risk-taking and competition revisited: New theory and new evidence.* International Monetary Fund WP/06/297.

Calem, P. S., Gordy, M. B., and Mester, L. J. (2006). Switching costs and adverse selection in the market for credit cards: New evidence. *Journal of Banking & Finance*, 30(6):1653–1685.

Canova, F. and Ciccarelli, M. (2013). *Panel vector autoregressive models: a survey.* ECB Working Papers.

Cetorelli, N. and Gambera, M. (2001). Banking market structure, financial dependence and growth: International evidence from industry data. *The Journal of Finance*, 56(2):617–648.

Claessens, S. and Laeven, L. (2005). Financial dependence, banking sector competition, and economic growth. *Journal of the European Economic Association*, 3(1):179–207.

de Guevara, J. F. and Maudos, J. (2011). Banking competition and economic growth: Cross-country evidence. *The European Journal of Finance*, 17(8):739–764.

Degryse, H. and Ongena, S. (2008). Competition and regulation in the banking sector: A review of the empirical evidence on the sources of bank rents. *Handbook of financial intermediation and banking*, 2008:483–554.

Dell'Ariccia, G. and Marquez, R. (2006). Lending booms and lending standards. *The Journal of Finance*, 61(5):2511–2546.

Drehmann, M., Borio, C. E., and Tsatsaronis, K. (2012). *Characterising the financial cycle: don't lose sight of the medium term!* BIS Working Papers.

Drehmann, M. and Tsatsaronis, K. (2014). The credit-to-gdp gap and countercyclical capital buffers: questions and answers. *BIS Quarterly Review.*

Fungáčová, Z., Solanko, L., and Weill, L. (2014). Does competition influence the bank lending channel in the euro area? *Journal of Banking & Finance*, 49:356–366.

Georgiadis, G. (2014). Towards an explanation of cross-country asymmetries in monetary transmission. *Journal of Macroeconomics*, 39:66–84.

Gerali, A., Neri, S., Sessa, L., and Signoretti, F. M. (2010). Credit and banking in a dsge model of the euro area. *Journal of Money, Credit and Banking*, 42(s1):107–141.

Goodhart, C. and Hofmann, B. (2008). House prices, money, credit, and the macroeconomy. *Oxford Review of Economic Policy*, 24(1):180–205.

Gourinchas, P.-O. and Obstfeld, M. (2012). Stories of the twentieth century for the twenty-first. *American Economic Journal: Macroeconomics*, 4(1):226–265.

Hellmann, T. F., Murdock, K. C., and Stiglitz, J. E. (2000). Liberalization, moral hazard in banking, and prudential regulation: Are capital requirements enough? *American economic review*, pages 147–165.

IMF (2013). Key aspects of macroprudential policy. Imf policy paper, IMF.

Jiménez, G., Lopez, J. A., and Saurina, J. (2013). How does competition affect bank risk-taking? *Journal of Financial Stability*, 9(2):185–195.

Judson, R. A. and Owen, A. L. (1999). Estimating dynamic panel data models: a guide for macroeconomists. *Economics Letters*, 65(1):9–15.

Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *The American Economic Review*, pages 1183–1200.

Kindleberger, C. (2000). *Manias, panics, and crashes: a history of financial crises*. Wiley.

Kiyotaki, N. and Moore, J. (1997). Credit cycles. *Journal of Political Economy*, 105(2):211–48.

Koetter, M., Kolari, J. W., and Spierdijk, L. (2012). Enjoying the quiet life under deregulation? evidence from adjusted lerner indices for us banks. *Review of Economics and Statistics*, 94(2):462–480.

Leroy, A. (2014). Competition and the bank lending channel in eurozone. *Journal of International Financial Markets, Institutions and Money*, 31:296–314.

Leroy, A. and Lucotte, Y. (2015). Heterogeneous monetary transmission process in the eurozone: Does banking competition matter? *International Economics*, 141:115–134.

Leroy, A. and Lucotte, Y. (2017). Is there a competition-stability trade-off in european banking? *Journal of International Financial Markets, Institutions and Money*, 46:199–215.

Loayza, N. V. and Raddatz, C. (2007). The structural determinants of external vulnerability. *The World Bank Economic Review*, 21(3):359–387.

Lowe, P., Borio, C., et al. (2002). *Asset prices, financial and monetary stability: exploring the nexus*. BIS Working Papers.

Lown, C. and Morgan, D. P. (2006). The credit cycle and the business cycle: new findings using the loan officer opinion survey. *Journal of Money, Credit and Banking*, pages 1575–1597.

Mandelman, F. S. (2011). Business cycles and the role of imperfect competition in the banking system. *International Finance*, 14(1):103–133.

Minsky, H. P. (1982). *Can it happen again?: Essays on instability and finance.* New York. ME Sharpe.

Muellbauer, J. and Murphy, A. (2008). Housing markets and the economy: the assessment. *Oxford Review of Economic Policy*, 24(1):1–33.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society*, pages 1417–1426.

Peia, O. and Roszbach, K. (2015). Finance and growth: time series evidence on causality. *Journal of Financial Stability*, 19:105–118.

Pesaran, M. H. and Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 68(1):79–113.

Ravn, M. O. and Uhlig, H. (2002). On adjusting the hodrick-prescott filter for the frequency of observations. *Review of Economics and Statistics*, 84(2):371–376.

Ravn, S. H. (2016). Endogenous credit standards and aggregate fluctuations. *Journal of Economic Dynamics and Control*, 69:89–111.

Reinhart, C. M. and Rogoff, K. S. (2009). *This time is different: eight centuries of financial folly.* Princeton University Press.

Ruckes, M. (2004). Bank competition and credit standards. *Review of Financial Studies*, 17(4):1073–1102.

Sá, F., Towbin, P., and Wieladek, T. (2014). Capital inflows, financial structure and housing booms. *Journal of the European Economic Association*, 12(2):522–546.

Schaeck, K. and Cihak, M. (2012). Banking competition and capital ratios. *European Financial Management*, 18(5):836–866.

Schaeck, K. and Cihák, M. (2014). Competition, efficiency, and stability in banking. *Financial Management*, 43(1):215–241.

Schaeck, K., Cihák, M., and Wolfe, S. (2009). Are competitive banking systems more stable? *Journal of Money, Credit and Banking*, 41(4):711–734.

Schularick, M. and Taylor, A. M. (2012). Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008. *American Economic Review*, 102(2):1029–1061.

Sørensen, C. K. and Werner, T. (2006). Bank interest rate pass-through in the euro area: a cross country comparison. Technical report, ECB working paper.

Towbin, P. and Weber, S. (2013). Limits of floating exchange rates: The role of foreign currency debt and import structure. *Journal of Development Economics*, 101:179–194.

Turk Ariss, R. (2010). On the implications of market power in banking: Evidence from developing countries. *Journal of banking & Finance*, 34(4):765–775.

Uhde, A. and Heimeshoff, U. (2009). Consolidation in banking and financial stability in Europe: Empirical evidence. *Journal of Banking & Finance*, 33(7):1299–1311.

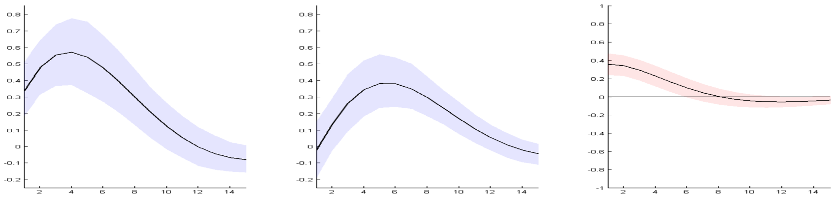
Van Leuvensteijn, M., Sørensen, C. K., Bikker, J. A., and Van Rixtel, A. A. (2013). Impact of bank competition on the interest rate pass-through in the euro area. *Applied Economics*, 45(11):1359–1380.

Woodford, M. (2003). Interest and prices.

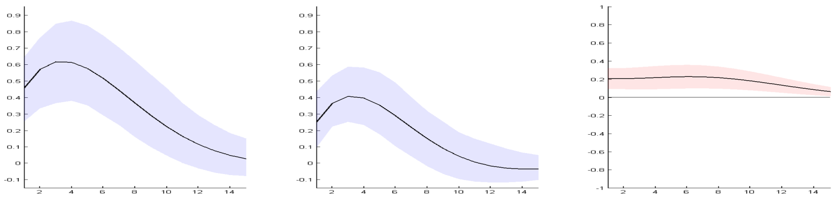
Appendix

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

(a) Total Credit



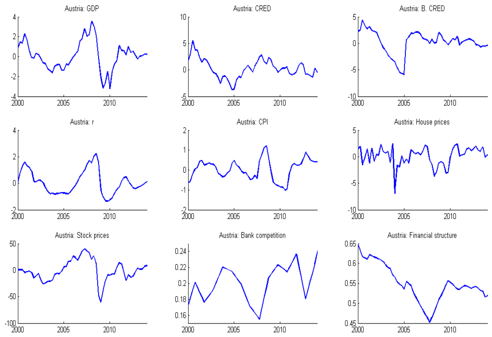
(b) Bank Credit



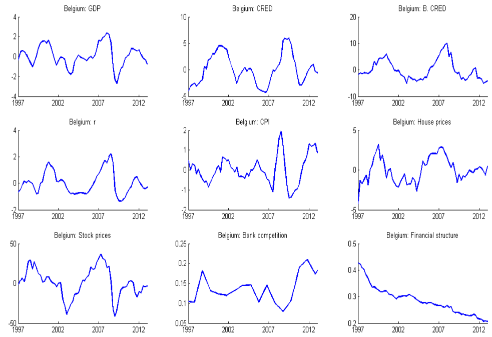
Note: This figure compares the impulse response functions of credit/bank credit to a one-unit shock in GDP for economies characterized by a low and a high level of competition in the banking industry. In order to split our initial sample into two groups, we rank the countries according to the country average Lerner index value. 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. The low bank competition sub-sample comprises Austria, Denmark, Greece, Ireland, Norway, Spain, Sweden and the United Kingdom. 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).

Figure A2: Time series by country

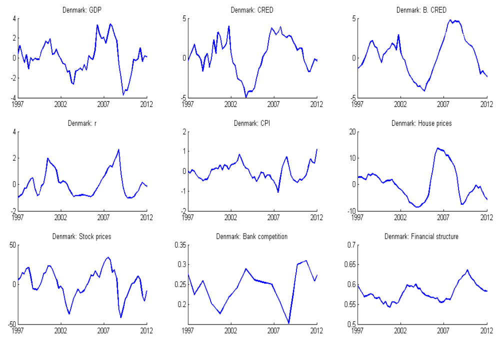
(a) Austria



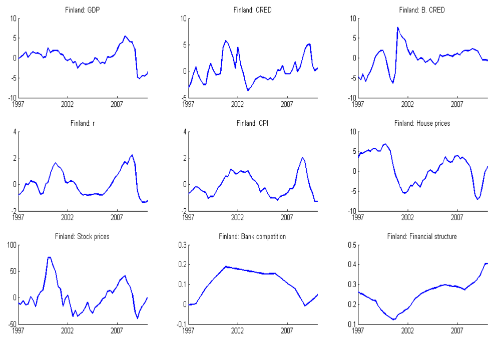
(b) Belgium



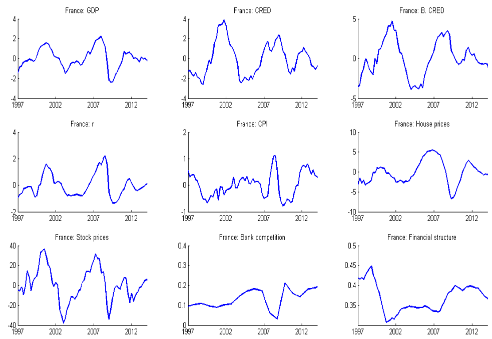
(c) Denmark



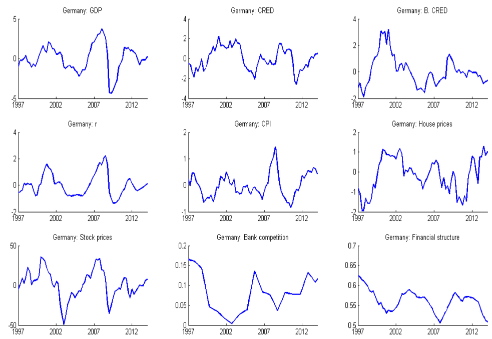
(d) Finland



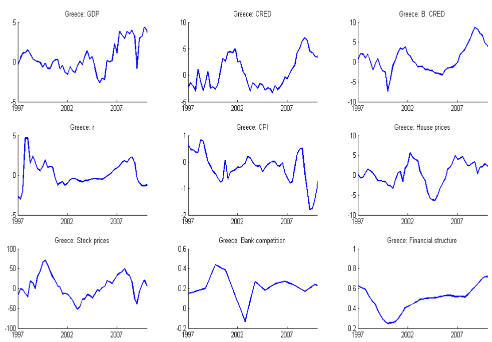
(e) France



(f) Germany



(g) Greece



(h) Ireland

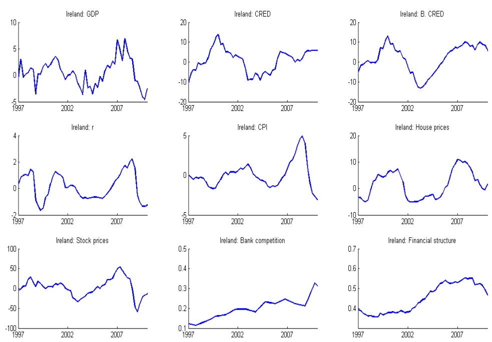
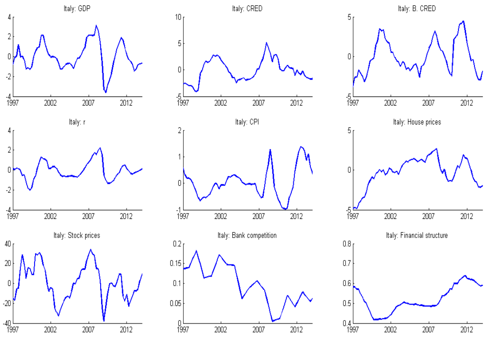
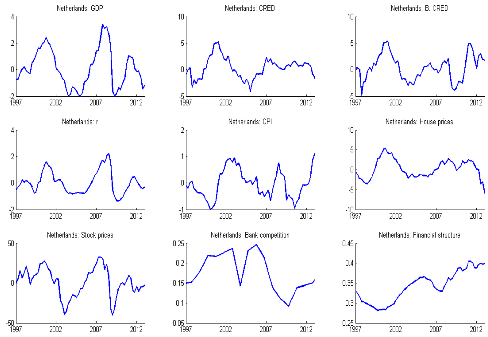


Figure A3: Time series by country

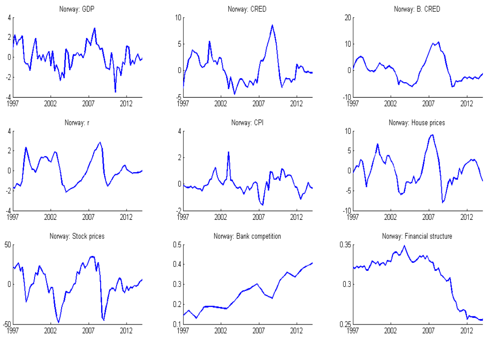
(a) Italy



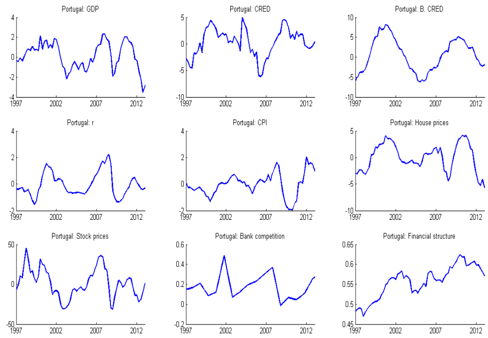
(b) the Netherlands



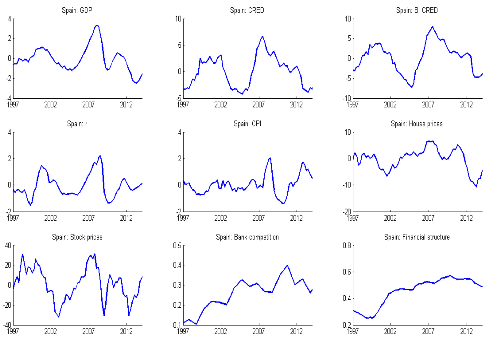
(c) Norway



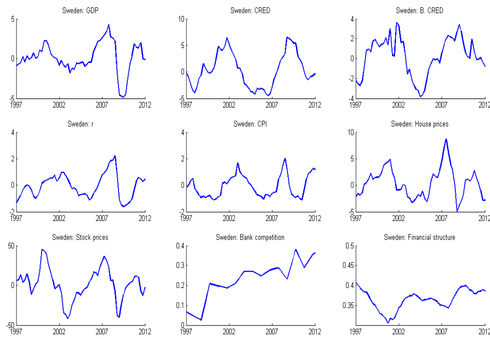
(d) Portugal



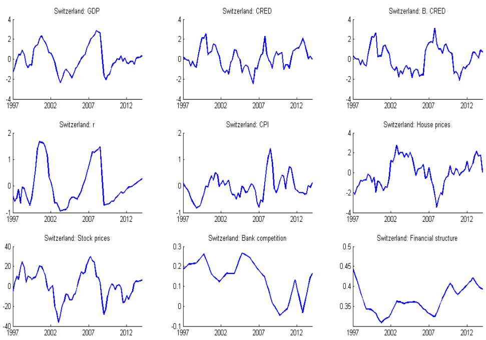
(e) Spain



(f) Sweden



(g) Switzerland



(h) UK

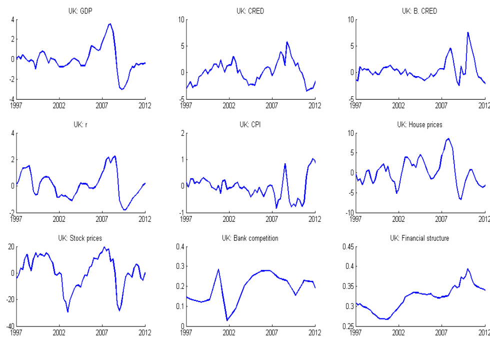


Table A1: Number of banks by country

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
Δ 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