The evolution and heterogeneity of credit procyclicality in Central and Eastern Europe

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Abstract

This paper presents empirical estimates of bank credit procyclicality for a sample of 11 Central and Eastern European countries (CEECs) for the period 2000Q1-2016Q4. In the first step we estimate a traditional-type panel VAR model and analyse the evolution of credit procyclicality in the CEECs by comparing the impulse response functions for different business cycle periods. The results confirm the existence of credit procyclicality in the CEECs and show that procyclicality is higher during boom periods. Furthermore we observe the heterogeneity of credit procyclicality in the different countries in our sample. To explain the cross-country heterogeneity in credit procyclicality we construct an interacted panel VAR model (IPVAR) and analyse whether bank level competition, proxied by the aggregate Lerner index, constitutes a driving force of credit procyclicality. Our findings indicate that bank competition affects credit procyclicality and explains the differences in credit dynamics across the CEECs. Specifically we show that the reaction of credit to a GDP shock is on average higher in a less competitive banking market.

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

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

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1 Introduction

In this paper we study how banking competition contributes to the procyclicality of credit for a group of Central and Eastern European countries (CEECs).

The strong growth in credit in the run up to the financial crisis in the CEECs has been called "one of the major pervasive developments" of the time (Enoch and Ötker-Robe, 2007). Zdzienicka (2011) shows that even when the convergence process towards Western European standards and country specific financial development indicators are accounted for, Bulgaria, the Czech Republic, Estonia, Latvia, Lithuania and Slovenia among the CEECs showed deviations in credit above the long-term equilibrium that can be determined from fundamentals. In Estonia, Latvia and Lithuania, those credit booms were followed by credit-to-GDP ratios that were not just below trend but well below credit crunch thresholds when the financial crisis reached its most severe stage in 2010 [1].

After the eruption of the financial crisis and the realisation of how necessary it was to improve the regulatory policies in the banking sector around the world, there has been increasing concern about how competition in the banking sector affects financial stability. Recent contributions are Cuestas et al. (2017) for the CEECs and Leroy and Lucotte (2017) for Europe. These two papers, highlight the existence of an inverse U-shaped link between financial stability and competition, reconciling the competition-fragility view and the competition-stability view.

This line of research needs to be complemented by an analysis of how banking competition may affect the procyclicality of credit observed in Central and Eastern Europe. The procyclicality of credit needs to be understood because it can exacerbate the economic cycle by making booms unsustainable much faster, and busts too painful, because it causes economic recovery to be delayed for too long. During recessions potential borrowers may be seen as riskier as their creditworthiness may have been affected by the drop in economic activity, and this then reduces the amount of credit that is released, affecting investment and consumption negatively. The opposite may occur during booms (Berger et al., 2004). A review of the most recent literature on the nexus between credit and the economic cycle can be found in Leroy and Lucotte (2019). As these authors point out, research in this area is moving towards identifying the factors that may contribute to the procyclicality of credit.

Following this recent strand of the literature, we aim to analyse how far the idiosyncratic reactions of credit to GDP innovations may be explained by differences in banking sector competition. Specifically we look to answer the following three questions: (1) does the procyclicality of bank credit vary over the phases of the business cycle? (2) Can we observe differences in credit procyclicality across the CEECs? (3) Does bank competition in these countries condition the procyclicality of credit? The first question is motivated by Jordà et al. (2013),

[1] Episodes of credit booms or crunches occur when the level of credit to GDP remains well above or below its long-term trend. For the estimation of boom and crunch thresholds we refer to Gourinchas et al. (2001).

who show that countries with a higher level of private indebtedness tend to experience deeper recessions. More recently Cuestas et al. (2017) show that there is a bidirectional causality between foreign liabilities and private domestic credit in some European countries from the periphery.

The second and third questions relate respectively to testing the hypotheses of competition-fragility and competition-stability in the banking sector. The competition-fragility view claims that high levels of competition may encourage banks to take on greater risks and behave less responsibly by lending more during boom times but curbing lending excessively during recessions, which would increase the procyclicality of credit. However, the competition-stability view claims that high levels of competition may reduce lending rates, shifting the focus to borrowers with high credit ratings and reducing the moral hazard incentives to engage in riskier projects. This would mean that less credit is released during boom times and so the procyclicality of credit is reduced. High levels of competition may also reduce asymmetric information as banks may seek to establish long-term relationships with their clients, meaning they hold more information on the creditworthiness of those clients (Boot and Thakor, 2000). This may also give an incentive to banks to increase their screening and monitoring of borrowers by investing in technology that can produce more detailed information (Gehrig, 1998).

The previous literature on the issue has produced mixed results. Bouvatier et al. (2012) show that competition in the banking sector does not seem to clarify the issue, as different countries with different degrees of banking competition do not seem to experience different degrees of cyclicality of credit. Leroy and Lucotte (2019) apply a different methodology based on interactive panel VARs (IPVAR) and find that differences in banking sector competition in a group of western European countries can actually explain why countries may show different degrees of procyclicality. To this extent the authors show that banking competition reduces procyclicality.

In this paper we follow the macro analysis of Leroy and Lucotte (2019) and apply the IPVAR method to a group of banks from Central and Eastern Europe to answer the three main questions. To the best of our knowledge this is the first attempt to focus on this group of countries. In this paper we use a panel Vector Autoregressive (VAR) model to analyse the evolution of bank credit procyclicality in the CEECs, and to assess how this procyclicality evolved in the aftermath of the subprime crisis. We then extend our empirical investigation by evaluating the cross-country heterogeneity in credit procyclicality. To this end, we estimate a country-specific VAR model and compare the differences in credit procyclicality across the CEECs. Finally, we use an IPVAR framework to test whether the differences in credit procyclicality across Central and Eastern European economies could potentially be explained by differences in banking sector competition, which is proxied by an aggregate Lerner index.

The remainder of the paper is organised as follows. Section 2 provides a summary of the literature on the issue. Section 3 shows some stylised facts about credit procyclicality in the CEECs. Section 4 explains the cross country idiosyncrasies in credit procyclicality in our target countries. In section 5 we explore whether banking competition matters for this heterogeneity, in section 6 we run some robustness checks, and then the final section concludes.

2 Related literature

The idea that financial shocks feed back to the real economy dates back at least to Fisher (1933), but after World War II the notion of financial booms followed by busts feeding into the real economy remained on the side-lines of macroeconomic debate. It was considered either that financial factors delayed the return of the economy to a steady state after the impact of economic shocks (Bernanke et al., 1999) or that they could be ignored in efforts to understand business cycle fluctuations (Woodford, 2011). The financial crisis of 2007-2008 has reinvigorated interest in understanding the interplay between financial factors and the business cycle. Macroeconomists have incorporated financial frictions into New Keynesian Dynamic Stochastic General Equilibrium (DSGE) models, and have analysed the pattern of credit-driven boom-bust cycles. In one seminal contribution Borio (2014) highlights some important points about the financial cycle, noting that it may be explained by taking credit and housing prices into account since it could be less frequent than the traditional business cycle, meaning that peak periods can be followed quickly by financial crises. The frequency and amplitude of the financial cycle depend on policy regimes, most importantly the financial regime, the monetary regime and the real-economy regime[2].

Procyclicality in the banking sector has been researched with a different focus. Some studies have for example analysed the behaviour of demand and supply of loans and their role in economic activity (Lown and Morgan, 2006; Bassett et al., 2014), while others have examined the procyclical behaviour of banking sector profits (Albertazzi and Gambacorta, 2009; Gambacorta, 2016). Most empirical findings indicate that bank credit tends to behave procyclically (Panetta et al., 2009; Bouvatier et al., 2014). As the variations in lending tend to be more directly linked to the real economy, the dynamics of the loan supply from banks tend to accentuate the business cycle (Berger et al., 2004). Furthermore, credit extensions during business-cycle boom periods are often followed by financial crises (Jordà et al., 2013).

Other studies analyse the determinants which may affect the procyclicality of the banking sector. Following Athanasoglou et al. (2014), the potential determinants are, amongst others, the regulatory and supervisory framework, monetary policy, the practices of financial firms like for example their behaviour in acquiring debt and their remuneration policies, and reports from credit rating agencies or the use of automated risk management systems. Various studies suggest that risk management systems such as the Basel I and II framework tend to rein-

[2]For a detailed discussion of boom-bust cycles see Borio et al. (2001); Lowe and Borio (2002); Tornell and Westermann (2002); Eichengreen and Mitchener (2004); Mendoza and Terrones (2008, 2012); Hume and Sentance (2009) and Schularick and Taylor (2012).

force banking sector procyclicality instead of smoothing it (Kashyap et al., 2008; Jokipii and Milne, 2008). The Basel I and II regulations featured loose capital requirements during periods of economic stability, but enforced tighter capital requirements during economic downturns, which throttled the supply of loans from banks. In contrast, the new Basel III regulations explicitly address the issue of procyclicality by introducing countercyclical capital buffers (Athanasoglou et al., 2014).

There is a lot less literature on the relationship between the structure of the banking sector and credit procyclicality. Dell'Ariccia and Marquez (2006) present a theoretical model in this vein of credit booms driven by increases in competition. Faced with the threat of competition, the incumbent switches from a detailed screening of lenders to lower lending standards, thus increasing the volume of lending but also causing a deterioration in the loan portfolio and so increasing financial fragility. However, the boom increases aggregate output, unlike the inefficient booms modelled by Petriconi (2015). His research shows how more competition between banks can generate inefficient lending booms and pronounced business cycles. This is firstly because the informed incumbent finds it optimal for a given precision of borrower screening to poison the well for uninformed competitors by lowering credit standards and providing financing for projects that have negative expected net present value. The study also finds that when borrower screening is chosen endogenously, competition during boom periods reduces screening precision to low and inefficient levels that can explain the lending cycles that diminish welfare.

Bouvatier et al. (2012) take the empirical point of view and investigate the relationship between the structure of the banking sector and credit procyclicality. Using hierarchal clustering methods to classify the structures of the banking systems of 17 OECD countries, they estimate a panel VAR model on the resulting sub-groups of countries. Their results highlight that while credit responds significantly to shocks to GDP, the structure of the banking sector is not a determinant of credit procyclicality. In related research Bouvatier et al. (2014) analyse the characteristics of credit that may be procyclical for sample OECD countries using a smooth transition regression model. They show that in some countries, nonlinearities in credit dynamics are driven by the position of the business cycle or by housing prices.

Leroy and Lucotte (2019) investigate how banking competition affects credit procyclicality for a large sample of Western European countries. Estimating an interacted panel VAR (IPVAR) model using macroeconomic data and a single-equation approach provides evidence that rapid credit increases and declines in lending are less important when banks compete fiercely. These results indicate that greater competition in the financial industry decreases the chances of financial distress.

Researchers have not studied the evolution or the heterogeneity of credit in CEECs in these terms. Given the specific characteristics of the banking sector in the CEECs, such as a highly concentrated banking sector in the Baltic States, our research contributes to the existing literature by analysing how credit procyclicality varies over the business cycle and across countries while also providing evidence that concentration in the banking sector can drive credit procyclicality.

3 The evolution of credit procyclicality in Central and Eastern Europe

We start our empirical analysis by investigating the evolution of bank credit procyclicality in the CEECs and whether this procyclicality varies over the phases of the business cycle. To this end, we use a panel VAR framework and consider four macroeconomic variables, which are real Gross Domestic Product (GDP), the Consumer Price Index (CPI), the real outstanding amount of credit to the private non-financial sector, and the nominal short-term interest rate. These variables are taken from the International Financial Statistics (IFS) of the International Monetary Fund[3]. We consider quarterly data over the period 2000Q1-2016Q4 for a sample of eleven CEECs, which are Bulgaria, Croatia, the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia.

Since our focus lies on short-term economic fluctuations, we remove trends and work over the cyclical components of the time series. This approach has at least two main advantages. From an economic point of view, it makes it possible to assess whether bank credit reacts to an unexpected change in GDP. From the econometric viewpoint, it ensures a stationary series. We isolate the cyclical components of the series by using the usual Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1981, 1997). The HP filter is applied to the seasonally adjusted series over the period 2000Q1-2016Q4 by setting a smoothing parameter at 1600, as is usual for quarterly data[4]. More precisely, we consider the percentage gap between the observed values and the trend values for the CPI, real GDP and the credit series, while the interest rate variable is the cyclical component deduced from the HP filter.

Our main variables of interest are the business cycle and the credit cycle. Following Bouvatier et al. (2012) and Leroy and Lucotte (2019), we define credit procyclicality as the orthogonalised impulse response function of the credit cycle to a business cycle shock. The reduced form of the panel VAR model that we estimate is:

$$Y_{i,t} = c_i + A(L)Y_{i,t} + \varepsilon_{i,t} \tag{1}$$

where i and t are country and time respectively, $Y_{i,t}$ is the vector of endogenous variables, $\varepsilon_{i,t}$ is the vector of errors, c_i is the country-specific intercepts matrix, and $A(L)$ is the polynomial matrix in the lag operator, L say. The opti-

[3]The data that support the findings of this study are openly available from the International Financial Statistics database.

[4]See Pedersen (2001) and Ravn and Uhlig (2002) for a discussion on the smoothing parameter.

mal number of lags L is determined by the Schwartz information criterion (BIC) and is equal to two.

The vector $Y_{i,t}$ is given by:

$$Y_{i,t} = (INF_{i,t}, OG_{i,t}, CRED_{i,t}, r_{i,t}) \tag{2}$$

where $INF_{i,t}$ is the inflation gap, $OG_{i,t}$ the output gap, $CRED_{i,t}$ the credit gap, and $r_{i,t}$ the cyclical component of the interest rate, and these gaps have been obtained as the cyclical component obtained by the HP filter above. We estimate Equation 1 using a fixed effects (FE) estimator. To obtain the impulse-response functions (IRFs) we first estimate the IPVAR, and apply the following ordering for the variables by means of Cholesky decomposition: INF, OG, $CRED$ and r. The positions of inflation and the output gap are customary in the literature. This implies that financial variables may respond contemporaneously to real shocks but the ordering of the financial variables is subject to some discussion. Following Assenmacher and Gerlach (2008) and Bouvatier et al. (2012), we place bank credit before the short-term interest rate in our recursive identification scheme. Indeed a number of papers that investigate the issue of monetary policy transmission (see e.g. Leroy and Lucotte (2015)) have shown that the bank interest rate pass-through is sluggish in the short term, explaining why credit does not respond immediately to an interest rate shock[5].

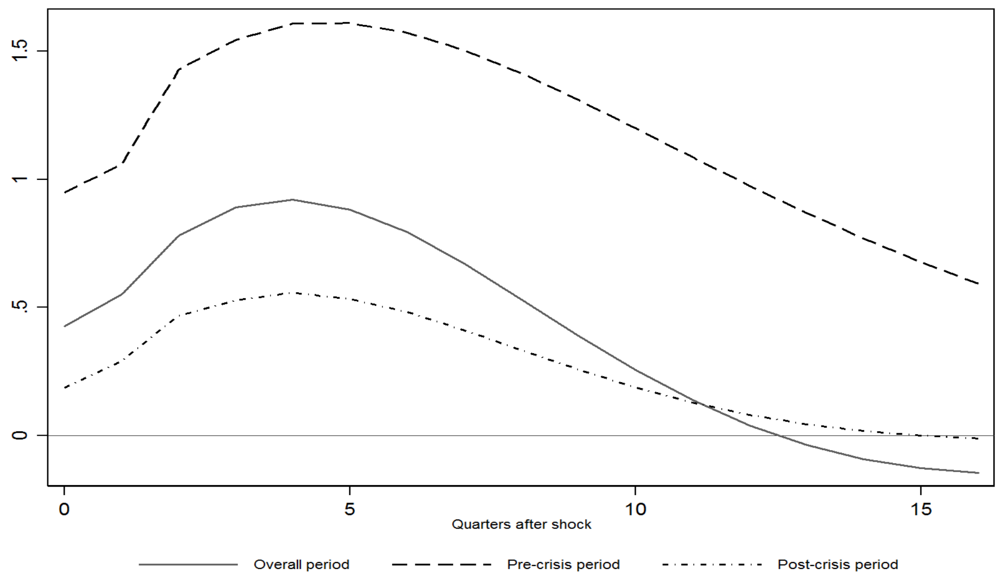
To assess the evolution of credit procyclicality in the CEECs, we estimate the panel VAR model by considering different sub-periods. We apply the analysis to panel data to gain robustness in the analysis by accounting for cross-section information, capturing both static and dynamic interdependencies, treating the links across countries or units in an unrestricted fashion easily incorporating time variations in the coefficients and in the variance of the shocks, and accounting for cross-sectional dynamic heterogeneities, which we would lose in a time series analysis. In addition in our IPVAR estimations we need to account for this cross-section information in order to condition the models. First, we distinguish between the periods before and after the financial crisis. Figure 1 displays the IRFs of bank credit to a one-unit shock in the output gap by considering three different periods: the overall period (2000Q1-2016Q4), the pre-crisis period (2000Q1-2007Q4) and the post-crisis period (2008Q1-2016Q4). For the sake of readability, we do not report the confidence bands, but the full set of results are reported in Figure A3 in the Appendix. The results obtained for the overall period confirm the existence of credit procyclicality in the CEECs and show that a GDP cycle shock has a positive and significant impact on bank credit. The peak impact occurs four quarters after the shock, and the effect of the output gap on the credit gap appears relatively persistent. More importantly, we observe that the degree of credit procyclicality is more or less pronounced depending on the economic conditions. The IRFs suggest that credit procyclicality was higher before the crisis and tended to be weaker in the aftermath of the subprime crisis.

[5]We check the robustness of our results by considering a different ordering for computing the IRFs. See Section 6 for more details.

We observe comparable patterns in Figure 2, in which we consider four overlapping sub-periods: 2000Q1-2006Q4, 2004Q1-2010Q4, 2008Q1-2014Q4, and 2012Q1-2016Q4. The degree of procyclicality appears relatively high over the period 2000Q1-2006Q4, with the peak impact occurring three quarters after the shock in GDP, and then it tends to decrease during the subsequent periods. As Figure A4 in the Appendix suggests, the effect of the output gap on the credit gap is not statistically significant over the period 2012Q1-2016Q4. Similar results are obtained when we estimate the panel VAR system on seven-year rolling windows. The IRFs reported in Figure [IRFrolling] clearly show a continued decline in the magnitude of bank credit procyclicality during the period considered, especially in the aftermath of the subprime crisis.

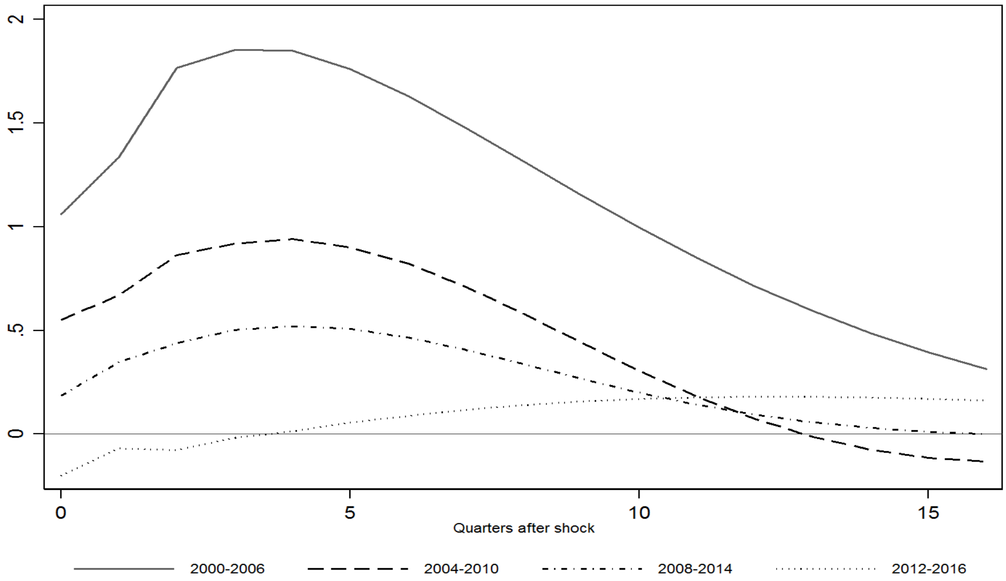
As Bouvatier et al. (2014) argue, the greater procyclicality of bank credit before the crisis could arise because these periods typically have large increases in property and share prices that, in turn, affect the credit gap. This means that the short-run credit behaviour of banks could also be driven by variables other than the business cycle, such as financial assets. Indeed, not only do rising housing prices exert wealth effect on credit demand, but asset and property prices also serve as a collateral, and this makes banks more willing to extend loans during booms and upturns in the business cycle, leading to an increase in the supply of credit to the private sector. Moreover, as Jiménez and Saurina (2006) show, such asymmetries in credit procyclicality could also be explained by the way that the credit policies of banks for collateral requirements depend on the business cycle position. Using bank-level data, Jiménez and Saurina (2006) show clear evidence that banks tend to relax credit standards in boom periods, while the opposite happens in recessions. More precisely, their results indicate that the likelihood of collateral being pledged decreases proportionally more in upturns than it increases in downturns, leading to a rapid growth in credit in good times. One potential explanation for the more lenient credit standards during expansion phases is the misperception of how risk evolves over time (Borio et al., 2001), which leads banks to underestimate risk during the upswing, and through this contributes to excessively rapid credit growth.

Figure 1: Evolution of credit procyclicality in CEECs in the aftermath of the subprime crisis



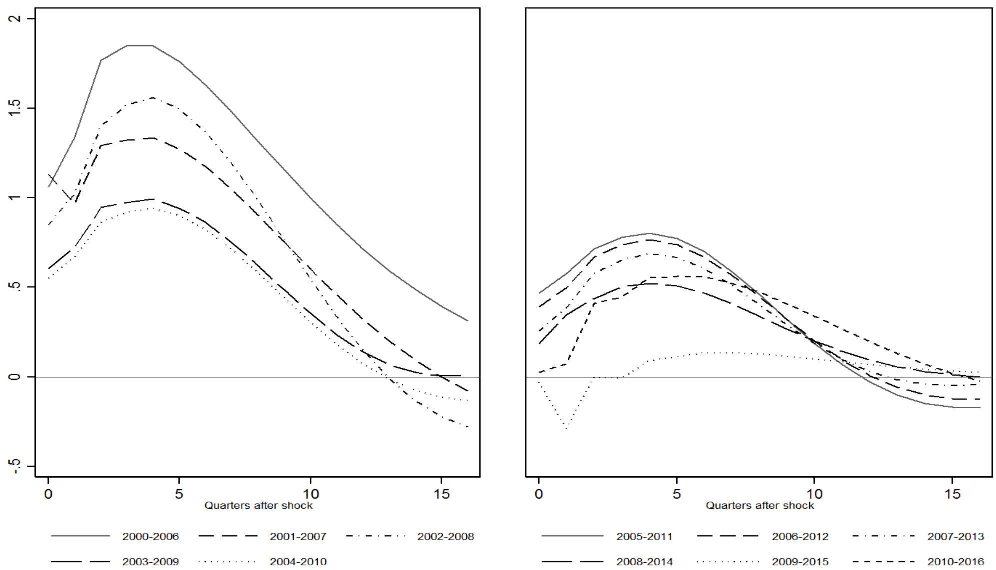
Note: The figure displays the impulse responses of bank credit to a one-unit shock in the output gap by considering three different periods: the overall period (2000Q1-2016Q4), the pre-crisis period (2000Q1-2007Q4) and the post-crisis period (2008Q1-2016Q4). Confidence intervals for each impulse response function are reported in Figure A3 in the Appendix.

Figure 2: Evolution of credit procyclicality in CEECs between 2000 and 2016



Note: The figure displays the impulse responses of bank credit to a one-unit shock in the output gap by considering four different overlapping sub-periods: 2000Q1-2006Q4, 2004Q1-2010Q4, 2008Q1-2014Q4, 2012Q1-2016Q4. Confidence intervals for each impulse response function are reported in Figure A4 in the Appendix.

Figure 3: Evolution of credit procyclicality in CEECs: rolling estimates



Note: The figure displays the impulse responses of bank credit to a one-unit shock in the output gap by considering 7-year rolling windows. Confidence intervals for each impulse response function are reported in Figure A5 in the Appendix.

4 Cross-country heterogeneity in credit procyclicality

We extend our previous empirical investigation by assessing the cross-country heterogeneity in credit procyclicality. As before, our main variables of interest are the output gap and the credit gap. Table 1 presents some descriptive statistics of these variables for each economy in our sample. More precisely, we report the first-order autocorrelation for each series and the pairwise correlation between the output gap and the credit gap by considering four different lag structures for the output gap, with 1 lag, 2 lags, 3 lags and 4 lags. These statistics are calculated for the overall period of 2000Q1-2016Q4. It is apparent that credit and business cycles typically have a relatively high degree of persistence, with a first-order autocorrelation of around 0.85, even if the heterogeneity between countries is more important for the credit cycle. More importantly, we can see that the correlation between the two cycles is positive and statistically significant, confirming that credit and business cycles are closely linked, even if this correlation appears more pronounced in some countries[6].

Table 1: Descriptive statistics: output gap and credit gap

	Output gap	Credit gap	Pairwise correlation - Overall period (2000Q1-2016Q4)			
	1^{st} order autocorr.	1^{st} order autocorr.	1 lag	2 lags	3 lags	4lags
Bulgaria	0.873	0.936	0.450*	0.550*	0.592*	0.569*
Croatia	0.842	0.776	0.504*	0.462*	0.416*	0.267*
Czech Rep.	0.882	0.895	0.618*	0.600*	0.547*	0.469*
Estonia	0.913	0.930	0.303*	0.389*	0.463*	0.530*
Hungary	0.872	0.625	0.181	0.319*	0.356*	0.331*
Latvia	0.919	0.891	0.347*	0.406*	0.463*	0.499*
Lithuania	0.881	0.971	0.322*	0.408*	0.511*	0.559*
Poland	0.752	0.901	0.373*	0.464*	0.542*	0.567*
Romania	0.840	0.901	0.502*	0.569*	0.602*	0.514*
Slovak Rep.	0.785	0.858	0.620*	0.624*	0.652*	0.553*
Slovenia	0.896	0.886	0.437*	0.483*	0.503*	0.510*
Mean	0.860	0.870	0.423	0.479	0.513	0.488
Median	0.873	0.895	0.437	0.464	0.511	0.514
St. Dev.	0.052	0.095	0.135	0.097	0.086	0.099

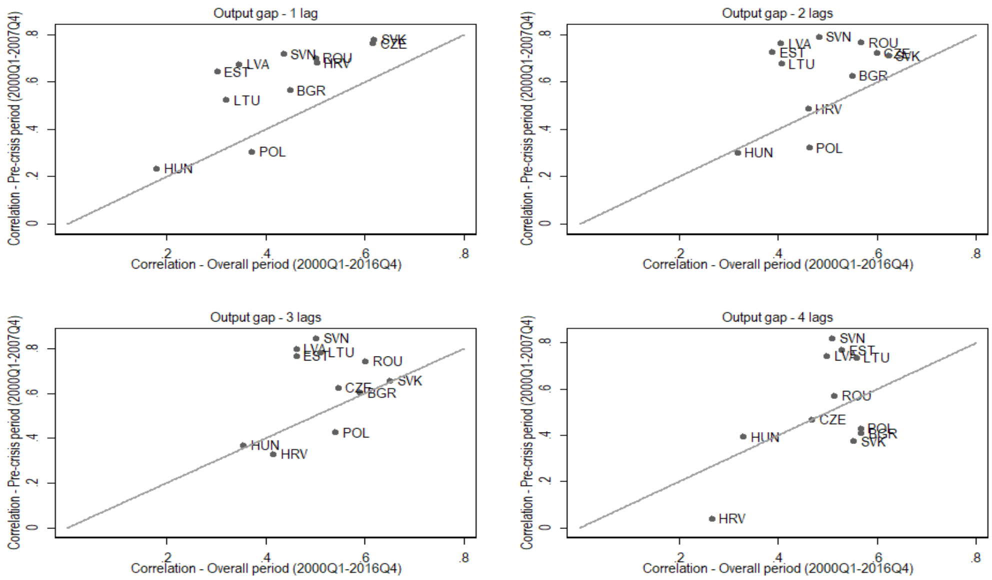
Source: Authors' calculations, International Financial Statistics, International Monetary Fund. Note: The correlation between the output gap and the credit gap is calculated by considering four different lag structures for the output gap: 1 lag, 2 lags, 3 lags and 4 lags. An asterisk indicates that the correlation is significant at the 5% level.

In Figure 4, we compare the correlation between the output gap and the credit gap in the overall period (2000Q1-2016Q4) and in the pre-crisis period (2000Q1-2007Q4). As in Table 1, we consider different lag structures for the output gap. In line with the panel VAR results discussed in the previous section, we can see that most of the countries are located above the 45 degree line, confirming that

[6]For an overview of the evolution of the correlation between the credit and business cycles over the period studied, please see Figure A2 in the Appendix.

the correlation between the two cycles was relatively important during the pre-crisis period, even if the heterogeneity among countries appears more important when the output gap is lagged three or four quarters.

Figure 4: Credit and business cycles correlation



Source: Authors' calculations, International Financial Statistics, International Monetary Fund. Note: This figure displays the pairwise correlation between the output gap and the credit gap for the overall period (2000Q1-2016Q4) and the pre-crisis period (2000Q1-2007Q4). The correlation is calculated by considering four different lag structures for the output gap: 1 lag, 2 lags, 3 lags and 4 lags.

To assess the differences in credit procyclicality across CEECs formally, we estimate a country-specific VAR model for each economy considered in our sample. The VAR model that we consider is the same as those presented above. It comprises the same four endogenous variables (INF, OG, $CRED$ and r) and the identification scheme for computing the individual IRFs is similar. For each country in our sample, we estimate the VAR model using an Ordinary Least Squares (OLS) estimator over the period 2000Q1-2016Q4 (68 observations), and the optimal number of lags is determined by the Schwartz information criterion (BIC).

Figure 5 displays the orthogonalised country-specific responses of bank credit to a one-unit shock in the output gap with a simulation horizon of 16 quarters[7]. For the sake of readability, we do not report the confidence bands, but the full set of results is reported in Figure A6 in the Appendix. In most countries, a GDP cycle shock affects the credit cycle contemporaneously and positively. The only

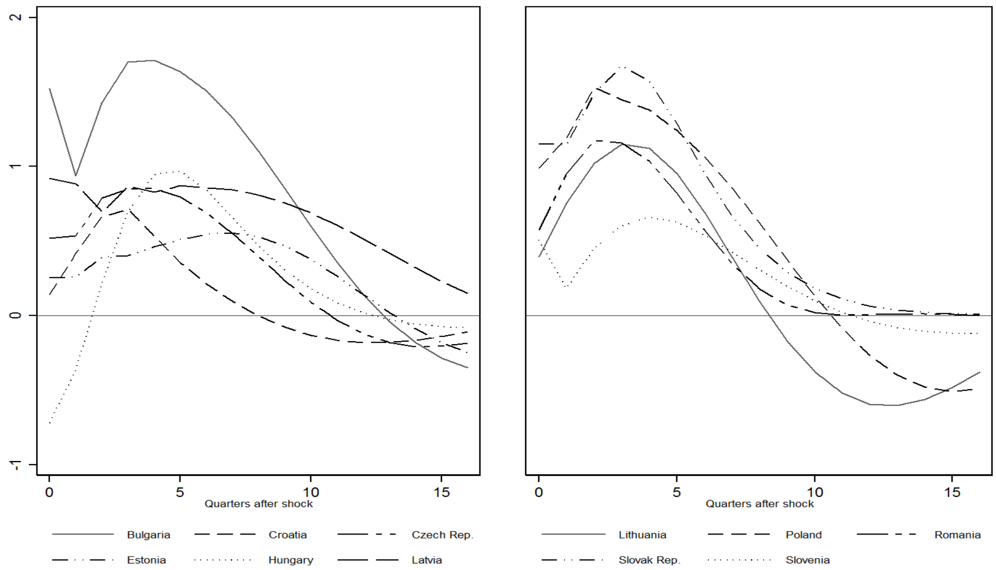
[7]Before the IRFs were computed, standard tests were applied to check for residual autocorrelation and to see that the moduli of the eigenvalues of matrix A are less than one. Figure A7 in the Appendix confirms that the VAR process is stable for each country in our sample.

exception is Hungary, where the response is initially negative and becomes positive and statistically significant after four quarters. Figure A6 in the Appendix suggests that for the Czech Republic and Slovenia, the confidence intervals are larger than they are for the other countries, rejecting the suggestion that the business cycle has a significant effect on the credit cycle. Overall, Figure 5 clearly shows that the magnitude and the persistence of an output gap shock are widely different across countries, suggesting major asymmetries in credit procyclicality within Central and Eastern European economies.

The comparison of the peak values in Figure 6 confirms the cross-country heterogeneity in credit procyclicality. Indeed, the peak value appears relatively high at more than 1.5 for Bulgaria, Poland, and the Czech Republic, while it is close to 0.5 for Estonia. In most cases, the peak impact occurs three or four quarters after the shock.

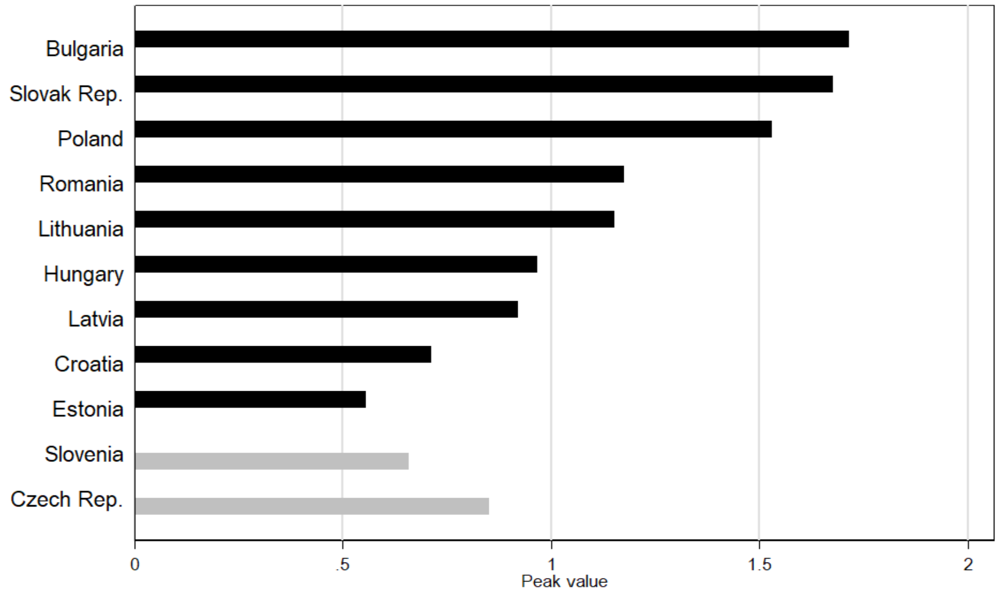
As mentioned in the previous paragraphs we observe a high degree of heterogeneity in the results. We have to bear in mind that we are mixing in the same pool countries with different degrees of financial and economic integration to the rest of the EU and with strong financial links with different EU countries. In addition the degree of economic and institutional development, which also differs between them, plays a role in determining the relationship between GDP shocks and the reaction of bank credit. Different central banks impose different capital buffers, which affected the response of the housing market during the crisis that started in 2008.

Figure 5: Country-specific impulse response functions of bank credit to a GDP shock



Note: The figure displays the country-specific impulse response functions of bank credit to a one-unit shock in the output gap on the overall period (2000Q1-2016Q4). Confidence intervals for each impulse response function are reported in Figure A6 in the Appendix.

Figure 6: Peak value of the response of bank credit to a GDP shock



Note: The figure displays the peak value of the response of bank credit to a one-unit shock in the output gap on the overall period (2000Q1-2016Q4). A grey bar corresponds to a peak which is not statistically significant. See Figure A6 in the Appendix for more details.

5 Does banking competition matter?

In this section, we investigate empirically if bank competition is an explanatory variable for the credit procyclicality in the CEECs, and then whether it could explain the cross-country heterogeneity in credit procyclicality highlighted above. Leroy and Lucotte (2019) have recently shown for a large sample of Western European countries that a low level of competition in the banking sector could increase the response of loans to the business cycle, increasing the speed of transmission of a real activity shock to the credit market.

Following the recent banking literature (see e.g. Berger et al. (2009); Beck et al. (2013), and Anginer et al. (2014)) we use the Lerner index as an inverse proxy for bank competition. The Lerner index is a non-structural measure of competition that is designed to measure the pricing power of firms. It corresponds to the mark-up of price over marginal cost. The Lerner index is bounded between 0 and 1, with the extreme value of zero corresponding to perfect competition, and the value of one to a pure monopoly. Formally, the Lerner index is calculated as the difference between price and marginal cost as a proportion of price:

$$Lerner_{it} = \frac{p_{it} - mc_{it}}{p_{it}} \tag{3}$$

with p_{it} as the price and mc_{it} as the marginal cost for bank i in period t. Under the assumption that the flow of services given by a bank is proportional to its total assets, the price p_{it} is obtained as the ratio of total bank revenue to total assets, while the marginal cost is computed using a translog cost function with respect to output (see Beck et al. (2013)).

Given the macroeconomic focus of our study, we consider for each country in our sample an aggregate Lerner index that corresponds to the median of the individual Lerner indexes. The variable is taken from the Global Financial Development Database (GFDD) of the World Bank and is available from 2000 to 2015. The Lerner index is computed annually, and so we match the variable to the quarterly frequency of our study by considering the same value of the Lerner index for each quarter of a given year[8].

To test whether the differences in credit procyclicality across Central and Eastern European economies could be explained by differences in the level of banking sector competition, we use the interacted panel VAR (IPVAR) framework proposed by Towbin and Weber (2013). As previously, we define credit procyclicality as the orthogonalised impulse response function of the credit cycle to a GDP cycle shock. The main advantage of the IPVAR framework is that the autoregressive parameters are functions of the cross-time-varying level of banking sector competition. In this way, we are accounting for the time-varying level of competition in the banking industry as an exogenous determinant affecting the credit response to a GDP shock.

The structural form of the interacted panel VAR model that we estimate is given by:

$$\begin{pmatrix} 1 & 0 & 0 & 0 \\ \alpha_{0,it}^{21} & 1 & 0 & 0 \\ \alpha_{0,it}^{31} & \alpha_{0,it}^{32} & 1 & 0 \\ \alpha_{0,it}^{41} & \alpha_{0,it}^{42} & \alpha_{0,it}^{43} & 1 \end{pmatrix} \begin{pmatrix} INF_{i,t} \\ OG_{i,t} \\ CRED_{i,t} \\ r_{i,t} \end{pmatrix} = \mu_i + \sum_{l=1}^{L} \begin{pmatrix} \alpha_{l,it}^{11} & \alpha_{l,it}^{12} & \alpha_{l,it}^{13} & \alpha_{l,it}^{14} \\ \alpha_{l,it}^{21} & \alpha_{l,it}^{22} & \alpha_{l,it}^{23} & \alpha_{l,it}^{24} \\ \alpha_{l,it}^{31} & \alpha_{l,it}^{32} & \alpha_{l,it}^{33} & \alpha_{l,it}^{34} \\ \alpha_{l,it}^{41} & \alpha_{l,it}^{42} & \alpha_{l,it}^{43} & \alpha_{l,it}^{44} \end{pmatrix} \begin{pmatrix} INF_{i,t-l} \\ OG_{i,t-l} \\ CRED_{i,t-l} \\ r_{i,t-l} \end{pmatrix} + \begin{pmatrix} \chi^{11} \\ \chi^{21} \\ \chi^{31} \\ \chi^{41} \end{pmatrix} Lerner_{i,t-4} + \varepsilon_{i,t} \quad (4)$$

where i and t are indexes of country and time respectively, $INF_{i,t}$ is the inflation gap, $OG_{i,t}$ the output gap, $CRED_{i,t}$ the credit gap, $r_{i,t}$ the cyclical component of the interest rate, $\varepsilon_{i,t}$ a vector of uncorrelated iid shocks, and L the number of lags. μ_i is a country specific intercept. The Lerner index ($Lerner_{i,t-4}$) is lagged four quarters to address the issue of potential endogeneity and is considered as an exogenous control variable. $\alpha_{l,it}^{jk}$ are deterministically varying coefficients as a function of the level of banking competition, which is proxied by the Lerner index.

In order to analyse whether the response of the credit cycle to a GDP shock varies with the level of bank competition, we allow for interaction terms so that

[8]See Figure A8 in the Appendix for more details concerning the evolution of the Lerner index in the CEECs. Please note that the Lerner index is only available until 2010 for Estonia. We also check the robustness of our results by linearly interpolating the values of the Lerner index and by considering the trend of the Lerner index. The results are reported in Section 6.

the coefficients in Equation 4 are given by:

$$\alpha_{l,it}^{jk} = \beta_l^{jk} + \eta_l^{jk} Lerner_{i,t-4} \quad (5)$$

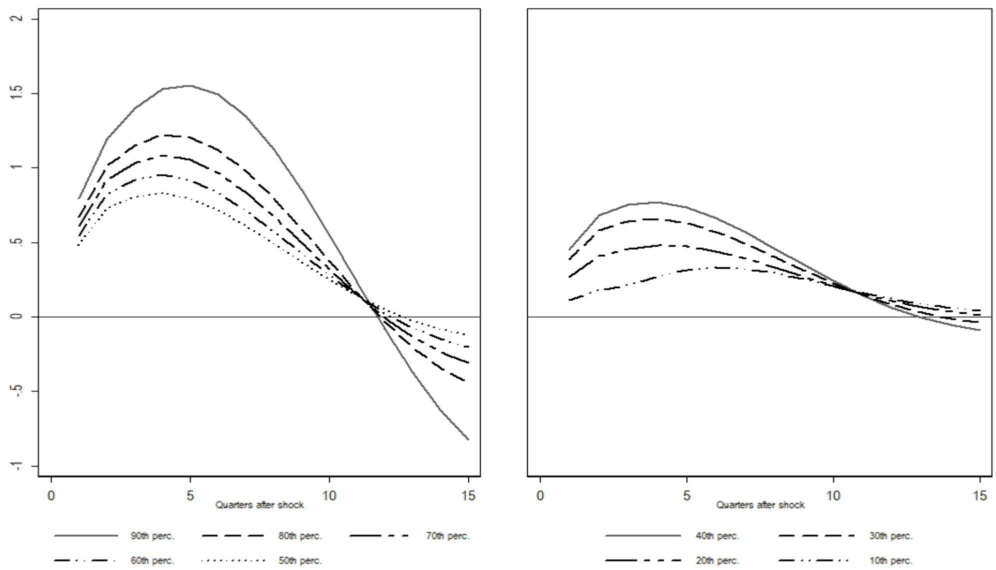
where β_l^{jk} and η_l^{jk} are two vectors of coefficients, and $Lerner_{i,t-4}$ is the aggregate Lerner index, which is a cross-time-varying inverse proxy for bank competition. Unlike in a traditional panel VAR model, the structural parameters $\alpha_{l,it}^{jk}$ vary over time and across countries with the level of competition in the banking sector. Moreover, we do not impose restrictions on the interaction terms and we assume that all the autoregressive parameters of the VAR system are dependent on competition, which means that all variable dynamics are conditional on the level of competition in the banking sector.

We estimate the IPVAR model using OLS and allow for country fixed effects to control for unobserved unit-specific factors. In this way, we control for structural characteristics other than banking competition that could explain the differences in credit procyclicality across the CEECs. Since the error terms are uncorrelated across equations by construction, we are able to estimate the IPVAR model equation by equation in an efficient way. The lag length and the Cholesky ordering are the same as for the panel VAR estimated in Section 3.

After the IPVAR is estimated, we conduct a structural analysis to assess whether the level of bank competition drives the response of credit to a GDP shock and so could explain differences in credit procyclicality across the CEECs. More precisely, we test in two ways whether the interactions with the degree of bank competition affect the dynamics of the variables. First, we generate the impulse responses of bank credit to a one-unit GDP cycle shock at different percentiles of the sample distribution of the Lerner index. Figure 7 displays the impulse response functions that we obtain[9]. All the impulse responses correspond to the average effects across the countries in our sample. Figure 7 clearly indicates that the response of the credit cycle to an output gap shock tends to decrease when the Lerner index decreases. As the Lerner index is an inverse proxy for competition, this means that the procyclicality of bank credit is greater when the competition within the banking industry is relatively weak, and it is less when the competition between banks is fierce.

[9] As previously, for the sake of readability we do not report the confidence bands, but the full set of results is reported in Figure A9 in the Appendix.

Figure 7: Impulse response functions of bank credit to a GDP shock for different levels of bank competition

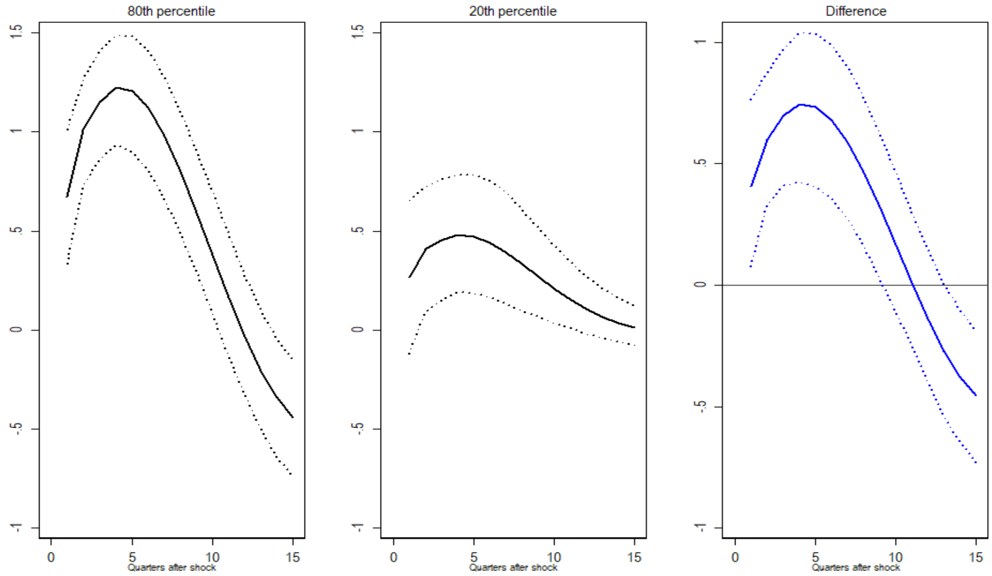


Note: The figure displays the impulse response functions of bank credit to a one-unit shock in the output gap evaluated at different percentiles of the Lerner index sample distribution. Confidence intervals for each impulse response function are reported in Figure A9 in the Appendix.

Second, we go a step further and assess whether the orthogonalised responses of bank credit to a GDP cycle shock are statistically different for lower and higher levels of bank competition. To this end, we set the Lerner index to be at the 80^{th} percentile and at the 20^{th} percentile of its sample distribution and calculate the difference between the two responses of interest. In this way, we clearly address our initial question of how credit procyclicality could potentially change if the level of competition in the banking sector moved from a lower level to a higher level. Figure 8 presents the IRFs that we obtain. The chart on the left of the figure presents the impulse response function obtained by setting a Lerner index at the 80^{th} percentile of the distribution, and hence it illustrates the mean response of credit in countries where the banking sector is more imperfectly competitive. The chart in the centre shows the impulse response function evaluated at the 20^{th} percentile of the Lerner index sample distribution, where competition between banks is relatively fierce. In both cases, the solid lines are the average responses with a 95% confidence band, obtained by a bootstrap with 1000 draws. Finally, the chart on the right displays the differences between the average response functions for the lower and the higher degrees of competition in the banking industry with a 95% confidence band.

The results that we obtain confirm our previous findings. Bank competition affects credit procyclicality and explains the differences in credit dynamics across the CEECs. Indeed, we find a positive and statistically significant difference between the two IRFs, which means that the reaction of credit to a GDP cycle shock is on average greater in a less competitive banking market. This indicates that credit increases and decreases are less pronounced when bank competition is stronger, and that more competition can absorb shocks more easily. Our results are similar to those obtained by Leroy and Lucotte (2019) for Western Europe.

Figure 8: Impulse response functions of bank credit to a GDP shock as a function of banking competition



Note: The figure displays the impulse response functions of bank credit to a one-unit shock in the output gap at the 80^{th} and 20^{th} percentiles of the Lerner index sample distribution. The chart on the right represent the difference between the two. The dotted lines represent the 95% confidence bands generated by bootstrapping (1000 draws).

Three main explanations can be advanced for this negative relationship between bank competition and the intensity of credit procyclicality. The first comes from the asymmetries of information between lenders and borrowers that are a feature of credit markets. Even though there is no consensus in the existing literature, some papers argue that competition could reduce the information gap between lenders and borrowers by affecting both the screening and following-up of the banks. As stated by the quiet life theory of Berger and Hannan (1998), fiercer competition could potentially lead banks to operate more efficiently, and this could then improve the results of the screening and monitoring of potential client borrowers. In this way, the problem of asymmetric information could somehow be relaxed, weakening the effect on financial conditions after a real shock.

A further improvement in the quality of screening can also come about because competition may increase the incentives for banks to generate information, and then may encourage them to invest more in screening technologies. Gehrig (1998) investigates a banking model with imperfect screening by allowing banks to choose the level of their screening effort. The benefits of investing in costly screening activities are two-fold. More precise screening reduces the probability of good projects being rejected erroneously, and it also reduces the probability of bad projects being accepted erroneously, and so it reduces credit risk and the cost of lending. As Gehrig (1998) shows, the compression of lending margins induced by fiercer competition between banks negatively impacts screening incentives if, and only if, the value from identifying good projects dominates the value from avoiding risky projects. In other words, in countries where the main benefit from screening is related to avoiding bad projects, intensifying competition in the banking sector may improve the incentives for screening and through this the overall allocation of credit. According to Gehrig (1998), this scenario is particularly relevant for transition economies and developing countries. The relationship between the degree of market competition and the screening incentives of banks is also analysed by Dell'Ariccia (2000), who shows that competition may have two opposite effects. One is that stronger competition is also related to a greater temptation for banks to deviate from a screening equilibrium, and hence it increases the incentive for them not to screen potential borrowers. The other is that fiercer competition between banks corresponds to a stronger adverse selection problem, as the proportion of borrowers known to each bank is reduced, encouraging them to invest more in screening activities. Dell'Ariccia (2000) argues that the sign of the relationship between competition and screening incentives depends on the relative strength of these two forces[10].

Competition may also reduce asymmetric information problems by encouraging banks to strengthen long-term relations with clients who borrow. Boot and Thakor (2000) argue that a more competitive environment may encourage banks to make more relationship loans, notably by becoming more client-driven and by customising the services that they offer. Yafeh and Yosha (2001) reach a similar conclusion. They show that the level of competition between financial intermediaries may strengthen the intensity of the relationships between banks and their clients, arguing that investment in bank-firm relationships can be used strategically by banks to limit competition in arm's length markets[11]. Since a longer-term relation between the bank and the client is one way to overcome asymmetric information, banks would be more inclined to smooth a real shock, by increasing credit during bad times for example (see e.g. Bolton et al. (2016); Gambacorta (2016)).

Second, our results are in line with the literature on bank competition and stability. Theoretical works (Boyd and De Nicoló, 2005; Allen et al., 2011) and empirical works (Uhde and Heimeshoff, 2009; Schaeck and Cihák, 2012; Anginer et al., 2014; Akins et al., 2016) show that an increase in the level of competition in the banking sector could imply that banks are more capitalised or are avoiding

[10] See also Caminal and Matutes (2002), who theoretically investigate the existence of a trade-off between monitoring and credit rationing by considering two extreme market structures, which are monopoly and Bertrand competition.

[11] See Presbitero and Zazzaro (2011) for an empirical examination of the link between bank competition and relationship lending.

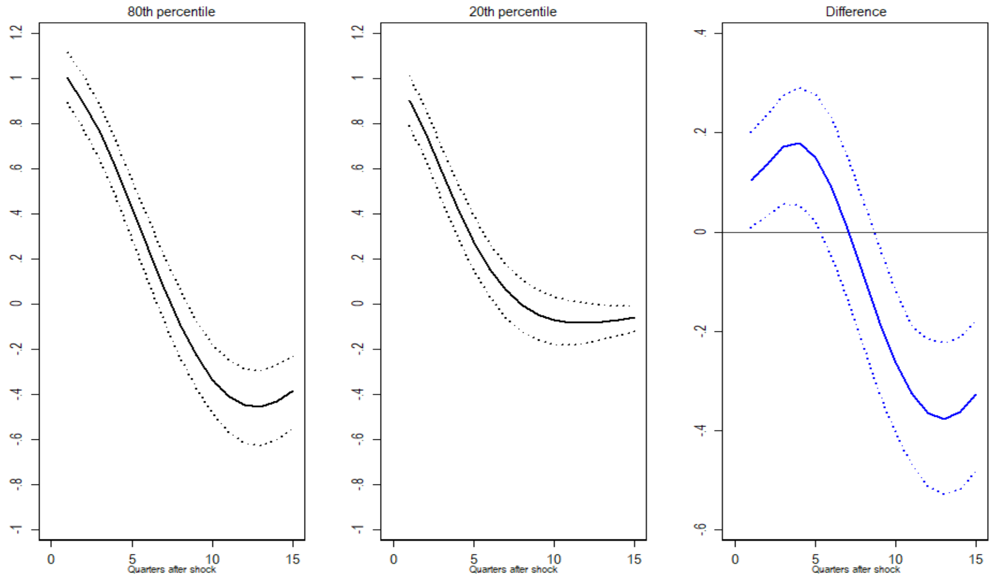
projects with higher risk. Taking on less risk implies that periods with rapid credit increases are less pronounced during the boom of the cycle, and banks experience lower losses in the decreasing period, which tends to maintain the equity capital of banks and their willingness to engage in newer risky projects and supply new credit in bad times. This would further be strengthened by the positive influence that stronger bank competition might have on policies related to risk management.

Finally, as argued by Leroy and Lucotte (2019), the greater credit procyclicality of banks in a less competitive environment could simply be explained by behaviour intended to maximise profits. Indeed, in general the optimal behaviour of a firm with market power is to adjust quantity rather than price after a variation in demand. Hence, market power would then mean both stronger credit fluctuations and higher bank interest rate hysteresis (Leroy and Lucotte, 2015).

These results imply that less competition in the banking industry is a financial accelerator as it means a shock to the output gap is transmitted faster in the credit market. In this sense the financial accelerator theory establishes that it could make the business cycle bigger, and the persistence of economic shocks is related to the amplitude of the consequences for financial conditions and for credit dynamics. If that is the case, we could expect that the response of GDP to a shock will be stronger in cases where bank competition is lower since this yields more credit fluctuations.

Figure 9 presents the GDP cycle response to an exogenous output gap shock. The differences between the mean response for low and high levels of bank competition confirm our expectation that a GDP cycle shock has a weaker effect on output when there is a higher level of competition in banking systems.

Figure 9: Impulse response functions of GDP to a GDP shock as a function of banking competition



Note: The figure displays the impulse response functions of the GDP cycle to a one-unit shock in the output gap at the 80^{th} and 20^{th} percentiles of the Lerner index sample distribution. The chart on the right represents the difference between the two. The dotted lines represent the 95% confidence bands generated by bootstrapping (1000 draws).

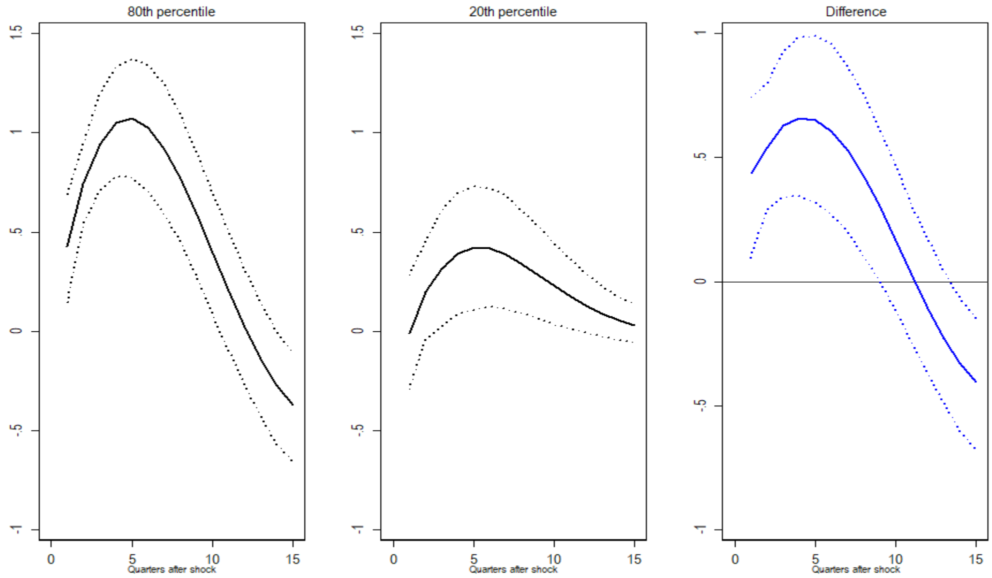
6 Robustness checks

We check the robustness of our previous findings in several ways. To save space, we only report the results of the IPVAR framework. The results of the panel VAR and of the country-specific VAR models are available upon request.

Alternative ordering of the variables. In our baseline identification scheme, we place the output gap before the credit gap. We check the robustness of our findings by considering credit as the first variable in the ordering. In this way, credit is considered to be more exogenous than it is in our baseline specification, as it is not contemporaneously affected by a shock to GDP. Figure 10 displays the IRFs obtained with this alternative ordering and confirms our previous results.

Hodrick-Prescott filtering. Several criticisms are frequently aimed at the HP filter (see e.g. Kaiser and Maravall (2001); Mise et al. (2005)). Most notably the HP filter suffers from a well-known start-point and end-point problem, which affects HP trend estimates at the start and at the end of the data period (Gersl and Seidler, 2012; Drehmann and Tsatsaronis, 2014). As Figure A1 in the Appendix suggests, the start-point bias is particularly notable for the bank credit series. One usual way of dealing with this problem is to drop the first and last

Figure 10: Impulse response functions of bank credit to a GDP shock as a function of banking competition: Alternative ordering or variables



Note: The figure displays the impulse response functions of bank credit to a one-unit shock in the output gap at the 80^{th} and 20^{th} percentiles of the Lerner index sample distribution. The chart on the right represent the difference between the two. The dotted lines represent the 95% confidence bands generated by bootstrapping (1000 draws).

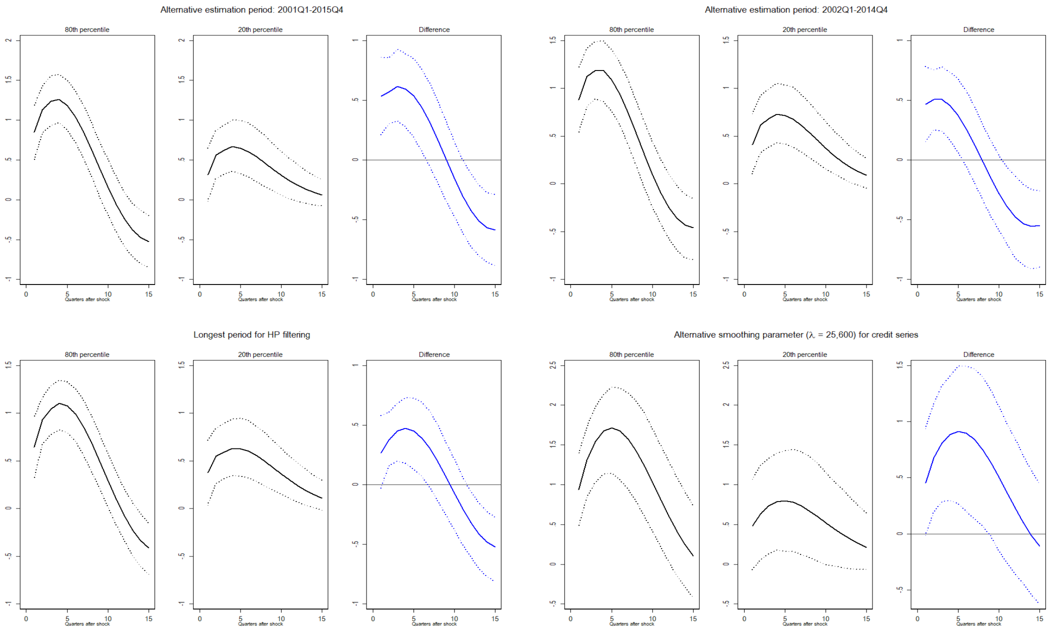
observations of the sample period. We then check the robustness of our previous findings by re-estimating our different VAR frameworks on a shorter period, for which we consider two alternative periods, 2001Q1-2015Q4 and 2002Q1-2014Q4. We also address the start-point problem by estimating a second series of gaps considering a longer period. The HP filter is now applied to the seasonally adjusted series over the 1995Q1-2016Q4 period, which is the longest period for which we can find a comparable data series for our sample countries[12]. A comparison of filtered series is provided in Figures A10 to A13 in the Appendix.

Finally, we consider alternative credit gap series by setting a larger smoothing parameter for the HP filter. The smoothing parameter is related to the length of the cycle. In our baseline investigation, we consider the same smoothing parameter of $\lambda = 1600$ for all four macroeconomic variables. This means that we assume that credit cycles have the same length as business cycles. However, as Drehmann and Tsatsaronis (2014) and Borio (2014) argue, financial cycles tend to be longer than standard business cycles. Given the relatively short length of our panel data, we assume that credit cycles are twice as long as business cycles. Then we follow the rule developed by Ravn and Uhlig (2002), which says that for quarterly data optimal λ of 1600 should be chosen and in addition it should be

[12] Please note that data for Bulgaria and Romania are only available from 1996Q1 and 1998Q1 respectively. Please also note that the interest rate series for Slovakia are not available before 2000Q1.

adjusted by taking the fourth power of the observation frequency ratio, and we set a λ of 25600. The results that we obtain for the IPVAR framework are reported in Figure 11. They confirm our previous findings. We still find that weaker competition in the banking sector tends to accelerate credit procyclicality[13].

Figure 11: Impulse response functions of bank credit to a GDP shock as a function of banking competition: Alternative HP filtering approaches



Note: The figure displays the impulse response functions of the GDP cycle to a one-unit shock in the output gap at the 80^{th} and 20^{th} percentiles of the Lerner index sample distribution. The chart on the right represent the difference between the two. The dotted lines represent the 95% confidence bands generated by bootstrapping (1000 draws).

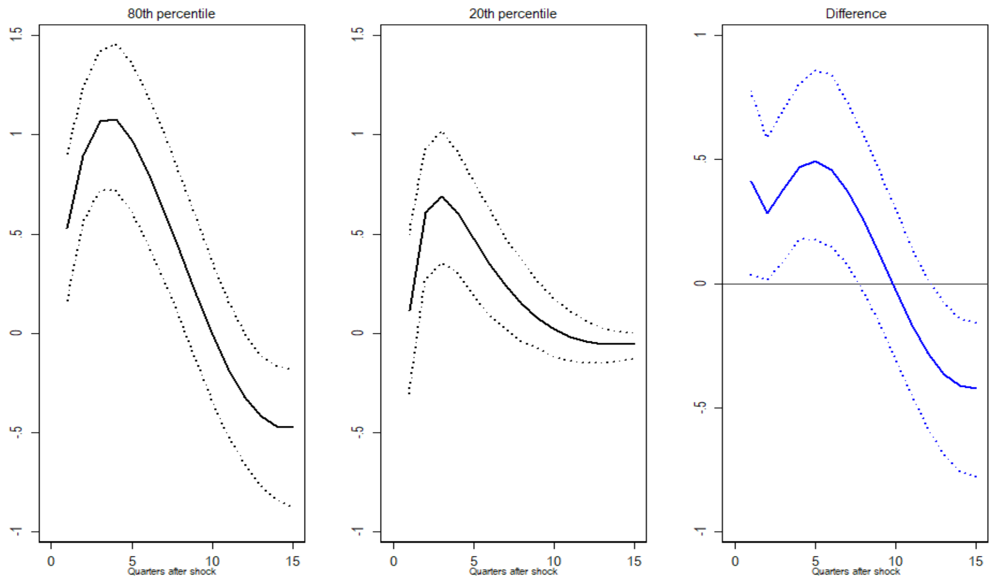
Mean group estimator. We include country fixed effects in our baseline IPVAR framework to control for unobserved unit-specific factors. In this way we control for structural characteristics other than banking competition that could explain the differences in credit procyclicality across the CEECs. However, by adding country fixed effects we cannot control for factors other than competition which could be correlated with competition. Not controlling for this unobserved dynamic heterogeneity could imply that our estimations become inconsistent (Pesaran and Smith, 1995).

To control for both unobserved country-specific variations and variations that are conditional on specific structural characteristics, Sá et al. (2014) run a mean group-type estimator. We follow their example and expand the initial IPVAR model, which means including the interaction of all the endogenous variables with country dummies. By doing this, we can observe the heterogeneity of the

[13]We also checked the robustness of our results by considering the interest rate in levels rather than its cyclical component. The results that we obtain, available upon request, are similar to those reported above.

coefficients, which is related to country-specific effects and which is caused by competition in the banking sector. The impulse response functions reported in Figure 12 confirm our previous results.

Figure 12: Impulse response functions of bank credit to a GDP shock as a function of banking competition: Mean group estimator

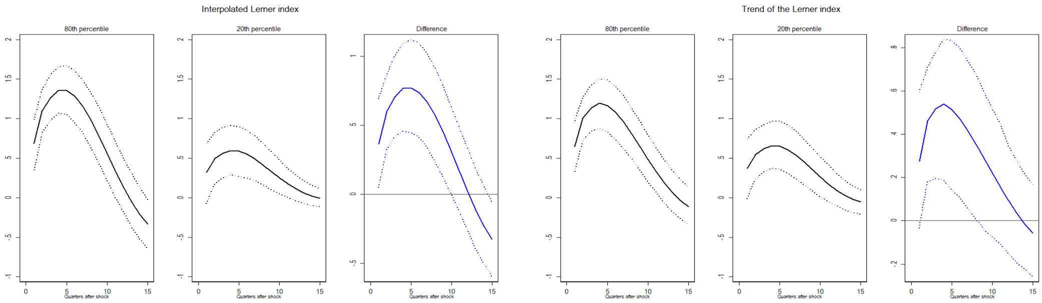


Note: The figure displays the impulse response functions of bank credit to a one-unit shock in the output gap at the 80^{th} and 20^{th} percentiles of the Lerner index sample distribution. The chart on the right represent the difference between the two. The dotted lines represent the 95% confidence bands generated by bootstrapping (1000 draws).

Alternative Lerner indexes. Finally, we check the sensitivity of our baseline results by considering two alternative Lerner indexes. First, rather than considering the same value of the Lerner index for each quarter of a given year, we use a linear interpolation procedure to match the variable to the quarterly frequency of our study. Second, we extract the trend component of the Lerner index using an HP filter[14]. Like our baseline estimates, these two alternative Lerner indexes are lagged four quarters. Figure 13 displays the IRFs obtained when we consider these alternative measures of the Lerner index, and it confirms our previous findings.

[14]See Figure A8 in the Appendix for a comparison of the three alternative Lerner indexes considered in our study.

Figure 13: Impulse response functions of bank credit to a GDP shock as a function of banking competition: Alternative Lerner indexes



Note: The figure displays the impulse response functions of bank credit to a one-unit shock in the output gap at the 80^{th} and 20^{th} percentiles of the Lerner index sample distribution. The chart on the right represent the difference between the two. The dotted lines represent the 95% confidence bands generated by bootstrapping (1000 draws).

7 Conclusion

This paper is the first in the literature to investigate empirically credit procyclicality in CEECs. Our findings point to three main results. First, our research indicates that credit procyclicality is more pronounced in boom periods. The comparison of the IRFs for different stages of the business cycle clearly shows that credit reacts to a shock in GDP positively with varying degrees of magnitude. These findings are in line with those of Bouvatier et al. (2014), who finds that the degree of credit procyclicality is more or less pronounced according to the position of the business cycle. This means that procyclicality is higher for the CEECs during boom periods. Boom periods in the CEECs are also characterised by large increases in property and share prices which, in turn, affect credit dynamics.

Second, we show that there are differences in credit procyclicality across the CEECs. Whereas Bulgaria, Slovakia and Poland show a stronger reaction of credit to GDP shocks, procyclicality is more muted in Estonia, Slovenia and the Czech Republic.

Third we analyse the drivers of credit procyclicality and find evidence in favor of the argument that more highly concentrated banking sectors augment credit procyclicality. This finding is in line with results obtained by Leroy and Lucotte (2017) but in contrast to theoretical predictions put forward by Petriconi (2015).

We have observed an important degree of heterogeneity in the impact of GDP shocks on bank credit, depending on the country analysed. The different degrees of financial and economic integration and differences in the development of institutions, in addition to their dependence on foreign banks, may explain why different countries respond differently. Our results also show that different levels of banking concentration can explain the differences in credit dynamics across the CEE countries.

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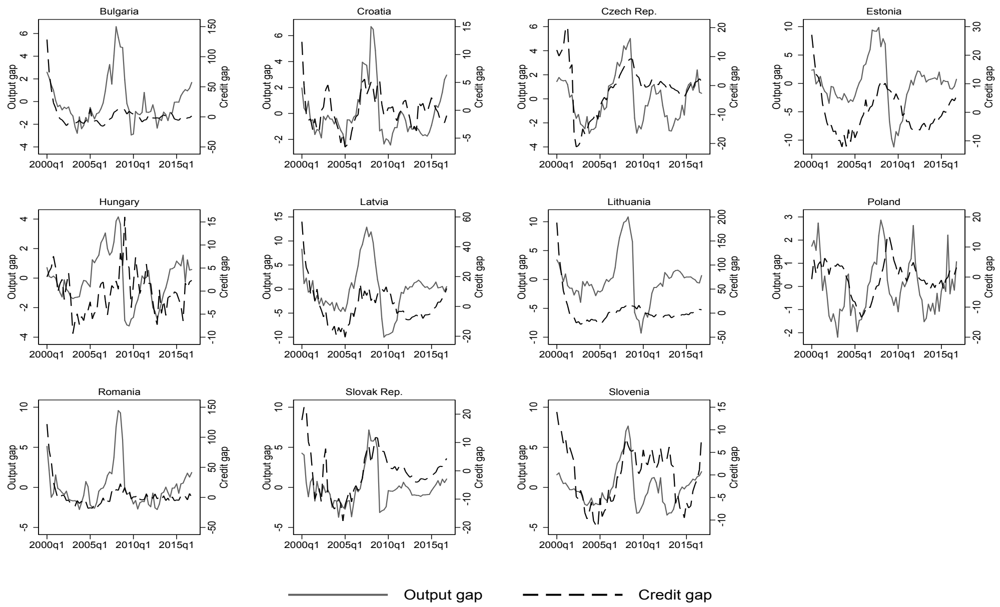
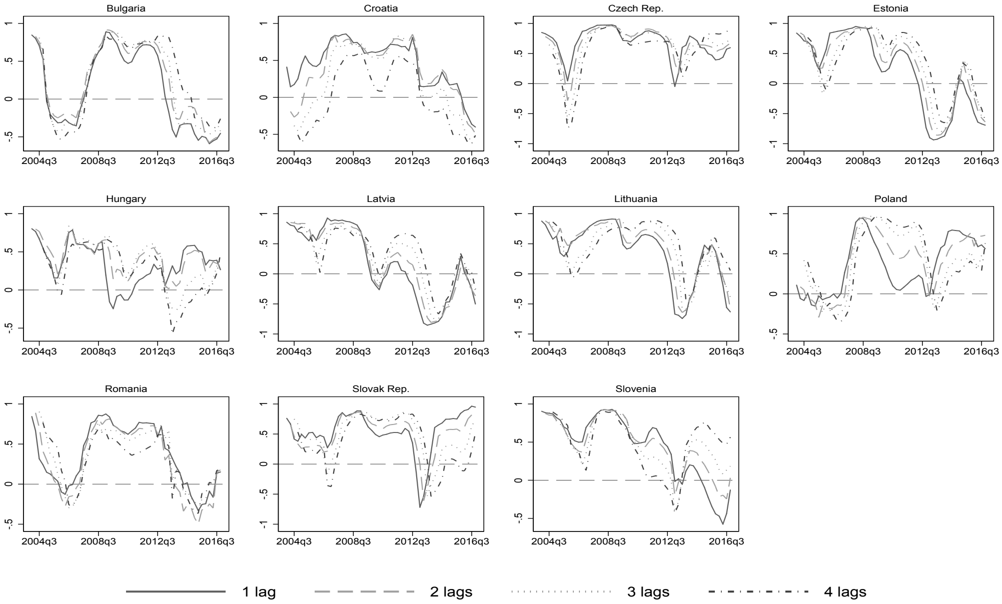
Appendix

Figure A1: Evolution of the business and credit cycles in CEECs



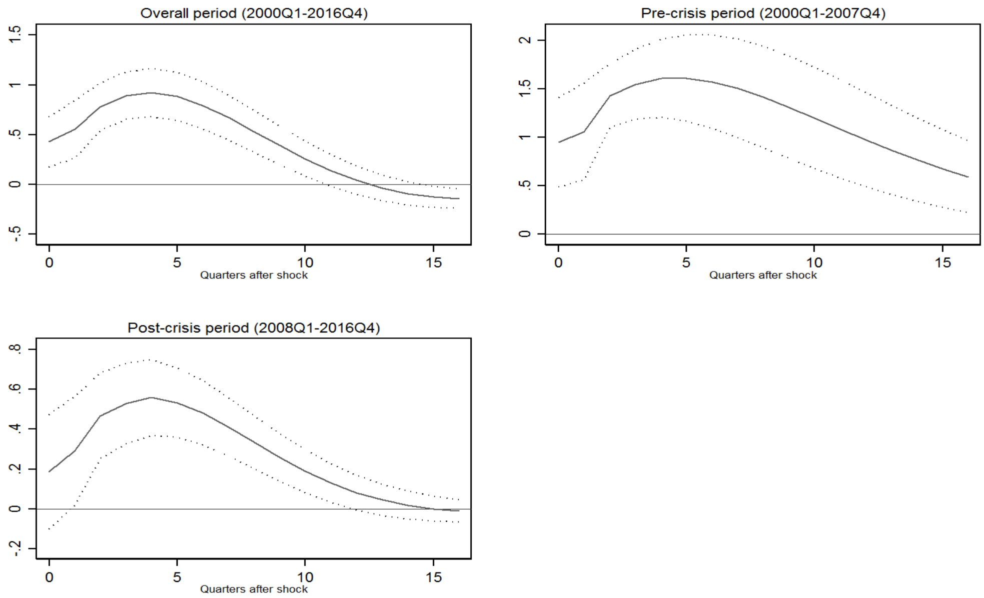
Source: Authors' calculations, International Financial Statistics, International Monetary Fund. Note: The business cycle and the credit cycle are obtained by isolating the cyclical components of real GDP and real credit series using the Hodrick-Prescott (HP) filter. They are defined as the percentage gap between the trend values and the observed values of the series.

Figure A2: Dynamic correlation between the business cycle and the credit cycle in CEECs



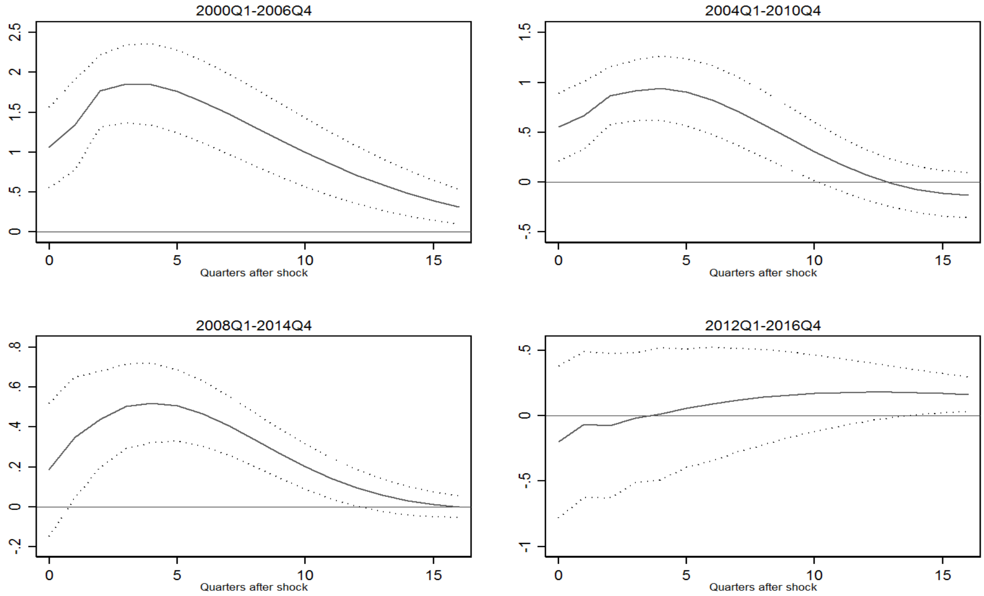
Source: Authors' calculations, International Financial Statistics, International Monetary Fund. Note: The dynamic correlation between the business cycle and the credit cycle is calculated by considering a 4-year rolling window. We consider four different lag structures for the business cycle: 1 lag, 2 lags, 3 lags and 4 lags.

Figure A3: Evolution of credit procyclicality in CEECs in the aftermath of the subprime crisis



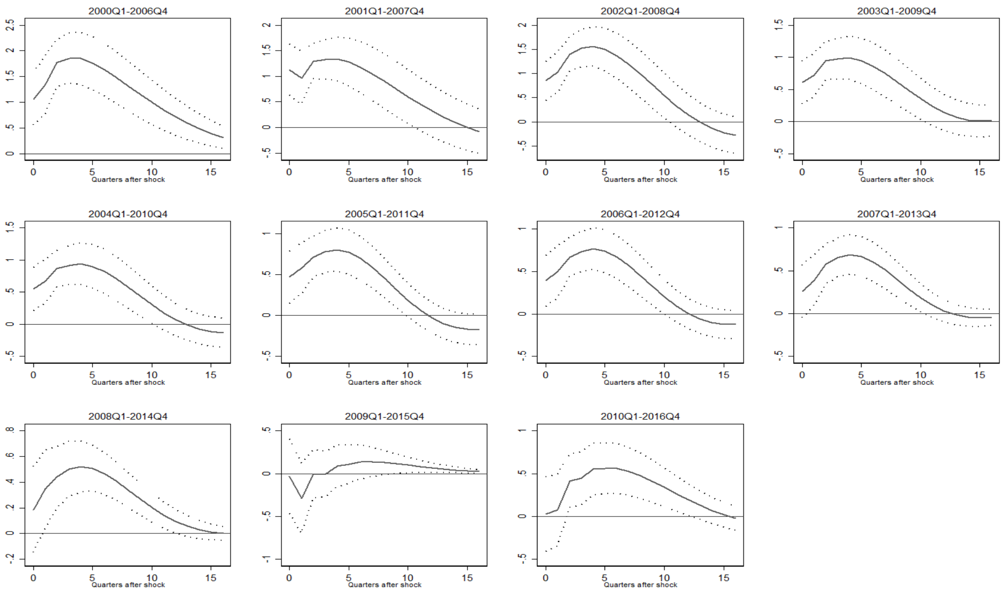
Note: The figures display the impulse responses of bank credit to a one-unit shock in the output gap by considering three different periods: the overall period (2000Q1-2016Q4), the pre-crisis period (2000Q1-2007Q4) and the post-crisis period (2008Q1-2016Q4). The dotted lines represent the 95% confidence bands generated by bootstrapping (1000 draws).

Figure A4: Evolution of credit procyclicality in CEECs between 2000 and 2016



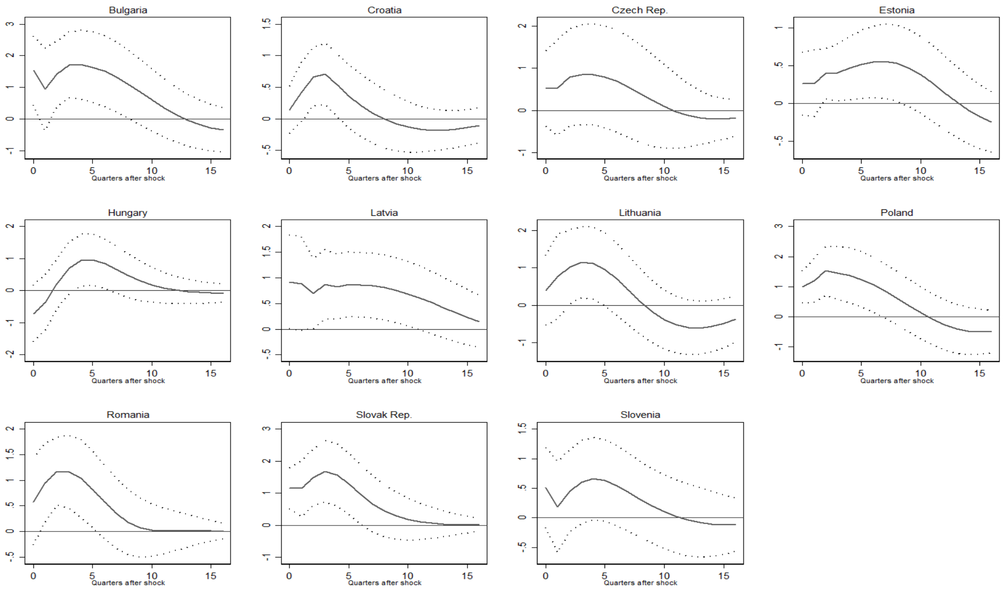
Note: The figures display the impulse responses of bank credit to a one-unit shock in the output gap by considering four different overlapping sub-periods: 2000Q1-2006Q4, 2004Q1-2010Q4, 2008Q1-2014Q4, 2012Q1-2016Q4. The dotted lines represent the 95% confidence bands generated by bootstrapping (1000 draws).

Figure A5: Evolution of credit procyclicality in CEECs: rolling estimates



Note: The figures display the impulse responses of bank credit to a one-unit shock in the output gap by considering 7-year rolling windows. The dotted lines represent the 95% confidence bands generated by bootstrapping (1000 draws).

Figure A6: Country-specific impulse response functions of bank credit to a GDP shock



Note: The figure displays the country-specific impulse response functions of bank credit to a one-unit shock in the output gap on the overall period (2000Q1-2016Q4). The dotted lines represent the 95% confidence bands generated by bootstrapping (1000 draws).

Figure A7: Stability of the country-specific VAR models

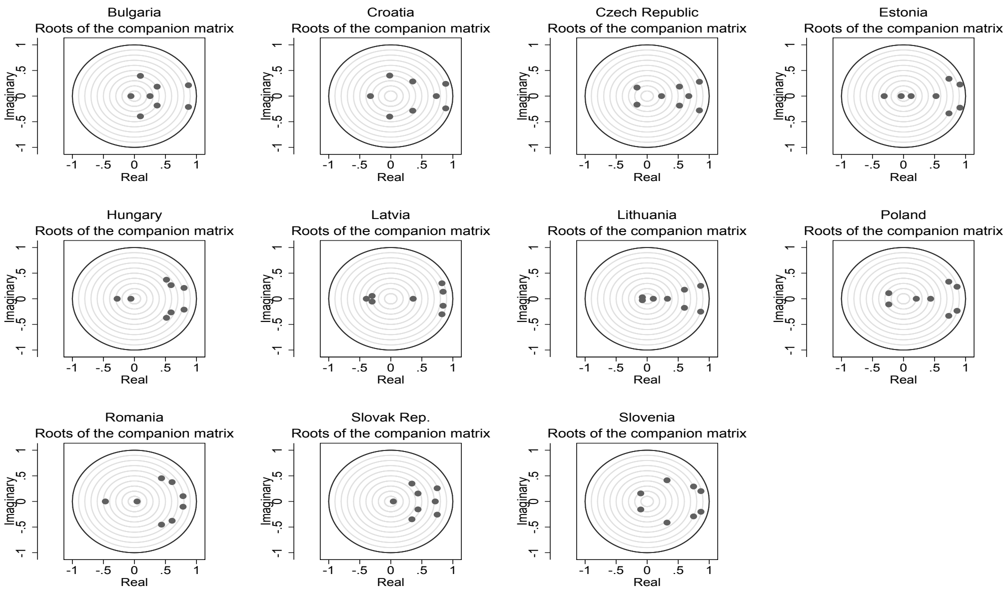
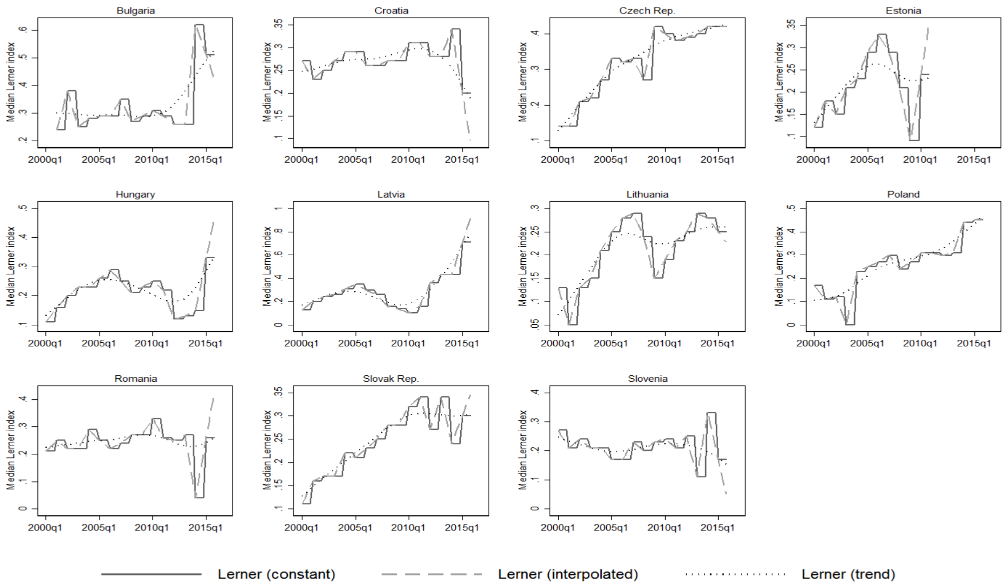
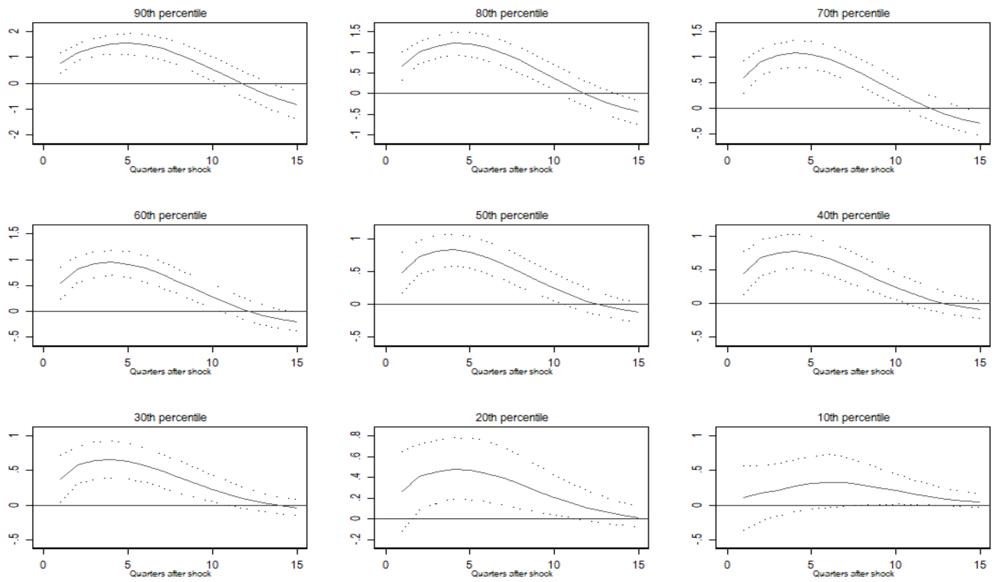


Figure A8: Evolution of the Lerner index in CEECs between 2000 and 2015



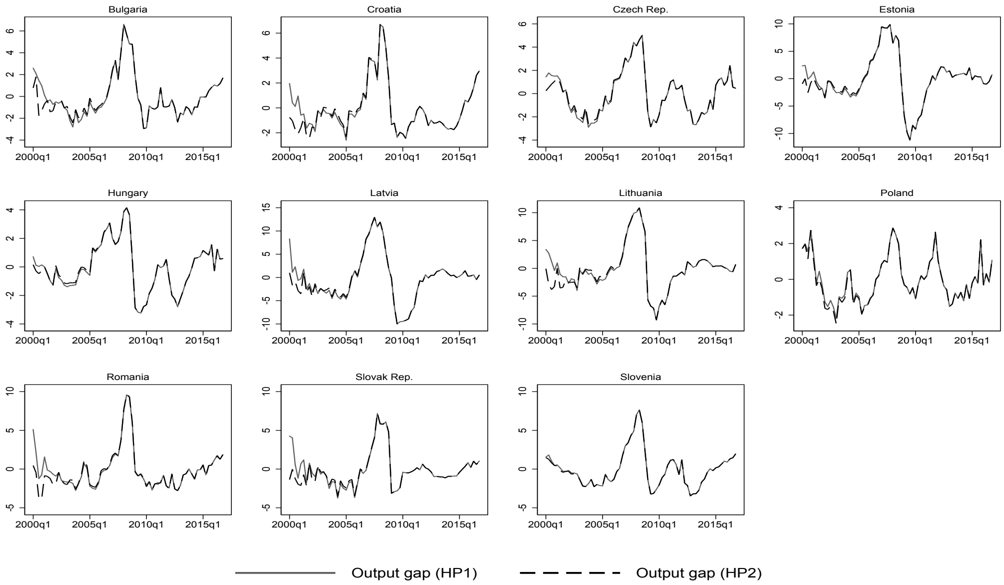
Source: Authors' calculations, Global Financial Development Database, The World Bank. Note: The Lerner index corresponds to the median of the individual Lerner indexes calculated using bank balance-sheet data from the Bankscope database. Please note that data for Estonia are only available until 2010.

Figure A9: Impulse response functions of bank credit to a GDP shock for different levels of bank competition



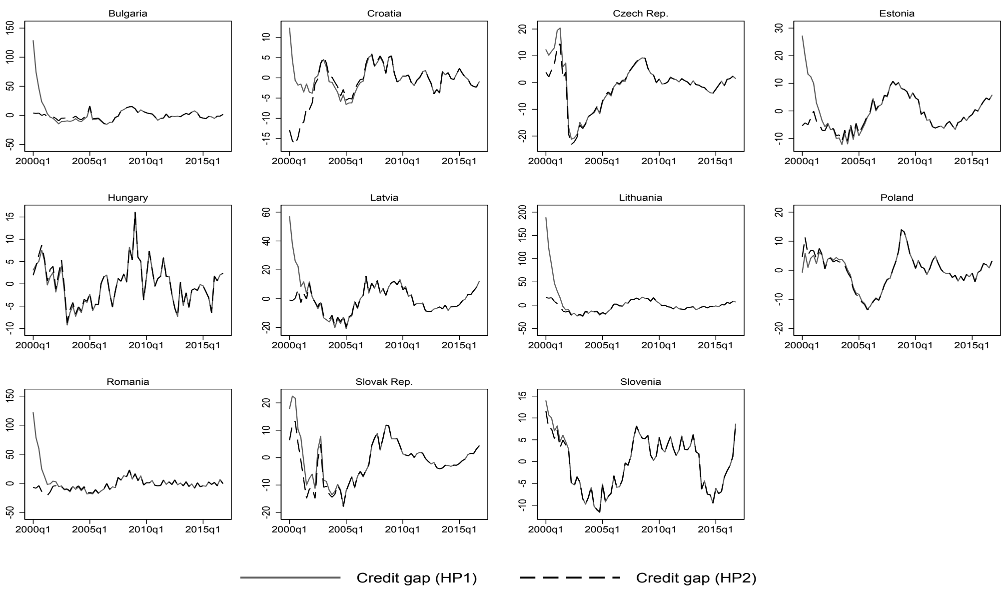
Note: The figure displays the impulse response functions of bank credit to a one-unit shock in the output gap evaluated at different percentiles of the Lerner index sample distribution. The dotted lines represent the 95% confidence bands generated by bootstrapping (1000 draws).

Figure A10: Output gap - Comparison of HP filtered series



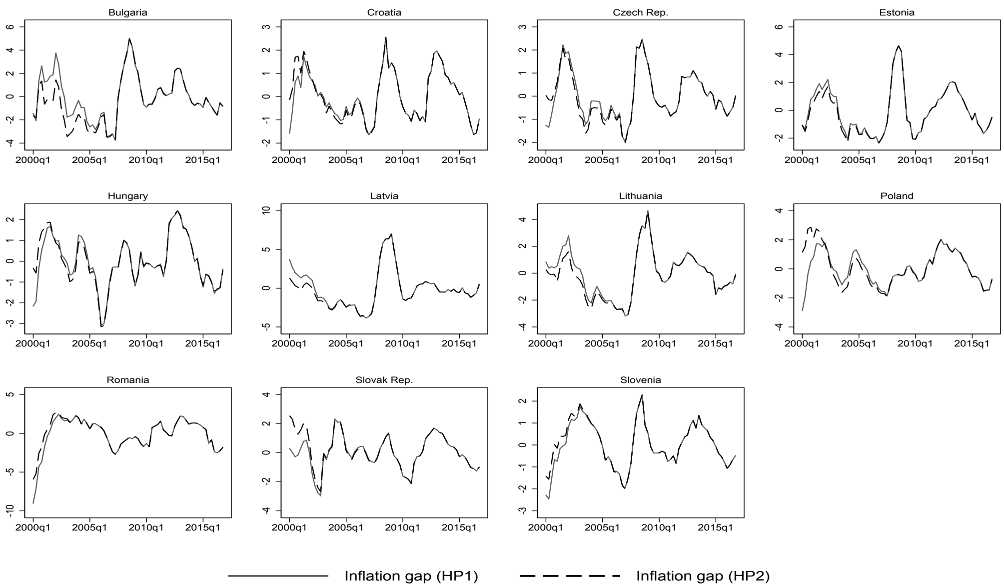
Note: Output gap (HP1) corresponds to the output gap based on a HP filter estimated from 2000Q1 to 2016Q4, and output gap (HP2) to the output gap based on a HP filter estimated from 1995Q1 to 2016Q4.

Figure A11: Credit gap - Comparison of HP filtered series



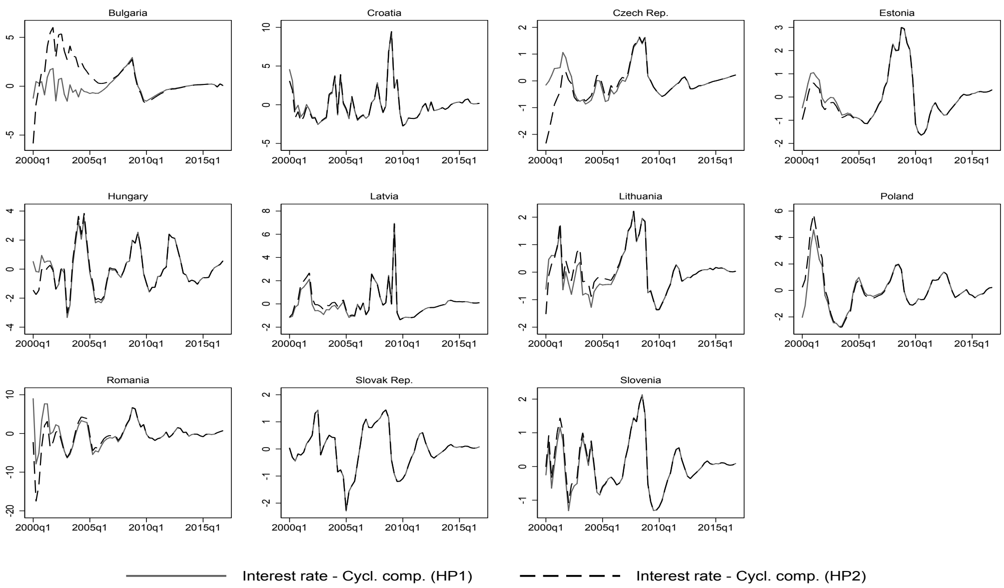
Note: Credit gap (HP1) corresponds to the credit gap based on a HP filter estimated from 2000Q1 to 2016Q4, and credit gap (HP2) to the credit gap based on a HP filter estimated from 1995Q1 to 2016Q4.

Figure A12: Inflation gap - Comparison of HP filtered series



Note: Inflation gap (HP1) corresponds to the inflation gap based on a HP filter estimated from 2000Q1 to 2016Q4, and inflation gap (HP2) to the inflation gap based on a HP filter estimated from 1995Q1 to 2016Q4.

Figure A13: Cyclical component of the interest rate - Comparison of HP filtered series



Note: Interest rate - Cycl. comp. (HP1) corresponds to the cyclical component of the interest rate based on a HP filter estimated from 2000Q1 to 2016Q4, and Interest rate - Cycl. comp. (HP2) to the cyclical component of the interest rate based on a HP filter estimated from 1995Q1 to 2016Q4.