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The art of conducting macropru

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Abstract

This paper empirically assesses how effective macroprudential policies are at preventing and mitigating excessive procyclicality for credit, and whether their effectiveness is driven by how such policies are conducted over the business cycle. We use a sample of 42 OECD and non-OECD countries over the period 1990Q1-2019Q4 and propose an original macroprudential policy stance index that gauges the degree of countercyclicality of a policy, and we estimate whether it is an important determinant of credit procyclicality. Our results are based on an IPVAR model and confirm that the intensity of credit procyclicality decreases significantly as the degree of countercyclicality of the macroprudential policy increases. We find that the credit cycle responds less to a business cycle shock when the macroprudential policy is conducted in a countercyclical way. Consequently, our empirical findings highlight that the key to making macroprudential policies effective is the art of moving instruments in the right direction at the right time.

JEL Codes: E02, E32, G21, G28.

Keywords: Macroprudential policy, Countercyclical policy, Credit procyclicality, Interacted Panel VAR, Financial stability.

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1 Introduction

Many lessons have been learnt from the global subprime crisis that erupted in mid-2007. One was that the Basel II regulation framework was widely recognised by academics, practitioners and policy makers to be procyclical in nature. By introducing more risk-sensitive capital requirements, the Basel II regime tended to magnify the procyclicality that is inherent in bank lending behaviour (Kashyap et al., 1997, Ly and Shimizu, 2021). The excessive growth in credit and leverage at the beginning of the 2000s and the contraction of the credit supply following the subprime crisis are a perfect illustration of these procyclical lending practices.

To address this issue, some countries have chosen to implement specific countercyclical prudential tools. One approach that garnered a lot of attention is the Spanish dynamic provisioning scheme, which was introduced in July 2000 to cope with a period of significant lending growth and a sharp increase in credit risk. Dynamic provisioning requires banks to earmark a portion of their capital by building a general provision during good times that can be used to offset losses during bad times, with the aim of protecting bank lending capacity during economic downturns.[1] Recognising the importance of the potential procyclical effects of the Basel II framework, the Basel Committee issued proposals at the end of 2009 for how to make the capital requirements less procyclical and promote the build-up of capital buffers in good times. However, it was not until the end of 2010 that the Basel Committee gave recommendations that clearly and formally dealt with the problem of the procyclicality of the loan supply, when the Basel III agreements added a macroprudential component to the existing banking regulation by introducing a number of countercyclical prudential tools.

The main objective of macroprudential policy is to regulate the financial system as a whole and to mitigate and prevent systemic risk. Such risk is usually defined as a risk of disruption to financial services that is caused by an impairment of all or part of the financial system and could have serious negative consequences for the real economy. Systemic risk has two key dimensions, the cross-sectional dimension and the time dimension (Borio, 2011), and there is a source of system-wide financial distress that corresponds to each dimension. The cross-sectional dimension is the risk that can arise from common exposures and interlinkages between financial institutions that could result in joint failures. This dimension of systemic risk concerns the way that a specific shock to the financial system can propagate itself and become systemic. The source in the time dimension is the procyclicality of the financial system. More precisely, this dimension covers the mechanism through which the financial system can amplify economic cycles, either by encouraging boom cycles during which risks accumulate and are underestimated or, conversely, by exacerbating disruptions during bust cycles through excessive risk aversion (Bennani et al., 2014). In the European Union, this time dimension of systemic risk constitutes the first intermediate objective formulated by the European Systemic Risk Board (ESRB/2013/1). This intermediate objective states that national macroprudential authorities should adopt and calibrate appropriate prudential tools to mitigate and prevent excessive credit growth and lever-

[1] See, for instance, Fernández de Lis and Garcia-Herrero (2010) and Basel Committee on Banking Supervision (2021) for more details about the Spanish dynamic provisioning regime. As shown empirically by Jiménez et al. (2017), this regime has helped to smooth credit supply cycles and to support firm performance in bad times.

age.

The procyclicality of the financial system is evidently at the heart of macroprudential concerns and there is still an intensive debate about it among practitioners and policy makers. The externalities of the credit cycle for systemic risk make it crucial to understand how macroprudential policy affects the supply of bank credit in good and bad times, but the academic literature that assesses the effects of macroprudential policies on credit procyclicality empirically is, surprisingly, relatively scarce. Furthermore, its findings are not conclusive and merit further investigation. Our paper consequently tries to fill this gap in the literature. More precisely, the aim of the paper is to investigate empirically at the macro-level whether the way that countercyclical macroprudential policies are conducted helps to contain the procyclicality of credit.

Our study introduces two innovations over the existing literature. The first is that we propose an original macroprudential index to gauge how discretionary macroprudential policies are conducted in a countercyclical way over the business cycle. To avoid confusion, a macroprudential policy is said here to be "countercyclical" if it prescribes the build-up of prudential buffers in good times, or conversely, if it relaxes prudential requirements in bad times. It is particularly important to measure the degree of countercyclicality of macroprudential policies since such policies are tricky to get right. Indeed, as argued by Danielsson et al. (2016), there could be some cases where the macroprudential authorities conduct policy in a procyclical way, notably because of a misperception of the underlying financial risks, which can induce delays in making macroprudential decisions. Second, we use an appropriate econometric framework in the form of an IPVAR model to assess whether heterogeneity across countries in their credit procyclicality is explained by differences in their conduct of macroprudential policy.

The econometric framework that we consider also allows us to assess formally the procyclicality of credit, which is usually defined as an overreaction of the credit supply to business cycle fluctuations. As discussed by Athanasoglou et al. (2014), several factors can contribute to strengthen or mitigate the procyclicality of the banking industry. Borio et al. (2001) argue that a common explanation for the procyclicality in the financial industry is that there are information asymmetries between lenders and borrowers. This means that collateral values rise and firms have better access to external finance when economic conditions are favourable, since banks are more willing to extend loans to the private sector. When economic conditions are depressed and collateral values are low however, information asymmetries imply that borrowers will have greater difficulties in obtaining funding, even those with profitable projects. This mechanism refers to the well-known "financial accelerator". Credit procyclicality can also be explained by the fact that the credit practices regarding collateral requirements depend on the position of the business cycle. In particular,Jiménez and Saurina (2006) show that banks tend to relax their credit standards in booms, while they tend to tighten their approval criteria for loans in bad times. One possible explanation for how lending standards evolve over the business cycle is the misperception of the evolution of risk over time (Borio et al., 2001). Due to difficulties in measuring the time dimension of risk correctly, financial institutions are prone to underestimating risk during economic upswings, leading to excessively rapid credit growth, while the opposite applies during downswings.

As mentioned above, the banking regulatory and supervisory framework can also be a source of credit procyclicality (Athanasoglou et al., 2014), especially when there are risk-sensitive capital requirements. During an economic upturn, the banking sector enjoys lower risk weightings and then needs to hold less capital to meet the minimum capital requirements ratio, which in turn allows banks to expand their credit volumes significantly. As risk-weightings tend to increase and loan losses to accelerate during an economic downturn though, banks need to raise new capital to reach the desired level of the capital adequacy ratio. This may induce banks to reduce the credit supply and increase their lending margins, thereby amplifying the procyclicality of bank lending. One of the main objectives of macroprudential policy is to overcome precisely this adverse effect of the risk-based capital requirements rule.

To assess whether countercyclical macroprudential policies are effective at containing and mitigating credit procyclicality, we use the IPVAR model developed by Towbin and Weber (2013), which is an empirical framework that has attracted growing interest in the academic literature over the past decade. We estimate this multivariate model on a sample of 42 OECD and non-OECD countries over the period 1990Q1-2019Q4. The results that we obtain confirm that macroprudential policies conducted in a countercyclical way are effective at alleviating the procyclicality that is inherent in bank lending behaviour. Our findings show that the degree of credit procyclicality is significantly lower when the macroprudential policy stance moves in the right direction across the business cycle, and they highlight that the essence of making macroprudential policies effective is the art of moving instruments in the right direction at the right time. To the best of our knowledge, this is the first paper in the empirical literature to give a formal and clear answer to this issue.

The remainder of the paper is structured as follows. Section 2 provides an overview of the empirical literature on the effectiveness of macroprudential policies, and discusses the few studies that give a first preliminary answer about the effect of the macroprudential policy stance on credit procyclicality. Section 3 presents the countercyclical macroprudential policy index used in this paper, while Section 4 describes the econometric framework and the data. Section 5 presents and discusses the empirical results, Section 6 is devoted to robustness checks, and Section 7 concludes and suggests potential orientations for further research.

2 Literature review

As the introduction highlights, preventing excessive credit procyclicality is one of the main objectives of macroprudential policies, and this explains why a number of macroprudential instruments have been designed to address this issue. Despite the growing interest of the academic literature about the effectiveness of macroprudential policies however, research into how these policies affect credit procyclicality is relatively scarce. Most of the existing empirical studies on macroprudential policy focus mainly on how it impacts various measures of financial vulnerability and stability at both the micro and macro-levels.[2]

[2] For a comprehensive literature review on the effects of macroprudential policy, see Galati and Moessner (2018).

The studies at bank-level usually analyse whether adopting a macroprudential policy framework helps in mitigating bank risk-taking. Altunbas et al. (2018) find for a large panel of banks for instance that tightening macroprudential policies reduces the individual probability of default for financial institutions, even if this effect depends on the characteristics and business models of the individual banks. Meuleman and Vander Vennet (2020) obtain similar results for a sample of European banks. They find that macroprudential policy is effective at containing individual risk and also bank systemic risk. Like those of Altunbas et al. (2018), their results confirm that the effects of macroprudential policies are heterogeneous among banks depending on their business models. Gaganis et al. (2020) go a step further and assess whether macroprudential policies and corporate governance interact in shaping bank risk. Their results show that the impact of bank corporate governance on risk-taking depends critically on the macroprudential policies in force.

In addition to these bank-level studies, there are also a number of cross-country studies that assess whether the macroprudential policy stance drives growth in credit and real estate prices significantly[3]. These studies include for instance McDonald (2015), Vandenbussche et al. (2015), Kuttner and Shim (2016), Zhang and Zoli (2016), Akinci and Olmstead-Rumsey (2018), Carreras et al. (2018). They tend to find support for a negative and significant relationship between macroprudential policy tightening and the growth rate of credit and housing prices. They also find that the effects of macroprudential policy decisions are not immediate and that transmission delays vary for different prudential instruments. More importantly, in line with the macroprudential policy index that we propose in this paper, McDonald (2015) finds that the relative effectiveness of tightening or loosening macroprudential measures depends on where in the housing cycle they were implemented. Similar results are obtained by Cerutti et al. (2017a), who find that macroprudential policies are more effective when the financial cycle is more intense.

Some other empirical papers extend the analysis by assessing how far the monetary policy stance affects the effectiveness of macroprudential policies (Bruno et al., 2017, Zhang and Tressel, 2017, Gambacorta and Murcia, 2020, Garcia Revelo et al., 2020). Garcia Revelo et al. (2020) consider a sample of emerging and advanced economies and show that macroprudential policies are more effective at curbing domestic credit growth when they are accompanied by a restrictive monetary policy. Their results also suggest that coordination between the two policies helps to reduce the delay in the transmission of macroprudential policy actions.

The previous studies use credit growth as the endogenous variable, but De Schryder and Opitz (2021) are the first in the literature to assess how macroprudential policy affects the credit cycle. It proposes an innovative narrative approach to identifying exogenous macroprudential policy shocks. Their results, based on the local projections method, indicate a persistently negative response of the credit-to-GDP ratio to a macroprudential policy shock. De Schryder and Opitz (2021) also find that the effects are stronger in credit cycle upturns, but her empirical results cannot be interpreted in terms of credit procyclicality, as they do not provide an answer as to whether the macroprudential policy stance drives the link between the business cycle and the credit cycle.

[3]Recent empirical papers also investigate how macroprudential policies affect growth-at-risk (Franta and Gambacorta, 2020, Galán, 2020).

To the best of our knowledge, only three empirical studies are close to our research question and try to capture the effect of the macroprudential policy stance on credit procyclicality (Lim et al., 2011, Budnik, 2020, Olszak and Kowalska, 2022). These studies generally define the procyclicality of lending as the sensitivity of credit growth to GDP growth, and assess whether different macroprudential instruments mitigate the relationship between the growth rates of GDP and credit. Econometrically, they simply extend their baseline estimates by adding an interactive term between the macroprudential instruments considered and GDP growth, and evaluate whether the coefficient associated with the interactive term is statistically significant.

The results obtained by Lim et al. (2011) for a sample of 48 countries over the period 2000Q1-2010Q4 suggest that five of the eight macroprudential instruments make credit significantly less procyclical. These instruments are the loan-to-value ratio, the debt service-to-income ratio, limits on credit growth, reserve requirements, and dynamic provisioning requirements. The results for the other macroprudential instruments are more mixed. It is particularly surprising that the countercyclical capital requirements do not significantly impact credit procyclicality in the baseline estimates, given that this macroprudential instrument is specifically designed to counteract procyclicality in the banking industry.

A similar empirical investigation is conducted by Budnik (2020) for a sample of 28 European Union member states over the period 1995Q1-2017Q4. She considers a large set of 18 macroprudential tools and estimates whether the adoption and the cumulative stance of each macroprudential instrument reduce the positive link between the rate of GDP growth and the rate of credit growth to the non-financial sector. Her results do not give a clear answer about the effectiveness of macroprudential policy in taming the procyclicality of credit, and largely depend on the instrument considered, while for some instruments Budnik (2020) finds the opposite results when she decomposes total credit to the non-financial sector into credit to non-financial corporations and credit to households. Unlike Lim et al. (2011) however, Budnik (2020) finds that the adoption of capital buffers by a large number of European countries has allowed those economies to contain credit procyclicality. Furthermore, the results obtained by Budnik (2020) seem to suggest that while adopting a limit on the a loan-to-value ratio mitigates the procyclicality of credit, it also reinforces the positive link between GDP growth and credit growth, even though this macroprudential tool is usually viewed by practitioners and policy makers as an effective instrument for containing excessive growth in housing credit.

More recently, Olszak and Kowalska (2022) extend the empirical investigation of Lim et al. (2011) by assessing whether bank competition matters for how macroprudential policy affects the procyclicality of lending. Using bank-level data for a large set of macroprudential instruments for a sample of 95 countries over the period 2004-2015, they find in their first step that, unlike in Lim et al. (2011), most of the macroprudential tools increase credit procyclicality. Their results for the role of competition in the link between macroprudential policy and credit procyclicality depend on the nature of the macroprudential instruments. For countercyclical macroprudential instruments, an imperfectly competitive environment in the banking sector is associated with a lower degree of credit procyclicality, while the result is the opposite for structural instruments.

Against this background, our paper goes a step further and empirically re-investigates whether macroprudential policy can mitigate the procyclicality of credit. We contribute to the existing literature on this issue in four ways. The first is that unlike Lim et al. (2011), Budnik (2020) and Olszak and Kowalska (2022), we consider a multivariate framework using a panel VAR model. Such a framework is suitable in our case since it provides a more accurate representation of the economy, and especially since it allows us to take account of the evolution of credit being dependent on monetary policy conditions. Indeed, as highlighted above, the monetary policy stance is a key driver of how effective macroprudential policy is at curbing credit growth. Second, we use this empirical strategy to visualise formally the dynamic response of the credit cycle to a business cycle shock. This lets us assess clearly the intensity of credit procyclicality. We augment the panel VAR model with an interactive term to check whether the intensity of the responses is conditional on the macroprudential policy framework. The third contribution is that we use an overall macroprudential policy index to gain a better view of the macroprudential policy stance across countries, rather than considering the macroprudential instruments one by one. Finally, we follow the empirical findings of McDonald (2015) and Cerutti et al. (2017a) and use an alternative macroprudential index that explicitly measures how macroprudential policy is conducted by gauging its countercyclical character.

3 Measuring macroprudential policy countercyclicality

The existing empirical literature usually assesses the effectiveness of macroprudential policies by considering the macroprudential policy stance and distinguishing between episodes of tightening and loosening (Cerutti et al., 2017b, Alam et al., 2019, Araujo et al., 2020, Garcia Revelo et al., 2020). They do this by considering for each country and each macroprudential instrument the number of easing and tightening measures in a given period. In this way they aim to capture the direction of macroprudential policy.

However, such a measure is not suitable for identifying whether the macroprudential policy is countercyclical or not. To be effective, the direction of macroprudential policy has to be adjusted over time to suit the position in the business cycle. This means in practice that a tightening of macroprudential instruments may be expected during an economic upturn in order to contain excessive credit growth and to increase the resilience of the banking sector to any economic shock, while macroprudential policy faced with a protracted economic downturn might ease the requirements in order to support lending to the real economy and so facilitate an economic recovery. A recent example of such a countercyclical macroprudential policy is the decisions taken by the European macroprudential authorities to tackle the Covid-19 crisis by softening regulatory capital and liquidity requirements, by reducing countercyclical or systemic risk buffers for example. Fully 12 of the 13 member countries of the ESRB (European Systemic Risk Board) that had previously set a countercyclical capital buffer above 0% lowered it quickly, in many cases to zero.

In this paper, we use the integrated Macroprudential Policy (iMaPP) database provided by Alam et al. (2019). This database covers a large set of 17 macroprudential instruments and details the actions taken to tighten and loosen each instrument. The policy instruments covered in the database are macroprudential in nature but can also serve other purposes, such as capital flow management. This means that each instrument considered by Alam et al. (2019) has a specific macroprudential goal and is likely to have a system-wide impact on the banking sector. A number of countries have in practice taken a range of prudential measures to preserve the stability of the financial system as a whole before the official full implementation of the Basel III framework. This explains why the database starts in 1990.

We modify the existing macroprudential policy measure initially proposed by Alam et al. (2019) to take account of whether the direction of the macroprudential policy actions is in accordance with the position in the business cycle. We do this in three steps.

For the first, we use all the macroprudential instruments considered by Alam et al. (2019) and compute the macroprudential policy stance for each country and each quarter. We decided to use an overall measure of the macroprudential policy stance because each instrument may impact the credit supply and they may complement each other. Furthermore, even though the ESRB provides an indicative list of macroprudential instruments for mitigating and preventing excessive credit growth and leverage, it also recognises that other tools in the toolkit may be used if they are efficient and effective at addressing credit procyclicality (ESRB/2013/1). The choice of instruments depends largely on the structure and characteristics of the financial system, but also on the lending practices of the banks. It is clear for instance that in countries where real estate serves as collateral and determines the ability of households to borrow, a loan-to-value ratio is more effective than a debt service-to-income ratio at containing housing credit growth. Our aim in this paper is different to that of the existing studies on this issue that consider each instrument individually and obtain relatively mixed results, as we want to gain an overall view of the effects of macroprudential policy on the procyclicality of credit. The stance corresponds to the difference between the number of tightening actions and the number of loosening actions. A positive difference then corresponds to a net tightening over a given quarter, while a negative difference corresponds to a net loosening.

Our second step aims to get a better view of how macroprudential policies evolve, and for this we sum the differences obtained for each quarter over a three-year rolling window. This approach allows us to capture the overall macroprudential environment, and also to take account of the sluggish transmission of macroprudential policy actions to the financial variables suggested by a number of empirical studies. Finally, we compare this overall measure of the macroprudential stance with the position in the business cycle, which is captured by the output gap.[4] The justification for gauging the countercyclical character of macroprudential policies from the output gap is that the business cycle is a leading indicator of financial cycles. The financial accelerator mechanism shows indeed that the tightness of financial constraints and the access to credit of firms and households varies over the state of the real economy. It may consequently be expected that the macroprudential authorities would conduct a pre-emptive and pro-active policy by taking measures that suit the position of the business cycle before signs of financial imbalances emerge.

As detailed in Table 1, we distinguish four cases. A macroprudential policy is considered

[4] As explained below, the output gap is computed using the Hamilton filter (Hamilton, 2018).

to be countercyclical for a given country in two of these cases. The first is when the output gap at time t is positive and is preceded by a tightening of the macroprudential stance over the previous three years, and the second is when the output gap at time t is negative and is preceded by a loosening of the macroprudential stance over the previous three years. The other two cases indicate a procyclical macroprudential environment.

Table 1: Countercyclical *vs.* procyclical macroprudential policy

		Output gap	
		Positive	Negative
MaP	Net tightening	**Countercyclical MaP**	Procyclical MaP
	Net loosening	Procyclical MaP	**Countercyclical MaP**

To obtain a macroprudential index that captures the countercyclical pattern of the policy on a common scale, which is an index where a positive value indicates a countercyclical macroprudential policy and a negative value a procyclical one, we multiply the index that was previously obtained by -1 when the output gap is negative. A positive and increasing value of the index then means there is greater countercyclicality in the conduct of macroprudential policy, while a negative and decreasing value of the index indicates there is greater procyclicality. An index equal to 0 can correspond to the two cases of no change in any instruments, or the same number of tightening and loosening actions over the period considered. More details about the index are provided in Figure A1, Figure A2 and Table A2 in the Appendix.

In this way, we measure the degree of countercyclicality of the macroprudential policies. To the best of our knowledge, this is the first measure in the existing empirical literature that explicitly gauges whether macroprudential policies are conducted in a countercyclical fashion. As detailed in the next section, we use this measure to assess empirically the link between macroprudential policy and credit procyclicality.

4 Econometric methodology

The main objective of our empirical analysis is to assess whether the macroprudential policy stance is effective at containing credit procyclicality. From the macroprudential supervisor's point of view, the behaviour of the banking sector in terms of credit supply is made procyclical by changes in risk-taking and leverage over the business cycle. This is because financial intermediaries tend to set procyclical credit standards, leading to relaxed lending policies during upturns and restrictive lending policies during downturns. In addition, excessive risk-taking by banks during economic booms is expected to increase the amount of non-performing loans significantly during economic slowdowns, amplifying the impact of a downturn on the contraction of the credit supply (Jiménez and Saurina, 2006). A positive relationship is then expected between the business cycle and the credit cycle.

Consequently, a formal way to assess the degree of credit procyclicality is to gauge the response of credit to a real activity shock. Capturing the intensity of such a response naturally calls for the well-known vector autoregressive (VAR) framework, which is also recognised as one of the most successful and flexible models for describing the dynamic behaviour of economic and financial series. To the best of our knowledge, the first empirical paper to use a VAR model to assess the degree of procyclicality is Bouvatier et al. (2012), which defines credit procyclicality as the orthogonalised impulse response function of the credit cycle to a business cycle shock.

Taking the definition of credit procyclicality proposed by Bouvatier et al. (2012), we formally assess in this paper whether cross-country heterogeneity in credit procyclicality is conditional on the macroprudential policy stance. We do this using the interacted panel VAR (IPVAR) framework recently developed by Towbin and Weber (2013). Unlike a traditional panel VAR approach, the IPVAR allows the response coefficients to be functions of the cross-time-varying macroprudential policy stance.

In line with Leroy and Lucotte (2019), the IPVAR model that we consider is parsimonious and comprises four quarterly macroeconomic variables, namely the consumer price index (CPI), the real gross domestic product (GDP), the real outstanding amount of credit ($credit$), and the policy interest rate (pr). Following De Schryder and Opitz (2021), we consider four alternative credit series, which are bank credit to the private non-financial sector, total credit to the private non-financial sector, total credit to households, and total credit to non-financial corporations. Bank credit covers credit extended by domestic banks to the private non-financial sector, while total credit to the private non-financial sector comprises financing from all sources, including domestic banks, other domestic financial corporations, non-financial corporations and non-residents. Total credit to the private non-financial sector is broken down into credit to households, including non-profit institutions serving households, and credit to non-financial corporations. This last credit series then includes not only loans from the banking sector, but also debt securities such as bonds and short-term papers. Given that macroprudential policies are expected to impact the domestic banking sector above all, our main variables of interest are consequently bank credit to the private non-financial sector, and total credit to households. The credit series are taken from the Bank for International Settlements (BIS), while due to data availability, the other macroeconomic series are taken from the BIS, the Organisation for Economic Co-operation and Development (OECD), and Refinitiv Eikon.

All the series except for the policy rate are first seasonally adjusted using the X-12-ARIMA US Census Bureau seasonal adjustment methodology. Furthermore, since we are interested in the cyclical behaviour of the economy, we remove the trend and isolate the cyclical component of the CPI, GDP and credit series by considering the percentage gap between the observed values and the trend values. The trend is obtained using the recent regression filter proposed by Hamilton (2018). The Hamilton filter addresses the main drawbacks of the widely used HP filter (Hodrick and Prescott, 1997), especially the end-of-sample bias and the phenomenon of spurious cycles.[5] Using the detrended series also ensures that the variables are stationary.

[5]However, De Schryder and Opitz (2021) argue that the HP filter and the Hamilton filter give qualitatively similar results for the credit-to-GDP gap.

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

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

where $CPI_{i,t}$, $GDP_{i,t}$, $credit_{i,t}$ and $pr_{i,t}$ correspond to the inflation gap, the output gap, the credit gap and the policy rate respectively. The sub-index i refers to countries, while the sub-index t refers to quarters. L is the number of lags. Based on the Akaike information criterion, we consider two lags. $\varepsilon_{i,t}$ is a vector of uncorrelated *iid* shocks. I_i is a set of country fixed effects that captures time-invariant cross-country heterogeneity, particularly the characteristics of the banking sector such as the level of bank competition. As shown by Leroy and Lucotte (2019), Cuestas et al. (2022) and Olszak and Kowalska (2022), banking competition is an important driver of credit procyclicality. Finally, $MaP_{i,t-k}$ is an exogenous variable corresponding to our macroprudential countercyclical index in country i at time $t-k$.

More importantly, the MaP variable also intervenes in the model as a conditional variable. As a cross-time-varying measure of the macroprudential policy stance, it lets us capture whether the degree of credit procyclicality, defined as the response of the credit cycle to a business cycle shock, depends on the prudential supervision stance. The structural parameters $\alpha_{l,i,t}$ distinguish a traditional panel VAR model from our framework and have the following form:

$$\alpha_{l,i,t} = \beta_l + \eta_l \, MaP_{i,t-k} \quad (2)$$

where β_l is a vector that corresponds to the traditional panel VAR coefficients, and η_l is a vector of coefficients specific to the IPVAR framework, as it depends on the conditional variable MaP. This means that the structural parameters $\alpha_{l,i,t}$ are allowed to vary across countries and over time according to the macroprudential policy stance. Consequently the left-hand side variables are regressed not only on the endogenous variables at various lags, but also on the endogenous variables interacted with the variable that captures the macroprudential policy. In other words, we assume that all the autoregressive parameters of the VAR system are dependent on macroprudential policy. Furthermore, to reduce a potential endogeneity issue, the lag order of the MaP variable is $k = L + 1$, so it is three lags in our case.[6]

The IPVAR model is estimated using ordinary least squares (OLS). As the error terms

[6] As argued by De Schryder and Opitz (2021), the potential endogeneity of macroprudential policy actions is an important issue. However, the narrative approach proposed by De Schryder and Opitz (2021), which excludes pre-announced macroprudential policy decisions, is not suitable in our case, as it would reduce considerably the number of macroprudential policy actions in our database, and then would not reflect the overall macroprudential framework.

are uncorrelated by construction, we can estimate the IPVAR model equation by equation in an efficient way. To obtain the impulse response functions (IRFs), we apply a recursive identification scheme via a Cholesky decomposition with the following ordering of variables: CPI, GDP, $credit$ and pr. The ordering of inflation and GDP as the first block and the financial variables as the second block is fairly standard in the macroeconomic literature using VAR models, as it implies that the financial variables may respond contemporaneously to real shocks. The consensus in the academic literature about the ordering of the financial variables in the second block is less clear though. In our baseline model we follow Assenmacher-Wesche and Gerlach (2008) and Bouvatier et al. (2012) in assuming that the monetary policy transmission is sluggish, and we put the credit cycle before the policy rate. This means that the credit cycle reacts with a lag to the short-term interest rate, and that the contemporaneous impact on credit is then restricted to zero.

VAR-based impulse responses are symmetric by construction. This means that the responses to positive and negative shocks are mirror images of each other. In our case, as explained above, this justifies the measure of countercyclical macroprudential policy that we consider in this paper. As one of the main objectives of macroprudential policy is to mitigate credit procyclicality, the appropriate direction for macroprudential policy actions is expected to be different depending on the nature of the shock, since tightening actions are expected during a boom period, while loosening actions are expected during a bust period.

The estimation of the IPVAR model is used to assess whether the size of the response of credit to a GDP cycle shock depends on the degree of countercyclicality of the macroprudential policy. One advantage of the IPVAR model is that we can test whether the impulse response functions obtained for different levels of the MaP variable are statistically different. As is usual in the empirical literature using the IPVAR framework, we consider the first and fourth quintiles of the sample distribution of the MaP variable. The fourth quintile corresponds to a high degree of macroprudential policy countercyclicality, while the first quintile tends to reflect procyclical behaviour by the macroprudential authority. We then expect the response of credit to a GDP cycle shock to be lower in the fourth quintile of the distribution than in the first quintile, which can be confirmed by calculating the difference between the two impulse response functions.

5 Empirical results

In this section, we present and discuss the results obtained from the IPVAR model. Before reporting the econometric results though, we present some preliminary descriptive statistics. The descriptive statistics and econometric results are based on a sample of 42 OECD and non-OECD economies over the period 1990Q1-2019Q4. The composition of the sample is based on the availability of the credit series from the BIS. The list of countries and the time span are shown in Table A1 in the Appendix.

5.1 Preliminary descriptive statistics

This sub-section has two aims. The first is to give some stylised facts about the procyclicality of credit in our sample of countries, and the second is to give some preliminary evidence about the link between our macroprudential countercyclicality index and the degree of credit procyclicality.

We start our empirical investigation by assessing the existence and the evolution of credit procyclicality in our sample. As we consider credit procyclicality as the evolution of credit following a change in the business cycle, our main variables of interest are the credit gap and the output gap. Table 2 reports the pairwise correlation between the credit gap and the output gap by considering the four credit series detailed above, and four different lag structures for the output gap, which are 1 lag, 2 lags, 3 lags and 4 lags. As expected, the correlation between the credit cycle and the business cycle appears positive and statistically significant at the conventional level for each credit variable and lag structure considered, confirming that the two cycles are closely linked, even if the correlation seems more pronounced for non-OECD countries.

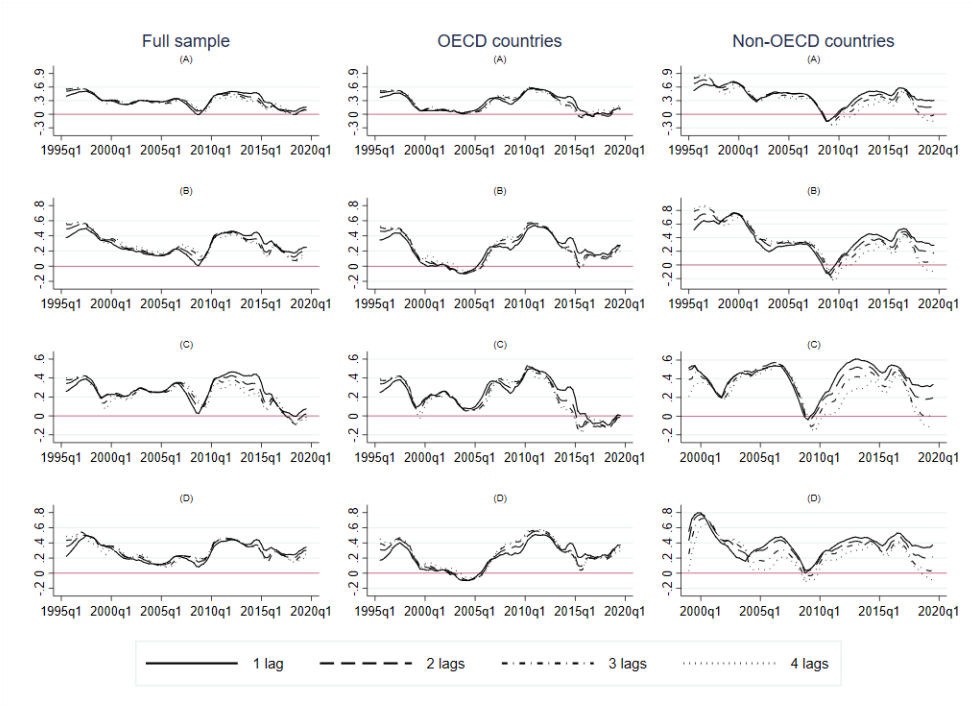
Table 2: Pairwise correlation between the business cycle and the credit cycle

	Full sample			
	No. of lags for the output gap			
Credit gap variables considered:	1 lag	2 lags	3 lags	4 lags
Bank credit to the private non-financial sector	0.2955*	0.2865*	0.2740*	0.2609*
Total credit to the private non-financial sector	0.2538*	0.2604*	0.2608*	0.2573*
Total credit to households	0.2440*	0.2326*	0.2173*	0.2020*
Total credit to non-financial corporations	0.2560*	0.2670*	0.2672*	0.2609*
	OECD countries			
	1 lag	2 lags	3 lags	4 lags
Bank credit to the private non-financial sector	0.2385*	0.2336*	0.2353*	0.2358*
Total credit to the private non-financial sector	0.1981*	0.2084*	0.2151*	0.2200*
Total credit to households	0.1715*	0.1624*	0.1566*	0.1516*
Total credit to non-financial corporations	0.1955*	0.2176*	0.2347*	0.2444*
	Non-OECD countries			
	1 lag	2 lags	3 lags	4 lags
Bank credit to the private non-financial sector	0.4332*	0.4137*	0.3683*	0.3243*
Total credit to the private non-financial sector	0.4031*	0.3995*	0.3841*	0.3602*
Total credit to households	0.4562*	0.4373*	0.3946*	0.3501*
Total credit to non-financial corporations	0.4453*	0.4240*	0.3750*	0.3225*

Source: Authors' calculations. Note: For each credit series considered, 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 statistically significant at the 5% level.

In Figure 1, we complete the analysis and compute from the total sample the dynamic correlation between the credit gap and the output gap by considering a five-year rolling window. As before, we consider alternative credit series and four different lag structures for the output gap. We can see that the correlation for the whole period between the two series appears generally positive, confirming the previous findings reported in Table 2. Of particular note is that the correlation is relatively high in OECD and non-OECD countries over the decade before the subprime crisis, but it tends to decrease in the aftermath of the global financial crisis and at the end of the period considered. The greater procyclicality observed before the subprime crisis could be explained by the large increases in property and share prices, which affected demand and supply for credit and then led to strong growth in credit in the economies considered in our sample.

Figure 1: Dynamic correlation between the business cycle and the credit cycle



Source: Authors' calculations. Note: The dynamic correlation between the business cycle and the credit cycle is calculated by considering a five-year rolling window on the whole sample. Panel (A) refers to bank credit to the private non-financial sector, panel (B) to total credit to the private non-financial sector, panel (C) to total credit to households, and panel (D) to total credit to non-financial corporations. For each credit series considered, 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.

In line with the main objective of our paper, we now analyse the link between the macroprudential countercyclicality index that we propose and credit procyclicality. To this end, we first calculate the pairwise correlation between our macroprudential index and a proxy for credit procyclicality, and this corresponds to a country by country correlation between the output gap and the alternative credit series considered over a five-year rolling window. As we can see in Table 3, all the correlation coefficients are negative and statistically significant for the full sample and for the sub-sample of OECD countries. For the sub-sample of non-OECD countries, all the correlation coefficients have the expected sign, but they are not always statistically significant. This is the first piece of preliminary empirical evidence that a macroprudential policy conducted in a countercyclical fashion is effective at reducing the degree of credit procyclicality.

Table 3: Pairwise correlation between the macroprudential index and credit procyclicality

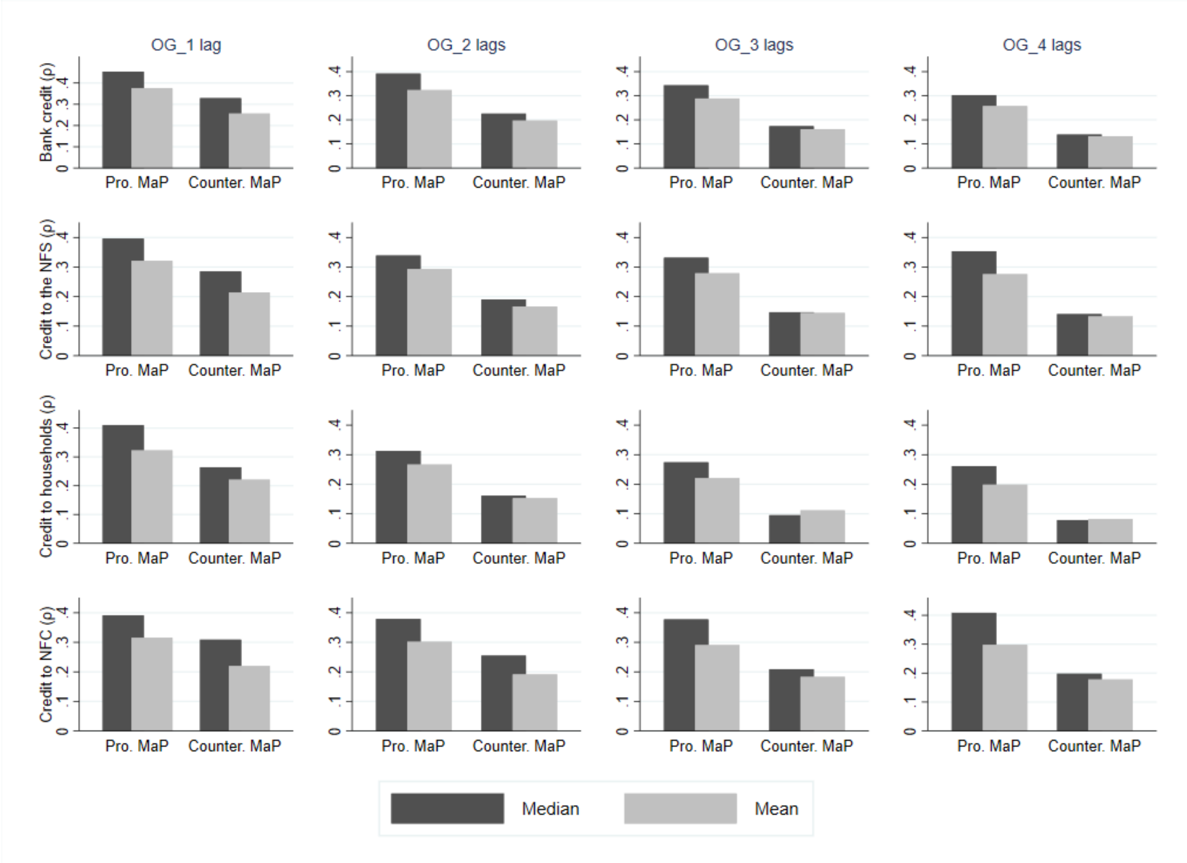
	Full sample			
	No. of lags for the output gap			
Credit gap variables considered:	1 lag	2 lags	3 lags	4 lags
Bank credit to the private non-financial sector	-0.0735*	-0.0873*	-0.0945*	-0.0900*
Total credit to the private non-financial sector	-0.0716*	-0.0912*	-0.1066*	-0.1073*
Total credit to households	-0.0901*	-0.0982*	-0.1010*	-0.0972*
Total credit to non-financial corporations	-0.0743*	-0.0933*	-0.0980*	-0.1003*
	OECD countries			
	1 lag	2 lags	3 lags	4 lags
Bank credit to the private non-financial sector	-0.1094*	-0.1187*	-0.1185*	-0.1057*
Total credit to the private non-financial sector	-0.1163*	-0.1296*	-0.1316*	-0.1186*
Total credit to households	-0.1242*	-0.1242*	-0.1167*	-0.0994*
Total credit to non-financial corporations	-0.1150*	-0.1324*	-0.1341*	-0.1259*
	Non-OECD countries			
	1 lag	2 lags	3 lags	4 lags
Bank credit to the private non-financial sector	-0.0538	-0.0702	-0.0871*	-0.0821*
Total credit to the private non-financial sector	-0.0461	-0.0771*	-0.1209*	-0.1209*
Total credit to households	-0.1279*	-0.1483*	-0.1566*	-0.1558*
Total credit to non-financial corporations	-0.0794	-0.0848	-0.0755	-0.0847

Source: Authors' calculations. Note: Credit procyclicality corresponds to the pairwise correlation between the output gap and the alternative credit gap variables computing country by country over a five-year rolling window. For each credit series considered, 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 statistically significant at the 5% level.

This initial evidence for a link between macroprudential policy countercyclicality and credit procyclicality is confirmed in Figure 2, in which we split the sample into two groups, namely the periods when there is a countercyclical macroprudential stance, and those characterised by a procyclical stance.[7] Both the median and the mean of the correlation coefficients between the credit gap and the output gap are lower for the countercyclical sub-sample than for the procyclical sub-sample. These preliminary findings are confirmed in the next sub-section, where we give the results obtained with the IPVAR model presented above.

[7]Figure A3 and Figure A4 in the Appendix report the descriptive statistics for the sub-samples of OECD countries and non-OECD countries respectively.

Figure 2: Degree of credit procyclicality: Procyclical *vs.* countercyclical macroprudential policy



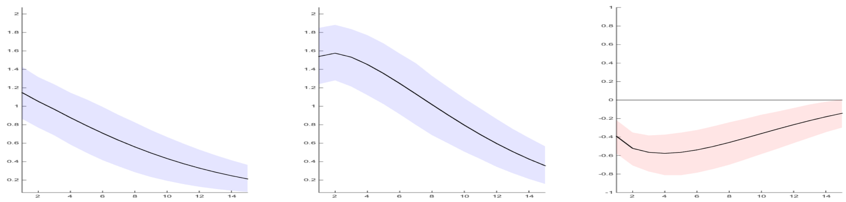
Source: Authors' calculations. Note: The figure represents the median and the mean of the correlation between the business cycle and the credit cycle according to the stance of the macroprudential policy as procyclical or countercyclical. A macroprudential policy is considered to be procyclical if the macroprudential index is negative over a five-year rolling window, and countercyclical if the index is positive. Each row refers to an alternative credit gap variable. 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.

5.2 IPVAR results

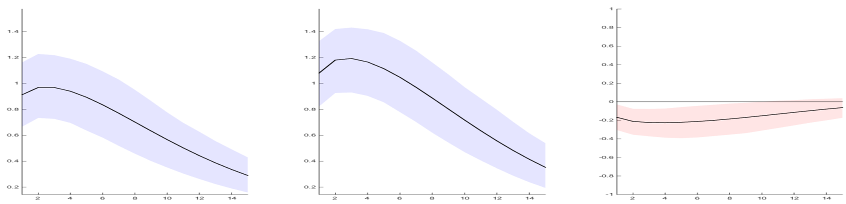
In this sub-section we present and discuss the results obtained by estimating Equation (1). As explained above, the main objective of the IPVAR model that we consider in our paper is to assess whether the orthogonalised responses of credit to a GDP cycle shock are statistically different according to the degree of macroprudential policy countercyclicality. To this end, we focus on the 80^{th} percentile and the 20^{th} percentile of the MaP index.

Figure 3 reports the impulse response functions (IRFs) that we obtain for the alternative credit variables considered. These IRFs represent the response of the credit cycle to an exogenous deviation of GDP from its trend by one percentage point. The charts on the left display the IRFs obtained when we set the MaP index at the 80^{th} percentile of its sample distribution, and so they illustrate the response of the credit cycle to a real activity shock for the highest level of countercyclicality in macroprudential policy. The charts in the centre show the IRFs evaluated at the 20^{th} percentile of the MaP index, which corresponds in our case to a procyclical macroprudential policy (see Table A2 in the Appendix for more details). In both cases, the solid line corresponds to the average impulse response, while the coloured band is the 95% confidence interval computed by a bootstrap with 1,000 draws. The lower bound of the band corresponds to the 2.5^{th} percentile and the upper bound to the 97.5^{th} percentile of the 1,000 bootstrapped impulse responses. Finally, the charts on the right report the difference between the two IRFs at the 80^{th} and 20^{th} percentiles of the MaP index, with a 95% confidence interval. These charts allow us to assess whether the difference between the two IRFs is statistically significant, and then to evaluate how effective a countercyclical macroprudential policy is at containing credit procyclicality.

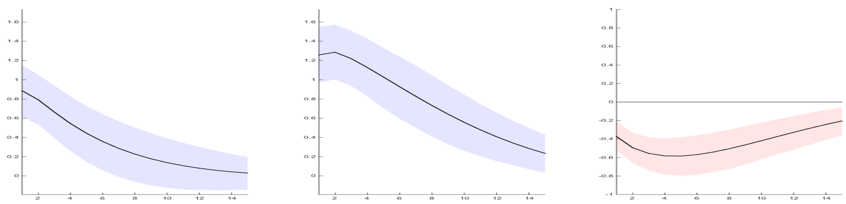
Figure 3: Impulse response functions of credit to a GDP shock: Baseline estimates



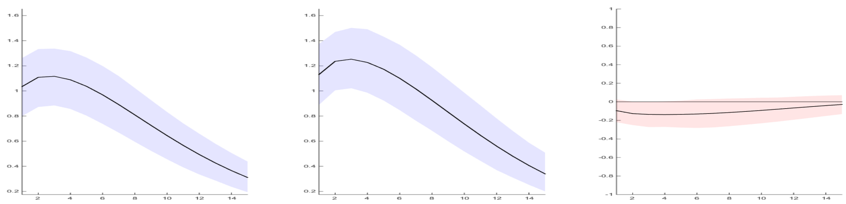
(a) Bank credit to the private non-financial sector



(b) Total credit to the private non-financial sector



(c) Total credit to households



(d) Total credit to non-financial corporations

Note: The figure shows the impulse response functions of the credit gap to a shock of one percentage point to the output gap evaluated (from left to right) at the 80^{th} and 20^{th} percentiles of the sample distribution of the MaP index. The charts on the right represent the differences between the two. The coloured bands represent the 95% confidence bands generated by bootstrapping (1,000 draws).

Regardless of the orientation of the macroprudential policy, the credit cycle responds positively to an output gap shock. However, the intensity of the response seems to be lower for the IRFs evaluated at the 80^{th} percentile of the MaP index, namely the periods characterised by a countercyclical macroprudential policy, than for those evaluated at the 20^{th} percentile. The charts on the right show that the negative difference between the two IRFs is relatively pronounced and statistically significant when we consider bank credit to the private non-financial sector and total credit to households as endogenous variables. For the other two credit variables, the difference is significant but less pronounced for total credit to the private non-financial sector, but it appears not to be statistically significant for total credit to non-financial corporations.

A simple explanation for these results can be that national macroprudential policies essentially impact the behaviour of the domestic banking sector and its credit policy. Consequently, it is not surprising that bank credit to the private non-financial sector and total credit to households are more sensitive to the macroprudential policy orientation, as they only cover bank loans. The other two credit series by contrast cover more financial instruments, as they also include debt securities such as bonds and short-term papers.

Overall, our empirical results confirm that the degree of credit procyclicality in our sample of countries is significantly driven by the conduct of macroprudential policy, as they indicate that countercyclical macroprudential policies are effective at curbing the credit cycle.

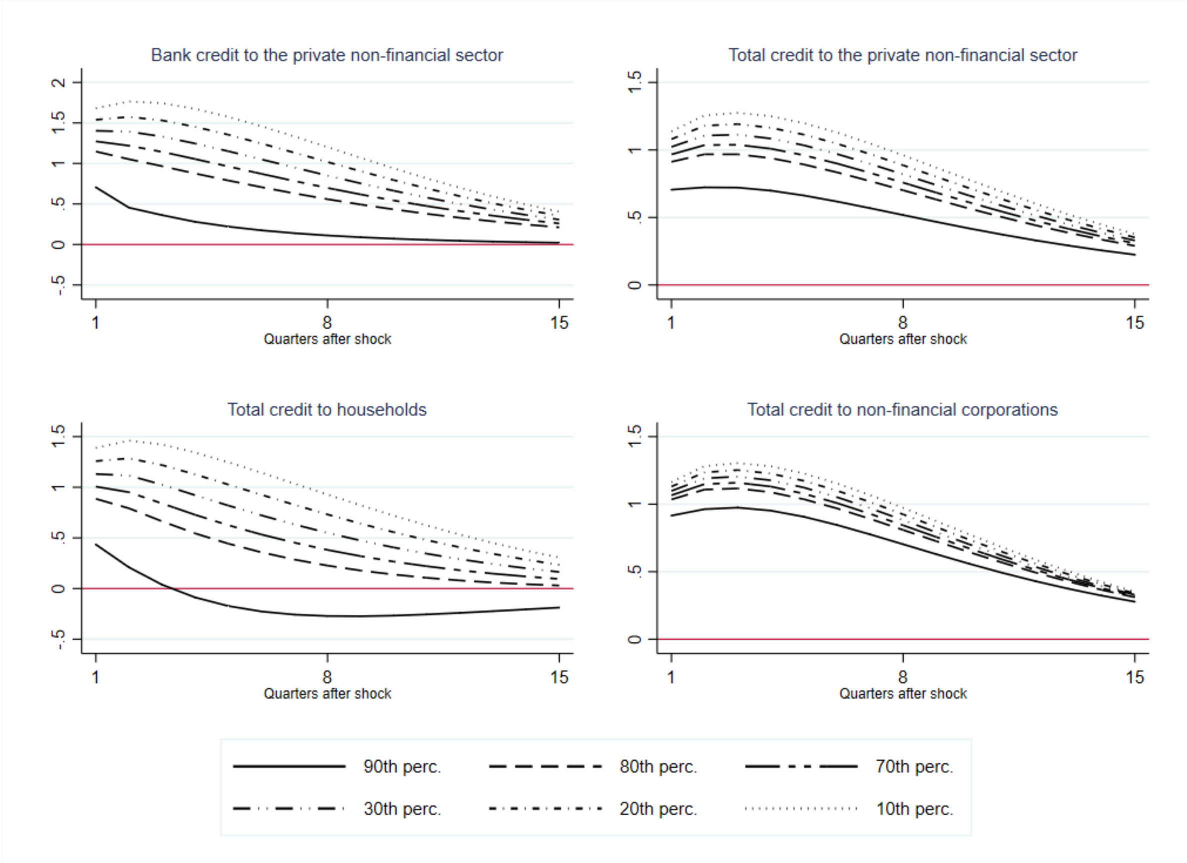
6 Robustness checks

To enhance the credibility and plausibility of our earlier empirical findings, we check the robustness of our baseline results in six ways.

Alternative percentiles for the interactive variable. In the baseline estimates, we assess whether the degree of countercyclicality of the macroprudential policies explains the heterogeneity in the credit procyclicality. To this end, we set the MaP index to be at the 80^{th} percentile and the 20^{th} percentile of its sample distribution. We go a step further and generate the average impulse responses of the credit cycle to an output gap shock by considering alternative percentiles of the sample distribution of the MaP index. More precisely, we compare the IRFs obtained for the 90^{th}, 80^{th}, 70^{th}, 30^{th}, 20^{th} and 10^{th} percentiles. The IRFs obtained with these different percentiles are reported in Figure 4 for each credit series.[8] As expected, they clearly indicate that the response of the credit cycle to a business cycle shock tends to decrease when the countercyclical MaP index increases. This confirms that credit is less procyclical when the macroprudential policy is conducted in a countercyclical way.

[8]Figure A5 in the Appendix displays the difference between the impulse response functions of the credit gap to a shock of one percentage point to the output gap evaluated at the 90^{th} and 10^{th} percentiles of the sample distribution of the MaP index, and at the 70^{th} and 30^{th} percentiles.

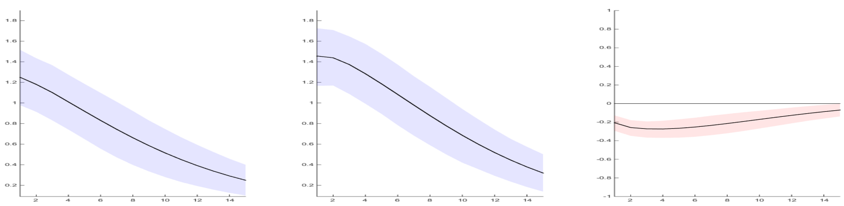
Figure 4: Impulse response functions of credit to a GDP shock: Different percentiles of the MaP index



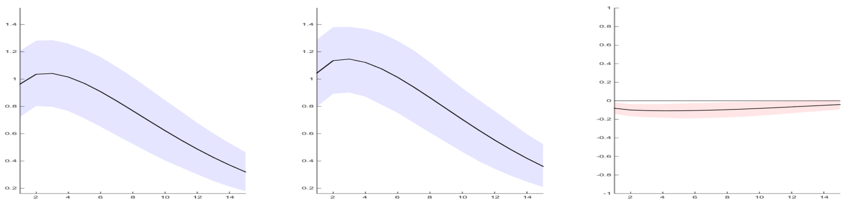
Note: The figure shows the impulse response functions of the credit gap to a shock of one percentage point to the output gap evaluated at different percentiles of the sample distribution of the MaP index.

Alternative rolling windows for computing the countercyclical MaP index. In the baseline estimates, the countercyclical macroprudential index used as an interactive variable in the IPVAR model is computed over a three-year rolling window. We check the sensitivity of our results by considering two alternative lengths for the rolling window, using two years and five years. The results that we obtain are reported in Figure 5 for the two-year rolling window and in Figure 6 for the five-year rolling window, and they confirm our previous findings. We still find that credit is less procyclical when the macroprudential policy stance is countercyclical.

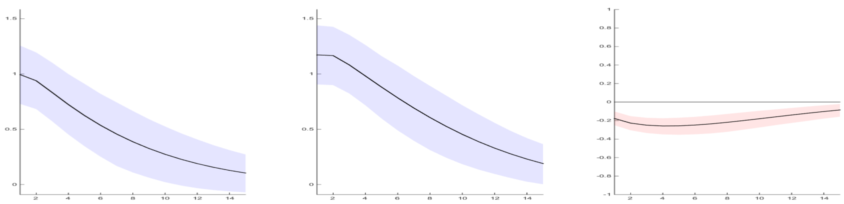
Figure 5: Impulse response functions of credit to a GDP shock: two-year rolling window



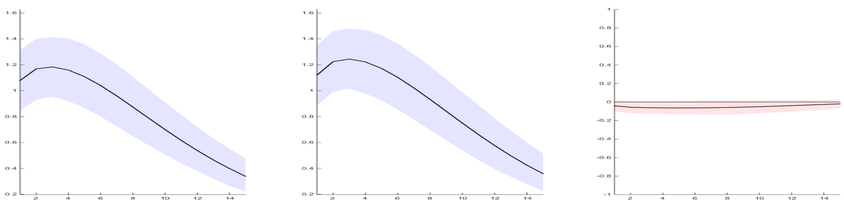
(a) Bank credit to the private non-financial sector



(b) Total credit to the private non-financial sector



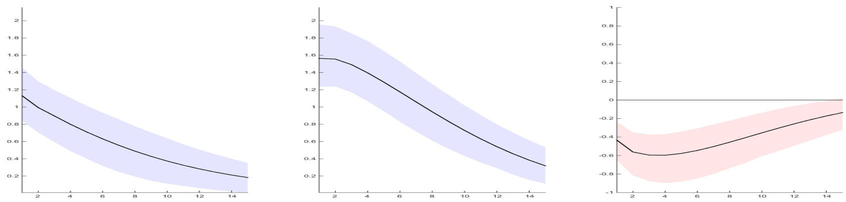
(c) Total credit to households



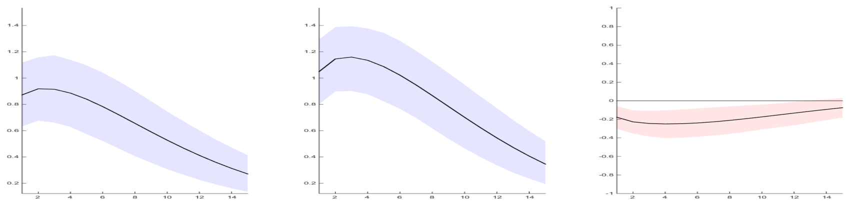
(d) Total credit to non-financial corporations

Note: The figure shows the impulse response functions of the credit gap to a shock of one percentage point to the output gap evaluated (from left to right) at the 80^{th} and 20^{th} percentiles of the sample distribution of the MaP index. The charts on the right represent the differences between the two. The coloured bands represent the 95% confidence bands generated by bootstrapping (1,000 draws).

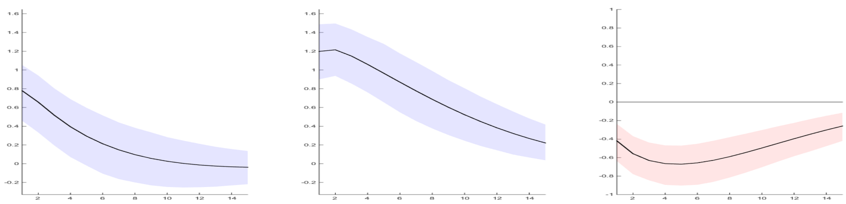
Figure 6: Impulse response functions of credit to a GDP shock: five-year rolling window



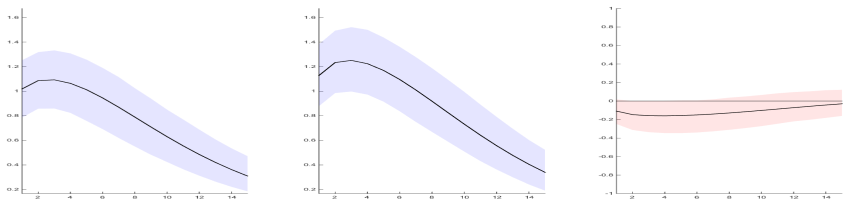
(a) Bank credit to the private non-financial sector



(b) Total credit to the private non-financial sector



(c) Total credit to households

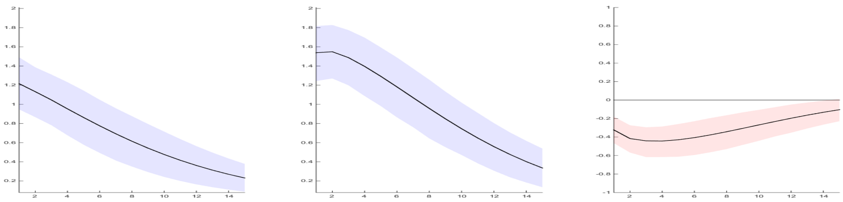


(d) Total credit to non-financial corporations

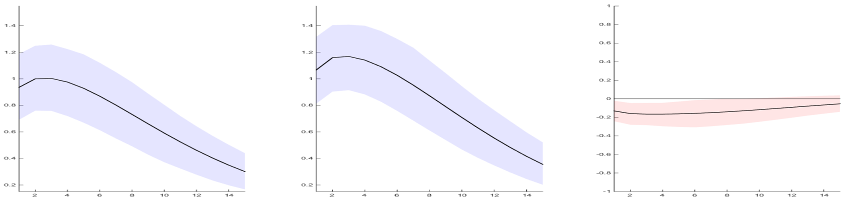
Note: The figure shows the impulse response functions of the credit gap to a shock of one percentage point to the output gap evaluated (from left to right) at the 80^{th} and 20^{th} percentiles of the sample distribution of the MaP index. The charts on the right represent the differences between the two. The coloured bands represent the 95% confidence bands generated by bootstrapping (1,000 draws).

Weighted countercyclical MaP index. In line with the previous robustness check, we consider another alternative method for computing the MaP index. This index, computed on a three-year rolling window, assigns a higher weight to the most recent macroprudential policy actions. The weighting scheme that we use is: $w_l = 1 - \frac{l}{L+1}$ with $l = 0, 1, 2, ..., L$, where l is the lag order of a given observation and L is the total number of lags contained in the rolling window. Since we consider a three-year rolling window, L is equal to 11 in our case. The weight w_l assigned to a given observation then decreases with the lag order l of this observation. In this way we take account of the behaviour and the credit policy of the banking sector being essentially influenced by the recent evolution of the prudential framework. Figure 7 displays the IRFs obtained when we use this alternative MaP index, and it confirms our previous results.

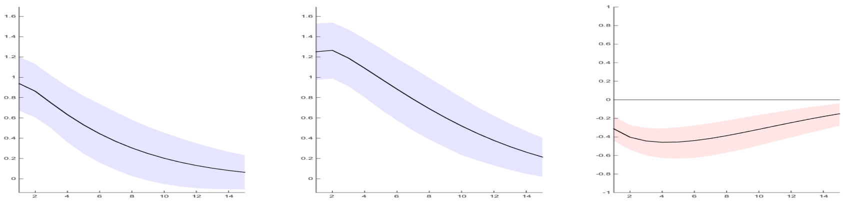
Figure 7: Impulse response functions of credit to a GDP shock: Weighted MaP index



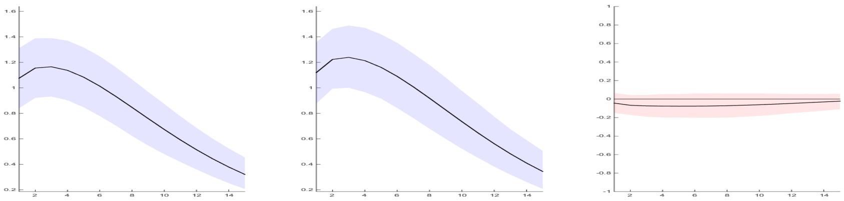
(a) Bank credit to the private non-financial sector



(b) Total credit to the private non-financial sector



(c) Total credit to households



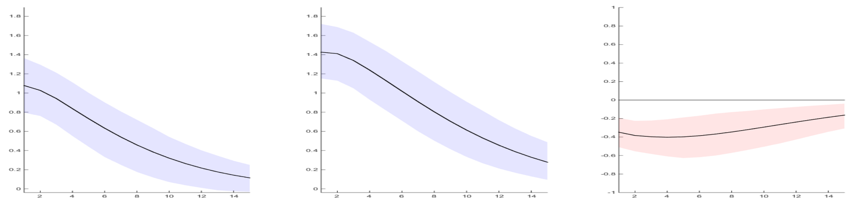
(d) Total credit to non-financial corporations

Note: The figure shows the impulse response functions of the credit gap to a shock of one percentage point to the output gap evaluated (from left to right) at the 80^{th} and 20^{th} percentiles of the sample distribution of the weighted MaP index. The charts on the right represent the differences between the two. The coloured bands represent the 95% confidence bands generated by bootstrapping (1,000 draws).

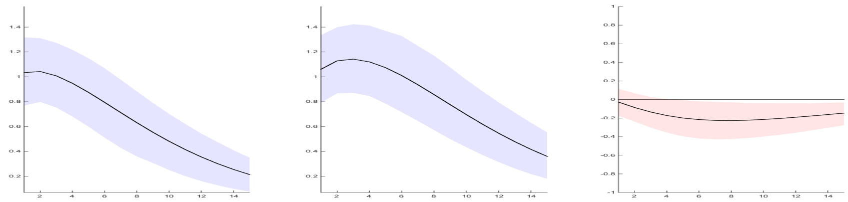
Alternative countercyclical MaP index. Boom-bust cycles in real estate markets have been major drivers of financial instability over the past decades, which explains why a number of macroprudential instruments have been designed to lean against the housing cycle. However, McDonald (2015) and Cerutti et al. (2017a) posit that the effectiveness of macroprudential policies depends on where in the housing cycle they are implemented. In line with this, we compute an alternative countercyclical MaP index based on the real estate cycle instead of the business cycle. A macroprudential policy in a given country is then considered to be countercyclical if we observe it being tightened during a housing boom or loosened during a housing bust. Like with the output gap, we use the Hamilton filter to de-trend the real property prices taken from the BIS.

Due to data availability, we only consider the prices of residential property.[9] The results that we obtain are displayed in Figure 8. They are consistent with the baseline results as they show that countercyclical macroprudential policies are more effective than procyclical policies at taming the procyclicality of credit.

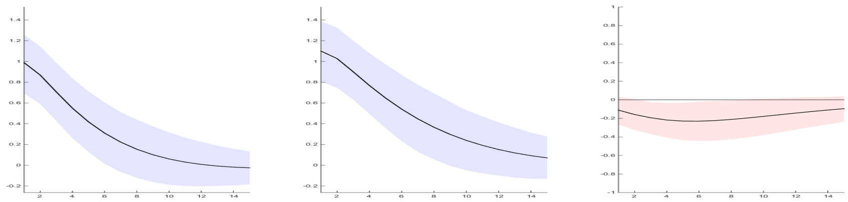
Figure 8: Impulse response functions of credit to a GDP shock: Alternative MaP index based on the housing cycle



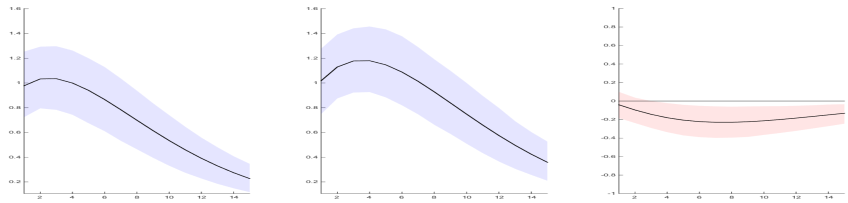
(a) Bank credit to the private non-financial sector



(b) Total credit to the private non-financial sector



(c) Total credit to households



(d) Total credit to non-financial corporations

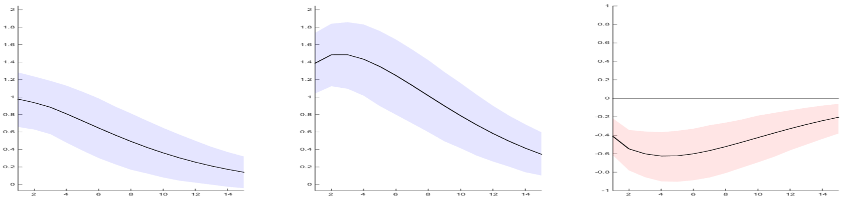
Note: The figure shows the impulse response functions of the credit gap to a shock of one percentage point to the output gap evaluated (from left to right) at the 80^{th} and 20^{th} percentiles of the sample distribution of the weighted MaP index. The charts on the right represent the differences between the two. The coloured bands represent the 95% confidence bands generated by bootstrapping (1,000 draws).

Alternative method of filtering. Following De Schryder and Opitz (2021), we check whether our baseline results are robust when we use the well-known Hodrick-Prescott filter (Hodrick and Prescott, 1997) to remove the trend from the series. In line with the recommendations of the BIS

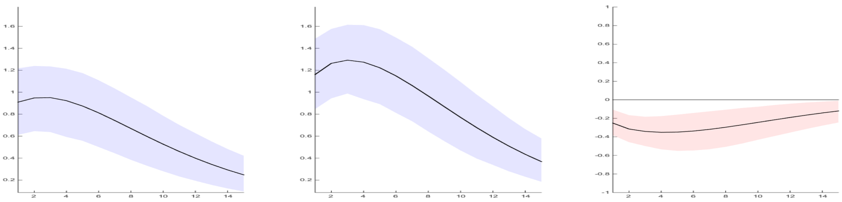
[9]Please note that the data are not available for Argentina for the whole period.

for computing the credit-to-GDP gap (Drehmann and Tsatsaronis, 2014), the trend component for the de-trended variables in our IPVAR model is obtained by applying the one-sided HP-filter. The smoothing parameter used for the GDP and CPI series is equal to 1,600 while, following the original work of Borio and Lowe (2002), the parameter is set to 400,000 for the alternative credit series. This decision to use a larger smoothing parameter was taken following the observation that credit cycles are on average four times longer than standard business cycles. The results that we obtain confirm our baseline estimates. To save space, these results are not reported but are available upon request.

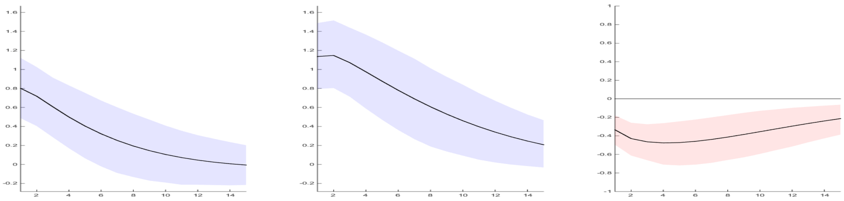
Figure 9: Impulse response functions of credit to a GDP shock: OECD countries sub-sample



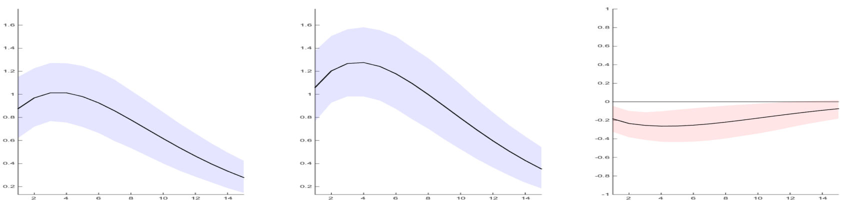
(a) Bank credit to the private non-financial sector



(b) Total credit to the private non-financial sector



(c) Total credit to households



(d) Total credit to non-financial corporations

Note: The figure shows the impulse response functions of the credit gap to a shock of one percentage point to the output gap evaluated (from left to right) at the 80^{th} and 20^{th} percentiles of the sample distribution of the MaP index. The charts on the right represent the differences between the two. The coloured bands represent the 95% confidence bands generated by bootstrapping (1,000 draws).

OECD countries sub-sample. Finally, we check the sensitivity of our baseline IPVAR results when we focus on the sub-sample of OECD countries. As indicated in Table A1 in the Appendix, this sub-sample contains 31 countries. Unlike with the preliminary descriptive statistics, we do not re-estimate the IPVAR model for the sub-sample of non-OECD countries as the number of economies in this category is too small. The IRFs obtained for the sub-sample of OECD countries are displayed in Figure 9. The figure shows that the differences between the IRFs are negative and statistically significant for all the credit series considered.

7 Conclusion

The procyclical behaviour of the banking industry is an important source of systemic risk and so it is at the heart of macroprudential policy concerns. There is still active debate among academics, practitioners and policy makers about how macroprudential policies affect the procyclicality of credit, and it remains an open question. This issue has indeed been largely ignored in the existing empirical literature.

With this background, our paper uses an appropriate econometric framework to fill this gap in the literature by empirically assessing for a large sample of OECD and non-OECD countries over the period 1990Q1-2019Q4 whether macroprudential policies are effective at alleviating credit procyclicality. It investigates whether this effectiveness depends on how macroprudential policy is conducted over the business cycle. To the best of our knowledge, it is the first empirical academic study to address this issue formally.

Our empirical findings are based on an IPVAR model and confirm that the way macroprudential policy is conducted is a key driver of how effective such policies are at mitigating and containing the procyclicality of credit. They show that the intensity of the response of the credit cycle to a business cycle shock decreases significantly as the degree of countercyclicality of the macroprudential policy increases. Our results are confirmed by a battery of robustness checks.

Our analysis reinforces the idea that a discretionary macroprudential policy has to be countercyclical to be fully effective. Moving macroprudential instruments in the right direction at the right time is of course easier said than done, and it is more an art than a science. The forward-looking nature of such a policy means that projections and leading indicators play a very important role in identifying the build-up of risk in the financial system and the underlying financial imbalances and vulnerabilities. This explains why the Basel Committee on Banking Supervision recommends that macroprudential authorities conduct their policy and calibrate the prudential tools by considering a large number of macroeconomic and financial indicators.

In practice, Danielsson et al. (2016) argue that macroprudential policies can move in the wrong direction for several reasons, resulting in perversely exacerbating boom-and-bust cycles. Danielsson et al. (2016) specifically highlight that one important difficulty faced by macroprudential authorities is accurately measuring and monitoring financial risks, especially systemic risk. This difficulty is amplified by the typical negative correlation between the contemporaneous risk and the underlying latent risk. In other words, the contemporaneous risk is usually low during economic upturns, leading to a potential misperception of the latent risk. This perceived low-risk environment can also encourage banks to take further risks. According to Danielsson et al. (2016), this could explain why macroprudential authorities may react with a lag and do not implement corrective policies quickly enough to prevent financial stability deteriorating.

One important factor that could explain the lag in the reaction of the macroprudential authorities and the conduct of procyclical policies is the political factor. Two very recent empirical studies, (Müller, 2019, Sever and Yücel, 2022), have shown that macroprudential policies are more likely to be less stringent before elections. As argued by Müller (2019), this electoral cycle in the conduct of macroprudential policies could be explained by political interference and by politicians not wanting to cut voters off from mortgages. This behaviour, known as the "inaction bias" (Knot, 2014), is expected to be more pronounced during economic upturns, and even more so when the macroprudential policy is conducted by the government or by a council chaired by the government. Consequently, one interesting extension of our paper could be to analyse empirically whether the institutional architecture and the governance framework of macroprudential policies constitute a significant determinant of the degree of countercyclicality of such policies, and so explain a part of the story of credit procyclicality. We leave the investigation of this issue for further research.

Bibliography

Akinci, O. and Olmstead-Rumsey, J. (2018). How effective are macroprudential policies? An empirical investigation. *Journal of Financial Intermediation*, 33:33 – 57.

Alam, Z., Alter, A., Eiseman, J., Gelos, G., Kang, H., Narita, M., Nier, E., and Wang, N. (2019). Digging deeper - Evidence on the effects of macroprudential policies from a new database. *IMF WP/19/66, International Monetary Fund.*

Altunbas, Y., Binici, M., and Gambacorta, L. (2018). Macroprudential policy and bank risk. *Journal of International Money and Finance*, 81:203–220.

Araujo, J. D., Patnam, M., Popescu, A., Valencia, F., and Yao, W. (2020). Effects of macroprudential policy: Evidence from over 6,000 estimates. *IMF WP/2020/067, International Monetary Fund.*

Assenmacher-Wesche, K. and Gerlach, S. (2008). Monetary policy, asset prices and macroeconomic conditions: A panel-VAR study. *NBB Working Paper Resaerch No.149, National Bank of Belgium.*

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.

Basel Committee on Banking Supervision (2021). The procyclicality of loan loss provisions: A literature review. *BIS Working Papers 39, Bank for International Settlements.*

Bennani, T., Després, M., Dujardin, M., Duprey, T., and Kelber, A. (2014). Macroprudential framework: Key questions applied to the French case. *Occasional Papers No. 9, Banque de France.*

Borio, C. (2011). Implementing a macroprudential framework: Blending boldness and realism. *Capitalism and Society*, 6(1).

Borio, C., Furfine, C., and Lowe, P. (2001). Procyclicality of the financial system and financial stability: Issues and policy options. In *Marrying the macro- and micro-prudential dimensions of financial stability*, volume 01, pages 1–57. Bank for International Settlements.

Borio, C. and Lowe, P. (2002). Asset prices, financial and monetary stability: Exploring the nexus. *BIS Working Papers 114, Bank for International Settlements.*

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

Bruno, V., Shim, I., and Shin, H. S. (2017). Comparative assessment of macroprudential policies. *Journal of Financial Stability*, 28:183–202.

Budnik, K. (2020). The effect of macroprudential policies on credit developments in Europe 1995-2017. *ECB Working Paper No. 2462, European Central Bank.*

Carreras, O., Davis, E. P., and Piggott, R. (2018). Assessing macroprudential tools in OECD countries within a cointegration framework. *Journal of Financial Stability*, 37:112–130.

Cerutti, E., Claessens, S., and Laeven, L. (2017a). The use and effectiveness of macroprudential policies: New evidence. *Journal of Financial Stability*, 28:203–224.

Cerutti, E., Correa, R., Fiorentino, E., and Segalla, E. (2017b). Changes in prudential policy instruments - A new cross-country database. *International Journal of Central Banking*, 13(2):477–503.

Cuestas, J. C., Lucotte, Y., and Reigl, N. (2022). The evolution and heterogeneity of credit procyclicality in Central and Eastern Europe. *International Journal of Finance & Economics*, 27(1):911–942.

Danielsson, J., Macrae, R., Tsomocos, D., and Zigrand, J.-P. (2016). Why macropru can end up being procyclical. *VoxEU/CEPR, Centre for Economic Policy Research*.

De Schryder, S. and Opitz, F. (2021). Macroprudential policy and its impact on the credit cycle. *Journal of Financial Stability*, 53:100818.

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

Fernández de Lis, S. and Garcia-Herrero, A. (2010). Dynamic provisioning: Some lessons from existing experiences. *BBVA Bank, Economic Research Department Working Papers, Banco Bilbao Vizcaya Argentaria*, (1014).

Franta, M. and Gambacorta, L. (2020). On the effects of macroprudential policies on growth-at-risk. *Economics Letters*, 196:109501.

Gaganis, C., Lozano-Vivas, A., Papadimitri, P., and Pasiouras, F. (2020). Macroprudential policies, corporate governance and bank risk: Cross-country evidence. *Journal of Economic Behavior & Organization*, 169:126–142.

Galati, G. and Moessner, R. (2018). What do we know about the effects of macroprudential policy? *Economica*, 85(340):735–770.

Galán, J. E. (2020). The benefits are at the tail: Uncovering the impact of macroprudential policy on growth-at-risk. *Journal of Financial Stability*, page 100831.

Gambacorta, L. and Murcia, A. (2020). The impact of macroprudential policies in Latin America: An empirical analysis using credit registry data. *Journal of Financial Intermediation*, 42:100828.

Garcia Revelo, J. D., Lucotte, Y., and Pradines-Jobet, F. (2020). Macroprudential and monetary policies: The need to dance the tango in harmony. *Journal of International Money and Finance*, 108:102156.

Hamilton, J. D. (2018). Why you should never use the Hodrick-Prescott filter. *The Review of Economics and Statistics*, 100(5):831–843.

Hodrick, R. J. and Prescott, E. C. (1997). Postwar U.S. business cycles: An empirical investigation. *Journal of Money, Credit and Banking*, 29(1):1–16.

Jiménez, G., Ongena, S., Peydró, J.-L., and Saurina, J. (2017). Macroprudential policy, countercyclical bank capital buffers, and credit supply: Evidence from the Spanish dynamic provisioning experiments. *Journal of Political Economy*, 125(6):2126–2177.

Jiménez, G. and Saurina, J. (2006). Credit cycles, credit risk, and prudential regulation. *International Journal of Central Banking*, 2(2).

Kashyap, A. K., Stein, J. C., et al. (1997). The role of banks in monetary policy: A survey with implications for the European monetary union. *Economic Perspectives - Federal Reserve Bank of Chicago*, 21:2–18.

Knot, K. (2014). Governance of macroprudential policy. *Financial Stability Review No. 18, Banque de France*, (18):25–32.

Kuttner, K. N. and Shim, I. (2016). Can non-interest rate policies stabilize housing markets? evidence from a panel of 57 economies. *Journal of Financial Stability*, 26:31–44.

Leroy, A. and Lucotte, Y. (2019). Competition and credit procyclicality in European banking. *Journal of Banking & Finance*, 99:237–251.

Lim, C. H., Costa, A., Columba, F., Kongsamut, P., Otani, A., Saiyid, M., Wezel, T., and Wu, X. (2011). Macroprudential policy: What instruments and how to use them? Lessons from country experiences. *IMF WP/11/238, International Monetary Fund.*

Ly, K. C. and Shimizu, K. (2021). Did Basel regulation cause a significant procyclicality? *Journal of International Financial Markets, Institutions and Money*, 73:101365.

McDonald, C. (2015). When is macroprudential policy effective? *BIS Working Papers 496, Bank for International Settlements.*

Meuleman, E. and Vander Vennet, R. (2020). Macroprudential policy and bank systemic risk. *Journal of Financial Stability*, 47:100724.

Müller, K. (2019). Electoral cycles in macroprudential regulation. *ESRB Working Paper Series No. 106, European Systemic Risk Board.*

Olszak, M. and Kowalska, I. (2022). Does bank competition matter for the effects of macroprudential policy on the procyclicality of lending? *Journal of International Financial Markets, Institutions and Money*, 76:101484.

Sever, C. and Yücel, E. (2022). The effects of elections on macroprudential policy. *Journal of Comparative Economics*, 50(2):507–533.

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.

Vandenbussche, J., Vogel, U., and Detragiache, E. (2015). Macroprudential policies and housing prices: A new database and empirical evidence for Central, Eastern, and Southeastern Europe. *Journal of Money, Credit and Banking*, 47(S1):343–377.

Zhang, L. and Zoli, E. (2016). Leaning against the wind: Macroprudential policy in Asia. *Journal of Asian Economics*, 42:33 – 52.

Zhang, Y. and Tressel, T. (2017). Effectiveness and channels of macroprudential policies: Lessons from the Euro area. *Journal of Financial Regulation and Compliance*, 25(3):271–306.

Appendix

Table A1: Sample of countries and time span

Country	Time span	Country	Time span
Argentina	1995Q3 - 2019Q4	Italy*	1990Q1 - 2019Q4
Australia*	1990Q1 - 2019Q4	Japan*	1996Q3 - 2019Q4
Austria*	1990Q3 - 2019Q4	Korea*	1999Q2 - 2019Q4
Belgium*	1997Q3- 2019Q4	Luxembourg*	2005Q3 - 2019Q4
Brazil	1998Q3 - 2019Q4	Malaysia	2007Q3 - 2019Q4
Canada*	1990Q1 - 2019Q4	Mexico*	1998Q4 - 2019Q4
Chile*	2005Q3 - 2019Q4	Netherlands*	1990Q3 - 2019Q4
China	1997Q3 - 2019Q4	New Zealand*	1990Q3 - 2019Q4
Colombia*	2007Q3 - 2019Q4	Norway*	1990Q1 - 2019Q4
Czech Republic*	1998Q3 - 2019Q4	Poland*	1997Q3 - 2019Q4
Denmark*	1997Q3 - 2019Q4	Portugal*	1997Q3 - 2019Q4
Finland*	1992Q3 - 2019Q4	Russia	2005Q3 - 2019Q4
France*	1990Q1 - 2019Q4	Singapore	1990Q1 - 2019Q4
Germany*	1993Q3 - 2019Q4	South Africa	1990Q1 - 2019Q4
Greece*	1997Q3 - 2019Q4	Spain*	1997Q3 - 2019Q4
Hong Kong SAR	1998Q3 - 2019Q4	Sweden*	1990Q1 - 2019Q4
Hungary*	1997Q3 - 2019Q4	Switzerland*	1990Q1 - 2019Q4
India	2013Q4 - 2019Q4	Thailand	1999Q2 - 2019Q4
Indonesia	2005Q2 - 2019Q4	Turkey*	2002Q1 - 2019Q4
Ireland*	1999Q3 - 2019Q4	United Kingdom*	1990Q1 - 2019Q4
Israel*	1997Q3 - 2019Q4	United States*	1990Q1 - 2019Q4

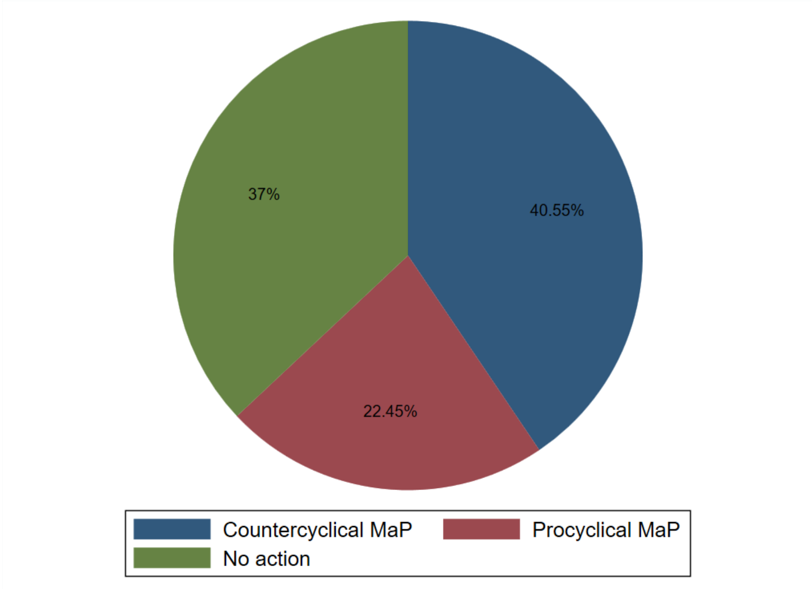
Note: The time span reported in the table for each country corresponds to the available observations in the baseline estimate when we consider the bank credit to the private non-financial sector as an endogenous variable. * indicates an OECD country member.

Table A2: MaP index: Descriptive statistics

No. obs.	Mean	Median	Min.	Max.	Std. Dev.
3,615	1.0949	0	-23	24	4.2867
		Percentiles			
10%	20%	30%	70%	80%	90%
-2	-1	0	1	3	7

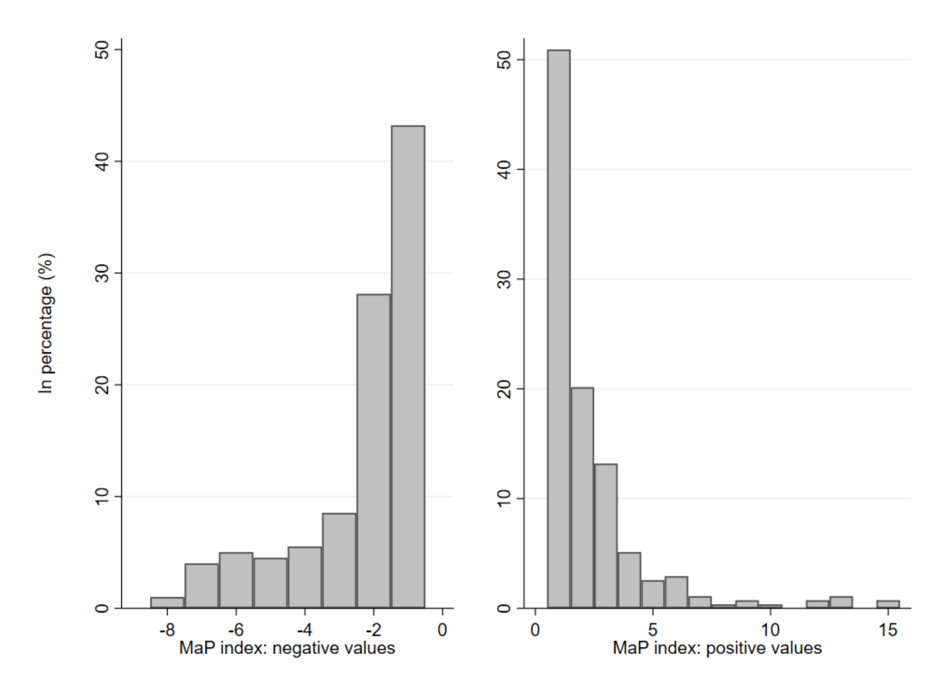
Source: Authors' calculations. Note: The sample consists of 42 countries over the period 1990Q1-2019Q4 (see Table A1 in the Appendix for more details).

Figure A1: Share of procyclical *vs.* countercyclical MaP observations



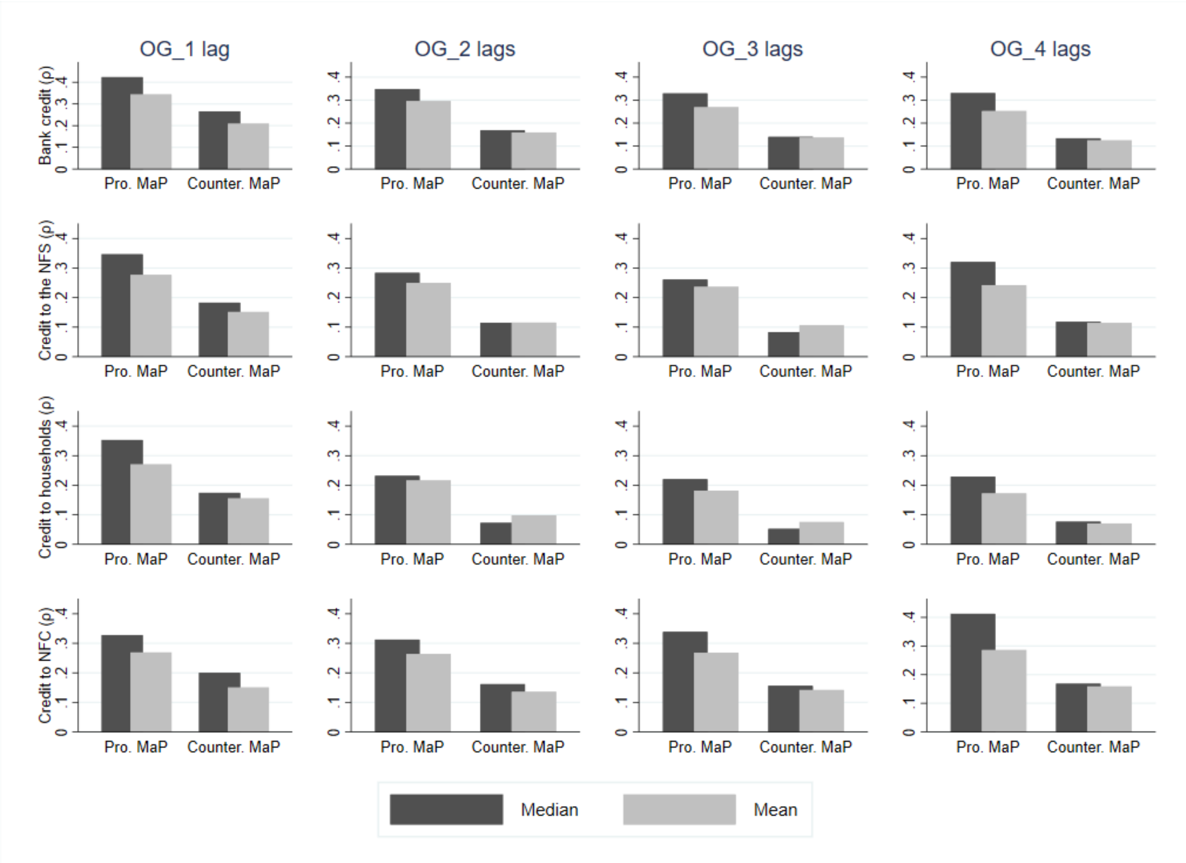
Source: Authors' calculations. Note: No action corresponds to no change in any instrument or to the same number of tightening and loosening actions over a three-year rolling window. The sample consists of 42 countries over the period 1990Q1-2019Q4 (see Table A1 in the Appendix for more details).

Figure A2: Distribution of the MaP index



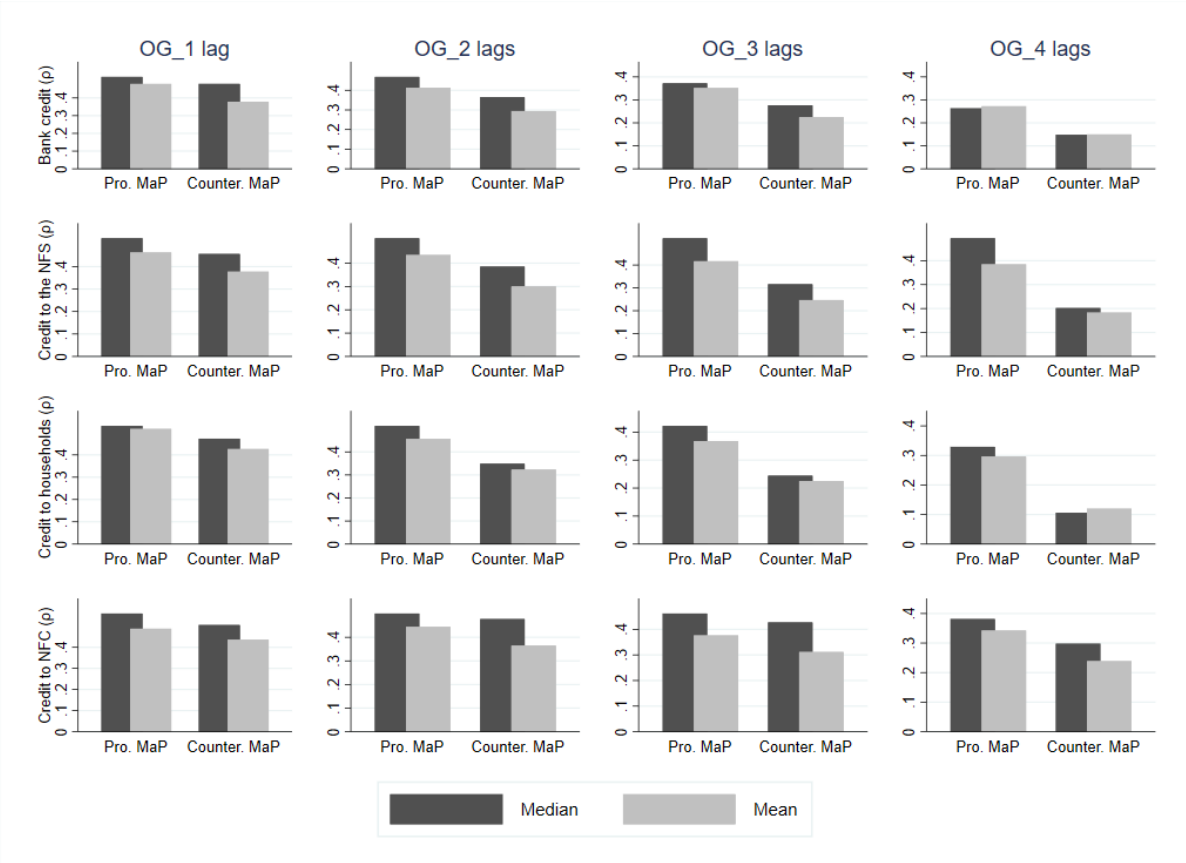
Source: Authors' calculations. Note: Negative values indicate a procyclical orientation of macroprudential policies, while positive ones indicate a countercyclical orientation. The sample consists of 42 countries over the period 1990Q1-2019Q4 (see Table A1 in the Appendix for more details).

Figure A3: Degree of credit procyclicality in OECD countries: Procyclical *vs.* countercyclical macroprudential policy



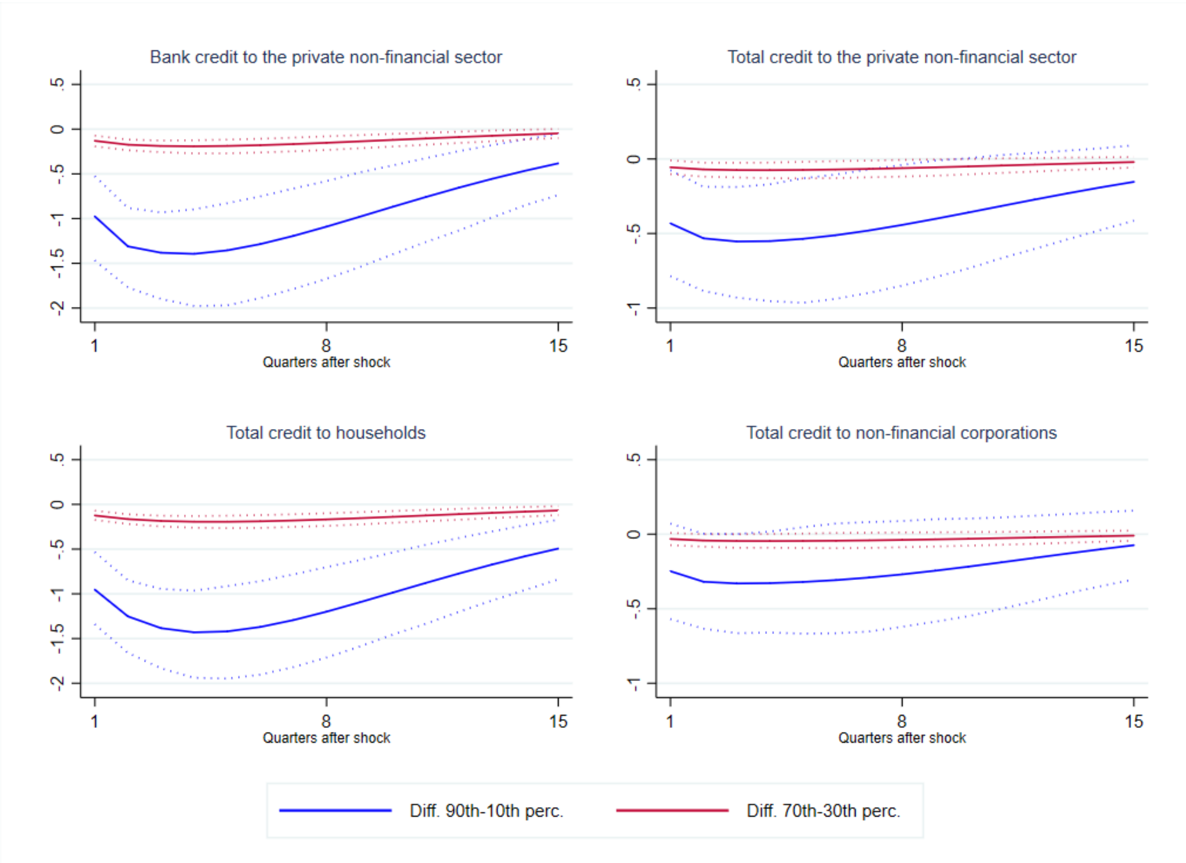
Source: Authors' calculations. Note: The figure represents the median and the mean of the correlation between the business cycle and the credit cycle according to the stance of the macroprudential policy as either procyclical or countercyclical. A macroprudential policy is considered to be procyclical if the macroprudential index is negative over a five-year rolling window, and countercyclical if the index is positive. Each row refers to an alternative credit gap variable. 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.

Figure A4: Degree of credit procyclicality in non-OECD countries: Procyclical *vs.* countercyclical macroprudential policy



Source: Authors' calculations. Note: The figure represents the median and the mean of the correlation between the business cycle and the credit cycle according to the stance of the macroprudential policy as either procyclical or countercyclical. A macroprudential policy is considered to be procyclical if the macroprudential index is negative over a five-year rolling window, and countercyclical if the index is positive. Each row refers to an alternative credit gap variable. 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.

Figure A5: Differences of IRFs for alternative percentiles



Note: The figure shows the difference between the impulse response functions of the credit gap to a shock of one percentage point to the output gap evaluated at the 90^{th} and 10^{th} percentiles of the sample distribution of the MaP index (blue line), and at the 70^{th} and 30^{th} percentiles of the sample distribution of the MaP index (red line). The dotted lines represent the 95% confidence bands generated by bootstrapping (1,000 draws).