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Abstract

I show that macroprudential policy has significant heterogeneous and time-varying effects on the credit growth distribution. These effects are particularly evident in reducing rightward skewness during expansionary periods of the financial cycle, thereby mitigating the upside risk of credit growth. Conversely, during financial crises, the relaxation of macroprudential policy positively impacts the left tail, reducing the risk of severe credit contractions. These findings align with previously documented benefits of macroprudential policy on the downside risk of GDP growth, providing evidence of the mechanism through which these policies act via credit growth. I also identify interactions between macroprudential policy, bank profitability and monetary policy. High bank profitability limits the effectiveness of macroprudential policy in curbing excessive credit growth, while macroprudential policy complements monetary policy by targeting tail risks, which affects the credit growth distribution more uniformly. I also find significant disparities based on the type of tool implemented and the sector targeted. Borrower-based measures are particularly effective in moderating household credit during expansions, whereas capital releases are especially supportive of credit to non-financial corporations during crises.

Keywords: credit growth, financial stability, systemic risk, macroprudential policy, quantile regressions.

JEL classification: C32, E32, E58, G01, G28.

Resumen

En este trabajo identifico que la política macroprudencial tiene efectos significativos, heterogéneos y variables en el tiempo sobre la distribución del crecimiento del crédito. Estos efectos son particularmente evidentes en la reducción de la asimetría hacia la derecha durante períodos expansivos del ciclo financiero, lo que mitiga el riesgo al alza del crecimiento del crédito. Por el contrario, durante las crisis financieras, la relajación de medidas macroprudenciales impacta positivamente en la cola izquierda, y esto reduce el riesgo de contracciones severas del crédito. Estos resultados se alinean con los beneficios previamente documentados de la política macroprudencial sobre el crecimiento del PIB en riesgo, evidenciando el mecanismo a través del cual estas políticas actúan mediante el crecimiento del crédito. También identifico interacciones significativas con la rentabilidad bancaria y con la política monetaria. Mientras que la rentabilidad bancaria limita su efectividad para contener el crecimiento excesivo del crédito, la política monetaria la complementa. Esto es, la política macroprudencial se enfoca en la mitigación de los riesgos de cola, mientras que la política monetaria afecta a la distribución del crecimiento del crédito de manera más uniforme. También encuentro disparidades significativas según el tipo de herramienta implementada y el sector objetivo. Las medidas basadas en los prestatarios son particularmente efectivas para moderar el crédito a hogares durante fases expansivas del ciclo financiero, mientras que las liberaciones de capital son especialmente favorables para soportar el crédito a empresas durante episodios de crisis.

Palabras clave: crecimiento del crédito, estabilidad financiera, política macroprudencial, regresiones cuantílicas, riesgo sistémico.

Códigos JEL: C32, E32, E58, G01, G28.

1. Introduction

There is broad consensus on the benefits of macroprudential policy (MaPP) in enhancing financial stability, as supported by theoretical and empirical literature following the global financial crisis. These benefits are primarily achieved by increasing the resilience of the financial sector (Dell'Ariccia et al., 2016; Altunbas et al., 2018). However, the empirical literature remains inconclusive regarding the secondary objective of many MaPP tools. That is, reducing the build-up of systemic vulnerabilities by taming the financial cycle and smoothing credit growth. Several meta-analyses of research studies addressing this issue reveal significant uncertainty surrounding the estimated values and conflicting results regarding the direction of the effects (see Araujo et al., 2020; Malovanà et al., 2024a; 2024b). A common characteristic of these studies is their focus on the effects of MaPP on the conditional mean of credit growth. Nevertheless, the goal of MaPP when taming the financial cycle is to reduce the risk of excessive credit growth during expansionary stages and large credit contractions during systemic events. In this context, MaPP aims to address extreme realisations of credit growth under non-standard conditions of the financial cycle, particularly those observed in the tails of the distribution.

Recent studies have identified significant positive effects of MaPP on the downside risk of GDP growth (Brandao-Marques et al., 2020; Franta and Gambacorta, 2020; Galán, 2024). This contrasts with the non-significant or negative effects found on the conditional mean (Richter et al., 2019; Noss and Toffano, 2016). Furthermore, the positive effects of MaPP on the left tail of the conditional GDP growth distribution have been found to offset the deterioration in the downside risk of GDP growth caused by the accumulation of cyclical imbalances and the materialisation of systemic risk (Galán, 2024). This evidence supports the notion that the effects of MaPP are more clearly observed in reducing the risk of extreme outcomes. Additionally, it is likely that the effects of MaPP on reducing the downside risk of GDP growth, which align with its ultimate objective, are achieved through more direct effects on intermediate objectives, such as reducing the risk of extreme credit growth realisations.

Against this background, I assess whether MaPP affects the tails of the credit growth distribution over the financial cycle, thereby changing its shape rather than its location. This could explain why previous studies focusing on the conditional mean are inconclusive. To this end, I extend the use of quantile regressions (QR) (Koenker and Basset, 1978) to assess the impact of MaPP on the conditional credit growth distribution. This method has gained popularity following the influential work by Adrian et al. (2019), who identified that traditional models focused on the conditional mean of GDP growth are unable to capture the impact of financial conditions on the left skewness of the GDP growth distribution. A key difference from previous studies using at-risk methods is that I do not centre the analysis solely on the left tail of the distribution, which is associated with the concept of credit-at-risk, but also examine in detail the impact on the right tail of the distribution. As described above, this is essential in analysing the effects of MaPP on the credit growth distribution, as the primary target of MaPP during expansionary stages of the cycle is the reduction of excessive credit growth. The intertemporal relationship between the effects on both tails of the distribution is highly relevant, as a a reduction in the probability of excessive credit growth during upswings may translate into improvements in credit-at-risk during downturns.

A significant challenge in identifying the causal effects of MaPP on financial variables is endogeneity, as MaPP decisions are often based on credit developments. Recent literature has begun to address this is issue through various approaches that resemble methods used in monetary and fiscal policy analysis. Typically, two-step procedures are employed, where the residuals of a first-stage regression of MaPP on macrofinancial variables are used as proxies for the non-systematic component of MaPP (i.e. the part not driven by macrofinancial developments) and then used as regressors in a second-stage regression (Boar et al., 2017;

Brandao-Marques et al., 2020). However, this procedure has been found to induce biases in the context of QR (Lloyd and Manuel, 2024). To avoid this issue, Fernández-Gallardo et al. (2023) propose a narrative approach to eliminate cycle-targeting policies. Nonetheless, this approach requires exact and detailed reporting of policies and excludes from the analysis those measures specifically intended to affect credit growth. Against this backdrop, in this study I follow an inverse propensity-score weighting (IPW) approach. This method, previously proposed in the empirical literature, aims to give more weight to policies that are difficult to predict based on observables and less weight to measures that may be endogenous due to other factors (Richter et al., 2019; Alam et al., 2024).

To perform this analysis, I rely on a granular and comprehensive data set of MaPP measures implemented in the European Union (EU) starting in 1990, which allows for controlling by unobserved country-specific heterogeneity. I conduct quantile local projections up to 16 quarters after the announcement of MaPP measures to derive the response of different quantiles of credit growth over time. Furthermore, I examine the heterogeneous effects of MaPP at different stages of the financial cycle, as well as in distinct bank profitability and monetary policy environments. The interaction of MaPP across these three dimensions is relevant and may reveal differential effects on credit growth.

Regarding the financial cycle, distinguishing its phases is crucial to properly identify the different effects that the direction of MaPP is intended to have on credit growth over the cycle. Galán (2024) shows that this distinction is key to identifying the benefits of MaPP on growth-at-risk. Bank profitability also becomes a relevant factor affecting the impact of MaPP on credit growth, as credit supply is influenced by bank decisions related to their performance. Indeed, bank profitability has been found to be a key variable reflecting the role of risk appetite and competition in lending decisions (Dell'Ariccia and Marquez, 2006), as well as predicting credit developments (Richter and Zimmermann, 2020). Moreover, recent findings provide evidence on the relationship between the cost of capital buffers in terms of credit growth and bank profitability (Herrera-Bravo et al., 2024). Finally, as monetary policy also affects credit growth, significant interactions with MaPP may arise (Carrillo et al., 2021; Kiley and Sim, 2017; Van der Ghote, 2021). Given the recent episodes of historically large and rapid tightening of monetary policy, and the expected relaxation in the coming years, studying this interaction gains importance. In this context, I further extend this analysis to account for monetary policy, as it has also been considered in growth-at-risk models (Duprey and Ueberfeldt, 2020; Franta and Gambacorta, 2020; Brandao-Marques et al., 2020).

I also disentangle the effects of MaPP on household (HH) and non-financial corporations (NFC) credit. This distinction is relevant since the credit dynamics for HH and NFC can differ in terms of speed, magnitude, and correlation with systemic events. Müller and Verner (2023) show that credit developments in tradable and non-tradable sectors have different associations with crises events. Empirically, previous studies also tend to find more significant effects of MaPP on credit to HH (Cerutti et al., 2017; Akinci and Olmstead-Rumsey, 2018; Alam et al., 2024). The different effects of MaPP by sector can also be related to the type of measures implemented. Borrower-based measures (BBM) usually target HH credit exclusively, while capital measures are used more generally. Thus, I also perform a separate analysis of these two main categories of MaPP. From a policy perspective, understanding the different effects of BBM and capital measures would provide useful insights for their implementation.

Results reveal significant effects of MaPP on the tails of the credit growth distribution, contrasting with the relatively small effects on the median. These effects are highly dependent on the position in the financial cycle. Tightening MaPP during expansions has a substantial negative impact on the right tail of credit growth distributions, indicating a strong effect on taming the cycle and reducing the risk of excessive credit growth. Conversely, easing MaPP during crises benefits the entire credit growth distribution, with more pronounced improvements in the downside risk of credit growth, which are transmitted rapidly. Regarding profitability, it is a crucial factor that increases the likelihood of extreme credit growth realisations. Bank profitability also diminishes the effectiveness of MaPP in reducing the upside risk of credit growth during upswings and improving credit-at-risk during crises. As for the interaction between MaPP and monetary policy, larger outcomes are achieved when both policies are implemented together, demonstrating their complementarity when acting countercyclically. These policies affect the credit growth distribution differently. Monetary policy has broad and relatively uniform effects across quantiles, shifting the entire distribution, while MaPP primarily impact the tails by reducing skewness. Additionally, the impact of MaPP tends to be more significant for NFC credit, potentially influenced by the type of measures implemented. BBM mainly affect HH credit, as these measures typically target this type of exposure, whereas capital measures have more substantial effects on the tails of the NFC credit growth distribution.

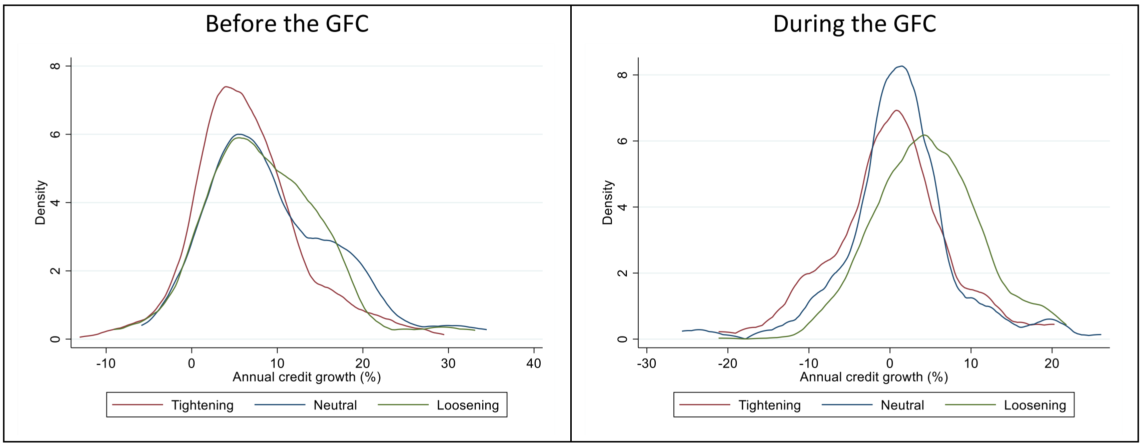
Interestingly, the identified effects are larger in the right tail, suggesting a relevant role of MaPP in reducing the risk of excessive credit growth. This is consistent with previous literature identifying significant benefits of MaPP in reducing the downside risk of GDP growth in the mid-term (Franta and Gambacorta, 2020; Galán, 2024). MaPP acts countercyclically by reducing excessive credit growth as part of its direct objective, and this moderation in risk exposures, together with strengthened resilience of the banking sector, translates into improvements in GDP-at-risk. In terms of policy, results suggest that capital measures are more effective in containing the probability of excessive NFC credit growth, while BBM are more relevant for reducing the upside risk of HH credit growth. The benefits of reducing the downside risk of credit growth are especially important when easing MaPP during systemic events. The timing of policies is also important, with BBM being more rapid than capital measures in reducing the upside risk of credit growth, particularly for HH credit. However, the benefits of easing BBM are limited during crises. These results highlight the importance of the sectoral dimension of MaPP. Moreover, the effectiveness of MaPP depends on the profitability of the banking sector, adding an important dimension when setting these policies and supporting recent findings on the lower costs of increasing capital buffers when bank profitability is high (Herrera-Bravo et al., 2024). Finally, the complementarity between MaPP and monetary policy provides useful insights for the implementation of MaPP in the current environment of rapid changes in policy rates.

Besides this introduction, the rest of the paper is organized into four additional sections. Section 2 describes the relationship between MaPP and credit growth. Section 3 presents the methodology, data, and empirical specification. Section 4 analyses the estimation results. Section 5 presents robustness exercises. Finally, Section 6 concludes the paper and discusses policy implications.

2. The relationship between MaPP and credit growth

The main aim of MaPP is to increase the resilience of the financial sector, particularly against cyclical financial risk. The most severe financial crises in the past have been preceded by the accumulation of large imbalances due to excessive credit growth (Drehmann et al., 2011; Schularick and Taylor, 2012). In this regard, the countercyclical use of MaPP helps to smooth the financial cycle. For instance, capital buffers achieve this by increasing the banks' cost of funding new loans during periods of excessive credit growth and allowing banks to use capital to maintain credit provision during downturns. Additionally, other types of MaPP measures, such as BBM, can achieve similar objectives by limiting excessive risk-taking during expansions, even if they are not used countercyclically.

Figure 1. 4-quarter ahead annual credit growth distributions of EU countries by their use of macroprudential policy before and during the GFC.



Note: Distribution of 4-quarter ahead annual credit growth in the period 2000-2007 (left panel) and the period 2008-2013 (right panel) in the EU, divided into countries that have tightened, loosened, or remained neutral in the use of MaPP. Tightening (loosening) countries are those that have implemented at least one MaPP measure during these periods, while neutral countries are those that did not implement any measures during these periods.
Source: ECB. Own elaboration.

In this context, previous empirical literature generally finds negative effects of MaPP on credit growth. However, there is large heterogeneity in the results depending on the type of instrument and the sector analysed (i.e., HH or NFC). Claessens et al. (2013) find that BBM reduce total bank annual credit growth by between 0.5 percentage points (pp) and 2 pp, while capital measures reduce it by around 1.5 pp. Nonetheless, they find that these effects are only significant during expansions, not crises. Noss and Toffano (2016) also find a low impact of capital requirements, identifying that a one standard deviation change in capital relative to total assets leads to a reduction of 0.25 pp in total credit. Similarly, Akinci and Olmstead-Rumsey (2018) identify that limits on loan-to-value (LTV) and debt-service-to-income (DSTI) ratios reduce total credit by 0.6 pp, primarily due to the impact on HH credit. These authors also find no significant effects of capital measures. Cerutti et al. (2017) also identify a significant effect of BBM on reducing HH credit (between 1pp and 2pp) but no effects on NFC credit. They also find no significant effects of capital measures. More recently, Alam et al. (2024) find that tightening one MaPP measure reduces HH credit by 0.9 pp. When disentangling by the type of measures, the reduction after tightening an LTV measure by about 10 pp is about 0.5 pp, while no significant effects are found for capital measures. Most of these studies focus on the tightening of MaPP, and only few differentiate by the phases of the cycle.

The short experience with the use of MaPP and the limited number of systemic events make it difficult to study the effects of loosening MaPP during crises. In this regard, Jiménez et al. (2017) find that releasing 1 pp of capital during busts results in a 9 pp smaller reduction in bank credit to firms over the following 12 quarters. Similarly, Sivec and Volk (2023) study the impact of a temporary deduction in capital calculation at the start of the global financial crisis in Slovenia. They find that firms borrowing from banks with 1 pp higher capital buffers received 11 pp more in credit. The recent Covid-19 crisis has provided an opportunity to test this effect in countries that had tightened MaPP in previous years. Bedayo and Galán (2024) identify that the release of the Countercyclical Capital Buffer (CCyB) in response to the pandemic helped support credit growth in jurisdictions where the instrument was released, with effects mainly evident in the most capital-constrained banks. Coulliaer et al. (2024) identify similar effects on NFC credit. Overall, previous studies have confirmed a negative but relatively small effect of tightening MaPP on credit. The main effect is usually identified for BBM and on HH credit, while the effect of tightening capital measures is often non-significant.

All the mentioned studies have focused on analysing the effects on the conditional mean of credit growth. However, as shown in Figure 1, the largest differences in the annual credit growth distributions of EU countries in terms of their use of MaPP are observed in the tails rather than in the central values. Specifically, before the GFC, a period of macrofinancial expansion in most countries, credit growth distributions exhibited large right-skewness in countries that remained neutral or even loosened MaPP compared to those that tightened measures during the same period. This indicates that excessive credit growth rates were more likely in countries that did not tighten MaPP measures during this period. Conversely, during the GFC, the distribution for countries that did not relax any MaPP measures or even tightened MaPP (mainly due to regulatory requirements) is not only shifted to the left but also more left-skewed compared to countries that loosened MaPP during this period. This suggests that countries that did not ease MaPP during the crisis experienced larger credit contractions. This is even more pronounced in countries that acted procyclically by tightening MaPP during that period. Overall, these figures highlight important differences in the tails of credit growth distributions that seem to be correlated with the use of MaPP and remain unidentified under conditional mean models.

3. Methodology

3.1. Panel quantile regressions

Quantile regressions (Koenker and Basset, 1978) have proven to be a useful tool for identifying heterogeneous effects of financial variables across the distribution of GDP growth (Adrian et al., 2019). This method has also been used to assess the impact of MaPP on growth-at-risk (Brandao-Marques et al., 2020; Franta and Gambacorta, 2020; Galán, 2024). Recent applications leverage panel data to include fixed effects, controlling for time-invariant unobserved heterogeneity. Koenker (2005) demonstrates that applying quantile models with fixed effects is straightforward, proceeding in a quantile-by-quantile fashion and allowing for different fixed effects at each quantile. Specifically, the fixed effects estimator in panel QR is equivalent to the LSDV estimator in linear regressions when *T* is large relative to *N* (Koenker and Geling 2001).[1] Although, the relationship between the size of *N* and *T* is crucial to ensure unbiased and asymptotic estimates in panel QR with individual effects (Kato et al. 2012), the required conditions are similar to those for fixed effects panel linear regressions (Galvao et al., 2020).[2] Thus, the quantile panel fixed effects model can be represented as follows:

$$\widehat{\boldsymbol{Q}}_{y_{it}|\boldsymbol{X}_{it},\alpha_i}(\tau|\boldsymbol{X}_{it},\alpha_i) = \widehat{\alpha}_{i\tau} + \boldsymbol{X}_{it}\widehat{\boldsymbol{\beta}}_{\tau} \tag{1}$$

$$\left(\widehat{\boldsymbol{\beta}}_{\tau},\widehat{\alpha}_{i\tau}\right) = arg\min_{\alpha_i,\boldsymbol{\beta}_{\tau}} \sum_{i=1}^{n}\sum_{t=1}^{T-h} \rho_{\tau}\,|y_{it} - \boldsymbol{X}_{it}\boldsymbol{\beta}_{\tau} - \alpha_i| \tag{2}$$

$$\rho_{\tau} = \tau \cdot \mathbf{1}_{(y_{i,t} \geq \boldsymbol{X}_{it}\boldsymbol{\beta}+\alpha_i)} + (1-\tau)\cdot \mathbf{1}_{(y_{i,t} < \boldsymbol{X}_{it}\boldsymbol{\beta}+\alpha_i)} \tag{3}$$

where, $\widehat{\boldsymbol{Q}}$ is the estimated quantile function; τ is a given percentile; y_{it} is the dependent variable; $\boldsymbol{X}_{it}$ is a vector of explanatory variables; α_i represents a vector of individual unobserved effects; ρ_{τ} are weights that depend on the quantile; and, $\mathbf{1}$ is an indicator function signaling whether the estimated errors are positive or negative. In particular, $\widehat{\boldsymbol{Q}}_{y_{i,t}|x_{it}}(\tau|\boldsymbol{X}_{it})$ is a consistent estimator of the quantile function of $y_{it}|\boldsymbol{X}_{it}$ (Koenker and Bassett, 1978). The model can be then solved as an optimization problem where the weighted sum of the absolute value of the residuals is minimized.

[1] However, if T is small relative to N or if T and N are of similar size, estimates of the common parameters may be biased or even under-identified, and an incidental parameters problem may arise. To solve these problems, several methods have been proposed in the literature, with quantile estimations via moments (Machado and Santos Silva, 2019) being one of the most recent approaches.

[2] Another key element is the existence of enough observations above and below the estimated quantile to ensure the fit is not an artifact of a few extreme observations. Moreover, the asymptotics of QR rely on there being enough observations on both sides to satisfy the conditional Central Limit Theorem. A rough rule of thumb is: min $\{n\tau, n(1-\tau)\} \geqslant 10p$, where *p* is the number of explanatory variables (see, Chernozhukov, 2005).

3.2. The empirical model

Given that the time series dimension is large relative to the cross-sectional dimension, including additive unobserved fixed effects in a panel QR provides consistent estimates (Kato et al., 2012). This condition is met with the sample used in this application, as described below. Thus, the baseline model to assess the impact of MaPP on the credit growth distribution is as follows:

$$\widehat{\boldsymbol{Q}}_{y_{i,t+h}|x_{it},\alpha_i}(\tau|\boldsymbol{X}_{it},\alpha_i) = \hat{\alpha}_{i\tau}^{h} + \hat{\beta}_{1\tau}^{h} y_{i,t} + \hat{\beta}_{2\tau}^{h} MPI_{it} + \widehat{\boldsymbol{\delta}}_{\tau}^{h} \boldsymbol{X}_{it}; \quad \tau = 5,10,\dots 90,95; \quad h = 1,\dots,16, \tag{4}$$

where, τ represents the 19 estimated quantiles from the 5th to the 95th percentile, α_i represents unobserved country fixed effects; $y_{i,t}$ is the contemporaneous annual credit growth rate to the non-financial private sector; *MPI* is an index capturing the use of MaPP, which I define further below; and $\boldsymbol{X}$ is a vector of control variables. This vector includes the annual GDP growth rate, the two-year average growth in house prices, a country-level index of financial stress (*CLIFS*), the return on equity (*ROE*) of the banking sector, and the monetary policy rate (*MoP*).

The first three variables capture economic and financial conditions that affect credit growth Cerutti et al., 2017; Alam et al., 2024). Bank profitability has been identified as a key variable reflecting the role of risk appetite and competition in lending decisions, and a significant predictor of credit imbalances (Dell'Ariccia and Marquez, 2006; Richter and Zimmermann, 2020). Finally, controlling for monetary policy interest rates has been found to improve the identification of the effects of MaPP on GaR (Duprey and Ueberfeldt, 2020; Franta and Gambacorta, 2020; Brandao-Marques et al., 2020). Regarding the latter, in some exercises I also use Taylor-rule residuals and monetary policy shocks obtained from the literature, which better identify the monetary policy stance. Finally, the variable of interest ($y_{i,t+h}$) is defined as the annualised average credit growth rate to the non-financial private sector from period *t* to *t+h* for every country *i*, as follows:

$$y_{i,t+h} = \ln\left(\frac{Credit_{i,t+h}}{Credit_{i,t}}\right) / \left(\frac{h}{4}\right); h = 1,\dots,16 \tag{5}$$

3.3. Data

The sample comprises quarterly data for the 27 EU countries plus the UK from 1990 to 2019. The main data source is the ECB Statistical Data Warehouse (SDW), from which data on GDP growth rates, the CLIFS index, and credit to the non-financial private sector (total and split by HH and NFC) is collected. This is complemented with data from the Bank of International Settlements (BIS) for house prices and monetary policy rates, the Federal Reserve Economic Data for ROE, and the ECB Macroprudential Policy Evaluation Database (MaPPED), supplemented by data from the European Systemic Risk Board (ESRB) for the computation of the MPI. In Table 1, I present summary statistics of the macrofinancial variables and the MPI for this sample.

Regarding the MPI, I compute it as the net sum of the announced MaPP measures each quarter, as reported in MaPPED from 1990Q1 to 2017Q4, and supplemented with information from the ESRB for the period 2018Q1 to 2019Q4, for which MaPPED is not updated. The measures are classified into 11 different categories, including capital requirements, capital buffers and BBM, which encompass most of the MaPP tools implemented during the sample period in the EU. In Appendix A, I provide a detailed description of all the measures in these and other categories. In contrast to most previous studies that use information from surveys, such as those launched by the IMF, MaPPED, introduced by Budnik and Kleibl (2018), was developed after consultations with European national macroprudential authorities. It offers advantages in

Table 1. Summary statistics.

Variable	p5	p25	p50	p75	p95
NFPS Credit (1y growth, %)	-5.41	-0.08	3.45	7.34	16.45
HH Credit (1y growth, %)	-3.87	1.98	6.66	12.89	29.65
NFC Credit (1y growth, %)	-4.90	0.64	4.71	9.48	21.07
GDP (1y growth, %)	-3.27	-1.15	2.69	4.25	7.51
House prices (2y av. growth, %)	-14.16	-0.22	7.59	15.34	29.95
CLIFS	0.03	0.06	0.09	0.16	0.32
ROE (pp)	-9.13	3.45	8.37	13.35	22.13
Monetary policy rate (pp)	0	0.50	2	3.75	9.48
MPI	-2	-1	0	1	2

Source: BIS, ECB, ESRB, Fed and IMF.

terms of the consistency of the reported information and a very granular classification of the measures, including their purpose (e.g., resilience, countercyclical, etc.), and the implementation and announcement dates. The subsequent information reported by the ESRB is also very granular and is based on notifications submitted by these national European authorities. The index is constructed as follows:

$$MPI_{it} = \left\{ \begin{matrix} -2 & Tight_{it} - Loose_{it} \leq -2 \\ -1 & Tight_{it} - Loose_{it} = -1 \\ 0 & Tight_{it} - Loose_{it} = 0 \\ 1 & Tight_{it} - Loose_{it} = 1 \\ 2 & Tight_{it} - Loose_{it} \geq 2 \end{matrix} \right\} \tag{6}$$

Thus, the index takes the discrete values {-2, -1, 0, 1, 2} if there were two or more loosening actions, one loosening action, no change, one tightening action, or two or more tightening actions in net terms during quarter t, respectively. It is important to note that only 0.5% of the observations report more than two net MaPP measures in the same quarter, which justifies grouping them within the categories for two or more measures. This computation of the index resembles the one performed by Brandao-Marques et al. (2020) using the IMF database and is similar in spirit to previous proposals in the literature.[3] Nonetheless, a feature of this index is that it allows for distinguishing the direction of the implemented policies.

3.4. Endogeneity of MaPP

As MaPP decisions are often based on credit developments, a challenge in identifying the causal effects of MaPP on financial variables is endogeneity. Countries may tighten (loosen) MaPP when the credit cycle is expanding (contracting), leading to reverse causality. Although I estimate local projection regressions where the dependent variable is 1 to 16 quarters ahead, expectations may play a role, particularly in short horizons. This issue has been recently addressed in the empirical literature through various approaches that resemble methods used for identifying monetary and fiscal policy shocks.

[3] Cerutti et al. (2017) compute an annual index for 119 countries from 2000 to 2013 based on previous versions of IMF surveys. However, it does not include changes in the level of measures already in place and does not distinguish between tightening and loosening policies. Boar et al. (2017) merge this database with others reported previously in Lim et al. (2011) to compute an index for 64 countries starting in 1990. However, this index accounts for yearly rather than quarterly data and does not distinguish the direction of policies either. Kim and Mehrotra (2018) compute a quarterly index that account for the direction of the policy, but only for four Asian economies (Duprey and Ueberfeldt, 2020, compute a similar index for Canada). Alam et al. (2024) and Galán (2024) use the IMF macroprudential database to compute an index that is the 4-quarter net sum of MaPP policies. Although it provides information for a wide group of countries, the reported information is not completely consistent with some policies informed by national authorities in Europe. It also lacks a classification of the purpose of the measures and distinctions between announcement and implementation dates.

One of the most used approaches is a two-step procedure, where the residuals of a regression of MaPP indexes on macrofinancial variables are used in the main regression to separate the non-systematic component of the MaPP (Boar et al,.2017; Brandao-Marques et al., 2020). Nonetheless, this approach has been identified to induce biases in a QR context (Lloyd and Manuel, 2024). Due to these difficulties, Fernández-Gallardo, et al. (2023) propose following a narrative approach by filtering out those MaPP measures with countercyclical objectives. Although the granularity of MaPPED allows this separation, it is still not guaranteed that policies not classified as cyclical, such as structural or systemic capital buffers have not been implemented following credit cycle developments.[4] Policymakers may target financial objectives without explicitly stating them when implementing macroprudential actions. This concern is raised by Richter et al. (2019), who, despite of following a narrative approach to identify the impact of LTV policies on output and inflation, state that in the case of financial variables, this approach would not be useful since most MaPP tools are designed to affect credit growth. This would lead to the exclusion of a large number of measures, which are precisely those whose impact we are interested in identifying.

Therefore, in this study, I follow an IPW approach, which has been previously proposed for identifying MaPP shocks on credit growth in the context of local projection models (Richter et al., 2019; Alam et al., 2024). This approach, introduced by Jordà and Taylor (2016) for identifying fiscal policy shocks, aims to weight more those policies that are difficult to predict based on observables and weight less those measures that can be endogenous due to other factors. This method has the advantage of accounting for all the information in the sample and avoids the potential bias problem in QR when using residuals of first-stage regressions.[5] In particular, I carry out an ordered probit regression of the MPI on the macroeconomic and financial variables in the baseline specification in Equation (4), including four lags of these variables. In the case of credit, since reverse causality may arise from the relationship between MaPP and future realisations of credit, I also include four leads of the variable. I also include country fixed effects to account for country-specific differences in the usage of MaPP. The estimated model is as follows:

$$Pr(MPI_{it}=j)=Pr\left(MPI_{j-1}<\ \alpha_i+\sum_{p=0}^{4}\boldsymbol{\delta_p}\boldsymbol{X}_{it-p}+\sum_{p=0}^{4}\beta_p y_{it-p}+\sum_{p=1}^{4}\gamma_p y_{it+p}+\varepsilon_{it}\leq MPI_j\right);$$

$$j=[-2,-1,\ 0,\ 1,\ 2]; \qquad (7)$$

The first step at this stage is to check the overlap of estimated probabilities between treatment and control groups (Jordà and Taylor, 2016). A relatively high overlap is desirable for the application of the IPW method to allow variability within groups. It is also expected that if endogeneity is a concern, there will be more mass close to 1 for observations with implemented MaPP (treatment group) and close to 0 for those not implementing MaPP (control group) (Richter et al., 2019). I show these probability distributions in Figure A1 in Appendix B. It is observed that the distributions of estimated probabilities are skewed towards 0 in the case of an MPI equal to 0, and towards 1 for an MPI different from 0.[6] These results suggest that MaPP decisions are more likely to be based on macrofinancial developments, while the large dispersion and overlap between groups validates the usefulness of the IPW approach. Based on these results, I use the inverse probabilities as weights in the quantile local projection regressions in Equation (4).

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[4] This is the case of the phase-in decisions taken by several EU countries during the implementation of the capital conservation buffer and the buffers for systemically important institutions after the global financial crisis.

[5] Although I use the IPW approach as the main method to deal with endogeneity concerns, in Section 5 I also perform robustness to the alternative methods.

[6] I show the estimation results in Appendix B. Although only a few coefficients are significant individually, jointly these variables significantly improve the predictive performance relative to a model with only fixed effects. These results validate the use of this method, while proving that there are no strong associations, mainly with leads of credit growth.

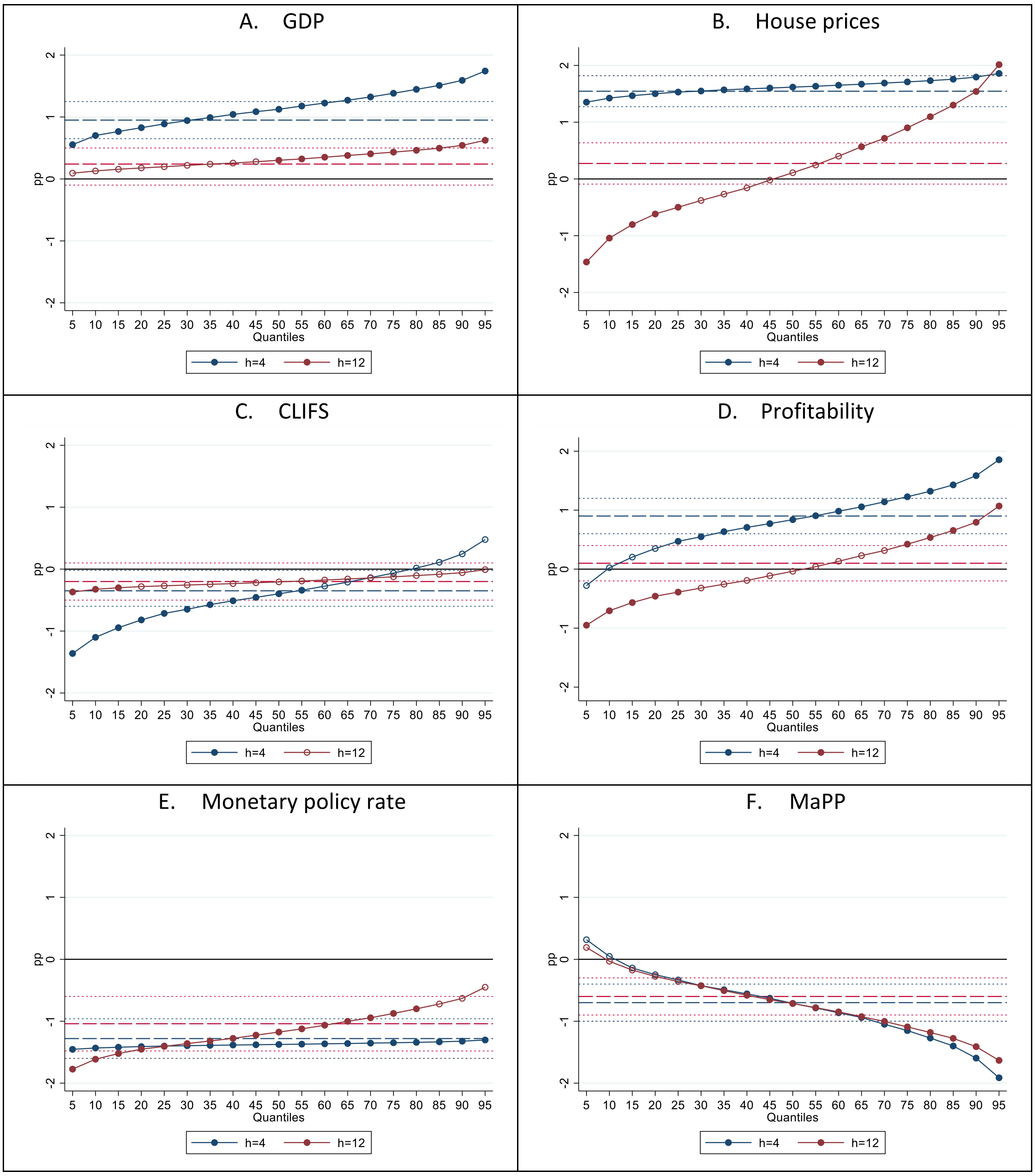
4. Results

I start the analysis by assessing the performance of the baseline model in Equation (4) and the contribution of the regressors by computing the quantile pseudo-R^2 (Koenker and Machado, 1999). In Figure A2 in Appendix C, it is observed that the full specification exhibits a satisfactory fit of the data at the tails and the median, and at short- and mid-term horizons. It is also observed that the marginal contribution of the regressors varies across quantiles and horizons. Growth rates of GDP, house prices, and credit itself are the most relevant drivers of future credit growth paths across quantiles and horizons. Monetary policy rates explain a lower portion of the variability of data, but their contribution is quite homogeneous across quantiles. In contrast, financial stress is a very relevant driver of the left tail of the credit growth distribution but only in the short-term. The contribution of bank profitability and MaPP to the variability of data is more persistent but particularly relevant at the tails of the credit growth distribution. Overall, these results support the use of quantile regressions to capture heterogeneous effects across the credit growth distribution and highlight the importance of moving away from conditional mean estimations to properly model the dynamics of the responses of credit to MaPP.

In Figure 2, I plot the estimated coefficients for the 19 quantiles (from 0.05 to 0.95) at 4- and 12-quarter horizons after standardising the regressors to facilitate comparisons, except for the MPI. I also add the estimated coefficients of fixed effects OLS regressions for comparison purposes with a conditional mean model. In general, control variables exhibit significant heterogeneous effects across quantiles of the credit growth distribution, with estimated QR coefficients at the tails outside the confidence bands of the OLS estimates. Relevant differences are also observed depending on the horizon assessed. GDP growth has positive effects across future credit growth distributions, but the impact is significantly larger on the right tail and at the 4-quarter horizon (Panel A). This suggests that economic growth is not only positively correlated with credit growth but also a relevant driver of the probability of excessive credit growth rates in the short-term. Conversely, the response of credit growth to house prices is positive but quite homogeneous in the short run, while it is highly heterogeneous in the mid-term (Panel B). House prices would foster excessive credit growth, an effect that becomes highly persistent, while increasing the downside risk of credit growth at long horizons. The results for financial stress are also very heterogeneous across quantiles and over time (Panel C). In this case, the main significant effects are observed on the left tail of the distribution but only in the short-term, suggesting that increases in financial stress are rapidly reflected in the risk of large credit contractions under severe scenarios. This indicates that the materialisation of stress events increases the left-skewness of the credit growth distributions, but this effect dilutes in the mid-term. This result is consistent with previous findings on the impact of financial conditions on the downside risk of GDP growth (Adrian et al., 2019).

Regarding bank profitability, the impact is highly heterogeneous across quantiles, with a positive and highly persistent effect on the right tail (Panel D). Similarly to house prices, profitability would induce a mid-term deterioration of the downside risk of credit growth, probably linked to the large impact on increasing the risk of excessive growth, which leads to an accumulation of vulnerabilities. These results highlight the role of bank profitability as a key variable characterising changes in the shape of credit growth distributions, mainly through effects on the right tail, and may validate the increased relevance of this variable for MaPP decisions (Herrera-Bravo et al., 2024). Concerning monetary policy, its effects are significant but very homogeneous across quantiles of the credit growth distributions, mainly in the short run (Panel E). This indicates that monetary policy tends to shift the location of the distribution rather than changing its shape. This is in line with previous effects of monetary policy identified on the conditional GDP growth distribution (Duprey and Ueberfeldt, 2020). Nonetheless, these effects seem to be more persistent on the median and the left tail. That is, an increase in policy rates

Figure 2. Estimated QR coefficients (4- and 12-quarter horizons).



Note: Points represent the estimated change in pp in the credit growth quantile, following a 1 standard deviation increase in the dependent variable represented in panels A to E, and 1 unit increase in the MPI (panel F). Hollow circles represent coefficients that are not statistically significant at a 90% of confidence after using bootstrapped standard errors with 500 replications. The blue and red continuous lines join the estimated quantile coefficients at 4 and 12 quarter horizons, respectively. The dashed lines signal the OLS estimates at 4 (blue) and 12 (red) quarter horizons, and the blue and red dotted lines indicate the corresponding 90% confidence bands. The horizontal continuous grey line signals the value 0.

helps contain the risk of observing excessive credit growth rates mainly in the short run, while the effect of a reduction in the interest rate would improve the downside risk of credit growth for longer periods.

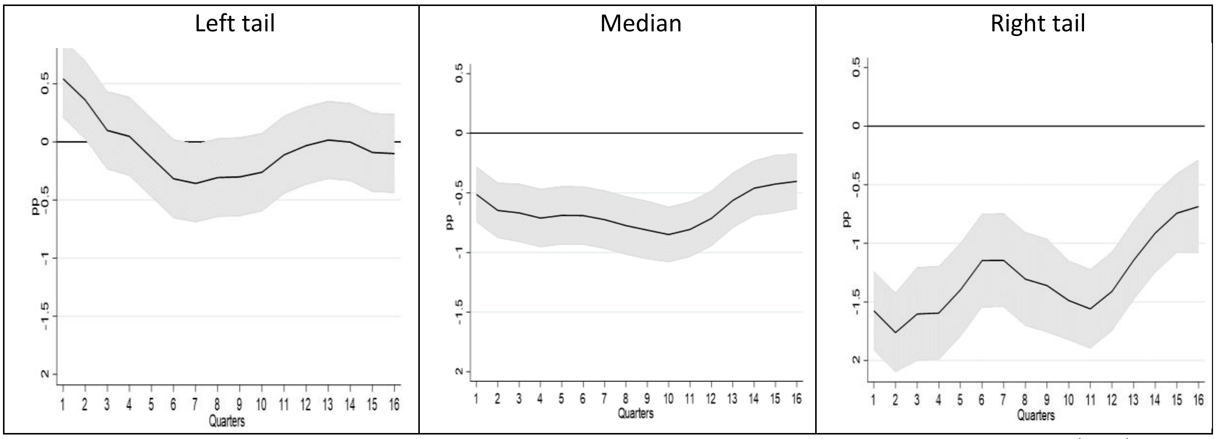
As to the variable of interest, MaPP exhibits a markedly heterogeneous impact across quantiles of the credit growth distribution, which is also persistent over a mid-term horizon (Panel F). In particular, the effects of tightening MaPP (i.e., a positive shock to the MPI) are negative and significant on the median, but especially large on the right tail. This indicates that MaPP has relevant effects on shaping the credit growth distribution through changes in its right skewness.

These results support the countercyclical effect of MaPP measures, as identified before in previous studies using conditional mean models (Claessen et al., 2013; Cerutti et al., 2017), but reveal that the main mechanism through which MaPP acts is by reducing the risk of excessive credit growth. This may explain the large dispersion of results in the literature assessing the impact of MaPP on the conditional mean of credit growth (see Araujo et al., 2020; Malovanà et al., 2024a, 2024b). Conversely, the impact on the left-tail of the credit growth distribution seems non-significant, implying that MaPP reduces the right skewness of the distribution without affecting the downside risk. Overall, this is a desirable outcome of MaPP during expansionary phases of the cycle, when taming excessive credit growth can be seen as a benefit of MaPP.

To analyse the impact of MaPP over time in more depth, I estimate the response of different quantiles of the credit growth distribution to MaPP shocks using the local projections specification. For this purpose, I select the 10th, 50th, and 90th quantiles to capture the dynamics at the tails and the median of the credit growth distribution over time. In Figure 3, I plot the estimated coefficients of MPI at horizons from 1 to 16 quarters ahead. It is observed that the effects shown above are rapidly transmitted after a MaPP shock and that they are quite persistent over time. In particular, the impact on the left tail remains non-significant during almost the entire period, while the impact on the median and the right tail remains negative and significant throughout the whole horizon. Interestingly, the negative effect on median credit growth is relatively small, about 0.5 pp, but quite stable over time. In contrast, the impact on the right tail is large, reaching about 1.7 pp during the first quarters after a positive MaPP shock, but starts to decrease 12 quarters after the change in MaPP.

Nonetheless, these effects might be conditional on the phase of the financial cycle, as identified previously with models studying the impact of MaPP on growth-at-risk (Galán, 2024). Moreover, assuming that the distribution remains unchanged throughout the financial cycle can have strong implications, such as the impact of loosening MaPP being opposite and symmetric to the impact of tightening policies. However, empirically this does not need to be the case, and the different characteristics of expansions and contractions of the financial cycle may affect the impact lag and the effectiveness of the measures. Asymmetric effects have been identified before when assessing the effect of MaPP on growth-at-risk (Galán, 2024), as well as in studies assessing the impact of MaPP on credit growth. Jiménez et al. (2017) find that accumulating capital buffers during credit expansions reduces the magnitude of bank credit contractions during systemic crises but magnifies the negative effect on credit and firms' probability of

Figure 3. IRF of the 10th, 50th, and 90th percentiles of the credit growth distribution to positive MaPP shocks.



Note: The lines represent the estimated coefficients of the MPI obtained using QR on credit growth at the 10th, 50th and 90th percentiles from 1 to 16 quarters ahead, respectively. The shaded areas represent the 90% confidence bands of the estimated coefficients computed using bootstrapped standard errors with 500 replications. The horizontal lines signal the value 0. The vertical axes represent the marginal effect in pp.

survival if they are accumulated during a downward phase. Claessens et al. (2013) and Cerutti et al. (2017) also identify that BBM are more effective in booms than in bust periods at reducing credit and house prices. Regarding the direction of MaPP policies, Poghosyan (2019) finds asymmetric responses to loosening and tightening measures. Certainly, loosening and tightening measures are intended to act in different stages of the cycle, when not only the response of real variables is different but also the way MaPP decisions are made differs in terms of intensity. This makes it necessary to account for this distinction in the model estimation, as performed below.

4.1. The effects of the direction of MaPP over the cycle

To account for different phases of the financial cycle and their interaction with MaPP, I create a binary variable $Crisis_{it}$, which takes the value 1 during the period a country experiences a financial crisis, as identified in Laeven and Valencia (2018), and 0 otherwise. I include this additional variable as well as its interaction with the MPI. I estimate the models for the three quantiles of interest (10th, 50th, and 90th) and for the entire horizon from 1 to 16 quarters ahead. The specification takes the following form:

$$\widehat{\boldsymbol{Q}}_{y_{i,t+h}|x_{it},\alpha_i}(\tau|\boldsymbol{X}_{it},\alpha_i) = \hat{\alpha}_{i\tau}^h + \widehat{\boldsymbol{\delta}}_\tau^h \boldsymbol{X}_{it} + \hat{\beta}_{1\tau}^h y_{it} + \hat{\beta}_{2\tau}^h MPI_{it} + \hat{\beta}_{3\tau}^h Crisis_{it} + \hat{\beta}_{4\tau}^h MPI_{it} Crisis_{it};$$
$$\tau = 10,50,90; h = 1, \dots, 16. \quad (8)$$

In Table 2, I show the estimated coefficients for MPI and its interaction with financial crises at four selected horizons of interest (4, 8, 12, and 16 quarters ahead). The coefficients obtained for MaPP are consistent with those identified above. They are largely negative and significant at the 90th percentile at both short- and mid-term horizons, lower in magnitude for the median, and not significant at the 10th percentile. This implies that the effects found earlier on MaPP's main impact on reducing the risk of excessive credit growth are mainly observed during normal times or financial cycle expansion periods. Nonetheless, during periods of financial crises, the effects of MaPP are significantly different, as observed from the significant coefficients of the interaction term. This is mainly evident in the tails, but with opposite implications. In the low quantile, the interaction is negative and significant, mainly at short horizons, implying that tightening (loosening) MaPP during crises has significant negative (positive) effects on credit-at-risk. Given that the magnitude of the coefficient of the interaction term is greater than that for MPI, this implies that loosening MaPP during those periods has significant benefits in reducing the downside risk of credit growth. In contrast, at the high quantile, the sign of the interaction becomes positive, implying that during crisis periods, the impact of tightening MaPP on the right

Table 2. Estimated QR coefficients for MaPP and its interaction with financial crises at different quantiles and horizons.

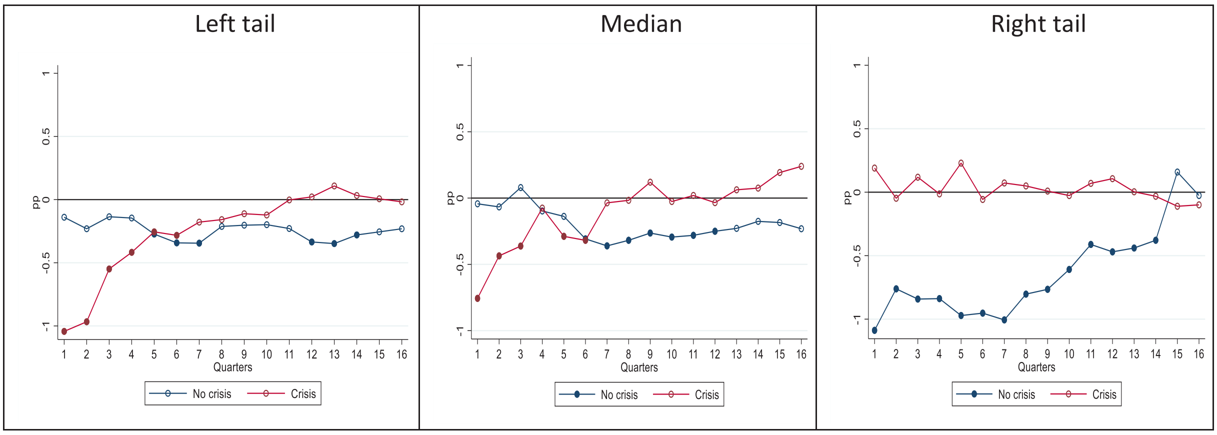
	$\tau = 0.10$				$\tau = 0.50$				$\tau = 0.90$			
	h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16	h=4	h=8	h=12	h=16
MPI_{it}	-0.206	-0.247	-0.375**	-0.251	-0.187	-0.327**	-0.265**	-0.269	-0.805***	-0.772***	-0.496***	-0.018
$MPI_{it}Crisis_{it}$	-0.214**	0.013	0.465*	0.202	0.009	0.295**	0.201*	0.486*	0.812***	0.860***	0.704***	-0.129
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2	0.74	0.71	0.69	0.63	0.67	0.67	0.64	0.61	0.76	0.74	0.72	0.68

Note: The table shows the estimated coefficients for the MPI and its interaction term with financial crises, of independent QR for credit growth at 4 different horizons (i.e., 4, 8, 12 and 16 quarters ahead) and 3 different quantiles (i.e., the 5th, 50th and 95th percentiles). ***, ** and * represent significance at the 99%, 95% and 90% confidence level, respectively.

tail is reduced. In this case, the magnitude of the coefficient of the interaction term is similar to that of the MPI, suggesting that the impact of MaPP on the right tail is offset during crises.

These results can be better observed in Figure 4, where I show the responses over time for the three quantiles of the distribution assessed above. The differences in the impact of MaPP during financial crises are confirmed. In particular, the impact on the right tail vanishes during periods of crises, while the impact on the left tail and the median becomes more relevant, mainly during the first six quarters. Specifically, the negative and significant impact of MaPP on the left tail of the credit growth distribution during crisis episodes indicates that easing MaPP (a negative variation in MPI) reduces the magnitude of severe credit contractions, thereby improving credit-at-risk in the short run. The benefits of relaxing MaPP in a crisis scenario reach about 1 pp in the first two quarters and are significant during the first six quarters. These benefits are also observed in the median of credit growth, although with somewhat lower intensity. This is consistent with previous studies identifying small negative effects on the conditional mean (Cerutti et al., 2017).

Figure 4. Response of the tails (10th and 90th percentiles) and the median (50th percentile) of the credit growth distribution to MaPP shocks during and outside of crises.

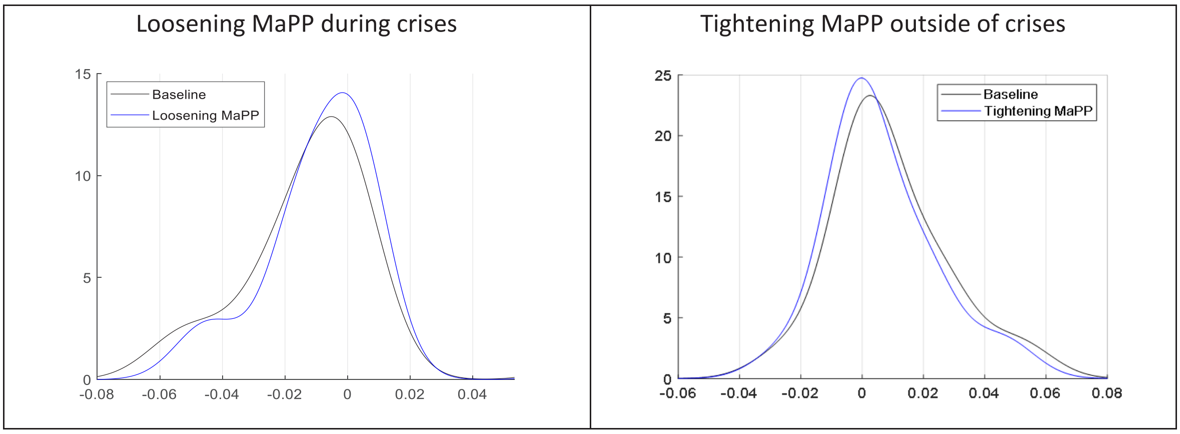


Note: The lines represent the estimated coefficients for the MPI (blue line) and the sum of this coefficient with that of the interaction between MPI and Crisis (red line), obtained using QR on credit growth at the 10th, 50th and 90th percentiles from 1 to 16 quarters ahead. Hollow circles represent coefficients that are not statistically significant at a 90% of confidence after using bootstrapped standard errors with 500 replications. The horizontal lines signal the value 0. The vertical axes represent the marginal effect in pp.

In Figure 5, I represent these results through density functions by mapping 19 quantile predictions (from the 5th to the 95th percentiles) in the two assessed scenarios (during and outside of financial crisis periods) using the method described in Appendix D. It can be observed that the main effect of MaPP in both cases is on the shape, particularly the skewness, rather than on the location of the distributions. Loosening MaPP during financial crises reduces the left skewness of the credit growth distribution given the higher impact on the left tail during these periods. In contrast, the highly significant impact of tightening MaPP outside of crisis periods reduces the right skewness of the credit growth distribution.

Overall, these results capture the large heterogeneity of the impact of MaPP on credit growth depending on the phase of the cycle, but mainly on its direction. Certainly, during financial crises, MaPP is expected to be relaxed to support financial stability and the provision of credit. The differences in the term structure of the responses to MaPP in these two different stages of the cycle can be related to the fact that MaPP is usually eased more rapidly than it is tightened, and that the intensity of loose measures is higher. In contrast, loosening MaPP during crisis events does not seem to affect the right tail of the credit growth distribution. The differences in the term

Figure 5. Conditional credit growth distributions 4 quarters after MaPP shocks over the cycle.



Note: The figures present the estimated credit growth distributions at 4-quarter horizons constructed by mapping the fitted values of the quantile functions obtained with the model in Equation (8) into a probability density function, using the kernel-based method in Appendix D. The black densities represent average values in periods of financial crises (Panel A) or excluding them (Panel B). The blue densities represent the credit growth distributions after a negative (Panel A) or positive (Panel B) change of 1 unit in the MPI in each scenario.

structure of the impact of MaPP depending on the phase of the financial cycle, and the opposite results on the tails of the credit growth distribution, provide evidence of the benefits of the countercyclical use of MaPP and uncover that the main benefits of these policies occur on the tails, where risk is usually manifested. These results are also consistent with previous findings on the impact of MaPP on growth-at-risk (e.g., Franta and Gambacorta, 2020; Galán, 2024), suggesting that the benefits observed in the improvement of GDP-at-risk can reflect the more direct effects of MaPP on the tails of credit growth.

4.2. Bank profitability and its interaction with MaPP

As identified above, bank profitability has significant positive effects on the right tail of credit growth distributions. This suggests an effect of profitability on the buildup of vulnerabilities associated with excessive credit growth, which seems to translate into a deterioration of the downside risk of credit growth some quarters ahead. In this context, the opposite results obtained for MaPP suggest that these policies may help offset the increase in risk associated with changes in bank profitability. However, the effectiveness of MaPP may be influenced by profitability conditions. For that purpose, I estimate an extension of the model in Equation (6) by adding an interaction term between profitability and MaPP. The estimated specification is as follows:

$$\widehat{\boldsymbol{Q}}_{y_{i,t+h}|x_{it},\alpha_i}(\tau|\boldsymbol{X}_{it},\alpha_i) = \hat{\alpha}_{i\tau}^h + \hat{\boldsymbol{\delta}}_\tau^h \boldsymbol{X}_{it} + \hat{\beta}_{1\tau}^h y_{it} + \hat{\beta}_{2\tau}^h MPI_{it} + \hat{\beta}_{3\tau}^h MPI_{it} Prof_{it}; \quad \tau = 10,50,90; h = 1,\dots,16 \qquad (9)$$

In Table 3, I show the estimated quantile coefficients for the MPI and the interaction term between the MPI and profitability at the quantiles and horizons assessed above. Both coefficients are significant mainly at the median and right tail across horizons, and at the left tail in short horizons. The signs confirm that higher profitability reduces the effects of positive MaPP shocks across the credit growth distribution. Higher profitability negatively affects the effectiveness of tightening MaPP (a positive shock) in reducing the risk of excessive credit growth (high quantile), but also reduces the benefits of loosening MaPP (a negative shock) in improving the downside risk of credit growth (low quantile). That is, higher bank profitability makes it more difficult for MaPP to reduce the right skewness of the credit growth distribution, implying that a more intense use of MaPP is needed to offset the increased upside risk. Conversely, loosening MaPP is more effective in improving credit-at-risk when profitability is low.

At the median, profitability affects MaPP less, as the coefficient of the interaction term is smaller, although still significant and positive.

The term structure of these effects can be better observed from the response functions of credit growth quantiles to MaPP shocks under low and high profitability scenarios. For this purpose, I take values of ROE that correspond to the 10th and 90th percentiles of its historical distribution in the sample (this coincides with ROE equal to 0 pp and 15 pp, respectively) and compute the responses of credit to MaPP shocks in these two scenarios. In Figure 6, I show these responses ($\hat{\beta}^h_{2\tau} + \hat{\beta}^h_{3\tau} Prof$) over the 16-quarter period, for the tails and the median of the credit growth distribution. It is observed that loosening MaPP (negative changes in MPI) benefits credit-at-risk (10th percentile) when profitability is low, and that these benefits would remain significant up to nine quarters after the shock. In contrast, in a high profitability situation, changes in MaPP have no significant effects on the left tail of the credit growth distribution. In the median and the right tail, the negative effects of MaPP are highly persistent and significant under both scenarios, but these effects are significantly reduced in a high profitability environment. These results imply that, under a high profitability environment, MaPP is less effective in reducing the risk of excessive credit growth, as represented by the right tail of its distribution. Nonetheless, if negative effects on median credit growth are interpreted as costs, in the same way it has been argued in the case of GDP growth (see Galán, 2024; Suarez, 2022), then these results suggest that if policymakers are more interested in minimising costs than in reducing the upside risk of credit growth, MaPP should be implemented when bank profitability is high. From a policy perspective, this finding supports the recent implementation of positive neutral rates of the CCyB in several European jurisdictions, where the high bank profitability environment has been a factor favouring the decisions (Herrera-Bravo et al., 2024).

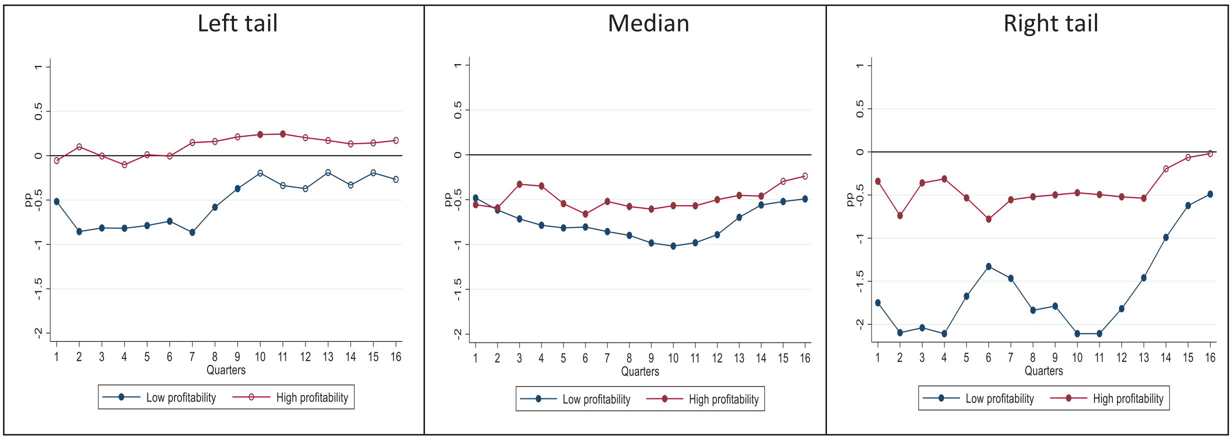
To illustrate the effects on the shape of the credit growth distributions, I plot in Figure 7 the densities of credit growth at a 4-quarter horizon, by mapping the predictions at each estimated quantile as before. I perform this for two profitability scenarios by splitting the sample using the median ROE. First, I compute baseline cases by predicting for average values of all variables in each sample and setting MPI equal to zero. Then, I compute the new densities by mapping the predictions after assuming tightening MaPP (i.e., MPI=1) in both samples. It is observed that the effects of MaPP are mainly manifested in shaping the tails of the distributions, particularly under a low profitability environment, where, as identified above, MaPP is more effective. In Panel A, it can be seen how easing MaPP in a low profitability scenario reduces the downside risk of credit growth. It also increases the right skewness, although this would not be the main target of MaPP

Table 3. Estimated QR coefficients for the interaction term between MaPP and bank profitability at different horizons.

	τ = 0.10				τ = 0.50				τ = 0.90			
	h=4	**h=8**	**h=12**	**h=16**	**h=4**	**h=8**	**h=12**	**h=16**	**h=4**	**h=8**	**h=12**	**h=16**
MPI_{it}	-0.743***	-0.511**	-0.386	-0.302	-0.767***	-0.900***	-0.873***	-0.496*	-2.176***	-1.782***	-1.761***	-0.508**
$MPI_{it}Prof_{it}$	0.051***	0.054***	0.047*	0.033*	0.026**	0.019**	0.030**	0.016*	0.119***	0.088***	0.081***	0.033*
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2	0.70	0.67	0.66	0.62	0.63	0.62	0.62	0.59	0.68	0.72	0.70	0.65

Note: The table shows the estimated coefficients of the MPI and its interaction term with ROE, of independent QR for credit growth at 4 different horizons (i.e., 4, 8, 12 and 16 quarters ahead) and 3 different quantiles (i.e., the 10th, 50th and 90th percentiles). ***, ** and * represent significance at the 99%, 95% and 90% confidence level, respectively.

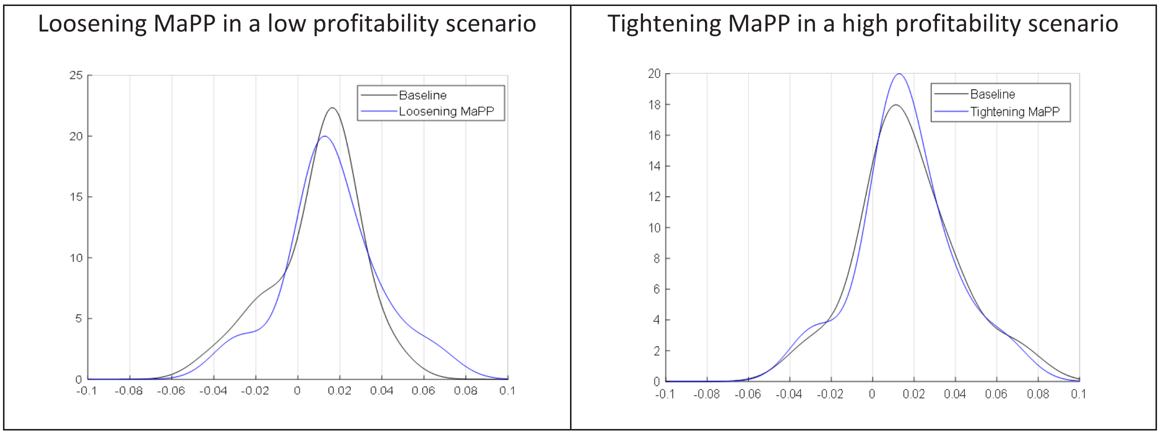
Figure 6. Response of the tails (10th and 90th percentiles) and the median (50th percentile) of the credit growth distribution to MaPP shocks in low and high profitability scenarios.



Note: The lines represent the sum of the estimated coefficients for the MPI and the interaction term between MPI and Profitability evaluated at the 10th (blue line) and the 90th (red line) percentiles of the historical value of ROE in the sample, which corresponds with values of 0 pp and 15 pp, respectively. The estimated coefficients are obtained using QR on credit growth at the 10th, 50th and 90th percentiles from 1 to 16 quarters ahead. Hollow circles represent coefficients that are not statistically significant at a 90% of confidence after using bootstrapped standard errors with 500 replications. The horizontal lines signal the value 0. The vertical axes represent the marginal effect in pp.

when it is eased. However, this reflects that a MaPP shock with the opposite sign (i.e., tightening) has a relevant impact on the right tail under low profitability environments. This contrasts with the negligible impact of tightening MaPP in a high profitability scenario, as shown in Panel B. These results reveal that bank profitability is an important factor that affects the effectiveness of MaPP, particularly when taming the buildup of cyclical risk.

Figure 7. Conditional credit growth distributions 4 quarters after a negative or positive MaPP shock in low or high profitability scenarios.



Note: The figures present the estimated credit growth distributions at 4-quarter horizons constructed by mapping the fitted values of the quantile functions obtained with the model in Equation (9) into a probability density function, using the kernel-based method in Appendix D. The black densities represent average values in periods of profitability below (Panel A) or above (Panel B) median values of the historical values of ROE in the sample. The blue densities represent the credit growth distributions after a negative (Panel A) or positive (Panel B) change in 1 unit in the MPI in each scenario.

4.3. Monetary policy and its interaction with MaPP

A question that has gained importance in the recent period of rapidly rising interest rates is how MaPP interacts with monetary policy. As identified above, monetary policy tightening has negative effects on credit growth, which is also an effect of MaPP. In this sense, depending on their orientation, monetary policy and MaPP may have either substitutive or complementary effects that may affect the effectiveness of MaPP. As shown above, monetary policy mainly affects the location of the credit growth distribution, while MaPP significantly affects its shape by reducing the right-skewness. Recent literature has also identified relevant interactions between both types of policies (Carrillo et al., 2021; Kiley and Sim, 2017; Van der Ghote, 2021). To explicitly study this interplay, and since the policy rate level does not reflect the monetary policy stance or the use of unconventional monetary policy, I estimate a simple Taylor rule by regressing policy rates on inflation and GDP growth, and then create a dummy variable equal to 1 for positive residuals.[7] To account for unconventional monetary policy, I use the shadow rates for the Euro area and the UK computed as in Wu and Xia (2016) for the period 2009 – 2016, when these rates are distinct from the monetary policy rate. Then, I use this variable to define MoP_{it} instead of the interest rate level. Finally, I add an interaction term between this dummy and MPI.[8] The estimated specification is as follows:

$$\widehat{\boldsymbol{Q}}_{y_{i,t+h}|x_{it},\alpha_i}(\tau|\boldsymbol{X}_{it},\alpha_i) = \hat{\alpha}^h_{i\tau} + \widehat{\boldsymbol{\delta}}^h_\tau \boldsymbol{X}_{it} + \hat{\beta}^h_{1\tau} y_{it} + \hat{\beta}^h_{2\tau} MPI_{it} + \hat{\beta}^h_{3\tau} MPI_{it} MoP_{it}; \\ \tau = 10,50,90; h = 1,\dots,16 \qquad (10)$$

In Table 4, I show the estimated coefficients for MPI and its interaction with monetary policy stance at the same quantiles and horizons presented earlier. In this case, the $\hat{\beta}^h_{2\tau}$ coefficient represents the impact of MaPP shocks on the credit growth distribution under an accommodative monetary policy stance, while the sum of the coefficients $\hat{\beta}^h_{2\tau} + \hat{\beta}^h_{3\tau}$ represents its impact under a restrictive monetary policy stance. It is observed that the coefficient of MPI is negative across quantiles and horizons, although its magnitude is less heterogeneous across quantiles and less significant at longer horizons. This indicates that the impact of positive MaPP shocks under accommodative monetary policy is less targeted on tail risk and less persistent over time.

Table 4. Estimated QR coefficients for MaPP and its interaction with monetary policy at different quantiles and horizons.

	τ = 0.10				*τ = 0.50*				*τ = 0.90*			
	h=4	**h=8**	**h=12**	**h=16**	**h=4**	**h=8**	**h=12**	**h=16**	**h=4**	**h=8**	**h=12**	**h=16**
MPI_{it}	*-0.501****	*-0.245*	*-0.357*	*-0.407*	*-0.402**	*-0.391***	*-0.397***	*-0.189*	*-0.382***	*-0.460****	*-0.226*	*-0.295*
$MPI_{it}MoP_{it}$	*0.368***	*0.017*	*-0.012*	*0.314**	*-0.296***	*-0.182***	*-0.325***	*0.081*	*-0.369***	*-0.401****	*-0.415***	*-0.262***
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2	0.72	0.64	0.62	0.60	0.69	0.66	0.64	0.60	0.72	0.74	0.70	0.66

Note: The table shows the estimated coefficients of the MPI and its interaction term with the restrictive monetary policy stance dummy, of independent QR for credit growth at 4 different horizons (i.e., 4, 8, 12 and 16 quarters ahead) and 3 different quantiles (i.e., the 5th, 50th and 95th percentiles). ***, ** and * represent significance at the 99%, 95% and 90% confidence level, respectively.

Regarding the interaction term, results are heterogeneous. It is negative and significant in the median and right tail, while it is generally positive in the left tail. This indicates that the heterogeneity of MaPP on the quantiles of the credit growth distribution is mainly evident under a restrictive monetary policy stance. In particular, the highly negative sign of the interaction at high quantiles implies that the large negative impact of positive MaPP shocks on the right tail of

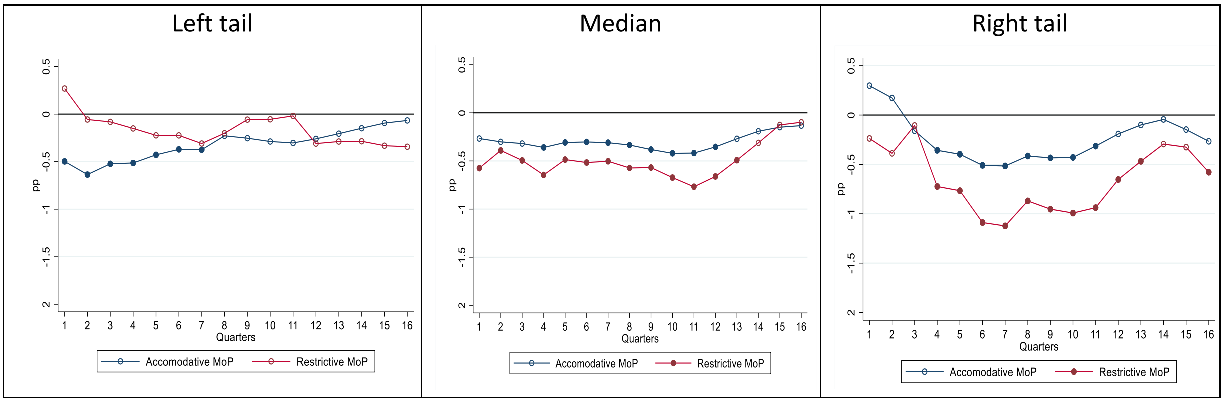
[7] For the Euro area, I estimate a panel regression with common coefficients (Maddaloni and Peydró, 2013).

[8] In Section 5.4, I conduct a robustness exercise by using directly monetary policy shocks as previously identified in the literature.

the credit growth distribution identified above is mainly observed when monetary policy is restrictive. This suggests that monetary policy complements MaPP by fostering its effectiveness in reducing the upside risk of credit growth when they are both restrictive. Conversely, the positive and significant sign of the interaction term on the left tail 4-quarters ahead implies that easing MaPP (i.e. a negative shock on MPI) is less effective when monetary policy is restrictive. Nonetheless, the significant negative coefficient of MPI in the left tail at the short-term horizon indicates that easing MaPP improves the downside risk of credit growth under accommodative monetary policy, which would reinforce the complementarity between both policies when they point in the same direction.

These effects can be more clearly observed in Figure 8, where I show the responses of credit growth in the three different quantiles to positive MaPP shocks over time under both monetary policy regimes. The complementarity between monetary and macroprudential policy is mainly evident in the right tail and at mid-term horizons. These results imply that a restrictive monetary policy environment improves the effectiveness of MaPP in reducing the upside risk of credit growth and that these enhanced effects are quite persistent. Median credit growth is also more affected when both policies signal a tight stance, though to a lower extent. On the left tail, this complementarity is mainly evident during the first quarters and, as explained above, indicates that an accommodative monetary policy environment helps MaPP be more effective in reducing the risk of large credit contractions.

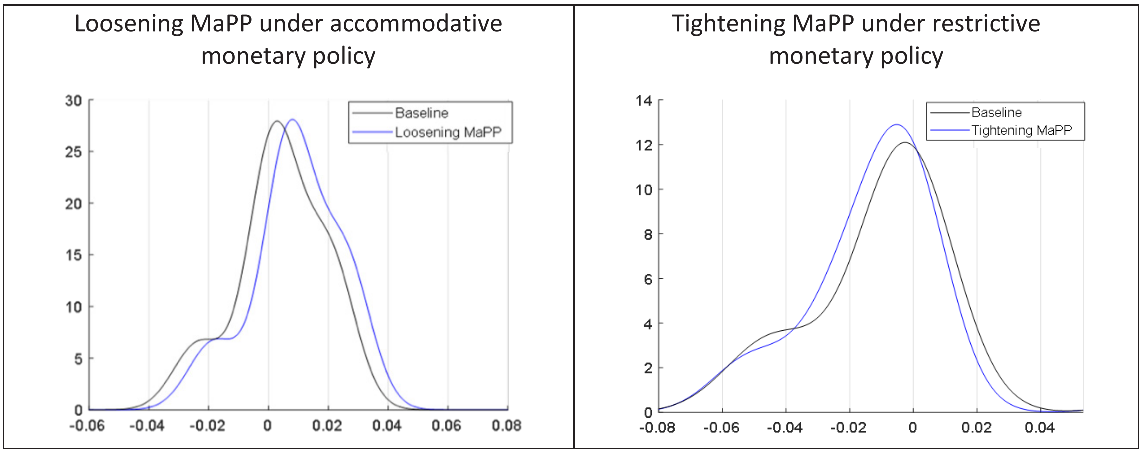
Figure 8. Response of the tails (10^{th} and 90^{th} percentiles) and the median (50^{th} percentile) of the credit growth distribution to MaPP shocks in accommodative or restrictive monetary policy scenarios.



Note: The lines represent the estimated coefficients for the MPI (blue line) and the sum of this coefficient with that of the interaction between MPI and the dummy representing a restrictive monetary policy stance (red line), obtained using QR on credit growth at the 10^{th}, 50^{th} and 90^{th} percentiles from 1 to 16 quarters ahead. Hollow circles represent coefficients that are not statistically significant at a 90% of confidence after using bootstrapped standard errors with 500 replications. The horizontal lines signal the value 0.

To illustrate the effects of both policies under different monetary policy environments, in Figure 9, I map the quantile estimates into density functions computed as detailed in Appendix D. For this purpose, I split observations depending on the monetary policy regime (i.e., accommodative or restrictive) as identified above. The estimated densities show, on the one hand, that loosening MaPP under accommodative monetary policy has mainly a shifting effect on the distribution to the right, improving credit growth homogeneously across quantiles. On the other hand, tightening MaPP under a restrictive monetary policy environment affects the shape of the distribution, mainly by reducing its right skewness. These results confirm that the effects of monetary policy are quite homogeneous across quantiles. This finding is consistent with previous studies assessing the impact of monetary policy on the GDP growth distribution. In this regard, Brandao-Marqués et al. (2020) find that monetary policy has limited benefits in leaning against the wind. In contrast, MaPP has strong differential effects across quantiles. In general, tightening MaPP in expansions reduces the right tail of the distributions while maintaining the left tail unaltered, thereby reducing the right skewness. The opposite is observed when loosening MaPP in crises. In this case, there is an important improvement in the downside risk of credit growth, but no relevant changes in the right tail, thereby reducing the left skewness. Overall, monetary policy acts countercyclically with no distinctions across quantiles of the distributions, while MaPP seems to be a more targeted tool, acting mainly on the tails of the distributions, which represent risk.

Figure 9. Conditional credit growth distributions 4 quarters after a negative or positive MaPP shock under accommodative or restrictive monetary policy scenarios.



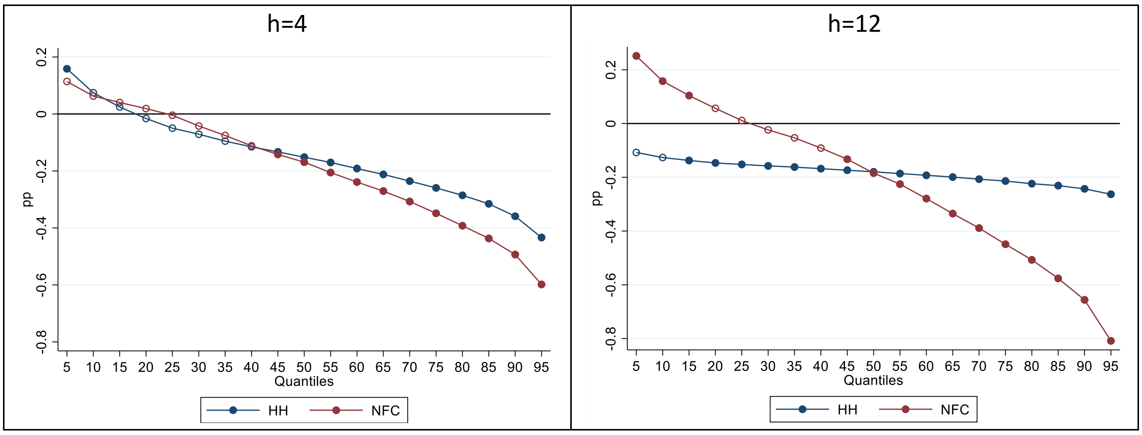
Note: The figures present the estimated credit growth distributions at 4-quarter horizons constructed by mapping the fitted values of the quantile model in Equation (10) into a probability density function using the kernel-based method in Appendix D. The black densities represent average values under an accommodative (Panel A) or restrictive (Panel B) monetary policy environment. The blue densities represent the credit growth distributions after a negative (Panel A) or positive (Panel B) change in 1 unit in the MPI in each scenario.

4.4. Disentangling the impact by sectors: HH and NFC credit

A relevant aspect when assessing the effects of MaPP on credit is to distinguish by type of borrower. Certainly, the credit dynamics for HH and NFC can differ in terms of speed, magnitude, and correlation with systemic events, making these sectors react differently to MaPP actions. Previous conditional mean studies have found heterogeneity when distinguishing by credit to HH and NFC (Cerutti et al., 2017; Akinci and Olmstead-Rumsey, 2018; Alam et al., 2024). Therefore, I estimate the baseline specification in Equation (4) for HH and NFC credit separately.

In Figure 10, I present the quantile estimates of the MPI coefficients for each sector at 4- and 12-quarter horizons. Results confirm the heterogeneous impact of MaPP across quantiles identified above for total credit, and the significantly large negative impact on the right tail. However, although at a short-term horizon there are not many relevant differences in these effects by sectors, at a mid-term horizon the situation changes. In the case of HH credit, the impact of MaPP continues to be negative and significant, but it becomes very homogeneous across quantiles as a result of the moderation of the impact on the right tail and a deterioration of the downside risk of credit growth. In contrast, the impact of MaPP on the NFC credit growth distribution is highly persistent across quantiles and this sector becomes the main driver of the negative impact on total credit at mid-term horizons.

Figure 10. Quantile estimates of MaPP at 4- and 12- quarter horizons by sectors (HH and NFC credit growth).

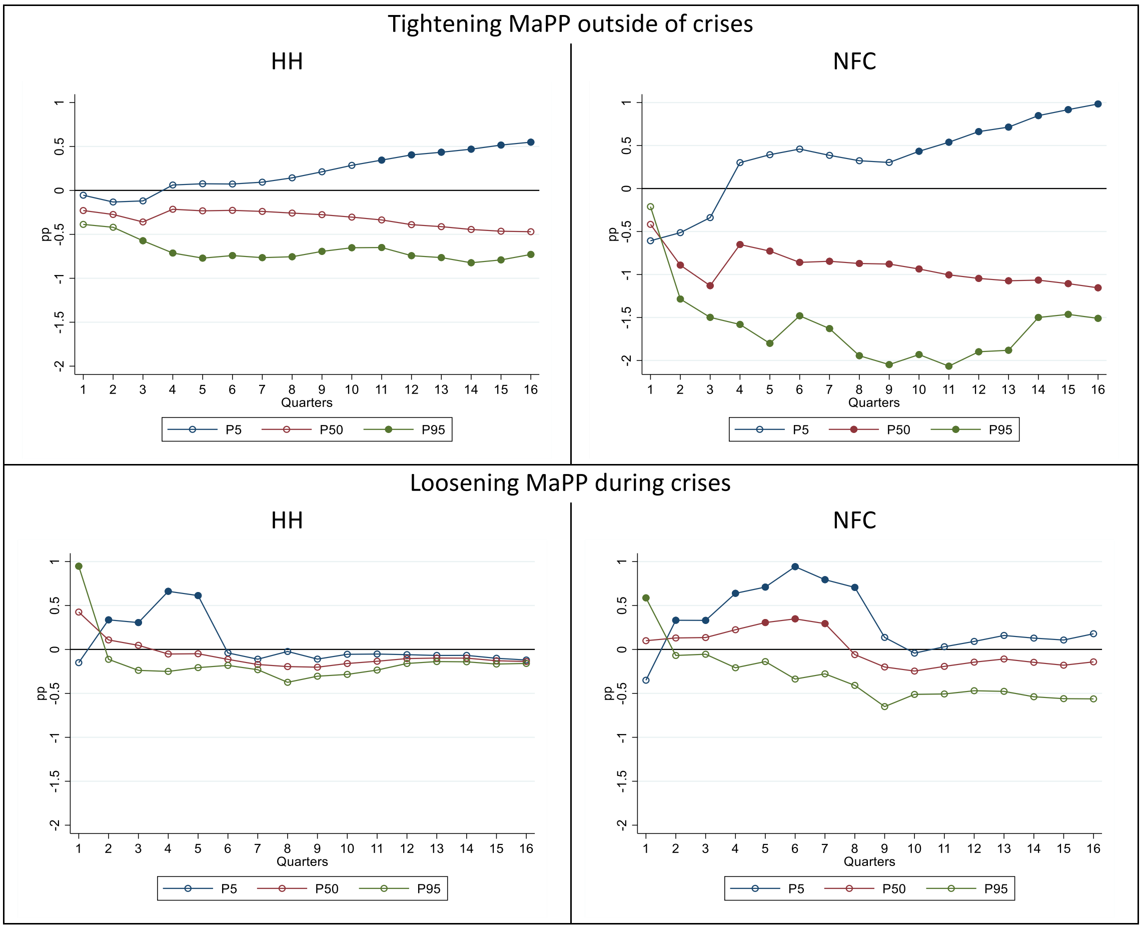


Note: Points represent the estimated coefficients for the MPI at the corresponding quantile (x-axes) and horizon (4 quarters ahead in the left panel, and 12 quarters ahead in the right panel), obtained using QR on credit growth for HH (blue line) and for NFC (red line). Hollow circles represent coefficients that are not statistically significant at a 90% of confidence after using bootstrapped standard errors with 500 replications. The blue and red lines joint the estimated quantile coefficients for HH and NFC credit growth, respectively. The vertical axes represent the marginal effect in pp. The horizontal continuous grey line signals the value 0.

These differences in the term structure of the effect of MaPP between sectors can be better identified through the local projections of the impact on the tails and median of the credit growth distributions by sector. Moreover, since it is very likely that the differences identified earlier in the effects of MaPP policies over the cycle are also observed when disentangling by type of credit, I replicate the estimation of the specification in Equation (8) by sector. In Figure 11, I show the results of the responses of HH and NFC credit growth to tightening MaPP during expansionary phases of the cycle and to loosening MaPP during financial crises over a 16-quarter period. Results confirm the higher persistence of the effects of MaPP on the distribution of NFC credit growth compared to that of HH credit growth, especially regarding the negative effect on the right tail when MaPP is tightened. This effect is also up to twice as large for NFC credit, suggesting that tightening MaPP is mainly effective in reducing excessive credit growth in the NFC sector. It is also observed that in the mid-term, tightening MaPP has significant effects on reducing the downside risk of credit growth. This would be a benefit derived from the reduction of the vulnerabilities associated with excessive credit in the previous periods. This is observed in both sectors, but again the positive effects are more evident and persistent for NFC credit than for HH credit. In the opposite situation, when MaPP is loosened during crises, the benefits are mainly observed in an improvement of credit-at-risk, which would be the desirable effect from a countercyclical point of view. This confirms previous results suggesting that loosening MaPP during systemic events reduces the probability of severe credit contractions, and that these benefits are rapidly observed. The positive impact on credit-at-risk is also more persistent and larger for NFC credit.

The type of instruments implemented could be behind these differences. Certainly, BBM, which usually target HH credit, are measures found to be less effective when they are relaxed than when they are tightened (Poghosyan, 2019; Galán, 2024). In contract, capital measures, which may affect NFC credit more importantly through risk weights, have been identified to have relevant benefits when they are eased (Bedayo and Galán, 2024; Couaillier et al., 2024). Therefore, in the next section, I study the specific effects of BBM and capital measures by segments of credit.

Figure 11. Response of the tails (10th and 90th percentiles) and the median (50th percentile) of the credit growth distribution to MaPP shocks during and outside of crises by sector (HH and NFC).



Note: The lines represent the estimated coefficients for the MPI depending on its direction and phase of the financial cycle, obtained using QR on credit growth by sector at the 10th (blue line), 50th (red line) and 90th (green line) percentiles from 1 to 16 quarters ahead. Hollow circles represent coefficients that are not statistically significant at a 90% of confidence after using bootstrapped standard errors with 500 replications. The horizontal lines signal the value 0. The vertical axes represent the marginal effect in pp.

4.4.1. Capital- and borrower-based measures.

The differences in the type of MaPP instruments used in different phases of the cycle and the sector targeted might explain the response of the credit growth distribution. Certainly, Galán (2024) identified that there are important differences in the timing and effectiveness between BBM and capital measures when assessing their impact on growth-at-risk. Therefore, in this section, I extend the specification in Equation (8) to the specific analysis of capital and BBM through the cycle by splitting the MPI into two indexes based on these categories of instruments: *MPIcap*, which encompasses capital requirements, capital buffers, and risk-weight measures, and *MPIbbm*, which includes limits on LTV, LTI, LSTI, DTI, and DSTI ratios, loan maturity, and amortization rules. These indexes are constructed following the same formula in Equation (6) by aggregating the corresponding categories and applying the IPW method in the same manner. Both indexes are interacted with the financial crises dummy variables to account for the effects of the cycle. The regressions are estimated for the entire credit growth horizon from 1 to 16 quarters ahead. The estimated specification is as follows:

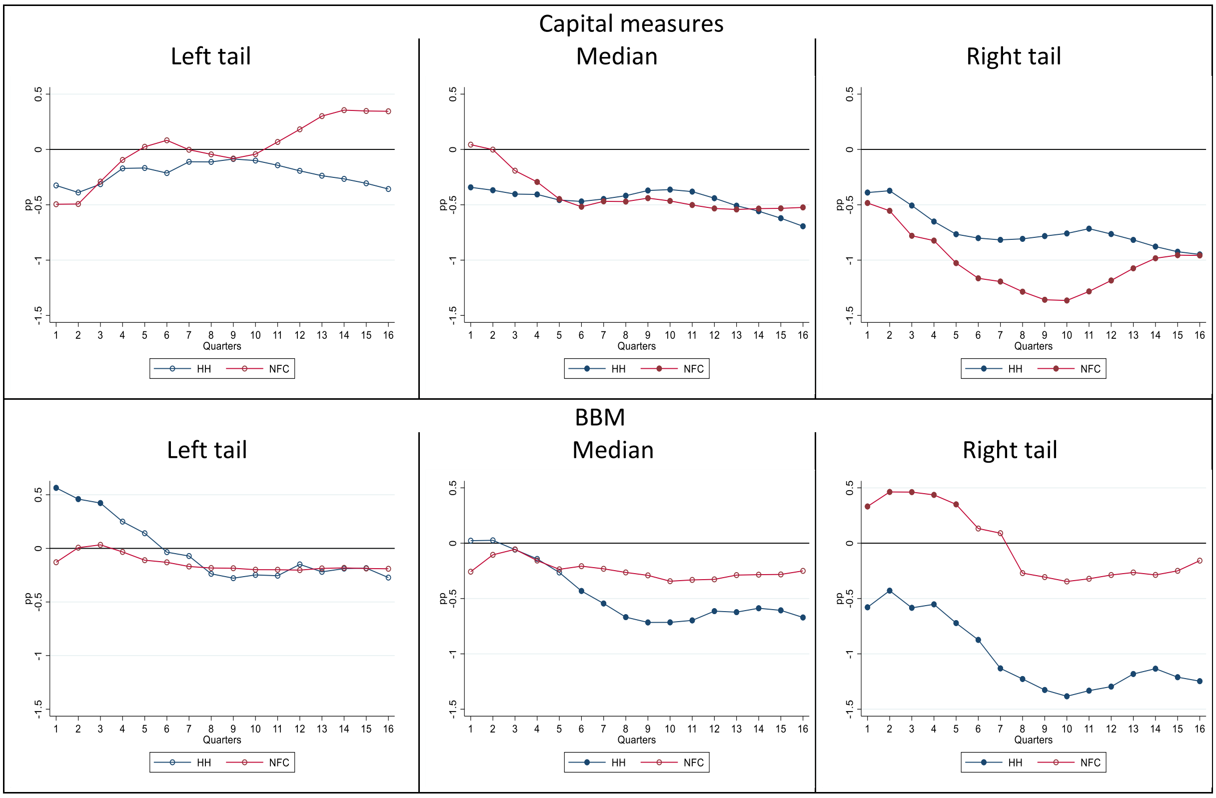
$$\widehat{\boldsymbol{Q}}_{y_{i,t+h}|x_{it},\alpha_i}(\tau|\boldsymbol{X}_{it},\alpha_i) = \hat{\alpha}_{i\tau}^h + \widehat{\boldsymbol{\delta}}_{\tau}^h \boldsymbol{X}_{it} + \hat{\beta}_{1\tau}^h y_{it} + \hat{\beta}_{2\tau}^h MPIcap_{it} + \hat{\beta}_{3\tau}^h MPIbbm_{it} + \hat{\beta}_{4\tau}^h Crisis_{it}$$

$$+\hat{\beta}_{5\tau}^h MPIcap_{it} Crisis_{it} + \hat{\beta}_{6\tau}^h MPIbbm_{it} Crisis_{it};\ \tau = 10{,}50{,}90;\ h = 1, \dots, 16 \quad (11)$$

In Figure 12, I show the response of credit growth by sector at the quantiles of interest to positive shocks in both types of measures during non-crisis periods. The results confirm the heterogeneity of the impact of these measures across quantiles and sectors. The most relevant differences are observed in the tails. Tightening capital measures has a particularly large negative impact on reducing the upside risk of credit growth in both sectors, though for NFC credit it can represent up to twice the impact on HH credit in the mid-term. In contrast, the impact of BBM in the right tail is only negative and significant for HH credit and can double the impact of capital tools on this sector in the mid-term. These findings are consistent with how these different tools affect each sector. While BBM are almost exclusively aimed at limiting HH credit, capital measures may have a larger impact on NFC credit through risk weights, which are typically higher for this type of credit. Interestingly, for BBM, the impact on the right tail of the NFC credit growth distribution is not only non-significant in the mid-term but also positive in the short run. This may indicate a credit substitution effect between these two sectors, suggesting that by limiting HH credit growth, BBM could induce banks to reallocate credit towards the NFC sector, albeit only in terms of upside risk. In the left tail, it is also interesting that, although the impact is generally non-significant, for HH credit it has a positive effect in the first quarters. This suggests that by tightening BBM the probability of observing low HH credit growth rates decreases, possibly due to an improvement in lending below BBM limits. At the median, the negative impact of capital measures is significant and very similar across sectors; however, for BBM, it is only significant for HH credit.

Regarding the impact of loosening these measures during crisis periods, relevant differences are observed between both types of measures across sectors (Figure 13). Easing capital measures has important benefits in improving the downside risk of credit growth in the short

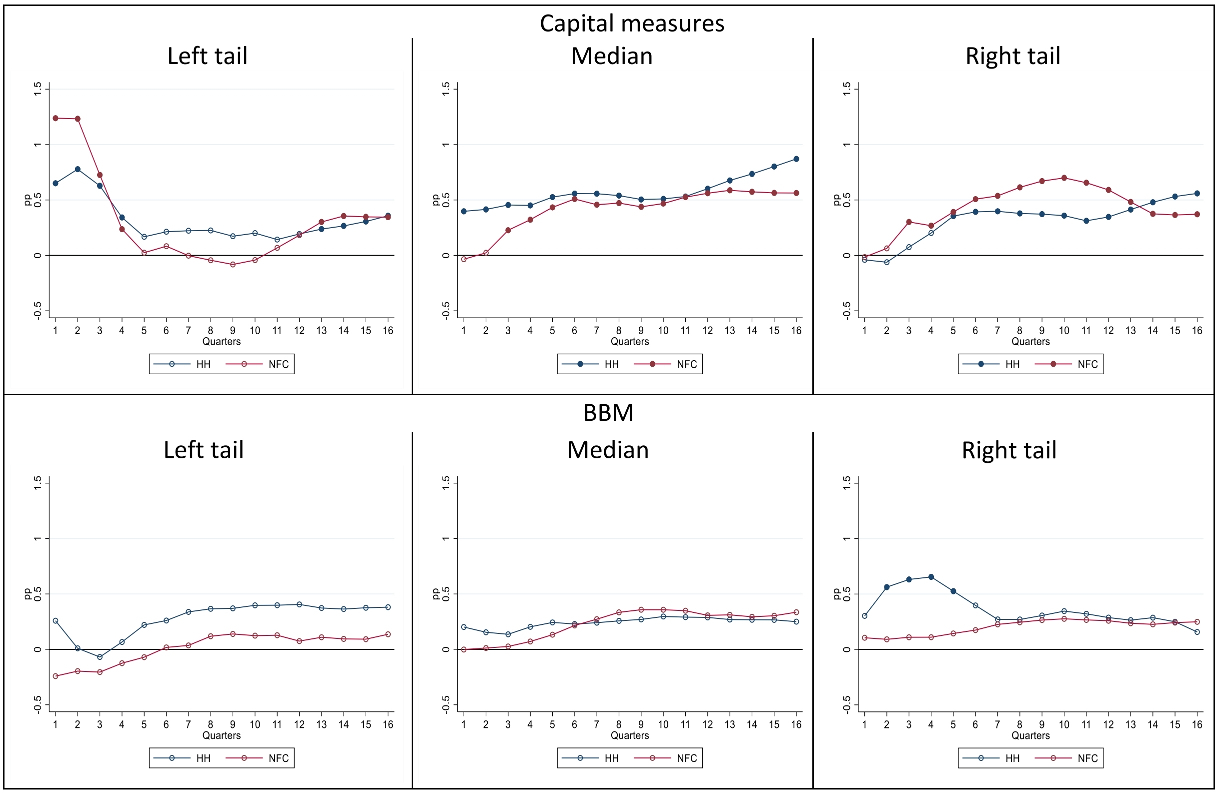
Figure 12. Response of the tails (10th and 90th percentiles) and the median (50th percentile) of HH and NFC credit growth distributions to tightening capital measures and BBM outside of crises.



Note: The lines represent the estimated coefficients for the MPI of capital-based measures (top figures) and for the MPI of BBM (bottom figures), obtained using QR on credit growth for HH (blue line) and for NFC (red line) at the 10th, 50th and 90th percentiles from 1 to 16 quarters ahead. Hollow circles represent coefficients that are not statistically significant at a 90% of confidence after using bootstrapped standard errors with 500 replications. The horizontal lines signal the value 0. The vertical axes represent the marginal effect in pp.

term in both sectors, although the benefits are higher for NFC credit. These measures also have significant benefits in improving the median and the right tail of credit growth distributions at longer horizons for both HH and NFC credit. Regarding BBM, the impact of easing these measures during crises is very limited and even non-significant for NFC credit. As discussed above, this is reasonable since these measures usually target HH credit. Moreover, BBM are not only used in a less countercyclical way, but there is also evidence of their low effectiveness in contractionary phases of the cycle. This is because lending standards are usually tightened by banks during downturns. Thus, a relaxation of these conditions by the regulator is not binding and would not have any real effect. This finding is in line with previous studies assessing the impact of BBM on mean credit growth during busts (Claessens et al., 2013; Cerutti et al., 2017), and on growth-at-risk (Galán, 2024).

Figure 13. Response of the tails (10th and 90th percentiles) and the median (50th percentile) of HH and NFC credit growth distributions to loosening capital measures and BBM during crises.



Note: The lines represent the negative of the sum of the estimated coefficients for the MPI and its interaction with financial crises (MPI for capital-based measures in top figures and MPI for BBM in bottom figures), obtained from QR on credit growth for HH (blue line) and for NFC (red line) at the 10th, 50th and 90th percentiles from 1 to 16 quarters ahead. Hollow circles represent coefficients that are not statistically significant at a 90% of confidence after using bootstrapped standard errors with 500 replications. The horizontal lines signal the value 0. The vertical axes represent the marginal effect in pp.

5. Robustness

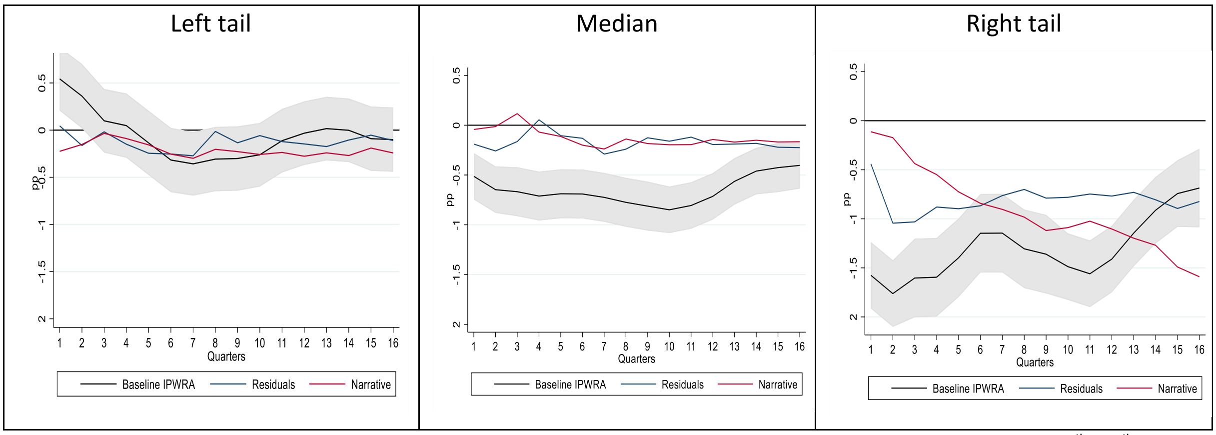
5.1. Alternative endogeneity treatment of MaPP shocks

As described in Section 3.4, I follow an IPW method to account for endogeneity issues between credit growth and MaPP, which could raise concerns about the causality of the identified effects. This method has been found to be very useful in the context of local projection models with policy shocks (Jordà and Taylor, 2016) and in assessing the impact of MaPP on credit growth

(Richter et al., 2019; Alam et al., 2024). However, other methods have been proposed for identifying the causal effects of MaPP on real and financial variables, such as using residuals from two-step regressions (Boar et al., 2017; Brandao-Marques et al., 2020) or following a narrative approach (Richter et al., 2019; Fernández-Gallardo et al., 2023).[9] Although both procedures have limitations, which is why I choose the IPW as the main procedure, I check the robustness of previous results using these alternative approaches to address endogeneity concerns.[10] Thus, I estimate the baseline model in Equation (6) using the two alternative approaches. For the residuals approach, I obtain them from an ordered-probit regression where the probability of the MPI being equal to -2, -1, 0, 1, and 2 is estimated based on the same specification as in Equation (7). For the narrative approach, I follow the classification in MaPPED to filter out measures classified as having countercyclical objectives.

In Figure 14, I show the responses of the tails and the median of credit growth to MaPP shocks over time using the three approaches. Interestingly, all methods provide similar results for the responses of credit growth at the left tail, but some differences arise in the median and the right tail. Although the overall conclusions wouldn't change in terms of the sign of the identified impacts and the large negative effect of positive MaPP shocks on the upper quantile, the results with the alternative approaches are statistically different from those obtained with the IPW method in the median and the right tail. In the median, the impact is negligible under the two alternative methods. For the effects on the right tail, the residuals method produces results of lower magnitude but with a similar term structure, while the narrative approach suggests that the negative impact increases over time, showing a negative trend during the 16-quarter horizon. These results are in line with those identified by Fernández-Gallardo et al. (2023) using a similar specification.

Figure 14. Response of the tails (10th and 90th percentiles) and the median (50th percentile) of the credit growth distribution to MaPP shocks using alternative endogeneity treatment procedures.



Note: The lines represent the estimated coefficients for the MPI, obtained using QR on credit growth at the 10th, 50th and 90th percentiles from 1 to 16 quarters ahead, employing the IPW (black line), residuals (blue line) and narrative (red line) approach, respectively. The shaded areas represent the 90% confidence bands of the estimated coefficients of the IPW method computed using bootstrapped standard errors with 500 replications. The horizontal lines signal the value 0. The vertical axes represent the marginal effect in pp.

[9] The two-step procedures consist of obtaining the residuals of a first step estimation where MaPP indexes are regressed on cyclical economic and macrofinancial variables and include them as the MaPP measure in the main regression. In the narrative approach MaPP shocks are identified by filtering out measures with countercyclical objectives. This allows for keeping only those measures that were not taken due to credit developments, alleviating endogeneity concerns.

[10] Using residuals from a first-stage regression has been found to induce biases in the context of QR (see Lloyd and Manuel, 2024). The narrative approach strongly relies on the classification of the measures, which may be subject to omitted information. In this regard, Richter et al. (2019) highlight that policymakers may target real or financial objectives without stating them explicitly when implementing macroprudential actions. Moreover, eliminating countercyclical measures would not account for the impact of those measures that are precisely intended to affect credit growth.

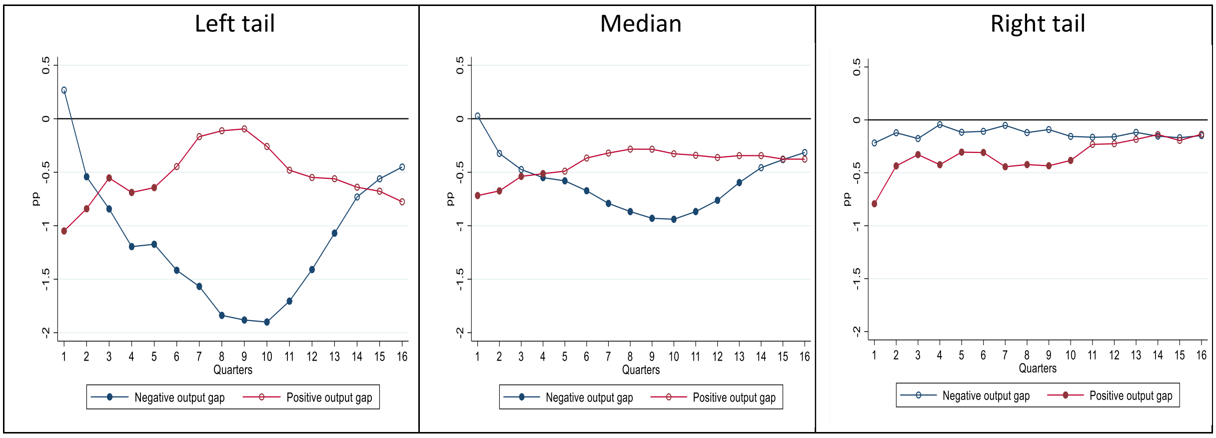
5.2. Differential effects over the business cycle

I identify the effects of MaPP as being dependent on the phase of the financial cycle. Nonetheless, it is likely that there are heterogeneous effects along the business cycle. Certainly, economic cycle indicators are a relevant part of the main indicators guiding the implementation of capital buffers in several jurisdictions.[11] To evaluate this, I estimate a state-dependent model where I distinguish between two states based on the sign of the output gap in each country each quarter. I prefer this approach instead of just adding an interaction of the MPI with GDP growth because, rather than the growth rate of the economy, the output gap is more directly connected to the position in the business cycle. For this purpose, I collected output gap data from the IMF. The well-balanced number of observations in each state allows me to perform this type of estimation.[12] In particular, I estimate the following model based on the specification in Equation (6):

$$\widehat{\boldsymbol{Q}}_{y_{i,t+h}|x_{it},\alpha_i}(\tau|\boldsymbol{X}_{it},\alpha_i) = I_{it}\left(\hat{\alpha}_{i\tau}^{h} + \hat{\beta}_{1\tau}^{h}y_{it} + \hat{\beta}_{2\tau}^{h}MPI_{it} + \widehat{\boldsymbol{\delta}}_{\tau}^{h}\boldsymbol{X}_{it}\right) + (1-I_{it})(\hat{\alpha}_{i\tau}^{h} + \hat{\beta}_{1\tau}^{h}y_{it} + \hat{\beta}_{2\tau}^{h}MPI_{it} + \widehat{\boldsymbol{\delta}}_{\tau}^{h}\boldsymbol{X}_{it}); \quad (12)$$

$$I_{it} = \begin{cases} 1\ if\ Output\,gap_{it-1} > 0 \\ 0\ if\ Output\,gap_{it-1} < 0 \end{cases}; \quad \tau = 10{,}50{,}90;\ h = 1,\ldots,16.$$

Figure 15. Response of the tails (10th and 90th percentiles) and the median (50th percentile) of the credit growth distribution to MaPP shocks in different states of the business cycle.



Note: The lines represent the estimated coefficients for the MPI under negative (blue line) and positive (red line) output gap states, obtained using QR on credit growth at the 10th, 50th and 90th percentiles from 1 to 16 quarters ahead. Hollow circles represent coefficients that are not statistically significant at a 90% of confidence after using bootstrapped standard errors with 500 replications. The horizontal lines signal the value 0. The vertical axes represent the marginal effect in pp.

In Figure 15, I plot the estimated responses of the tails and median of the credit growth distribution to positive MPI shocks over a 16-quarter horizon in both states. The heterogeneous impact of MaPP across quantiles is confirmed, but it is mainly evident under a negative output gap state. In particular, the sensitivity of the left tail is much higher than that obtained before with our baseline specification and when considering the position in the financial cycle. This suggests not only that the position in the business cycle is very relevant for MaPP decisions but also that it is key for their impact on the downside risk of credit growth, which contrasts with the main effects in the right tail obtained above when distinguishing by phases of the financial cycle. For policy purposes, these results indicate that easing MaPP when the output gap is negative

[11] See EU CCyB notifications to the ESRB (https://www.esrb.europa.eu/national_policy/ccb/html/index.en.html).

[12] 54% of observations in the sample presents a positive output gap and 46% a negative output gap.

has relevant benefits in reducing the risk of large credit contractions in the mid-term. When the output gap is positive, tightening MaPP has significant benefits in reducing the upside risk of credit growth, although it seems to have less heterogeneous effects across the distribution than those identified earlier in normal times or expansionary phases of the financial cycle.

5.3. A continuous measure of MaPP: The combined buffer requirement (CBR).

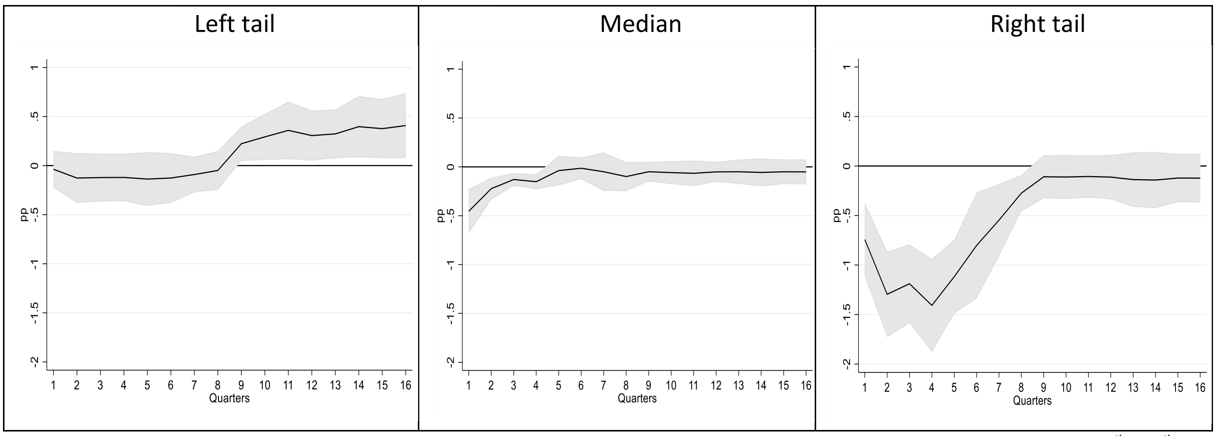
Although the use of indexes of MaPP actions allows for accounting for many different types of policies across countries over a long period, this type of measure does not consider differences in the scope or intensity of the measures taken. In general, it is very complex to create intensity measures for the different types of instruments in the sample. However, it is possible to focus on a set of MaPP tools that are easily represented in a continuous variable, namely capital buffer requirements. It is possible to compute information on the CBR, which is composed of the capital conservation buffer, buffers for domestic and global systemic institutions, systemic risk buffers, and the CCyB. Nonetheless, a limitation of this data is the short time series available, as these buffers derive from Basel III regulation, and the first decisions made in Europe regarding its components were taken at the end of 2013. Thus, to overcome this limitation, I rely on a recently developed QR approach that provides consistent and unbiased estimators in panel regressions with short time series. This is the method of moments introduced by Machado and Santos Silva (2019), which is based on location-scale models. Thus, I estimate the following specification:

$$\widehat{\boldsymbol{Q}}_{y_{i,t+h}|x_{it},\alpha_i}(\tau|\boldsymbol{X}_{it},\alpha_i) = \widehat{\alpha}_{i\tau} + \hat{\beta}_{1\tau}y_{it} + \hat{\beta}^h_{2\tau}CBR_{it} + \boldsymbol{\delta}^h_\tau\boldsymbol{X}_{it};\ \tau = 10{,}50{,}90;\ h = 1, \dots, 16; \quad (12)$$
$$\alpha^h_{i\tau} = \alpha^h_i + \theta^h_i Qu^h_\tau;\ \boldsymbol{\delta}^h_\tau = \boldsymbol{\delta}^h + \boldsymbol{\varphi}^h\, Qu^h_\tau;\ \beta^h_{k\tau} = \beta^h_k + \gamma^h_k Qu^h_\tau;\ k = 1 \dots J,$$

where CBR represents the combined buffer requirement as described above, and the variables in vector $\boldsymbol{X}$ are the same as those included before. Thus, I am interested in estimating the response of the tails and median of the credit growth distribution to changes in the CBR, represented by $\hat{\beta}^h_{2\tau}$.

In Figure 16, I present these results. In general, the results are very consistent with the previous findings, both in terms of signs and heterogeneity across quantiles. This implies that an increase in the CBR leads to a significant reduction in the risk of observing large credit growth rates and has a negative impact on the median, although of lower magnitude. In the left tail, the

Figure 16. Response of the tails (10th and 90th percentiles) and the median (50th percentile) of the credit growth distribution to changes in 1 pp of the CBR.



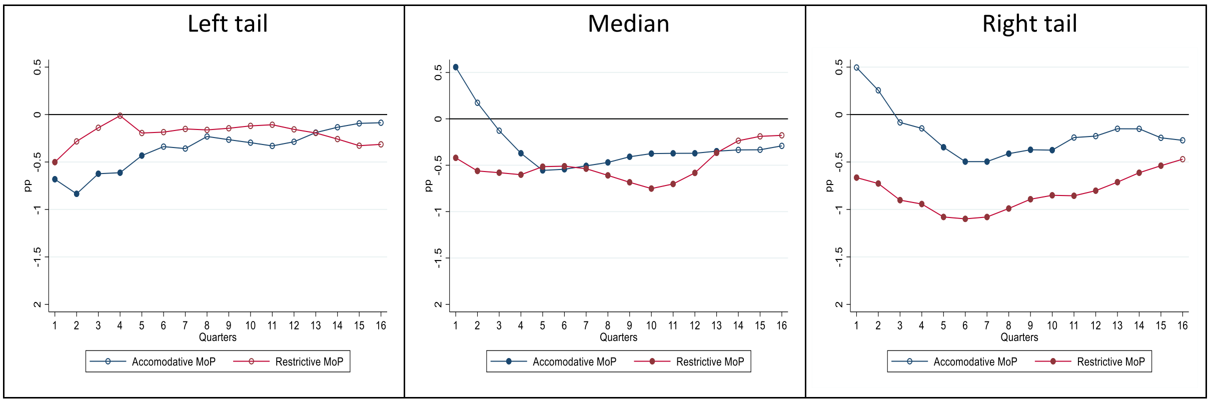
Note: The lines represent the estimated coefficients for the CBR, obtained using QR on credit growth at the 10th, 50th and 90th percentiles from 1 to 16 quarters ahead, respectively. The shaded areas represent the 90% confidence bands of the estimated coefficients computed using bootstrapped standard errors with 500 replications. The horizontal lines signal the value 0. The vertical axes represent the marginal effect in pp.

impact is also negative in the short run but positive in the mid-term, suggesting that the reduction of the upside risk of credit growth in the first quarters translates into an improvement of credit-at-risk at longer horizons. These results are in line with those obtained before using the index of capital measures but provide useful information on the elasticities to changes in the magnitudes of CBR. A 1 pp increase in buffer requirements leads to small reductions in median growth of less than 0.5 pp in the first quarters. However, the reduction in the credit growth rates observed in the 90th percentile of the distribution could reach up to 1.4 pp during the first 4 quarters. In contrast, 1 pp of additional CBR would improve the growth rates observed in the 10th percentile by around 0.4 pp between 9 and 16 quarters after the increase in buffer requirements.

5.4. Accounting for monetary policy shocks

Previously, I used the residuals from a Taylor rule to identify monetary policy stance regimes that allow for estimating the interaction between monetary policy and MaPP. However, an alternative approach is to directly identify negative and positive monetary policy shocks. To test how robust the previous results are to a more accurate identification of monetary policy stance, I use monetary policy shocks based on intra-day asset price movements, as identified in Jarocinski and Karadi (2020) for the Euro Area during the period 1999-2017. In this case, the number of observations decreases but still comprises more than two-thirds of the sample. Then, I create a dummy variable equal to 1 when a positive monetary policy shock is observed and replicate the estimations in Equation (10) by replacing the definition of MoP_{it} with this dummy variable.

Figure 17. Response of the tails (10th and 90th percentiles) and the median (50th percentile) of the credit growth distribution to MaPP shocks in accommodative and restrictive monetary policy scenarios. Alternative approach.



Note: The lines represent the estimated coefficients for the MPI (blue line) and for the sum of this coefficient with that of the interaction between MPI and MoP (red line), obtained using QR on credit growth at the 10th, 50th and 90th percentiles from 1 to 16 quarters ahead. Hollow circles represent coefficients that are not statistically significant at a 90% of confidence after using bootstrapped standard errors with 500 replications. The horizontal lines signal the value 0. The vertical axes represent the marginal effect in pp.

In Figure 17, I show the estimated coefficients for MPI and for the sum of that coefficient and its interaction with the restrictive monetary policy variable, using the two variables defined above. The results are consistent with those identified earlier. Specifically, MaPP is more effective at reducing large credit growth rates in the right tail when monetary policy is restrictive, confirming that both policies are complementary in this objective. In the median and the left tail, differences are less evident, but the implications are similar to those found above in Section 4.3. That is, tightening MaPP under an accommodative monetary policy stance induces a deterioration of the growth rates observed in the left tail. Conversely, this indicates that loosening MaPP in this scenario fosters its benefits in reducing the downside risk of credit growth. In general, the previous results hold when using these two more robust approaches for the monetary policy stance, although the magnitude of the estimated impact of MaPP is lower in the right tail (between 30% and 50%) and slightly higher in the median and the left tail.

5.5. Heterogeneous effects over the financial cycle. A state-dependent approach.

In Section 4.1, I showed that credit growth distributions react differently depending on the use of MaPP at different stages of the financial cycle. In particular, I distinguish between the impact during financial crises and outside these periods by interacting a dummy variable identifying crises with the MPI. However, an alternative is to identify periods of financial expansions and contractions with respect to long-term trends, which allows for a more symmetric sample in the two states and for applying a state-dependent approach, similar to that conducted in Section 5.2. A caution with this exercise is that defining states that are endogenous to the outcome variable has been found to induce biases in local projection regressions (Cloyne et al., 2023; Gonçalves et al., 2024). In this context, using predetermined states that do not account for future information of the outcome variable, such as those derived from a one-sided HP filter, can reduce these concerns (see Alloza et al., 2022). Nonetheless, it is worth noting that although this approach may not eliminate biases, the problem is reduced if the state is defined with a lag of at least the maximum horizon used in the analysis and if the ratio between the magnitude of the shock and its standard deviation is small (Gonçalves et al., 2022; 2024).[13]

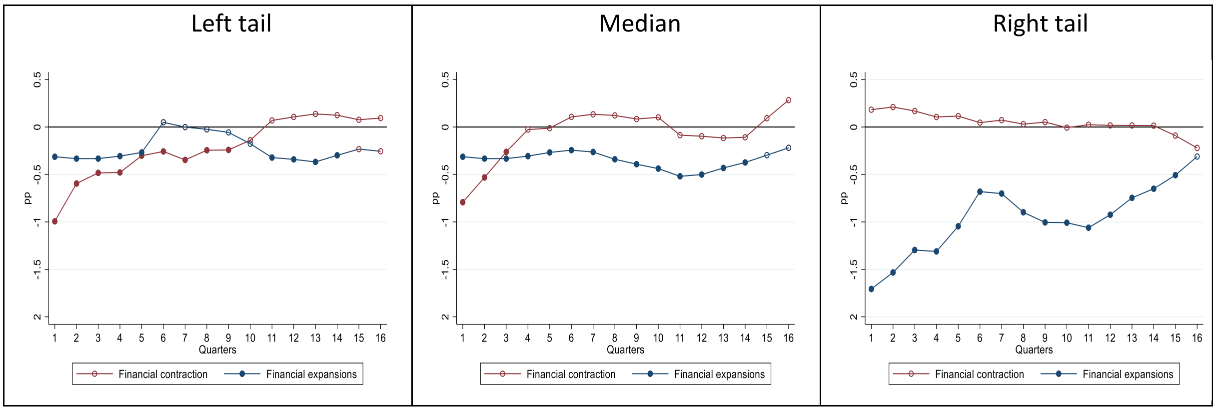
Thus, I define the financial expansion and contraction states based on either positive or negative gaps in credit growth with respect to its long-term trend, computed with a one-sided HP filter. Following Gonçalves et al. (2022), I use the state observed 16 quarters before *t* (given that the maximum assessed period in this study is 16 quarters). I also allow for 16-quarter window to initialise the filter, which reduces the sampling period to between 1998 and 2019. The estimated specification is as follows:

$$\begin{aligned} \widehat{\boldsymbol{Q}}_{y_{i,t+h}|x_{it},\alpha_i}(\tau|\boldsymbol{X}_{it},\alpha_i) = {} & I_{it}\left(\hat{\alpha}^h_{i\tau} + \hat{\beta}^h_{1\tau}y_{it} + \hat{\beta}^h_{2\tau}MPI_{it} + \widehat{\boldsymbol{\delta}}^h_{\tau}\boldsymbol{X}_{it}\right) + \\ & (1 - I_{it})(\hat{\alpha}^h_{i\tau} + \hat{\beta}^h_{1\tau}y_{it} + \hat{\beta}^h_{2\tau}MPI_{it} + \widehat{\boldsymbol{\delta}}^h_{\tau}\boldsymbol{X}_{it}); \\ & I_{it} = \begin{cases} 1 \; if \; credit\,gap_{it-16} \geq 0 \\ 0 \; if \; credit\,gap_{it-16} < 0 \end{cases}; \;\; \tau = 10{,}50{,}90; \; h = 1,\ldots,16. \end{aligned} \tag{13}$$

The estimated responses in Figure 18 show results that are very consistent with those obtained previously using the crisis dummy. In particular, a positive MaPP shock has very significant effects on the upper tail of the credit growth distribution during financial expansions but is not significant during contractions. Compared to the impact identified above outside of crises, the estimated magnitude in this case is noticeably larger (between 50% and 100% higher across horizons). This is expected since, in this exercise, a financial expansion only encompasses periods where credit is growing above long-term trends, and not all periods not classified as crises, which may include recovery periods. This result also suggests that MaPP is especially useful for containing the upside risk of credit growth during these periods. In the median and left tail, the identified responses are quite similar to those found with the crisis dummy, which also makes sense given that MaPP is usually eased when a crisis materialises, and accounting for a broader definition of financial contraction makes little difference.

[13] In this case, the shock is equal to 1 and the standard deviation of the MPI is 0.74 resulting in a ratio equal to 1.36, which is small to produce relevant biases. Gonçalves et al., (2024) identify that ratios above 5 can induce significant biases.

Figure 18. Response of the tails (10th and 90th percentiles) and the median (50th percentile) of the credit growth distribution to MaPP shocks during financial expansions and contractions.



Note: The lines represent the estimated coefficients for the MPI in the financial contraction (red line) and expansion (blue line) states, obtained using QR on credit growth at the 10th, 50th and 90th percentiles from 1 to 16 quarters ahead. Hollow circles represent coefficients that are not statistically significant at a 90% of confidence after using bootstrapped standard errors with 500 replications. The horizontal lines signal the value 0. The vertical axes represent the marginal effect in pp.

6. Conclusions and policy implications

Most empirical literature studying the effects of MaPP on credit growth has focused on the conditional mean, where findings remain inconclusive (see Araujo et al., 2020; Malovaná et al., 2024a; 2024b, for meta-analyses of many of these studies). However, the goal of MaPP in taming the financial cycle is more related to reducing excessive credit growth during expansionary stages (i.e., the part of credit growth associated with increased financial risk) and supporting the provision of credit to the economy during crises (i.e., reducing the magnitude of credit contractions). In this context, MaPP aims to tackle extreme realisations of credit growth rather than the mean outcome. Against this background, I employ QR to estimate the impact of MaPP on the conditional credit growth distribution. This method has proven to be very useful for identifying the heterogeneous effects of macrofinancial variables on the GDP growth distribution (Adrian et al., 2019) and the benefits of MaPP on growth-at-risk (Franta and Gambacorta, 2020; Galán, 2024). Given the concern of endogeneity between MaPP and credit growth, I leverage the IPW approach, previously proposed to identify policy shocks in the context of local projections (Jordà and Taylor, 2016) and to assess MaPP shocks on credit growth (Richter et al., 2019; Alam et al., 2024).

I uncover significant effects of MaPP on the tails of the credit growth distribution, which contrast with the relatively small effects on the median. However, I find that these effects are highly dependent on the position in the financial cycle. Tightening MaPP during expansions has negative effects on the right tail of both types of credit, while easing MaPP during financial crises has small but positive effects on the left tail. These results confirm the countercyclical properties of MaPP and provide evidence of its relevance, particularly for taming the cycle and reducing excessive credit growth. These findings are consistent with previous literature identifying the benefits of MaPP in improving GDP-at-risk in the mid-term (Franta and Gambacorta, 2020; Galán, 2024), as these effects reflect the more direct impact of MaPP on reducing the tail risk of credit growth.

I also find that bank profitability is a key factor interacting with the impact of MaPP on the credit growth distribution. On one hand, bank profitability has large positive effects on the right tail but small effects on the left tail and median. Like MaPP, bank profitability mainly affects the right skewness of the credit growth distribution, but in the opposite direction. These results uncover effects of profitability on credit growth that remain unclear with conditional mean models (Nier and Zicchino, 2008) and explain why profitability has been found to be an early indicator of credit imbalances (Richter and Zimmermann, 2020). On the other hand, profitability negatively affects the effectiveness of MaPP in reducing the right skewness of the credit growth distribution. Specifically, the impact of tightening MaPP on the right tail could be up to four times lower in a high bank profitability scenario compared to a low profitability environment. Similarly, loosening MaPP is more effective in improving the downside risk of credit growth when profitability is low. From a policy perspective, these results suggest that MaPP must be used more intensively to achieve the same outcomes when bank profitability is high. However, the negative impact on median credit growth is smaller under high profitability, indicating that the costs of implementing MaPP are also lower in this scenario. This suggests that implementing structural tools or others with no clear countercyclical objectives could be less costly when bank profitability is high. This finding supports the recent implementation of positive neutral CCyB rates in most European jurisdictions, where the high bank profitability environment has been a relevant factor in favour of these decisions (Herrera-Bravo et al., 2024).

Regarding monetary policy, I find that it complements MaPP in acting countercyclically. Tighter monetary policy enhances the benefits of implementing MaPP in reducing excessive credit growth. Conversely, a more accommodative monetary policy reinforces the benefits of easing MaPP on credit-at-risk, primarily by extending its benefits over time. The complementary nature of these two policies is evident through their effects on the credit growth distribution. On the one hand, monetary policy has a relatively homogeneous effect across the distribution, causing a shifting effect but being less effective in reducing risk at the tails. On the other hand, MaPP appears to be a more targeted tool, acting mainly on the tails of the distribution. Specifically, it reduces the risk of excessive credit growth during expansions and the risk of large credit contractions during systemic crises. These findings support recent theoretical results on the benefits of coordinating between monetary policy and MaPP (Carrillo et al., 2021; Kiley and Sim, 2017; Van der Ghote, 2021).

The analysis by sectors reveals significant differences in the effects of MaPP on HH and NFC credit, with more pronounced and persistent effects on NFC credit, particularly on the right tail of its distribution. These results are related to the type of MaPP instruments used. Specifically, BBM are only relevant for containing the upside risk of HH credit growth, while capital measures are effective at reducing the risk of excessive credit growth in both sectors, with a greater impact on NFC credit. This could be related to the fact that BBM typically target mortgages, while most capital tools are linked to risk weights, which tend to be higher for corporate lending. Interestingly, there are indications of potential spillover effects of tighter BBM, leading to an increase in the upside risk of NFC credit growth, although this is only significant in the short run. During financial crises, the benefits of easing BBM are very limited, while releasing capital significantly reduces the severity of credit contractions, mainly for corporate lending.

Overall, I uncover significant countercyclical effects of MaPP through the reduction of tail risk in credit growth, which remain unidentified by traditional empirical models focusing on the conditional mean. These benefits are highly dependent on the position of the financial and business cycles, banking profitability, and the stance of monetary policy. From a policy perspective, these results highlight the importance of accounting for these factors when implementing MaPP over the cycle. On the one hand, bank profitability may dampen the effectiveness of MaPP, making it necessary to act more aggressively if the profitability of the banking sector is high. On the other hand, since MaPP mainly targets tail risk, it complements monetary policy well, which tends to have more homogeneous effects across the credit growth distribution. There is also significant heterogeneity in how MaPP affects credit growth by sector and the type of instruments employed, highlighting the importance of considering the sectoral dimension when implementing MaPP tools.

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Appendix

A. Policy measures in MaPPED.

Table A1. Categories of MaPP policies in MaPPED and the type of tools included.

Category	Specific Measures
Minimum Capital Requirements	- Capital Adequacy Ratio (CAR) - Tier 1 capital ratio - Common Equity Tier 1 capital ratio (CET1)
Capital Buffers	- Capital conservation buffer (CCoB) - Countercyclical capital buffer (CCyB) - Systemic risk buffer (SyRB) - Global systemically important institutions (G-SII) buffer - Other systemically important institutions (O-SII) buffer - Other capital requirements targeting important institutions - Other capital surcharges and own funds requirements - Profit distribution restrictions
Risk Weights	- Risk weights for loans backed by residential and commercial properties - Other sectoral risk weights
Leverage Ratio	- Leverage ratio limits and leverage requirements
Loan Loss Provisioning Systems	- Loan classification rules - Minimum specific provisioning - General provisioning - Capital treatment of loan loss reserve
Lending Standards Restrictions	- Loan-to-value (LTV) limits - Loan-to-income (LTI) limits - Debt-to-income (DTI) limits - Debt service-to-income (DSTI) limits - Limits on interest rates on loans - Maturity and amortisation restrictions - Other income requirements for loan eligibility - Other restrictions on lending standards
Limits on Credit Growth and Volume	- Limits on credit growth or volume of loans for HHs and NFCs - Reserve requirements related to banks' liabilities - Asset-based reserve requirements
Levies and Taxes on Financial Institutions	- Financial activity taxes - Taxes on assets or liabilities
Large Exposures and Concentration Limits	- Limits on individual or single-client exposures - Limits on intragroup exposures - Sector and market segment exposure limits - Funding concentration limits - Limits on qualified holdings outside the financial sector - Other exposure and concentration limits
Liquidity Requirements and Limits on Currency and Maturity Mismatch	- Loan-to-Deposits (LTD) ratios - Liquidity coverage ratios (LCR) - Net stable funding ratios (NSFR) - Limits on foreign currency mismatches - Other liquidity requirements
Other measures	- Margin requirements - Limits on deposit rates - Debt resolution policies - Crisis management tools - Changes in regulatory frameworks and structural measures - Other regulatory restrictions on financial activities

Source: Budnik and Kleibl (2018).

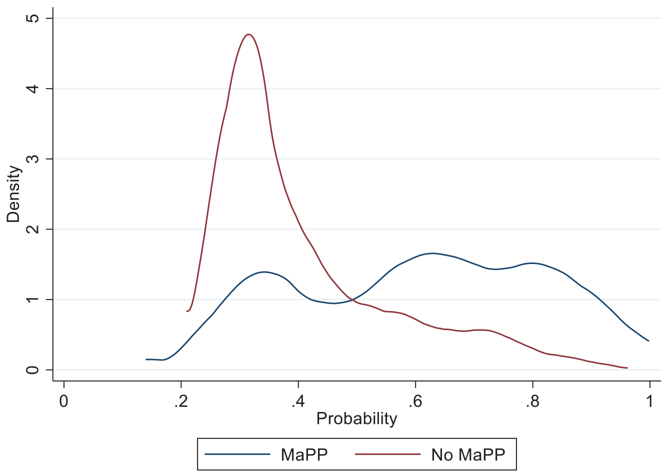
B. Results of the first step procedure for the IPW approach.

Table A2. Estimation results of the ordered probit model.

	Coefficient	Std. error
d4lncred	-0.668	0.963
L1.	-0.398	0.908
L2.	0.382	1.016
L3.	-0.452	1.120
L4.	0.655	0.881
F1.	0.021	0.963
F2.	0.242	0.977
F3.	-0.396	0.965
F4.	-1.018	0.728
d4lngdp	9.332***	2.312
L1.	-1.181	2.791
L2.	-0.799	2.858
L3.	1.129	2.894
L4.	-1.985	2.289
hpg2y	-0.216	1.043
L1.	1.828	1.581
L2.	-0.946	1.562
L3.	-0.395	1.541
L4.	1.219	0.966
clifs	0.107	0.410
L1.	0.099	0.490
L2.	-0.554	0.504
L3.	-0.693	0.506
L4.	-1.275***	0.436
ROE	-0.007**	0.003
L1.	-0.001	0.004
L2.	0.002	0.005
L3.	-0.002	0.004
L4.	-0.001	0.003
int_rate	-0.563***	0.111
L1.	0.217	0.182
L2.	-0.049	0.178
L3.	0.143	0.171
L4.	-0.233**	0.105
C-Index		
P(MPI=-2)	0.179	0.007
P(MPI=-1)	0.179	0.007
P(MPI=0)	0.223	0.009
P(MPI=1)	0.714	0.010
P(MPI=2)	0.821	0.001
Observations	1,682	
Pseudo-R2	0.22	
C-index	0.83	
Country FE	Yes	

Note: The table shows the estimated coefficients of the ordered probit regression in Equation (5), where the probability of different values of the MPI is estimated considering lagged values of the macroeconomic and financial variables in the baseline QR as well as lags and leads of credit growth. ***,** and * represent significance at the 99%, 95% and 90% confidence level, respectively. The C-index assesses the ability of the model to correctly classify the observations in each category. The index ranges between 0.5 (prediction capacity equivalent to a random assignment), and 1 (perfect predictive capacity). Values above 0.7 are considered acceptable. Jackknife standard errors are showed for the C-index.

Figure A1. Empirical distributions of treatment propensity scores.



Note: The blue and red densities represent the distribution of the estimated probabilities of treated units (implementing MaPP) and control units (not implementing MaPP), respectively.

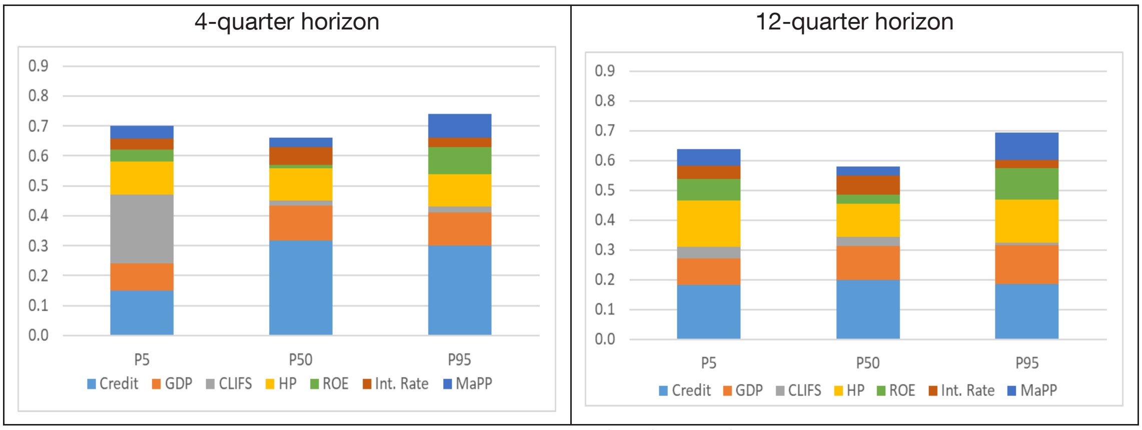
C. Model performance and contribution of variables at the tails and median

To assess the goodness of fit of the models, I compute the pseudo-R^2 ($\tilde{R}^2$) proposed by Koenker and Machado (1999). This measure is dependent on the quantile, so it is a local measure of fit of the quantile specific regression and differs from the OLS R^2. In particular, the measure compares the sum of weighted deviations for the model of interest with the same sum from a model in which only the intercept appears, and is defined as follows:

$$\tilde{R}^2(\tau,h) = 1 - \frac{\sum_{t=1}^{T}\rho_\tau(Y_{t+h} - \widehat{\alpha}_i(\tau) - \boldsymbol{X}_t\widehat{\boldsymbol{\beta}}(\tau))}{\sum_{t=1}^{T}\rho_\tau(Y_{t+h} - \widehat{\alpha}_i(\tau))}; h = 1, \ldots, 16$$

I compute the $\tilde{R}^2$ using the baseline model in Equation (4) for three different quantiles (0.05, 0.50, 0.95) and two different horizons (h=4 and h=8). I perform this by adding regressors progressively. I start with the contemporaneous credit growth rate, then I add GDP growth, the CLIFS, house price growth, ROE, policy rates and the MPI. Figure A2 presents the pseudo-R2 for each specification, computed as in Equation (A1).

Figure A2. Contribution of variables to the pseudo-R2 of the credit growth models at different quantiles and horizons.



Note: The bars represent the value of the pseudo-R2 of QR at the 5th, 50th and 95th percentiles. The coloured areas represent the contribution of each variable to the pseudo-R2.

D. Mapping the quantiles estimates into a Kernel-based density.

After obtaining the estimates of the parameters in the panel QR, I compute, for every country and period, the predictions of $y_{i,t+h}$ for 19 different quantiles, from 0.05 to 0.95 with steps of 0.05. The predicted values shape the conditional distribution of $y_{i,t+h}$, which enables the estimation of a probability density function. To map the estimates of the quantile function into a probability density function parametric and nonparametric methods can be used. Adrian et al. (2019) proposes estimating it parametrically by fitting a skewed-t distribution to the predicted values. However, this method introduces strong assumptions regarding the density function. Thus, I prefer to follow a non-parametric fit using a weighted kernel interpolation method, which has the advantage to provide a smooth and monotone cumulative distribution function (cdf) while allows for more flexibility (Escanciano and Goh, 2014).

In particular, I follow a weighted Kernel interpolation method, where the Kernel *cdf* would be represented by:

$$\sum_{j=1}^{p} w_j \Phi\left(\frac{x-q(\theta_j)}{B}\right),$$

where $\Phi(\cdot)$ is the standard Gaussian *cdf*; *p* is the number of points, which in this application is equal to 19 (0.05, 0.10,…, 0.95); θ_j represents the quantile *j*; *B* is the smoothing parameter; and w_j represents the weights $(w_1, w_2, \dots, w_p)'$ that minimize the squared distance between the quantile level and its associated *cdf*.

The bandwidth is computed as $B = 1.06\, min(\hat{s}, \hat{r})\, p^{-1/5}$, where $\hat{s}$ is the standard deviation and $\hat{r}$ is the interquartile range of the quantile functions.

After differentiating the Kernel *cdf*, the following conditional density is obtained:

$$\frac{1}{B}\sum_{j=1}^{p} \widehat{w}_j \phi\left(\frac{x-q(\theta_j)}{B}\right),$$

where $\phi(\cdot)$ is the standard normal density function.

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