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From losses to buffer - calibrating the positive neutral CCyB rate in the euro area

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Abstract

We study the impact of cyclical systemic risks on banks' profitability in the euro area within a panel quantile regression model, with the ultimate goal to inform the calibration of the Countercyclical Capital buffer (CCyB). Compared to previous studies, we augment our model to control for unobserved bank-specific characteristics and year-fixed effects and find a lower degree of heterogeneity in the estimated effects across the conditional distribution of bank returns on assets. We propose a simple yet intuitive framework to calibrate the CCyB through the cycle, including the so-called "positive neutral" rate. The model suggests a target positive neutral rate for the euro area ranging from 1.1% to 1.8%. Furthermore, the calibrated CCyB rates are consistent with the evolution of domestic cyclical systemic risks in the countries considered. The results further show that the adoption of a positive neutral CCyB approach allows for an earlier and more gradual build-up of the buffer, but does not lead to higher CCyB requirements at the peak of the cycle. Importantly, a positive neutral CCyB strategy would have implied that most euro area countries would have had a positive CCyB in place at the onset of the COVID-19 pandemic.

JEL classification: E52; G11; G23
Key words: Macropudential Policy; Systemic Risk; Bank Capital; Quantile Regression; Local Projection

Non-technical Summary

The Countercyclical Capital Buffer (CCyB) is a crucial macroprudential capital requirement introduced in the Basel III framework, aimed to build resilience in the banking sector during periods of excessive credit growth and to mitigate financial instability during downturns. Its purpose is to accumulate capital during the upturn of the financial cycle, i.e. when credit is growing rapidly and vulnerabilities are building up, which can be released during crises, allowing banks to absorb losses and continue lending, thereby limiting financial amplification effects resulting from bank deleveraging.

Due to the limited evidence of broad cyclical systemic risks in the years prior to the COVID-19 pandemic, the CCyB had been activated by only a handful of countries in the banking union. However, the pandemic highlighted the importance of holding releasable capital buffers to support the banking sector in the event of unexpected shocks. In light of this experience, macroprudential authorities in the banking union started adopting a "positive neutral" approach to the use of the CCyB, setting a positive rate for this buffer even in the absence of excessive credit developments. Such a proactive approach to the setting of the CCyB aims to ensure that banks hold some releasable capital buffers in the early phases of the financial cycle, to increase resilience against potential unidentified risks and/or unexpected shocks which may occur at any phase of the financial cycle. While the literature on the calibration of the CCyB to address emerging cyclical systemic risks has expanded significantly since the introduction of this instrument into the macroprudential toolkit, research on methodologies for calibrating the target positive neutral CCyB rate remains limited. Furthermore, integrated quantitative approaches for the setting of the CCyB through the cycle, including the positive neutral CCyB rate, are still scarce.

Against this background, this paper aims to provide policymakers with an integrated framework for the calibration of the CCyB through the cycle. Specifically, the paper proposes a novel method to calibrate the CCyB in all phases of the financial cycle, including the calibration of a target positive neutral CCyB rate. The main advantage of this methodology is that it is intuitive and flexible, and therefore a potentially attractive tool for policymakers to inform the setting of the CCyB.

The methodology is based on a quantile panel regression model with local projections, estimated using data for 318 euro area banks from 2005 to 2019. The aim of the exercise is to disentangle bank losses (i.e. negative realisations of banks' return on assets) associated with cyclical systemic risk from those attributable to unobserved factors not necessarily related to the financial cycle, while controlling for bank characteristics and macroeconomic developments. Bank losses due to cyclical systemic risks are used to estimate the additional capital required to cover such losses, and to calibrate the CCyB rate in the upturn of the cycle, when systemic risk is elevated. The remaining unexplained losses are used to

calibrate the target positive neutral CCyB rate at the euro area level. To inform the setting of the CCyB through the cycle, the paper proposes a simple rule to guide the build-up, maintenance, and the release of the buffer, delivering country-specific and time-varying calibrations of the buffer. In addition, the choice of targeting different severities of bank losses allows us to account for different preferences of the policymaker, as well as country-specific conditions to determine the timing of activation and build-up speed.

The results show that the proposed methodology performs well in guiding the calibration of the CCyB rate to address cyclical systemic risks, regardless of the adoption of a positive neutral CCyB. The calibrated CCyB rates are consistent with the evolution of domestic cyclical systemic risks in the countries considered. In the absence of a positive neutral CCyB, the model suggests low calibrated CCyB rates in the years preceding the outbreak of the COVID-19 pandemic. This is consistent with the little evidence of cyclical systemic risks during that period in the countries considered. However, had positive neutral approaches to the setting of the CCyB been adopted, most euro area countries would have had a positive CCyB rate in place at the onset of the COVID-19 pandemic, which could have been released to provide relief to the banking sector and support credit to the economy. Regarding the calibration of the target positive neutral CCyB rate, the model suggests target rates ranging from 1.1% to 1.8% for the euro area, depending on the policymaker's preferences regarding the severity of losses it aims to cover. Finally, the simple rules for the build-up, maintenance, and release of the positive neutral CCyB ensure an earlier and more gradual accumulation of the buffer. Importantly, the introduction of a positive neutral CCyB does not result in higher CCyB requirements for the banking system at the peak of the financial cycle, as the maximum CCyB rates achieved when cyclical systemic risks are at their peak are not affected by the adoption of a positive neutral CCyB approach.

From a methodological standpoint, the paper contributes to the existing literature by employing a location-scale quantile regression model and incorporating it into a local projection framework. This allows us to control for both unobserved bank-specific characteristics and year-fixed effects, and delivers a lower degree of heterogeneity in the estimated effect of cyclical systemic risks across the conditional distribution of bank returns on assets.

1 Introduction

The Countercyclical Capital Buffer (CCyB) was introduced in the Basel III capital framework in 2010, as a crucial macroprudential tool to enhance the resilience of the banking sector during periods of excessive credit growth and mitigate procyclicality.[1] The CCyB is designed to be accumulated during the upturn of the financial cycle, i.e. when credit is growing rapidly and vulnerabilities are building up, and released during downturns to allow banks to absorb losses and continue to provide credit to the economy, thereby limiting financial amplification effects produced by bank deleveraging.[2] However, due to the limited evidence of broad cyclical systemic risks in the years prior to the COVID-19 pandemic, the CCyB had been activated by only a handful of countries in the banking union. In the fourth quarter of 2019, eight countries had announced positive CCyB rates, with a weighted (by risk-weighted assets) average of announced CCyB rates of 0.23%, leaving little room for macroprudential authorities to release it when the pandemic hit.[3]

Overall, the pandemic sparked discussions on the effectiveness of the capital buffer framework and highlighted the desirability of holding higher releasable macroprudential capital buffers. After the release of a capital buffer, banks can maintain lower capital ratios without violating the combined buffer requirement (CBR), thereby reducing or eliminating potential obstacles to buffer usability, due for example to market stigma or automatic distribution restrictions.[4] Furthermore, the experience from the pandemic proved the effectiveness of capital buffer releases in supporting bank credit supply.[5]

In the aftermath of the pandemic, macroprudential authorities in the banking union started engaging in a more active use of the CCyB, by setting a positive rate for this buffer even in the absence of excessive credit developments.[6] In some cases, national macroprudential authorities set an explicit target rate for the CCyB in a "neutral risk environment", called a "positive neutral" CCyB (PN CCyB) rate. Currently, 10 out of the 15 banking union countries with a positive CCyB rate have implemented a PN CCyB rate. The main

[1] In the EU, the use of macroprudential capital requirements, including the CCyB, is disciplined by the Capital Requirements Directive, entered into force in 2014.

[2] The theoretical underpinnings of CCyB calibration primarily draw from the macroeconomic and financial stability literature. Several studies (Kindleberger, 1978; Schularick and Taylor, 2012; Jorda et al., 2013; Aikman et al., 2015) have shown that excessive credit booms have a significant role in preceding banking crises and in amplifying their effects on the real economy.

[3] While banking union authorities released more than €140 billion in capital during the pandemic, amounting to roughly to 1.5% of aggregate risk-weighted assets, only €20 billion of the release was due to macroprudential adjustments, of which only €6 billion was due to domestic CCyB releases (Behn et al., 2023)

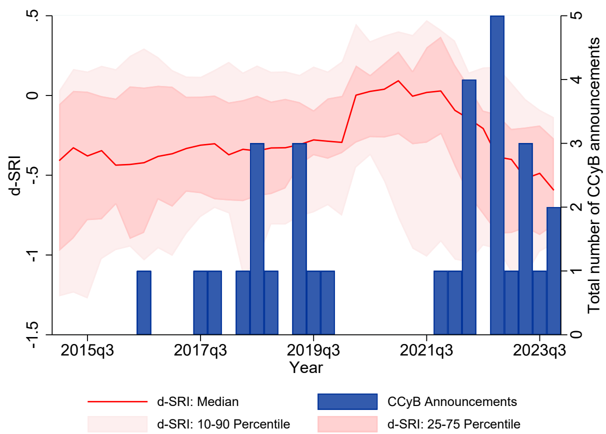
[4] Empirical evidence using micro-level data by Couaillier et al. (2022) shows that the proximity to the CBR was associated with lower growth in credit supply and stronger risk weight reductions over the course of the pandemic. These results suggest that banks are reluctant to use their capital buffers and choose to maintain some headroom above the CBR to safeguard against a potential breach should losses materialise.

[5] Couaillier et al. (2024) show that prudential capital relief measures in the banking union effectively supported bank credit supply during the pandemic.

[6] See figure (1) which plots CCyB announcements together with the d-SRI, a cyclical systemic risk indicator developed by Lang et al. (2019).

objectives are to: i) raise the CCyB early in the financial cycle, to allow a more gradual increase of capital buffers over time; ii) hold capital buffers that can be released in the event of shocks occurring early in the financial cycle, even if these shocks are unrelated to the materialisation of domestic credit-related imbalances; and iii) ensure that capital is available to cover potential unidentified risks, or risks that have not yet been captured by the established cyclical systemic risk indicators due to data lags (ECB and ESRB, 2025).

Figure 1: Cyclical systemic risk and CCyB announcements.



Notes: The red line represents the d-SRI, developed by Lang et al. (2019), which is a composite indicator for cyclical systemic risk comprising commonly used early warning indicators of systemic financial crises.

The calibrated target rates for the PN CCyB range from 0.5% to 2%. The heterogeneous target rates across countries reflect country-specific characteristics, policymakers' preferences, and different methodologies used for its calibration. These include, for instance, analyses of historical losses, stress test models, assessments of the impact of buffer releases during the pandemic, and expert judgment (see Table 1 in Behn et al., 2023). While the literature on the calibration of the CCyB to address emerging cyclical systemic risks has expanded significantly since the introduction of this instrument into the macroprudential toolkit (see Section 2), research on methodologies for calibrating the PN CCyB remains limited. Furthermore, integrated quantitative approaches for the joint calibration of the PN CCyB rate and the CCyB rate to address cyclical systemic risks are still scarce.

This paper fills this gap by proposing a rigorous yet intuitive method to calibrate the CCyB in all phases of the financial cycle, considering the adoption of a target PN CCyB rate. We rely on a quantile panel regression model with local projections, as in Lang and Forletta (2020) and Passinhas and Pereira (2023), to target losses in the banking system and use data on 318 euro area banks at the highest level of consolidation, from 2005 to 2019. We breakdown historical bank losses into two components: those associated with cyclical systemic risk, as measured by the domestic systemic risk indicator proposed by Lang et al. (2019), and those attributable to unobserved factors not necessarily related to the financial cycle, while controlling for bank characteristics and macroeconomic developments. Bank losses due to cyclical systemic risks are used to estimate the additional capital required to cover such losses, and to calibrate the CCyB rate in the upturn of the cycle, when systemic risk is elevated. The remaining unexplained losses are used to calibrate the target PN CCyB rate. The intuition behind this approach is to calibrate the target PN CCyB rate to cover losses arising from adverse developments that are not linked to the materialisation of cyclical systemic risks, and/or may be related to unidentified risks. We propose a simple rule to guide the build-up, maintenance, and the release of the PN CCyB rate, and obtain country-specific and time-varying calibrations of the CCyB through the financial cycle.

From a methodological standpoint, we employ a location-scale quantile regression model for panel data, developed by Machado and Santos Silva (2019), and incorporate it into a local projection framework (Jordà, 2005). This approach allows us to capture the potentially asymmetric impact of the covariates, especially cyclical systemic risk, on different quantiles of the conditional distribution of bank profitability, and at different future horizons. One advantage of this methodology is that it is intuitive and flexible. The choice of targeting various quantiles allows to account for different preferences of the policymaker regarding the severity of losses covered by the PN CCyB, as well as country-specific conditions to determine the timing of activation and build-up speed. Furthermore, it allows to calibrate the CCyB rate in different phases of the cycle within the same modelling framework. From a technical point of view, the main advantage of using a location-scale model over other simpler quantile-based models stands in its ability to include unit-specific fixed effects. This feature is particularly useful in our case, given our focus on banks' profitability.

The results show that our model performs well in guiding the calibration of the CCyB rate to address only cyclical systemic risks. The calibrated rates are consistent with the evolution of domestic cyclical systemic risks in the countries considered. Our model suggests low calibrated CCyB rates in the years preceding the outbreak of the COVID-19 pandemic. This is consistent with the little evidence of cyclical systemic risks during that period. When considering a PN CCyb in the policy framework, we find that the target rate ranges from 1.1% to 1.8%, depending on the policymaker's preferences regarding the severity of losses it aims to cover. The results also show that the proposed simple rules for the build-up, maintenance, and release of the PN CCyB facilitate an earlier and more gradual accumulation of the buffer. Importantly, introducing a PN CCyB does not result in higher CCyB requirements for the banking system at the peak of the financial cycle, as the maximum CCyB rate achieved when cyclical systemic risks are at their peak is not affected by the presence of a PN CCyB rate. Finally, based on our proposed methodology, most euro area countries would have had a positive CCyB rate in place at the onset of the COVID-19 pandemic, which could have been released to provide relief to the banking sector and support credit supply.

2 Literature review

Since the introduction of the CCyB into the macroprudential toolkit, quantitative "buffer guides" based on the evolution of cyclical systemic risks were developed to inform the calibration of this tool. The Basel Committee on Banking Supervision introduced a linear calibration rule based on the deviations of the credit-to-GDP ratio from its long-term trend, the Basel gap (Basel Committee, 2010). Early contributions by Drehmann et al. (2011) and Repullo and Saurina (2011) integrate macroeconomic indicators like GDP growth and credit-to-GDP gaps into the calibration process, providing a theoretical foundation for the dynamic adjustment of capital requirements. Due to the shortcomings of the Basel gap in identifying emerging credit imbalances[7], several studies have then examined the usefulness of considering a broader set of risk indicators to guide the calibration of the CCyB. These studies have explored both parametric and non-parametric approaches and assessed the ability of these other indicators to predict systemic banking crises (see Behn et al., 2013; Detken et al., 2014; Ferrari and Pirovano, 2016; Castro et al., 2016; Anundsen et al., 2016; Tölö et al., 2018; Coudert and Idier, 2018, among others). They broadly conclude that, in addition to credit variables, other indicators such as equity and house prices as well as banking sector variables help to predict vulnerable states of the economy. Based on these findings and guided by the recommendations of the European Systemic Risk Board (2014/1), euro area macroprudential authorities developed frameworks for calibrating the CCyB, whereby the buffer rate is determined based on whether the selected indicators breach their associated early-warning thresholds.

Structural macroeconomic approaches, such as DSGE models, have also been used to structurally calibrate the CCyB, through the optimization of a given objective function. This function typically takes the form of either the maximization of social welfare or the minimization of an ad hoc credit volatility function (see Clerc et al., 2015; Bennani et al., 2016; Muñoz and Smets, 2024, among others). These models have also been used to derive optimal calibration rules for the CCyB, exploring different indicators to guide its build-up. For example, using a small open economy DSGE model with financial frictions, Lozej et al. (2018) find that the optimal calibration rule depends only on the house price, rather than on the credit gap. Relying on the framework by Clerc et al. (2015), Aguilar et al. (2019) find that the optimal calibration rule for the CCyB should respond to movements in total credit and mortgage lending spreads, when capital requirements are already set at their optimal level.

Other approaches to the calibration of the CCyB focus on linking the buffer level to simulated losses coming from hypothetical stress scenarios or to historical observed losses. Stress test approaches simulate adverse scenarios, and compute the corresponding capital shortfall, which is then used to set the CCyB rate (see for example Dees et al., 2017;

[7] See for example Lang and Welz (May 2017)

Couailler and Scalone, 2021; Van Oordt, 2023). More recently, panel data models based on bank-level data have been used to calibrate the CCyB to cover bank losses that, historically, have occurred in periods of elevated cyclical systemic risks. Lang and Forletta (2020) study the impact of cyclical systemic risk on future bank profitability for a large representative panel of EU banks between 2005 and 2017. Based on a linear local projections model, they show that high levels of cyclical systemic risk predict large drops in the average bank-level return on assets several years in advance. Building on these findings, the estimated average impact of the cyclical systemic risk measure on future bank capital is then used to inform the calibration of a linear rule for setting the CCyB. Using a similar framework based on linear projections combined with a quantile regression and a panel of banks, Passinhas and Pereira (2023) propose a CCyB calibration rule based on the impact of cyclical systemic risk on bank losses, while also taking into account the prevailing capital-resilience in the banking sector at each point in time. In their framework, the CCyB rate is set to a value that guarantees that the contribution of cyclical systemic risk not already covered by existing capital to bank losses in the medium-term horizon is non-positive.

Recently, as several countries have revised their CCyB frameworks to include the setting of a positive CCyB rate even when cyclical systemic risks are not elevated, methodologies for its calibration have been developed; however, the literature is still scarce. The Basel Committee (2024) provides an overview of the range of practices in implementing a PN CCyB rate. At the country level, the Central Bank of Ireland relies on a macroprudential stress testing framework, simulating an adverse but not overly severe scenario, consistent with an environment of neither elevated nor subdued risk.[8] This framework informs the calibration of the 1.5% target rate for the PN CCyB rate, and guides the timing and pace of its build-up after a crisis (Morell et al., 2022). In the Czech Republic, the 1% target rate for the CCyB in a risk-neutral environment is informed by two methodologies (Plašil, 2019). The first approach calculates the median historical values of the indicators in the financial cycle indicator and maps them to the corresponding CCyB rate using the Czech Republic's CCyB buffer guide (Hájek et al., 2017). The second approach determines the optimal PN CCyB rate by evaluating the sustainable level of credit growth, defined as a year-on-year growth rate of the ratio between total credit provided to the private non-financial sector and GDP below 1% in the long term. In Lithuania, the macroprudential authority set the 1% target rate for the CCyB in normal times using the historical losses incurred by the banking sector during average economic downturns (Lietuvos Bankas, 2017). Finally, the Bank of England increased its PN CCyB from 1% to 2% to ensure that the banking sector is capitalised against risks at the peak of the financial cycle, considering historical losses in the banking sector. The PN CCyB is expected to be accumulated when indicators of underlying cyclical financial vulnerabilities are at or around their long-term historical

[8] See Central Bank of Ireland, 2023, "A framework for macroprudential capital – CCyB addendum" available at: https://www.centralbank.ie/docs/default-source/financial-system/financial-stability/macroprudential-policy/central-banks-framework-for-macroprudential-capital-ccyb-addendum.pdf

average and an assessment of banks' resilience to potential and actual shocks suggests they are likely to be able to absorb a shock rather than amplify it (Bank of England, 2023).

With this paper, we leverage on the works by Lang and Forletta (2020) and Passinhas and Pereira (2023) to develop a novel, integrated framework for calibrating the CCyB rate both at the early stages of the financial cycle (the PN CCyB rate) and at its peak according to the evolution of cyclical systemic risk, using a panel quantile regression model. Quantile regression models were originally introduced by Koenker and Bassett (1978) and allow to estimate the asymmetric and heterogeneous effect of the covariates on different quantiles of the conditional distribution of the dependent variable. In other words, the estimator quantifies the effects of the covariates on different quantiles of the distribution, rather than focusing solely on a central measure like the mean, as is typical in conventional OLS regressions. However, integrating this approach into a panel data model while controlling for unobserved heterogeneity with fixed effects introduces the incidental parameter problem, which leads to biased estimates of the impact of the covariates on the relevant variable (Canay, 2011). Several models have been developed to address this misspecification issue in panel data models. Canay (2011) developed a model that removes fixed effects by treating them as location shift variables, which impact all quantiles in the same way. In turn, Koenker (2004) provides a regularization method that shrinks individual fixed effects to a common value. Our approach borrows from the contribution of Machado and Santos Silva (2019) and estimates a location-scale quantile model that differentiates between location and scale shifts in the effects of the covariates. The location shift effect (location parameter) provides the average effect of the covariate across all quantiles of the distribution of the variable of interest, while the scale effect captures the deviations from the average effect on the specific quantile. One advantage of this estimator over others is that it prevents quantile crossing in the estimates, a common issue in quantile regression models (Bondell et al., 2010).

3 The model

Our focus is on studying the response of the conditional distribution of future bank profitability to changes in cyclical systemic risk, while controlling for other factors that affect bank profits and losses. To achieve this, we estimate a location-scale quantile model, as developed by Machado and Santos Silva (2019), and incorporate it into a local projection framework (Jordà, 2005). The use of a quantile regression approach allows us to reflect the arguably asymmetric impact of the covariates, especially cyclical systemic risk, on the quantiles of the conditional distribution of bank profitability. Using local projections allows us to account for the 12-month implementation lag occurring between the announcement of a decision to increase the CCyB and its entry into force (Aikman et al., 2019).

Our conditional quantile model for bank profitability then takes the following form:

$$\begin{aligned} Q_{\pi_{i,j,t+h}}(\tau|X_{i,t}, Y_{j,t}) &= X'_{i,t}\left[\beta^h_{(l)} + \beta^h_{(s)}q(\tau,h)\right] + Y'_{j,t}\left[\delta^h_{(l)} + \delta^h_{(s)}q(\tau,h)\right] + \\ &\quad \left[\alpha^h_{i,(l)} + \alpha^h_{i,(s)}q(\tau,h)\right] + \left[\lambda^h_{t,(l)} + \lambda^h_{t,(s)}q(\tau,h)\right] + \epsilon_{i,j,t+h} \\ &= X'_{i,t}\beta^{\tau,h} + Y'_{j,t}\delta^{\tau,h} + \alpha^{\tau,h}_i + \lambda^{\tau,h}_t + \epsilon_{i,j,t+h}, \end{aligned} \tag{1}$$

where i indexes the banks with $i = 1, \ldots, N$, j indexes the countries with $j = 1, \ldots, J$, t indexes the time period $t = 1, \ldots, T$, h indexes the projection horizons, and τ indexes the percentiles. The set of covariates covers both bank-specific variables, $X_{i,t}$, and macro-financial or country-specific variables, $Y_{j,t}$, among which the measure of cyclical systemic risk is our main variable of interest. More information about the selected covariates is provided in Section (4). The unknown location parameters indexed by (l) are $\left(\beta^h_{(l)}, \delta^h_{(l)}, \alpha^h_{i,(l)}, \lambda^h_{t,(l)}\right)$, while $\left(\beta^h_{(s)}, \delta^h_{(s)}, \alpha^h_{i,(s)}, \lambda^h_{t,(s)}\right)$ represent unknown scale parameters, which are indexed by (s). The error term is denoted by $\epsilon_{i,j,t+h}$ and the quantile function $q(\tau, h)$ guarantees that $Pr(\epsilon_{i,j,t+h} < q(\tau, h)) = \tau$. The marginal effects of the covariates result from the combination of the location parameter vectors $\beta^h_{(l)}$ or $\delta^h_{(l)}$ with the scale parameter vectors multiplied by the quantile function $\beta^h_{(s)}q(\tau, h)$ or $\delta^h_{(s)}q(\tau, h)$, respectively. The first term of the marginal effect provides the average effect, and the second term provides the percentile-specific effect of the covariate.

We include bank fixed effects in our model to control for unobserved heterogeneity across banks. This is captured by the term $\alpha^h_{i,(l)} + \alpha^h_{i,(s)}q(\tau, h)$. The location parameter $\alpha^h_{i,(l)}$ provides the average effect of bank i in country j over the entire distribution of bank profitability at horizon h, $\pi_{i,j,t+h}$, whereas $\alpha^h_{i,(s)}q(\tau, h)$ captures the percentile-specific effect of bank i. We also include time fixed effects, captured by the term $\lambda^h_{t,(l)} + \lambda^h_{t,(s)}q(\tau, h)$, to control for unobserved factors that vary over time but are constant across banks. The respective location parameter $\lambda^h_{t,(l)}$ provides the average effect of time period t across the entire distribution, while $\lambda^h_{t,(s)}q(\tau, h)$ captures the effect on the τ-percentile of the conditional distribution.

4 Data and estimation strategy

This section discusses the control variables included in the quantile panel model in equation (1) and introduces our measure of bank profitability. It then discusses the identification and estimation strategy.

4.1 Data

Our dataset comprises both bank-level and country-level data. We use bank-level data to control for bank-specific characteristics and country-level data to reflect macro-financial conditions in our estimation.

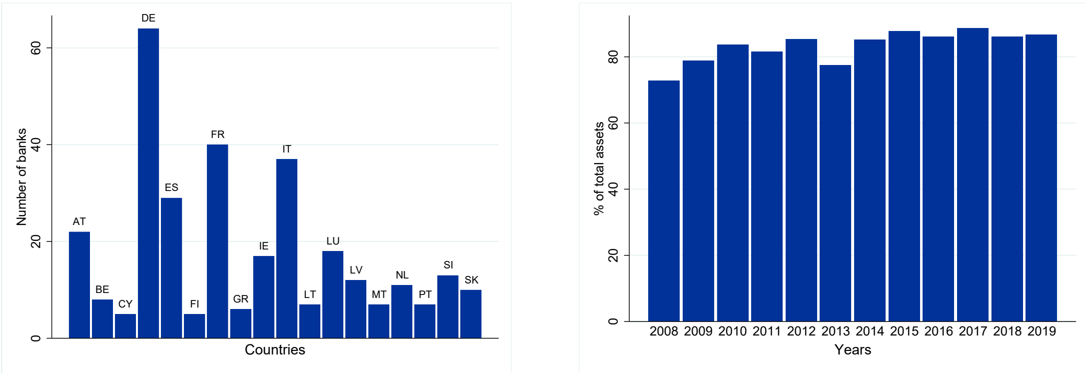
4.1.1 Bank-level data

The bank-level dataset is based on balance sheet and income statement variables collected from SNL Financials. The original dataset consists of $4,297$ banks from the euro area as well as Denmark, Sweden, and Great Britain, and covers the sample period from 2005 to 2019 at annual frequency. However, for the purpose of this analysis, we restrict our sample to euro area countries only. We include each bank only at its highest level of consolidation within a country to prevent double-counting of balance sheet positions. This means we exclude subsidiaries whose parent company is in the same country but retain subsidiaries of foreign parent banks. We further consider only banks for which data is available also during the height of the financial crisis in 2008 and 2009. But, we keep banks that are characterised by large balance sheets (larger than the country median) even if data for these banks is not available in 2008 and 2009, as they account for a significant share of domestic total assets in their countries. Lastly, we remove all observations with missing information for the balance sheet variables included in our model. Our final estimation sample comprises 318 euro area banks.

Figure (2a) shows the total number of banks per country included in our final sample. These banks cover between around 73% and 89% of total assets of the consolidated banking sector in the euro area between 2008 and 2019 as shown in Figure (2b). This suggests that our sample is representative of the heterogeneity in the relative distribution of the number of banks across euro area countries and covers a sufficiently large share of total assets every year. It is worth noting that, while our dataset provides a rich setting to study the interaction between cyclical systemic risk and bank profitability, the relatively short time span limits our ability to conduct robustness checks across different sub-periods without a significant loss of estimation precision. This constraint should be considered when interpreting our results, as extending the sample period is not feasible due to data limitations.

Figure 2: Data coverage per country and over time.

(a) Number of banks per country (b) Total coverage of assets per year

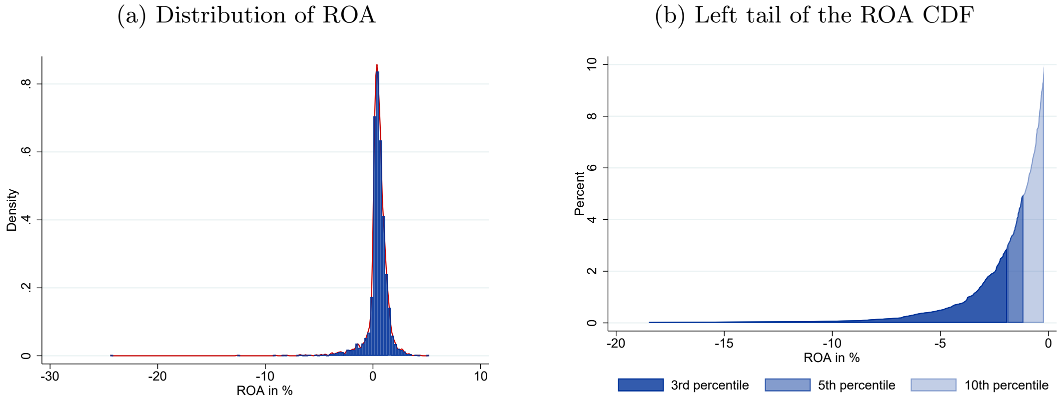


Notes: Panel (a) shows the number of banks per country in our sample. Panel (b) presents the ratio of total assets of the banks to the total assets of the consolidated banking sector in the euro area, by year. Data for the consolidated banking sector are sourced from CBD2 and are only available from 2008.

The dependent variable in our model is bank profitability, measured by the pre-tax return on assets (ROA). The focus on ROA is justified by a number of reasons. First, since negative levels of returns directly imply a reduction in bank capital, the negative impact of cyclical systemic risk on ROA can provide useful information regarding the amount of capital needed to offset risks of capital depletion stemming from these risks. Moreover, ROA reflects banks' ability to absorb losses and generate earnings, which is crucial for maintaining resilience during financial downturns. Unlike capital levels, profitability is a direct determinant of banks' ability to accumulate capital buffers organically, reducing the need for external capital-raising or deleveraging during crises. As such, ROA is a key metric for macroprudential policy conduct.

The pre-tax ROA distribution is shown in Figure (3). The ROA distribution is left skewed with outliers concentrated on the left tail of the distribution, as depicted in Figure (3a). Given the skewness of the distribution, standard estimation techniques might fail to capture the asymmetric and potentially non-linear response of ROA at different percentiles of the distribution. This feature was of key importance to identify the appropriate estimation technique. Observations at the far left tail of the distribution are most relevant from a financial stability perspective since they represent losses to the banking sector. Figure (3b) plots different percentiles of the left tail of the pre-tax ROA cumulative density function.

Figure 3: Distributional characteristics of the pre-tax ROA.



Notes: Panel (a) displays an histogram for the pre-tax ROA distribution and an estimated kernel distribution (red line). Panel (b) shows the left tail of the pre-tax ROA cumulative distribution function (CDF).

Bank-specific variables are included to control for bank-specific characteristics, which may drive institution-specific losses and are relevant for the setting of bank-specific capital requirements such as Pillar 1 and Pillar 2 requirements. Our set of bank-specific control variables broadly follows Lang and Forletta (2020). We include the logarithm of total assets to control for the size of the bank, impairments over total assets to proxy for asset quality, and the net interest margin and net loans over total assets to control for banks' business model. We further include the cost to income ratio to reflect cost inefficiencies and risk-weighted assets over total assets to capture the riskiness of the asset portfolio. Finally, we measure banks capitalisation and their resilience against shocks using two variables: tangible equity over tangible assets and Tier 1 capital ratio.[9] Detailed information about the selected variables is provided in Appendix (A).

4.1.2 Country-level data

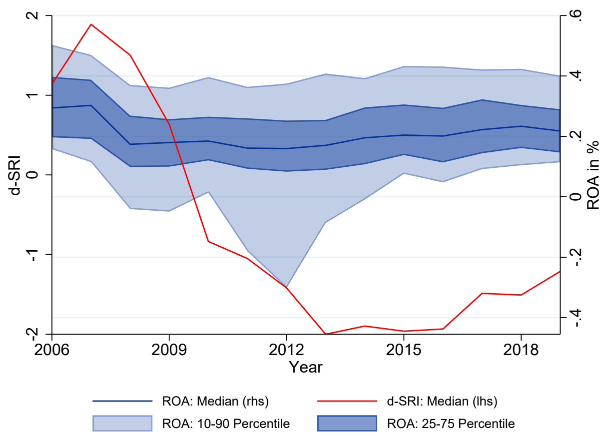
The main variable of interest in our analysis is a measure of domestic cyclical systemic risk, which is relevant for setting the CCyB. For this purpose, we use the domestic Systemic Risk Indicator (d-SRI) proposed by Lang et al. (2019), which is regularly used by the ECB to assess cyclical systemic risks. The d-SRI is a composite, country-level indicator synthesizing cyclical systemic risks stemming from various sources, including the domestic credit cycle, real estate markets, asset valuations, and external imbalances.[10] The d-SRI captures those facets of systemic risk that are important to policymakers as they have been identified as prominent factors triggering financial crises (Borio and Lowe, 2002, 2004; Lang et al., 2019). Another important feature of this indicator relates to its early-warning

[9]Under EU regulation, banks need to hold capital to meet requirements imposed by a risk-based capital framework and a leverage ratio framework, which acts as a backstop. We use tangible equity over tangible assets as a proxy for the leverage ratio given that we do not have data on off-balance sheet exposures.

[10]For more details on the calculation an components of the d-SRI, see Lang et al. (2019).

properties regarding the detection of financial crises, making it well-suited to inform the calibration of the CCyB to address elevated cyclical systemic risk. Figure (4) plots the distribution of pre-tax ROA together with the d-SRI over the entire sample period. While the upper percentiles of the ROA distribution remain largely stable, the lower tail has seen a downward shift starting during the Great Financial Crisis (GFC) and intensifying during the Sovereign Debt Crisis (SDC). This shift in the distribution is preceded by a peak in the d-SRI ahead of the start of the GFC, consistent with the build-up of cyclical systemic risks in that period. Furthermore, the large swings in the lower tail of the ROA distribution lend further support to the assumption that the impact of the d-SRI is asymmetric over the distribution. As these shifts seem to be time dependent, it is important to consider time-fixed effects in our estimation approach. In the regression, we include an interaction term between the d-SRI and the bank capital ratio, to capture how existing resilience affects the impact of cyclical systemic risk on future bank profitability. This implies that the marginal effect of cyclical systemic risk on bank profitability depends on the capital ratio. To estimate these marginal effects, we follow the approach of Passinhas and Pereira (2023), and use the pooled average of the Tier 1 capital ratio.

Figure 4: Cyclical systemic risk and bank profitability.



Notes: The country-level d-SRI is initially available on a quarterly basis and is subsequently converted to an annual frequency using a simple average. The cross-sectional median is then derived from the annual d-SRI values across countries.

Finally, we include in the model macro-financial variables that have arguably an impact on bank profitability in the short and medium term, while remaining parsimonious due to the short time sample. Specifically, we include the real GDP growth rate to capture business cycle dynamics and the procyclicality of banks' profits (Albertazzi and Gambacorta, 2009), and the spread of government bonds yields, defined as the difference between the 3-month Euribor and the country-specific 10-year government bond yield, to account for the prevailing monetary policy stance.

Further information on the data sources and summary statistics can be found in Appendix (A) and Table 4 in Appendix (B), respectively. The ROA pooled unweighted mean in the sample is 0.42% and the standard deviation is 1.12%, which indicates some degree of variability in profitability across banks and over time. The mean lays slightly below the median, reflecting the skewness of the profitability distribution driven by the outliers on its left tail dating back to the aftermath of the GFC and SDC. In addition, our sample shows an average Tier 1 capital ratio of 14.08% and a ratio of risk-weighted assets to total assets of 48.68%. Banks were operating on average with a net-interest margin of 1.56%, while the cost-to-income ratio was at 62.90% on average in our sample.

4.2 Identification and estimation strategy

Our analysis focuses on uncovering the impact of a one-unit increase in the cyclical systemic risk indicator on selected quantiles of the conditional distribution of euro area banks' future profitability. However, the identification of these relationships is threatened by the potential presence of endogeneity in the model. Endogeneity concerns arise because factors that drive cyclical systemic risk, such as credit growth and asset prices, may also directly affect bank profitability. This overlap could lead to biased coefficient estimates, making it more difficult to isolate the direct effect of the cyclical systemic risk on banks' returns. The use of a local projection framework, where future profitability is regressed on current levels of cyclical systemic risk, helps to mitigate this concern. While current levels of cyclical systemic risk influence future profitability, the reverse relationship – where future profitability would influence current cyclical systemic risk – does not hold, reducing simultaneity issues. Another potential source of endogeneity is omitted variables bias, where unobserved factors influence both the dependent and the conditioning variables. The inclusion of bank- and time-fixed effects in our specification helps to address this issue. By controlling for unobserved heterogeneity across banks and over time, we reduce the likelihood that the error term is correlated with our conditioning variables.

The estimation strategy is tailored to account for the characteristics of our dataset, which, as discussed in Subsection (4.1), comprises 318 banks (N) from 18 countries (J) over a 14-year period (T). The relatively short time dimension of our panel dataset may introduce asymptotic bias into our parameter estimates. This arises because the quantile estimator used to estimate the parameters in equation (1) converges to the true parameters with an additional term proportional to $1/T$. To correct this potential bias, we apply the split-sample jackknife correction proposed by Dhaene and Jochmans (2015).[11] Machado and Santos Silva (2019) demonstrate that this correction effectively mitigates bias associated

[11] The jackknife correction is implemented as follows: (1) estimate the unknown parameters using the full sample, (2) estimate the unknown parameters separately for each half-sample, (3) use the estimates of δ and $q(\tau, h)$ from steps 1 and 2 to obtain bias-corrected estimates of δ and $q(\tau, h)$ using equation (3.4) in Dhaene and Jochmans (2015), (4) obtain the bias corrected estimate of $\beta(\tau)$ by adding the product of the bias-corrected estimates of δ and $q(\tau, h)$ to the estimate of β from step 1.

with small T values, while maintaining estimation precision.[12] The estimator precision, as measured by the standard error and mean squared error, improves as $N \times T$ increases. However, given that the bias decreases with increasing T and the variance decreases with increasing $N \times T$, the asymptotic distribution of the estimator may exhibit bias when the ratio N/T is large (Hahn and Newey, 2004). Specifically, when N/T exceeds 10, the coverage of the confidence interval centered on Machado and Santos Silva (2019) estimator declines markedly. Centering confidence intervals around bias-corrected estimates, however, significantly improves coverage, resulting in more reliable intervals. Given that in our sample the ratio of N to T is 22, which surpasses the critical threshold of 10, we center our confidence intervals around the split-panel bias-corrected estimates to improve their coverage. In addition, to account for the presence of autocorrelation and heteroskedasticity in the error term, we cluster standard errors at the bank level and derive estimates for standard errors from bootstrapping. We consider projection horizons $h = 1, \ldots, 6$ and six different percentiles $\tau \in \{5, 10, 25, 50, 75, 90\}$ in our estimates.

5 Impact of cyclical systemic risk on bank profitability

Figure (5) shows the marginal effect of a one-unit increase in the level of cyclical systemic risk on six percentiles of the conditional profitability distribution over the selected projection horizons. Three main findings emerge from these results. First, we find that, regardless of the percentile of the distribution considered, an increase in the cyclical systemic risk indicator is associated with a decline in bank profitability. This finding is in line with the two papers closest to ours - Lang and Forletta (2020) and Passinhas and Pereira (2023). Second, we find that the magnitudes of the estimated impacts of the cyclical systemic risk indicator are quite stable across percentiles of the conditional distribution, and, third, the degree of uncertainty around the estimated impact increases as we move towards the lower percentiles of the distribution.

Regarding the magnitude of the impacts, the results show that they are slightly stronger in the lower percentiles of the conditional distribution, yet fairly stable, and they reach their peak effects always in the fourth year of the horizon considered. The impacts range between -0.7 and -0.9 percent. The results also suggest that the responses across percentiles vary in their shape. In the higher percentiles, the responses rebound sharply after reaching their peak, whereas in the left tail of the conditional distribution, the responses are flatter after reaching the peak. For example, at the 5th percentile (panel (f)), the peak effect of -0.7 percent occurs at the fourth projection horizon and remains at -0.5 in the subsequent year. In contrast, the impact at the 90th percentile (panel (a)) peaks in the same year at a

[12] Machado and Santos Silva (2019) show this only for models with unit-specific fixed effects. Our model also includes time-fixed effects. Given the large size of N in our sample, the inclusion of time-fixed effects should not cause major concern, as each time-fixed effect is estimated using a large number of observations.

similar magnitude, but it reverts back more quickly with a value of -0.3 percent in the year after reaching its peak. Taken together, these results do not seem to support the finding that an increase in cyclical systemic risk leads to an increase in the left-side skewness of the conditional distribution of bank profitability. However, they suggest that the impact of an increase in cyclical systemic risks on profitability is slightly more persistent for banks in the lower percentiles of the conditional distribution. These findings contrast with the results found in Lang and Forletta (2020), which finds a significant shift in the conditional distribution of bank profitability following an increase in the d-SRI.

The two main modelling differences between our approach and that of Lang and Forletta (2020) relate, first, to the choice of the estimator which, in our case, allows for the inclusion of bank-fixed effects in the model specification and, second, to the inclusion of an interaction term between the cyclical systemic risk indicator and the Tier 1 capital ratio. Not controlling for unobserved bank-specific characteristics can be one of the drivers of the identified differences in the estimated impact of cyclical systemic risks on profitability for at least two reasons. First, despite the inclusion of several control variables, there might still be unobserved cross-bank heterogeneity, which we control for with bank fixed effects. This heterogeneity can be driven by various unobservable factors, such as management quality, market power, and risk appetite, which are likely to have a non-negligible influence on bank profitability. Second, and most importantly, unobservable bank-specific characteristics can be correlated with aggregate cyclical financial conditions; therefore, their omission from the model could lead to biased estimates of the relationship between cyclical systemic risk and bank profitability (omitted variable bias). For instance, heterogeneous risk appetite and risk management practices across banks can influence how they respond to changes in aggregate credit dynamics. These factors, which are not easily captured by the variables included in the model, can affect how aggregate cyclical dynamics impact bank performance. Hence, modeling the impact of cyclical systemic risk on bank profitability without controlling for unobservable bank-specific characteristics might lead to the impact of these characteristics being confounded with the impact of changes in domestic cyclical dynamics. Eliminating this potential bias may explain the greater stability observed in our estimated parameters across the percentiles, compared to a model where these characteristics are not accounted for.

Figure (5) also shows that the degree of uncertainty around the estimated parameter is higher at lower percentiles and gradually decreases as we move towards higher percentiles of the distribution. This may result from higher data scarcity in the lower quantiles of the profitability distribution. As shown in Figure (3) and detailed in Table 1, the unconditional profitability distribution is highly left-skewed. The lower tail range, as measured by the distance between the 5th percentile and the minimum value of the distribution, is substantially longer than the upper tail range, as measured by the distance between the maximum value and the 95th percentile. As we move towards the left quantiles of the distribution, the number of observations in the unconditional distribution decreases significantly. For example, below the 25th percentile of the profitability distribution, the number of observations is 704, compared to $2,338$ observations above the 75th percentile.[13]

Table 1: Tails range and number of observations across percentiles of the profitability distribution

	p99	p95	p90	p75	p25	p10	p5	p1
Upper and lower tail ranges		3.61					23.26	
No. observations above percentile	1,662	1,774	1,915	2,338				
No. observations below percentile					704	281	140	28

Notes: The upper tail range is defined as the difference between the maximum value and the 95th percentile of the sample, whereas the lower tail range is defined as the different between 5th percentile and the minimum value of the sample. The second row shows the number of observations above each percentile for the upper tail (p75 and above) while the third row shows the number of observations below each percentile for the lower tail (p25 and below).

Another factor potentially contributing to differences in the precision of estimates across percentiles is the greater dispersion in the responses of banks pertaining to the lowest percentiles to increases in cyclical systemic risk. Arguably, banks with lower profitability tend to be smaller in size (Regehr and Sengupta, 2016), which could explain the more disperse responses in lower percentiles of the conditional distribution. Larger banks tend to show more standardised risk management practices, better access to capital, and more diversified portfolios, as well as geographical focus with more subsidiaries (see Laeven et al., 2014), which help them manage swings in the financial cycle more uniformly. However, we do not find evidence of a prominence of smaller banks in the lower percentiles of the profitability distribution, at least in the sample considered (see Table 5 in Appendix B).[14]

Finally, we perform a robustness check of our results using an alternative model specification to address concerns about potential endogeneity between cyclical systemic risk and profitability. In particular, we replace the cyclical systemic risk indicator with the residuals resulting from a regression of the cyclical systemic risk indicator on bank profitability. These residuals capture the component of the cyclical systemic risk that is not driven by profitability. This approach ensures that the estimated impact of the cyclical systemic risk on future profitability reflects only the variation in the cyclical systemic risk that is not driven by common factors or reverse causality. The impulse responses obtained from this alternative model specification are shown in Appendix C.1. We also assess the robustness of our results to our choice of the estimation sample and dependent variable (ROA). Appendix C.2 shows the results of considering three different estimation samples:

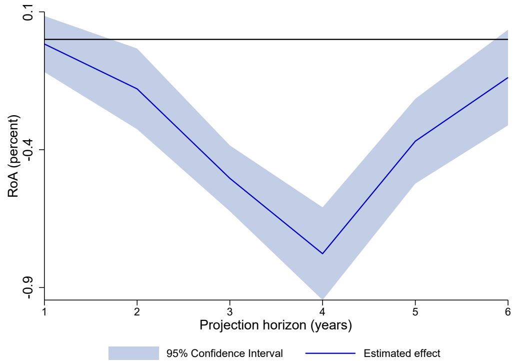
[13]The estimation of quantile regression models uses the whole sample. However, the limited number of observations at the tails can still affect the precision of the estimates for the extreme quantiles, as observations below (above) the fitted line for lower (higher) quantiles are assigned higher weights.

[14]The relationship between bank size and profitability seems not to be conclusively answered in the literature. While there seems to be a consensus that more efficient banks tend to be associated with higher ROA, the relationship between size and efficiency hinges on many aspects such as the translation of regulatory standards into banks' business model, economies of scale and the degree of diversification of the asset portfolio (among others, see Gržeta et al., 2023; Bolívar et al., 2023; Pasiouras et al., 2009).

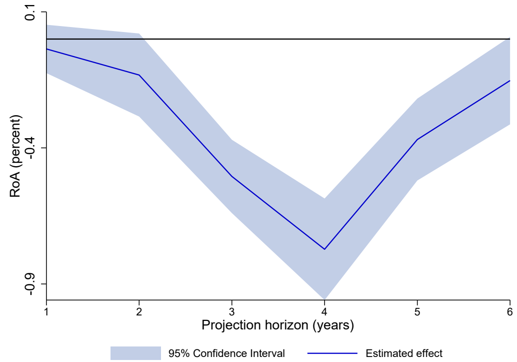
one extended to include non-EA countries, one with only large banks, and another one with only small banks. Appendix C.3 presents the results if we were to use the return on risk-weighted assets as our dependent variable instead of ROA.

Figure 5: Marginal effect of cyclical systemic risk on selected quantiles of the distribution of future bank profitability

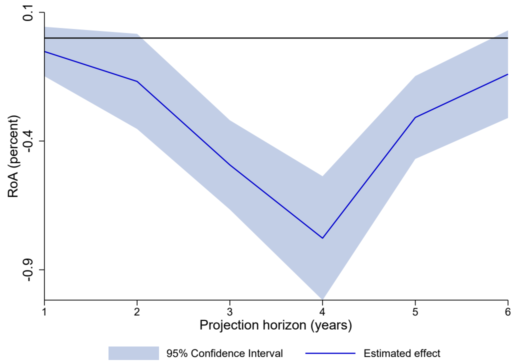
(a) 90th Percentile



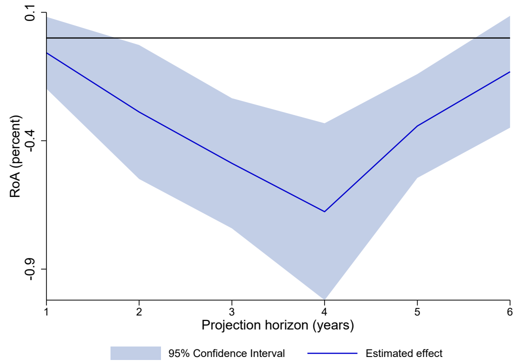
(b) 75th Percentile



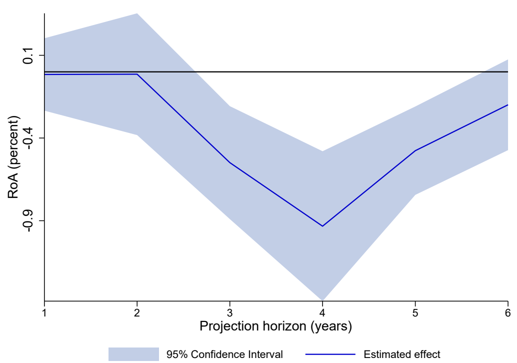
(c) 50th Percentile



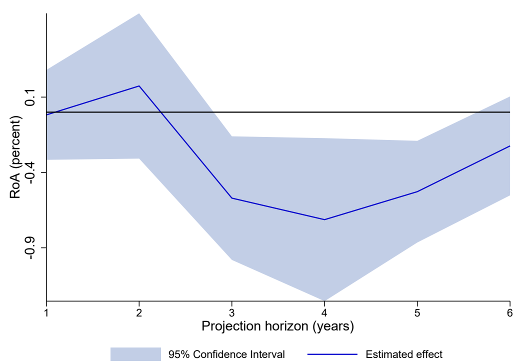
(d) 25th Percentile



(e) 10th Percentile



(f) 5th Percentile



Notes: The figure shows the marginal effect of cyclical systemic risk evaluated at the pooled average of Tier 1 capital ratio. The confidence intervals are set at the 95% confidence level, with bootstrapped standard errors clustered at the bank level.

6 From bank losses to buffers: calibration of the CCyB

In this section, we use the results of our estimated model to inform the calibration of the overall CCyB rate through the cycle, that is, including the positive neutral rate. First, we leverage on the approach proposed in Lang and Forletta (2020) to calibrate the CCyB in its most commonly known use, namely to provide resilience against domestic cyclical systemic risk. Second, we propose a rule for determining the target PN CCyB rate, which is the highest positive rate for the buffer when cyclical systemic risks are not yet elevated. We also propose rules to guide the build-up, maintenance, and the release of the PN CCyB rate. Finally, we combine the two approaches to obtain the CCyB rate in all phases of the financial cycle.

6.1 Calibration of the CCyB to address cyclical systemic risk

To calibrate the CCyB to address domestic cyclical systemic risk, we rely on a simple linear rule to convert the impact of the d-SRI on future bank profitability, obtained in Section (5), into a capital buffer requirement. We translate the estimated cumulative negative impact of the d-SRI on future bank profitability into units of regulatory capital ratio by rescaling it by the inverse of average risk weights. By doing so, we implicitly assume that banks maintain normal dividend payments, also during crisis times. This rule delivers a CCyB rate that, on average, ensures that bank capital ratios remain above regulatory requirements when systemic risk materializes, even if banks continue to pay dividends at a rate consistent with non-crisis profitability.

As discussed in previous subsections, cyclical systemic risk has a negative and statistically significant impact on future bank profitability over a three- to five-year ahead horizon, with the strongest impact occurring in the fourth year. Accordingly, the cumulative negative impact of the d-SRI on bank profitability over this window is used as the basis for the following linear CCyB calibration rule:

$$\text{CCyB}_{j,t}(\tau) = \max\left\{0, \frac{-\sum_{h=3}^{5}\left(\hat{\theta}^{\tau,h}_{\text{d-sri}} + \hat{\nu}^{\tau,h}_{\text{d-sri}\times\text{T1R}}\right)}{\overline{rw}_{j,t}} \times \text{d-SRI}_{j,t}\right\} \tag{2}$$

where $\overline{rw}_{j,t}$ is the average risk-weight for country j in year t, which is used to re-scale the impact on profitability into the impact on the risk-weighted capital ratio, $(\hat{\theta}^{\tau,h}_{\text{d-sri}}+\hat{\nu}^{\tau,h}_{\text{d-sri}\times\text{T1R}})$ represents the estimated impact of a one-unit increase in cyclical systemic risk on future bank profitability, evaluated at the country-level average of Tier 1 capital ratio, and d-SRI$_{j,t}$ represents the level of cyclical systemic risk in country j in year t.[15]

[15] For notational convenience, we subsume the location and scale effects of the d-SRI and the interaction

The main differences between our approach to calibration and the one in Lang and Forletta (2020) are: i) the use of results stemming from a quantile regression model rather than a linear regression model, and ii) the consideration of the marginal impact of cyclical systemic risk as a function of the level of existing capitalisation in the banking system. Using a quantile-based approach allows us to derive the rates needed to target different severities of losses, as measured by the percentile of the conditional distribution, and, thus, provide CCyB rates for different policymaker preferences.

Figures (6) and (7) illustrate the application of the calibration rule in equation (2) to various countries, alongside the cyclical systemic risk indicator. We present the CCyB calibration for two levels of loss severity: the median (in dark blue) and the 10th percentile (in light blue) of the conditional distribution of future bank profitability. As noted in the previous section, the marginal effect of the d-SRI tends to increase as we move from higher to lower quantiles of the profitability distribution. Consistent with this, the linear calibration rule delivers higher CCyB rates for the lower quantile of the conditional distribution. Results also show that the calibrated CCyB rates are consistent with the evolution of domestic cyclical systemic risks in the countries considered. In the early years of the sample, encompassing the years preceding the Great Financial Crisis, the model suggests CCyB rates as high as 6% in some countries. This is not surprising for three reasons. First, the years before the Great Financial Crisis were characterised by elevated cyclical systemic risk, as demonstrated by the values of the d-SRI. Second, bank capitalisation was relatively low at the time, as the Basel III rules which significantly strengthened bank capital requirements were agreed upon in 2010.[16] Third, the Great Financial Crisis caused very severe losses for the banking sector, which, in hindsight, would have required significantly higher buffers to absorb them.

The CCyB calibration obtained with our model further suggests broadly zero CCyB rates during the Sovereign Debt Crisis and at most low calibrated CCyB rates in the years preceding the outbreak of the COVID-19 pandemic. This is consistent with the little evidence of cyclical systemic risks during that period, where emerging vulnerabilities were mostly concentrated in the residential real estate sector. Interestingly though, the model suggests positive CCyB rates for countries that, during that period, have implemented a positive CCyB rate to address cyclical systemic risks, such as France, Ireland, Lithuania, Luxembourg, and Slovakia. However, the calibrations suggested by our model are in most cases higher than the actually implemented rates. Taken together, these results suggest that our model performs well in guiding the calibration of the CCyB to address cyclical

between the d-SRI and the Tier 1 capital ratio as follows: $\hat{\theta}^{\tau,h}_{\text{d-sri}} = \hat{\delta}^{h}_{(l),\text{d-sri}} + \hat{\delta}^{h}_{(s),\text{d-sri}}\hat{q}(\tau,h)$ and $\hat{\nu}^{\tau,h}_{\text{d-sri}\times\text{T1R}} = \left(\hat{\beta}^{h}_{(l),\text{d-sri}\times\text{T1R}} + \hat{\beta}^{h}_{(s),\text{d-sri}\times\text{T1R}}\hat{q}(\tau,h)\right) \times \overline{T1R}_{j,t}$.

[16] The 2010 BCBS package of reforms increased the minimum common equity requirement from 2% to 4.5%. In addition, banks were required to hold a capital conservation buffer of 2.5% to withstand future periods of stress, bringing the total common equity requirements to 7%. This reinforced the stronger definition of capital and the higher capital requirements for trading, derivative, and securitisation activities.

systemic risk.

6.2 Calibration of the positive neutral CCyB

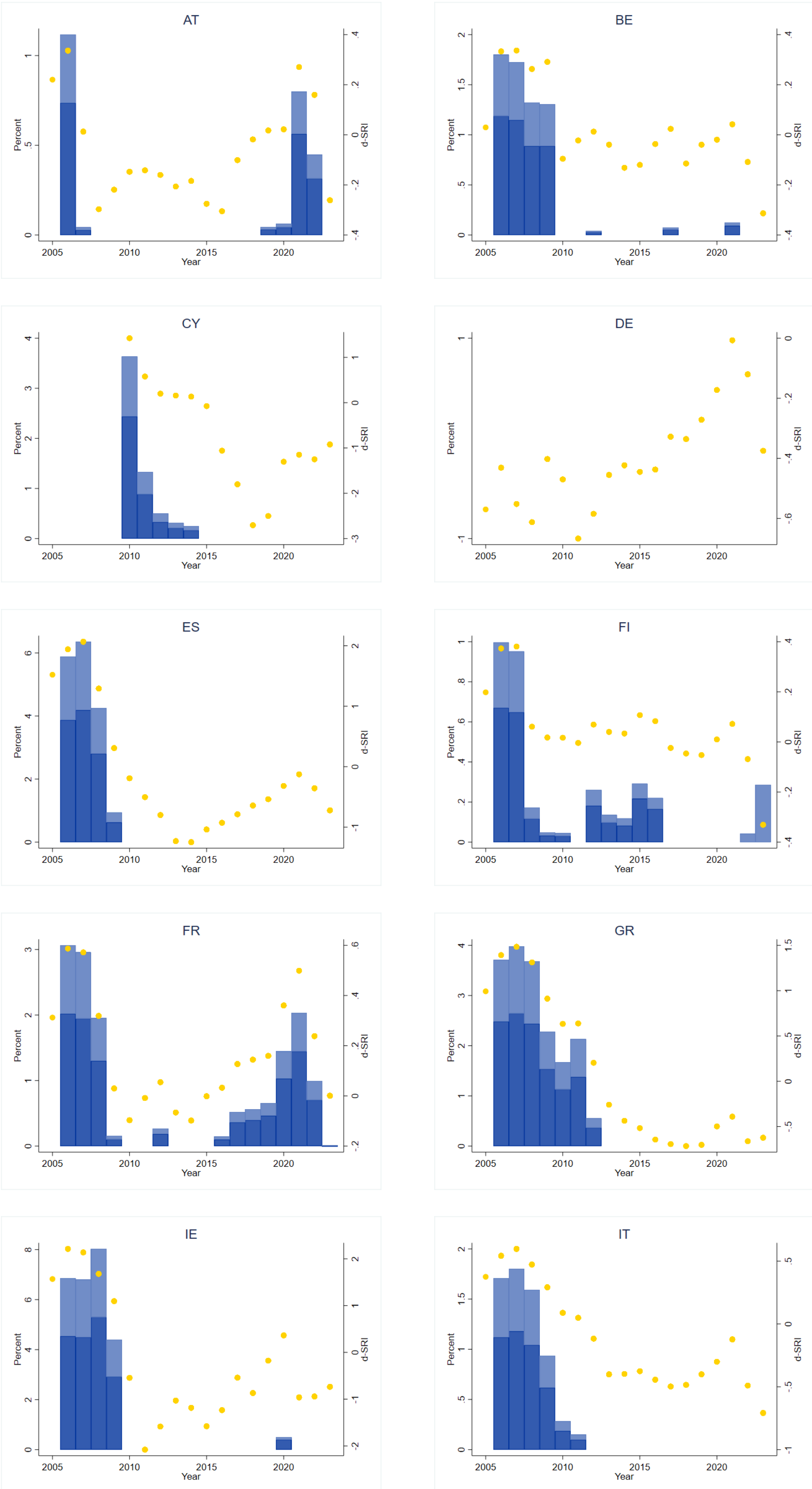
In this subsection, we propose an approach for calibrating the PN CCyB rate. The first step is to determine a target rate for the PN CCyB, which reflects the desired degree of resilience in the banking system in a "neutral risk environment". The second step consists of defining the rules for building up, maintaining, and releasing this PN CCyB rate.

6.2.1 Calibration of the target positive neutral rate

To understand the rationale for our proposed calibration approach, it is worth recalling that one of the objectives of using the CCyB in a positive neutral way by national authorities is to build up the buffer early in the cycle, to ensure that the banking sector has releasable buffers available also in the early phases of the financial cycle. Such releasable buffers may be used to cover losses stemming from adverse shocks that may happen at any phase of the cycle and/or to account for the uncertainty in the measurement of cyclical systemic risks, which may lead to an under-calibration of the CCyB. When calibrating prudential requirements, macroprudential authorities consider other buffers or requirements already applicable, in order to avoid overlaps (ECB and ESRB, 2025). In our approach, we strive to eliminate potential overlaps in two ways. First, we include in the model other variables which are used to calibrate other micro or macroprudential requirements. While the d-SRI is the relevant variable to guide the calibration of the CCyB at the peak of the cycle, bank-specific characteristics are relevant for the calibration of microprudential requirements such as Pillar I or Pillar 2. Second, we calibrate the target rate for the PN CCyB by targeting realisations of bank profitability laying below the median of the conditional distribution, but we avoid the extreme tails. Extremely adverse losses would overlap with those associated with highly adverse macroeconomic scenarios used to calibrate Pillar 2 guidance requirements. In addition, selecting extreme percentiles can deliver less precise estimates due to higher data sparsity typically found in the tails of the distribution (as discussed in section 5). Hence, we focus on the 25th and 10th percentiles of the conditional profitability distribution. For illustration purposes, we also report the target rate estimated at the median. In addition, we focus on the one-year ahead conditional distribution of profitability to account for the 12-month implementation lag of the CCyB imposed by the applicable regulation.[17]

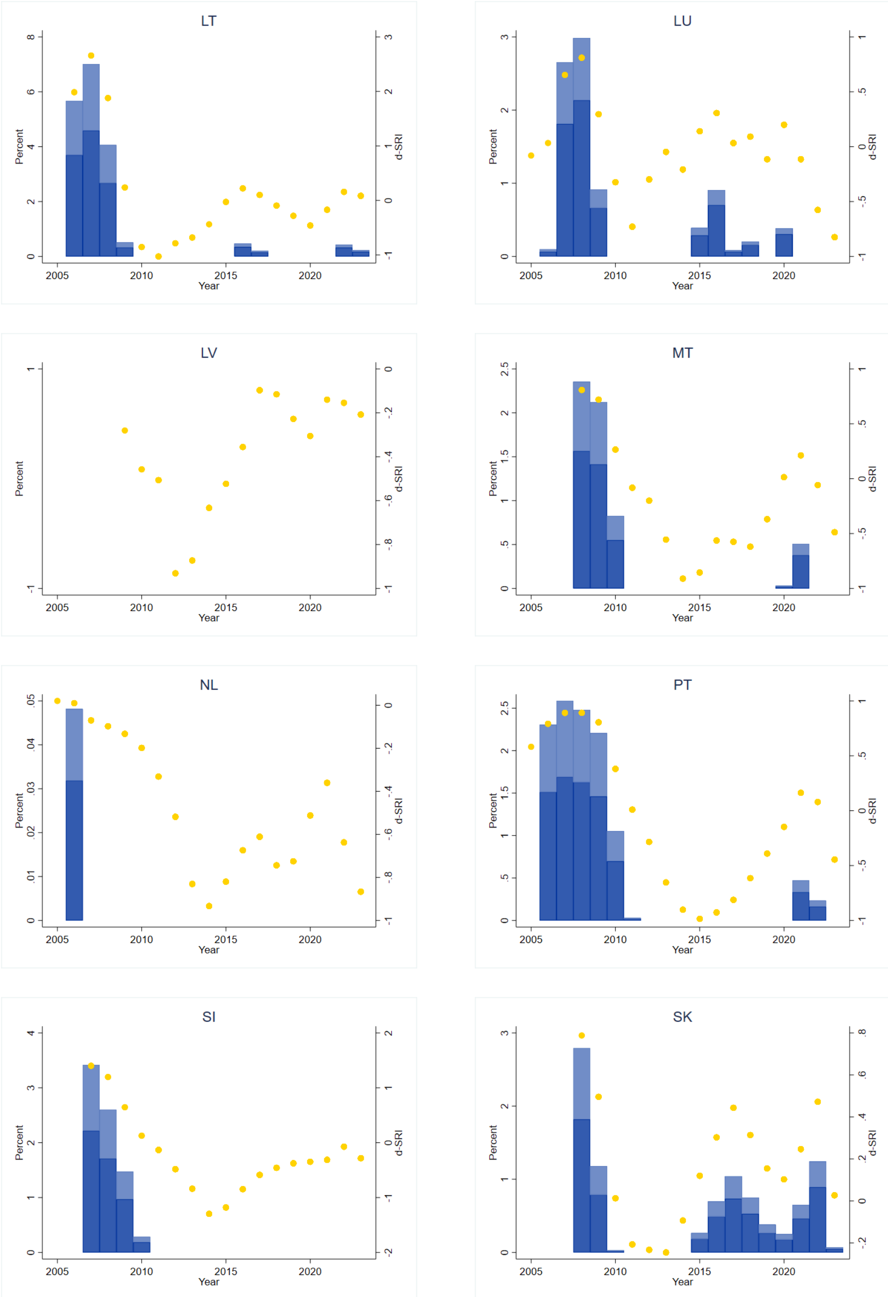
[17] According to the European banking regulation, any macroprudential authority, which intends to activate or replenish the CCyB, has to allow for a period of 12 months for the implementation of the measure, with the goal of providing the banking sector sufficient time to adjust their balance sheets to the new requirement without creating economic costs.

Figure 6: CCyB rates needed to cover losses from cyclical systemic risk under different policymakers preferences



Notes: The light blue part of each bar shows the buffer rates needed to cover losses at the 10th percentile of the conditional profitability distribution, while the dark blue part shows the buffer rates needed to cover losses at the median. These buffer rates are estimated from equation (2). The yellow dots represent the cyclical systemic risk indicator (rhs axis).

Figure 7: CCyB rates needed to cover losses from cyclical systemic risk under different policymakers preferences (cont.)



Notes: The light blue part of each bar shows the buffer rates needed to cover losses at the 10th percentile of the conditional profitability distribution, while the dark blue part shows the buffer rates needed to cover losses at the median. These buffer rates are estimated from equation (2). The yellow dots represent the cyclical systemic risk indicator (rhs axis).

To calibrate the target PN CCyB rate, we focus on the component of bank profitability at the selected percentiles of the conditional distribution related to unobserved and time-varying factors. This component is captured by the time-fixed effects. Concretely, we quantify the negative impact of unobservable factors on profitability, in a given year and for a given quantile, using the estimates of the statistically significant and non-positive coefficients associated with the time-fixed effects included in the model. These estimates represent the negative changes of ROA that, in each year, are not explained by other bank-level or macro-financial factors relevant for the calibration of other capital requirements.[18] A desirable feature of the time-fixed effects coefficients is that they are invariant across banks (as opposed to bank-fixed effects), consistent with the intention of capturing unobserved factors that simultaneously affect all banks in each time period and are not otherwise accounted for in the model. As such, the information contained in these coefficients is useful to calibrate a capital buffer which i) is macroprudential in nature, and hence set to address systemic as opposed to bank idiosyncratic risks, and ii) aims to increase banking sector resilience by covering losses stemming from adverse shocks that may occur even in the early phases of the financial cycle.

The coefficients associated with the time-fixed effects show the effect of each time period (year) on bank profitability relative to a given reference period. This is due to the fact that time-fixed effects are included in the model with a dummy variable for each time period, and, to avoid perfect collinearity, one time dummy is dropped and set as the reference year. This technical issue implies the choice of a reference year, which has important implications for the interpretation of our results. We select our reference year on the basis of a number of considerations. First, we choose a reference year that represents a stable period for the banks in our sample to ensure that the deviations captured by the other time dummies are meaningful. Second, we avoid years characterised by the occurrence of extreme events, such as financial crises and major regulatory changes, since our analysis does not specifically focuses on uncovering the impact of these events. Finally, we aim for our reference year to have a reliable and as much as possible complete data coverage. To this end, we rely on the ECB Dataset on financial crises in European countries by Lo Duca et al. (2017) and select the years in which nearly all countries in our sample are indicated as being out of systemic crises periods. These years are 2018 and 2019.[19] Since 2019 cannot be used as the reference year, due to the fact that we use the one-year ahead ROA projections, we select 2018 as the reference year for our baseline results. This year also shows a coverage of total assets of more than 80% (see Figure (2b)).

[18] For convenience, we will refer to negative changes in ROA as "losses".

[19] In both cases, only Greece is still considered being in a systemic crisis.

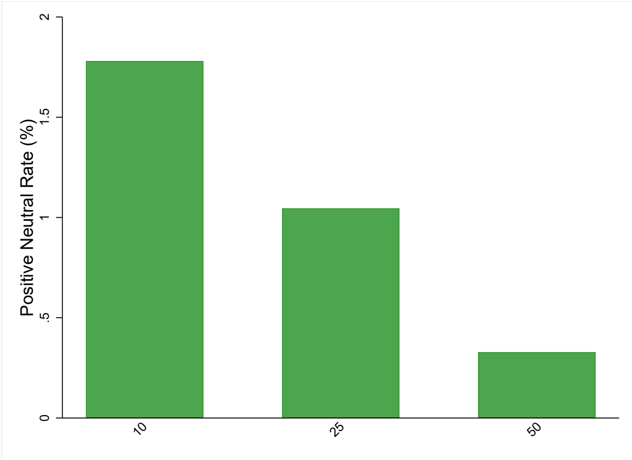
We derive the target positive neutral CCyB rate for the euro area using the following rule:

$$\text{PN Target Rate}(1,\tau) = \frac{1}{T^*}\sum_{t=1}^{T^*} max\left\{0, \frac{-\lambda_t^{\tau,1}}{\overline{rw}_t}\right\} \tag{3}$$

where $\lambda_t^{\tau,1}$ is the marginal impact of the year-specific unobserved factors on the τ-quantile of the conditional distribution of bank profitability one-year ahead, T^* is the number of time periods in which time-fixed effects are non-negative and statistically significant at least at the 10% significance level, and $\overline{rw}_t$ is the cross-sectional average of banks' risk weights in year t. As mentioned above, we compute a range of target rates for the PN CCyB considering different percentiles of the conditional profitability distribution, specifically the 50th, 25th, and 10th percentiles. The target rate obtained for each percentile delivers the buffer rate required to cover the corresponding unexplained negative changes in profitability. These rates can, therefore, be interpreted as reflecting three different preferences of the policymaker regarding the severity of losses they aim to target, ranging from moderate to more severe (albeit not extreme) losses.

Figure (8) displays the target rates for the PN CCyB for the euro area banking system as a whole for the three selected percentiles. As before, the share of unexplained dynamics of bank losses, and hence the required buffer to cover them, is larger if the policymaker targets the lower percentiles of the conditional profitability distribution, consistent with a lower risk appetite. In particular, a target PN CCyB rate of 1.8% would cover up to the 10th percentile of ROA realisations. Alternatively, buffers set to 1.1% and 0.3% would cover the 25th and the 50th percentiles of one-year ahead losses, respectively. All derived buffers are below the 2.5% threshold set in the regulation for mandatory CCyB reciprocity, providing policymakers with flexibility to further increase the buffer to address emerging cyclical systemic risk, if needed. As a robustness exercise, we assess our choice of reference year by re-estimating the model using each available year as the reference year. The corresponding results, presented in Appendix (C.4), show that the target rates derived from the baseline approach represent a lower bound. As a second robustness exercise, we calibrate the PN CCyB rate by including the non-negative time-fixed effects coefficients, regardless of their statistical significance. The resulting rates for the 50th, 25th, and 10th percentiles are 0.2%, 0.7%, and 1.3%, respectively.

Figure 8: Target rates for the positive neutral CCyB for the euro area



Notes: Target rates for the positive neutral CCyB based on estimated models for the 50th, 25th, and 10th percentiles of the conditional distribution of profitability one-year ahead.

6.2.2 Rules to inform the setting of the positive neutral CCyB rate

The next step to obtain a time-varying PN CCyB rate over the sample period is to define rules for the build-up speed of the positive neutral rate towards the selected target, as well as the conditions for its activation, maintenance, and release. To this end, we propose three illustrative sets of conditions that provide straightforward rules for the build-up, maintenance, and release of the positive neutral rate, drawing from the literature and practical experience (ECB and ESRB, 2025). The scope of this exercise is merely illustrative, while we leave a more thorough discussion and analysis of the derivation of these rules to future research. We largely base our rules on the prevailing conditions of the banking system and financial markets within a given country and year. Both empirical and theoretical literature have shown that these conditions play a key role in determining the economic costs associated with raising capital requirements. Specifically, for each possible scenario (build-up, maintenance, and release) we define three conditions, as outlined in Table 2. These conditions have been designed to minimise the economic costs associated with changing capital buffers in each phase of the financial cycle.

First, favorable banking sector conditions, in particular in the form of high bank profits and internal capital generation capacity, minimise the adverse effects associated with increasing capital requirements on lending and GDP (Lang and Menno, 2023). The simple idea underlying this is that more profitable banks can increase equity through retained earnings, reducing the likelihood that higher requirements will affect the maximum loan quantity that banks are able to hold on their balance sheets, as shown by Lang and Menno (2023). In line with the latter, we define the speed of build-up as a simple linear function of the banking sector profits, in a given country and year. We set the build-up speed of the positive neutral CCyB in each year equal to 25% of a country's bank profitability, $\pi_{j,t}$.[20] Second, widespread high profitability (with a low associated standard deviation) across banks is also considered a condition to activate the PN CCyB. This guarantees that the PN CCyB is built up during periods of relative strength in the banking sector. Finally, episodes of financial stress tend to precede macroeconomic downturns and deleveraging episodes. Hence, a low level of financial market distress, as measured by the Composite Indicator of Systemic Stress (CISS) proposed by Holló et al. (2012), is considered a desirable condition to increase the buffer rate. In contrast, episodes of high financial distress could be used to guide the full release of the buffer. While our focus is on full buffer releases, policymakers may opt for a gradual release, particularly during periods when losses materialize slowly or risks gradually recede.

Table 2: Conditions for build-up, maintenance, and release of the positive neutral CCyB

	Condition 1	Condition 2	Condition 3
Build-up			
	High bank profitability	Low dispersion	Low financial distress
	$\text{ROA}_{j,t} > \text{Median}_{ROA_j}$	$\sigma_{ROA_{j,t}} < \text{Median}_{\sigma_{ROA_j}}$	$\text{CISS}_t < \text{Median}_{CISS} + 2\sigma_{CISS}$
Maintenance			
	Medium bank profitability	Low dispersion	Low financial distress
	$0 < \text{ROA}_{j,t} < \text{Median}_{ROA_j}$	$\sigma_{ROA_{j,t}} < \text{Median}_{\sigma_{ROA_j}}$	$\text{CISS}_t < \text{Median}_{CISS} + 2\sigma_{CISS}$
Release			
	Negative ROA		High financial distress
	$\text{ROA}_{j,t} < 0$		$\text{CISS}_t > \text{Median}_{CISS} + 2\sigma_{CISS}$

Notes: σ denotes the standard deviation of the variable indicated in the subscript and CISS stands for composite indicator of systemic stress (Holló et al., 2012).

A mechanical application of these simple rules delivers PN CCyB rates that vary across countries and over time. This, combined with the rule for calibrating the CCyB to address emerging cyclical systemic risk, allows us to calibrate the CCyB through the financial cycle.

6.3 Calibration of the overall CCyB through the cycle

In this section, we combine the results in the previous two sections and consider the calibration of the overall CCyB rate. Specifically, we present the potential counterfactual values that the CCyB rate would have assumed for each country and year in our sample, if the PN CCyB rates suggested by our model for the euro area had been in place. The overall CCyB rate is determined by re-calculating the CCyB rate designed to address cyclical systemic risk (see Section 6.1), while accounting for the additional capital in the system due

[20] This is an arbitrary choice that accounts for the fact that approximately 50% of bank profits in 2022 was distributed as dividends and buybacks (44% in 2017-2018), although with considerable differences across banks, particularly regarding share buybacks.

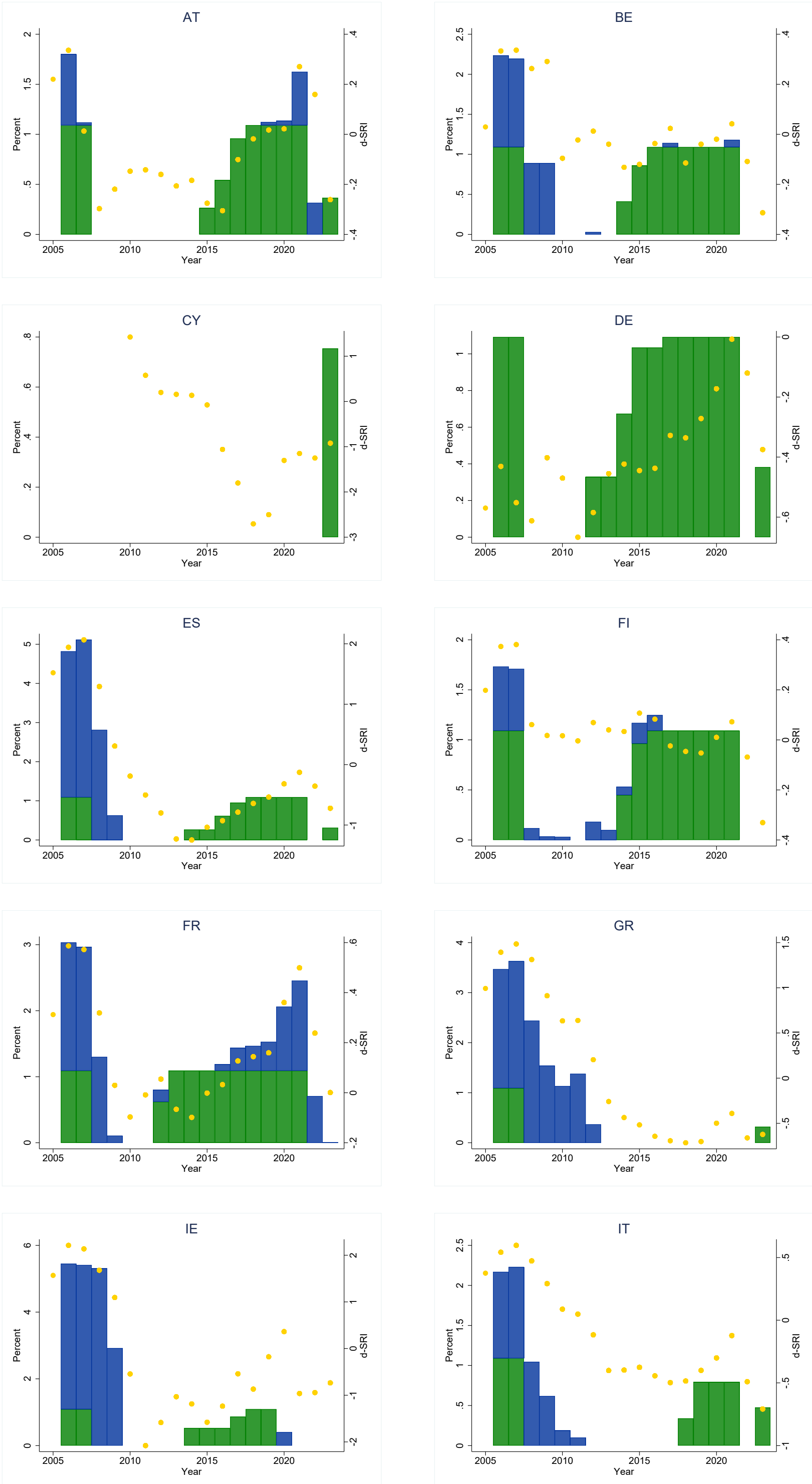
to the introduction of the PN CCyB.[21] We use 1.1% as the target PN CCyB rate, namely the buffer rate required to cover the 25th percentile of losses one-year ahead (see Section 6.2). We select this target rate that reflects the intention to cover moderate losses to balance two key considerations. First, it reflects a preference for focusing on ROA realizations below the median of the conditional distribution, providing insights into relatively weaker profitability outcomes across banks and over time. Additionally, analyzing off-median percentiles is particularly interesting, as the calibration of the PN CCyB relies on the estimated coefficients of the time-fixed effects. At these percentiles, the role of unobservable factors, after controlling for standard macroeconomic and bank-level characteristics, is likely more relevant than at the median. Second, we intentionally avoid focusing on the extreme tails of the distribution for two reasons. This choice minimises potential overlap with Pillar 2 requirements, which are designed to cover losses under extremely adverse scenarios typically represented by the left tail of the distribution, and it also preserves the precision of our estimates. To calibrate the CCyB to address emerging cyclical systemic risks, we instead use the buffer rate required to cover the 50th percentile of losses associated with cyclical systemic risks over a three- to five-year ahead horizon as presented in equation 2.

Figures (9) and (10) show the results for the overall calibration of the CCyB for a set of euro area countries between 2006 and 2023 together with the indicator of cyclical systemic risk. The results are disaggregated into two components: the PN CCyB rate (green part of the bars) and the CCyB rate targeting cyclical systemic risk (blue part of the bars). First, the results show that, as in Section (6.1), our model delivers calibrations of the overall CCyB rate in the expansionary phases of the financial cycle (i.e. when cyclical systemic risks are building up), consistent with the evolution of domestic cyclical systemic risks in the countries considered. Second, we find that the adoption of a positive neutral approach to the setting of the CCyB allows for an earlier and more gradual build-up of the buffer. A more gradual build-up of the buffer is associated with lower costs to the banking sector and the economy, as it is less burdensome for banks to adjust to increased capital requirements in smaller steps. Furthermore, the earlier build-up of the buffer implied by a PN CCyB approach delivers positive buffer rates also in periods where cyclical systemic risks were not building up. Importantly, the results show that adopting a PN CCyB approach does not lead to higher CCyB requirements at the peak of the cycle, as the maximum CCyB rates achieved when cyclical systemic risks are at their peak are not affected by the presence of a PN CCyB rate. Third, our simple build-up rule suggests a gradual build-up of the positive neutral rate starting in the aftermath of the Sovereign Debt Crisis. The speed of the build-up of the PN CCyB towards the target rate is country-specific, and set according to the profitability and financial conditions prevailing in the banking sector. Importantly, such a strategy would have implied that most euro area countries, with the exception of

[21] This consists of adding the PN CCyB rate, as computed in 6.2, to the country-level average of Tier 1 capital ratio.

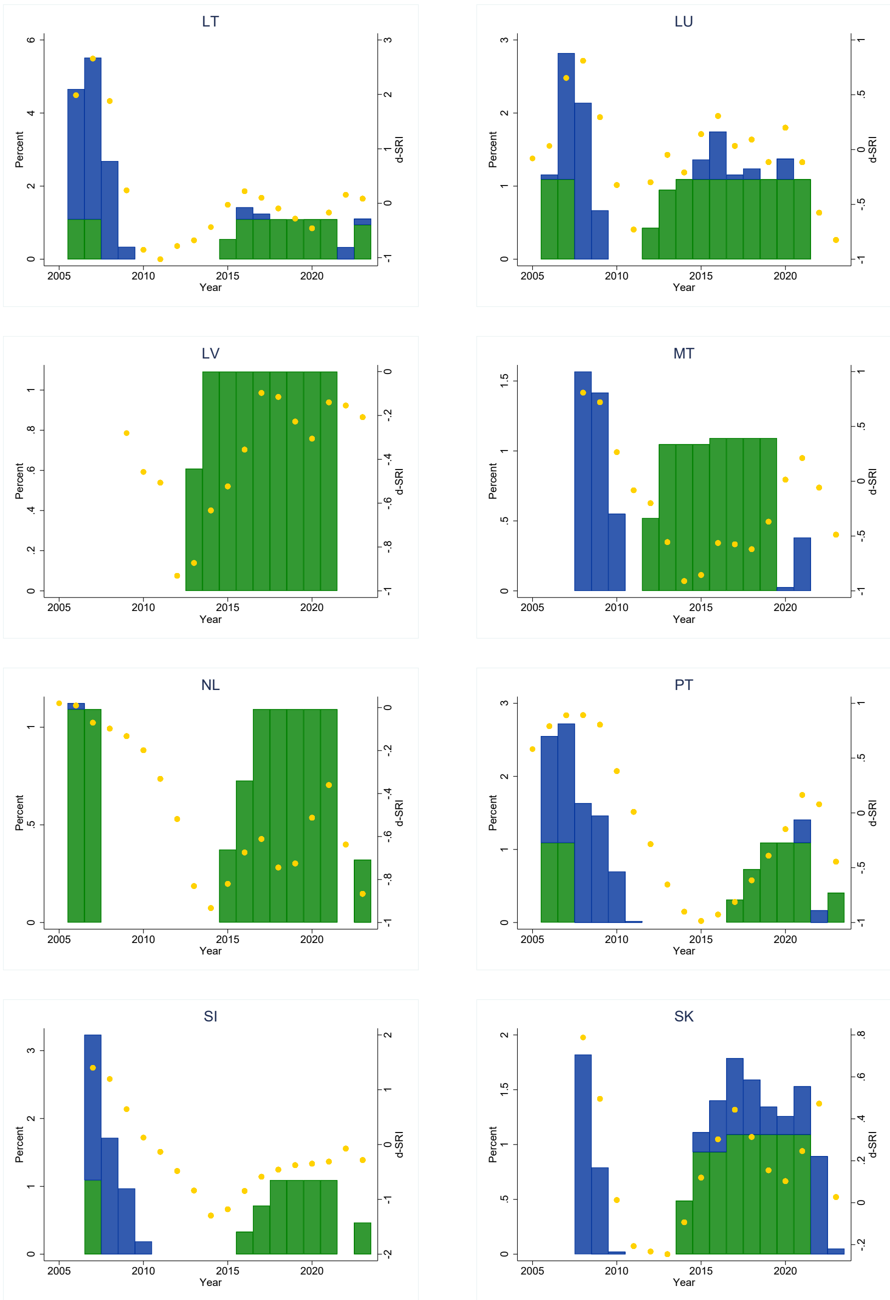
Cyprus and Greece, would have had a positive CCyB in place at the onset of the COVID-19 pandemic, which could have been released to provide relief to the banking sector and support credit supply. Overall, our calibration approach suggests higher average calibrated CCyB rates over the sample than those observed, as it accounts for losses arising from both unobserved factors and domestic cyclical systemic risks.

Figure 9: Overall CCyB rates by country over time



Notes: The green part represents the PN CCyB considering a target rate of 1.1%, while the blue part of the bars corresponds to the CCyB rate targeting cyclical systemic risk (both in lhs axis). These latter rates would be the rates needed to cover losses at the 50th percentile of the conditional distribution of one-year ahead profitability, after accounting for the resilience created by the PN CCyB rate. The yellow dots stand for the cyclical systemic risk indicator (rhs axis).

Figure 10: Overall CCyB rates by country over time (cont.)



Notes: The green part represents the PN CCyB considering a target rate of 1.1%, while the blue part of the bars corresponds to the CCyB rate targeting cyclical systemic risk (both in lhs axis). These latter rates would be the rates needed to cover losses at the 50th percentile of the conditional distribution of one-year ahead profitability, after accounting for the resilience created by the PN CCyB rate. The yellow dots stand for the cyclical systemic risk indicator (rhs axis).

7 Conclusion

We study the impact of cyclical systemic risks on banks' profitability in the euro area by incorporating a quantile regression model within a local projection framework, with the ultimate goal to contribute to the literature on the calibration of macroprudential capital buffers. We do so by providing a framework to calibrate the CCyB through the financial cycle, considering the adoption of a positive neutral CCyB. The latter refers to a newly emerged way of setting the CCyB even in the absence of cyclical systemic risk, which is currently at the center of the macroprudential policy debate. Despite the increased adoption of such an approach by several macroprudential authorities in the banking union, quantitative methods to inform its calibration are still under development. This paper aims to provide a contribution to this emerging policy aspect, while at the same time contributing to the literature on the impact of cyclical systemic risks on banking sector profitability in the euro area.

We estimate a panel quantile regression model with local projections using data on 318 euro area banks from 2005 to 2019 to uncover the impact of a change in the cyclical systemic risk on the conditional distribution of banks' return on assets. In line with the existing literature, we find that, regardless of the percentile of the distribution considered, an increase in the cyclical systemic risk indicator is associated with a decline in bank profitability. However, in contrast with the existing literature, we find that an increase in cyclical systemic risk does not lead to a significant increase in the left-side skewness of the conditional distribution of bank profitability. We argue that this result stems from including in the model unobservable bank-fixed effects and an interaction term between the cyclical systemic risk and bank capitalisation.

We use this model to propose a framework for the calibration of the CCyB through the financial cycle, including the positive neutral CCyB rate. Specifically, we first use the marginal impact of the cyclical systemic risk indicator on bank profitability to inform the calibration of the CCyB to address risks stemming from imbalances in the cyclical domestic dynamics. Then, we propose an approach to calibrate a target rate for the PN CCyB for the euro area as a whole, which we then use at the country level. To calibrate the target PN CCyB rate, we focus on the losses at various percentiles of the profitability distribution that are unexplained by the information included in the model. We assume that the latter information aims to capture the bank-level and country-level characteristics that inform the calibration of other existing micro- and macro-prudential capital instruments. We quantify the impact of unobserved factors on historical losses for a given year and quantile using the time fixed effects coefficients from our model. These coefficients represent the change in a specific percentile of the profitability distribution in each year after controlling for the other factors. Since these coefficients are invariant across banks, they effectively capture period-specific unobserved factors affecting all banks simultaneously, in line with the main objective of the PN CCyB adopted in various jurisdictions. The different percentiles considered reflect different policymakers' preferences regarding the level of losses they aim to cover with the PN CCyB. Finally, we combine the two approaches to obtain an overall CCyB rate that varies throughout the financial cycle and across countries by setting out simple rules to guide the build-up, maintenance, and release of the PN CCyB as well as determine the pace of its build-up or release over time.

The advantages of this methodology are that it is intuitive and flexible, as it allows us to account for different preferences of the policymaker in terms of the severity of losses covered by the PN CCyB, as well as country-specific conditions to determine the timing of activation and build-up speed. Furthermore, it allows us to calibrate the CCyB rate in different phases of the financial cycle within the same modelling framework. The results show that our model performs well in guiding the calibration of the CCyB to address cyclical systemic risks in a scenario without a PN CCyB. The calibrated CCyB rates are consistent with the evolution of domestic cyclical systemic risks in the countries considered. On one hand, our model suggests at most low calibrated CCyB rates in the years before the COVID-19 pandemic, which is consistent with the limited evidence of cyclical systemic risks during that period. On the other hand, the model suggests positive CCyB rates for countries that, during that period, have decided to start accumulating the CCyB to address cyclical systemic risks. However, in most cases, the calibrations suggested by our model are higher than the rates that were actually implemented. We find that PN CCyB rates are below the 2.5% regulatory cap and range from 1.1% to 1.8%, depending on the policymaker's preferences regarding the severity of losses it aims to cover. This means that policymakers retain the flexibility to increase the CCyB further if needed to address emerging cyclical systemic risk, even when adopting a CCyB framework with a PN rate. The results for the overall calibration of the CCyB rate over the financial cycle (that is including the PN CCyB rate) show that the proposed simple rules for the build-up, maintenance, and release of the PN CCyB lead to an earlier and more gradual build-up of the buffer. Importantly, however, the presence of a PN CCyB does not lead to higher CCyB requirements at the peak of the cycle. The maximum CCyB rates achieved when cyclical systemic risks are at their peak are not affected by the PN CCyB rate. Furthermore, if euro area countries had adopted a PN CCyB rate, most would have had a positive CCyB rate in place at the onset of the COVID-19 pandemic. This could have been released to provide relief to the banking sector and support credit supply. Finally, the overall calibration of the CCyB suggests higher CCyB rates than those observed, as it accounts for losses arising from factors not necessarily related to domestic cyclical imbalances and not covered by other capital buffers, in addition to those linked to the accumulation of cyclical systemic risk.

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Appendix

A Data Sources

Table 3: Data Sources

Data Series	Source
Bank-level variables	
Pre-tax return on assets, (%)	SNL Financials
Net Interest Margin (%)	SNL Financials
Cost-to-Income (%)	SNL Financials
Impairments / Total assets, (%)	SNL Financials
Net Loans/ Assets (%)	SNL Financials
Risk-weighted Assets/ Assets (%)	SNL Financials
Tangible Equity/ Tangible Assets (%)	SNL Financials
Tier 1 Ratio (%)	SNL Financials
Log of Assets	SNL Financials
Country-level variables	
GDP growth (%)	ECB Data Portal
d-SRI	Internal Calculations
Yield Spread (%)	Bloomberg and Datastream

B Descriptive statistics

Table 4: Summary statistics of model variables

	Mean	Std.	p5	p10	p25	p50	p75	Min.	Max.
Bank-level variables									
Pre-tax return on assets (%)	0.42	1.12	-1.14	-0.21	0.19	0.48	0.86	-24.4	5.23
Net Interest Margin (%)	1.56	0.78	0.38	0.59	1.03	1.49	2.02	-0.086	5.49
Cost-to-Income (%)	62.90	18.51	35.42	44.45	52.81	62.30	71.95	3.70	178.5
Impairments / Total assets, (%)	0.43	0.77	-0.08	-0.01	0.05	0.20	0.53	-1.72	7.65
Net Loans/ Assets (%)	58.93	19.89	15.70	29.95	48.70	63.55	73.43	0.11	98.8
Risk-weighted Assets/ Assets (%)	48.68	19.07	17.62	23.99	34.26	48.42	62.55	1.82	109.7
Tangible Equity/ Tangible Assets (%)	7.09	3.82	2.29	2.98	4.59	6.31	8.98	-2.28	29.7
Tier 1 Ratio (%)	14.08	6.25	6.65	7.66	9.95	13.11	16.61	-3.68	53.3
Log of Assets	3.31	1.63	0.82	1.37	2.29	3.07	4.25	-0.97	7.70
Country-level variables									
GDP growth (%)	1.33	2.91	-4.14	-2.67	0.47	1.51	2.59	-16.1	21.8
d-SRI	-0.21	0.59	-1.04	-0.79	-0.49	-0.28	0.04	-2.72	2.66
Yield Spread (%)	1.78	1.90	-0.07	0.12	0.69	1.28	2.41	-0.61	22.9
Observations	2,818								

Table 5: Bank size by bank profitability

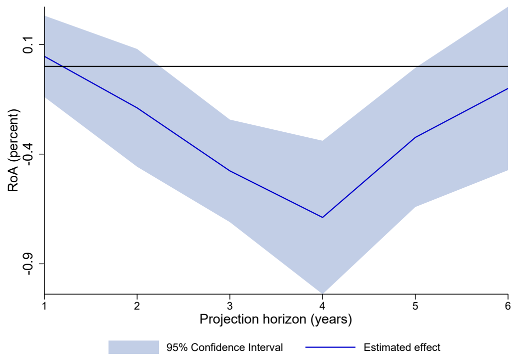
	Total Assets (in billion EUR)				
	Obs.	Mean	Std.	Min.	Max.
ROA > p99	28	14.62	14.34	0.44	73.69
ROA > p95	140	27.59	60.56	0.44	502.20
ROA > p90	281	27.66	52.99	0.44	502.20
ROA > p75	704	54.41	144.74	0.44	1459.27
ROA > p50	1,409	98.89	266.23	0.44	2164.71
ROA < p50	1,409	135.75	306.48	0.37	2202.42
ROA < p25	704	121.26	264.39	0.37	2202.42
ROA < p10	281	90.41	212.77	0.60	2202.42
ROA < p5	140	60.33	125.90	0.60	859.53
ROA < p1	28	34.04	45.62	1.05	179.91

C Robustness exercises

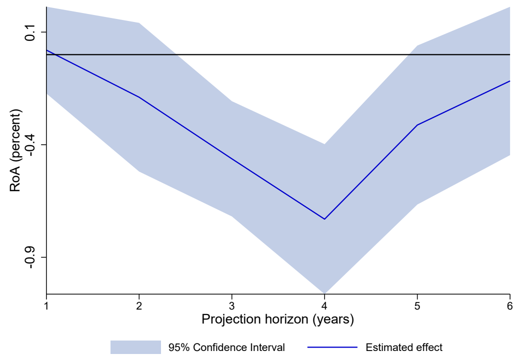
C.1 Results from alternative model specification to address endogeneity

Figure 11: Marginal effect of cyclical systemic risk on selected quantiles of the distribution of future bank profitability

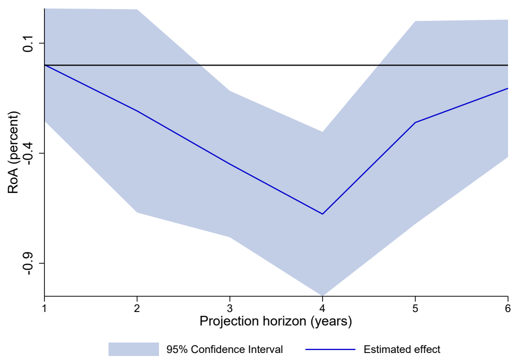
(a) 90th Percentile



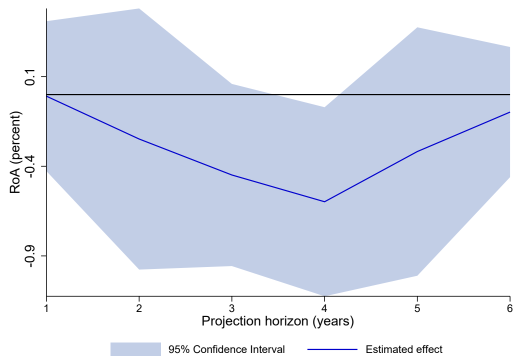
(b) 75th Percentile



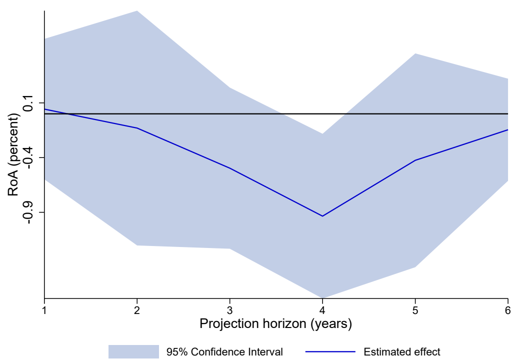
(c) 50th Percentile



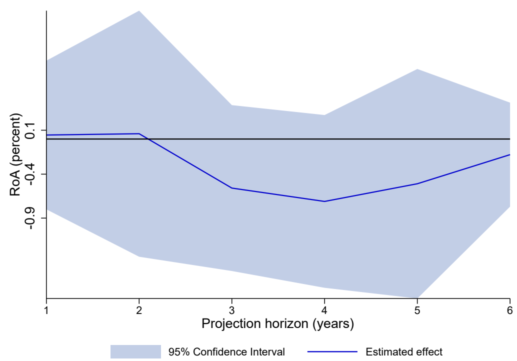
(d) 25th Percentile



(e) 10th Percentile



(f) 5th Percentile



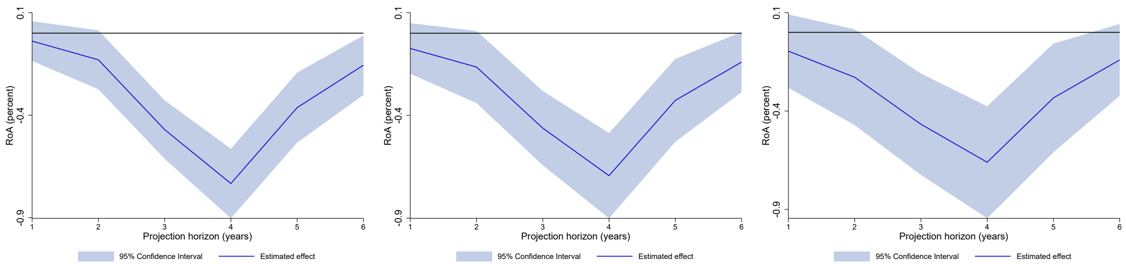
Notes: The figure shows the marginal effect of cyclical systemic risk evaluated at the pooled average of Tier 1 capital ratio. The confidence intervals are set at the 95% confidence level, with bootstrapped standard errors clustered at the bank level.

C.2 Results from considering alternative estimation samples

We test the robustness of the results to our chosen estimation sample by re-estimating the impact of cyclical systemic risk on bank profitability and re-calibrating the PN CCyB rates using the following alternative samples: 1) current sample extended to include three non-EA countries, namely Denmark, the UK, and Sweden; 2) sample with only large banks defined as those with total assets above sample median; and 3) sample with only small banks defined as those with total assets below sample median. The marginal effects of cyclical systemic risk on bank profitability over different projection horizons are shown in Figures 12 to 14, respectively, for three selected quantiles. The estimated target rates for the PN CCyB are shown in Table 6. Across the various estimation samples considered, the results remain qualitatively and quantitatively similar to those obtained with the baseline model. The target rates for the PN CCyB span within the range 0.28% and 1.36%, depending on the estimation sample and percentile selected.

Figure 12: Marginal effect of cyclical systemic risk on selected quantiles of the distribution of future bank profitability - sample extended to include non-EA countries

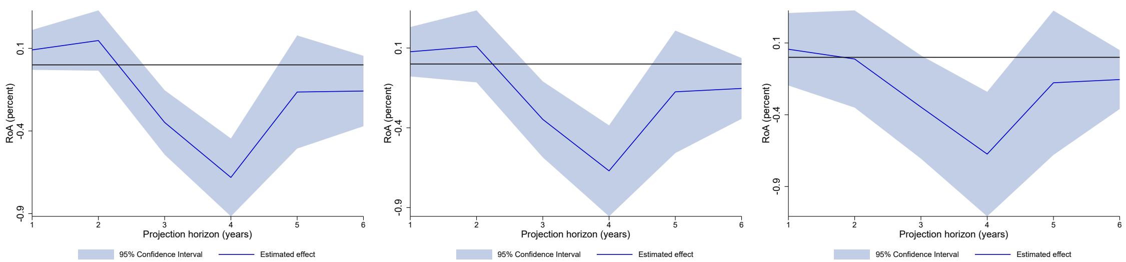
(a) 75th Percentile (b) 50th Percentile (c) 25th Percentile



Notes: The figure shows the marginal effect of cyclical systemic risk evaluated at the pooled average of Tier 1 capital ratio. The confidence intervals are set at the 95% confidence level, with bootstrapped standard errors clustered at the bank level.

Figure 13: Marginal effect of cyclical systemic risk on selected quantiles of the distribution of future bank profitability - sample with only large banks

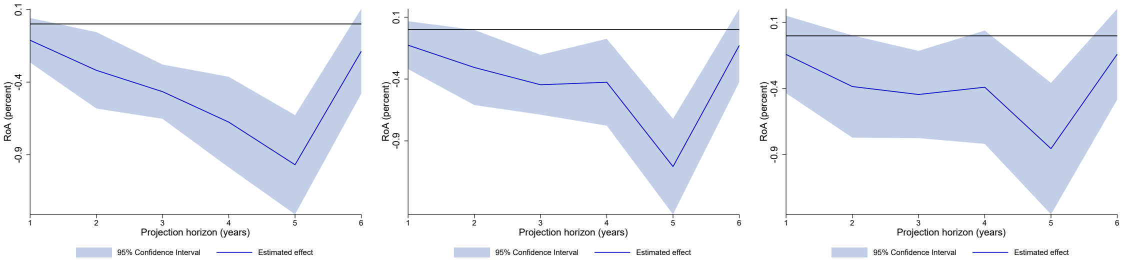
(a) 75th Percentile (b) 50th Percentile (c) 25th Percentile



Notes: The figure shows the marginal effect of cyclical systemic risk evaluated at the pooled average of Tier 1 capital ratio. The confidence intervals are set at the 95% confidence level, with bootstrapped standard errors clustered at the bank level.

Figure 14: Marginal effect of cyclical systemic risk on selected quantiles of the distribution of future bank profitability - sample with only small banks

(a) 75th Percentile (b) 50th Percentile (c) 25th Percentile



Notes: The figure shows the marginal effect of cyclical systemic risk evaluated at the pooled average of Tier 1 capital ratio. The confidence intervals are set at the 95% confidence level, with bootstrapped standard errors clustered at the bank level.

Table 6: Target rates for PN CCyB using alternative estimation samples

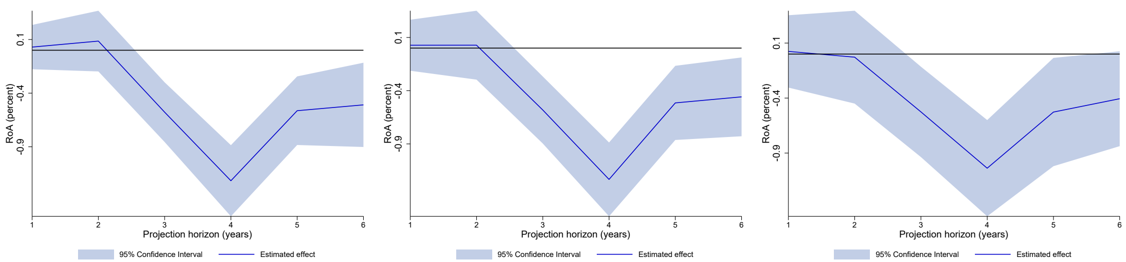
	Including non-EA countries	Large banks	Small banks
p50	0.28	0.49	0.21
p25	0.80	0.80	0.50
p10	1.23	1.36	0.85

C.3 Results from considering a risk-adjusted profitability measure

The estimation period considered in our analysis is a period in which important regulatory changes have been implemented and, consequently, they might have resulted in changing banks' risk and returns. In order to take this into account, we perform a robustness exercise in which we consider as dependent variable in the model a risk-adjusted ROA measure (adjusted for banks' risk-weighted assets, RORWA). The results remain qualitatively similar, both for the impact of cyclical systemic risk on bank profitability (Figure 15) and for the calibration of the target rate of the PN CCyB (1.36%, 1.01%, 0.54% for the 10th, 25th and 50th, respectively).

Figure 15: Marginal effect of cyclical systemic risk on selected quantiles of the distribution of future bank profitability - RORWA

(a) 75th Percentile (b) 50th Percentile (c) 25th Percentile



Notes: The figure shows the marginal effect of cyclical systemic risk evaluated at the pooled average of Tier 1 capital ratio. The confidence intervals are set at the 95% confidence level, with bootstrapped standard errors clustered at the bank level.

C.4 Results from considering different reference years for time fixed effects

To address concerns about the chosen reference year, we re-estimate our model by iterating over all possible years as the reference year for the time-fixed effects. We then calculate the average of the resulting target PN CCyB rates. Averaging across all possible reference years results in target PN CCyB rates of 0.4%, 1.1%, and 1.95% when targeting the 50th, 25th, and 10th percentiles of the conditional distribution of profitability, respectively. In comparison, our baseline model, which sets 2018 as the reference year, produces lower estimates of 0.3%, 1.1%, and 1.8% for the same percentiles. Thus, our baseline estimation of the target PN CCyB rate represents a lower bound given that the results fall slightly below the estimated average target rate derived from considering alternative reference years.

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