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From risk to buffer: calibrating the positive neutral CCyB rate in the euro area

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Abstract

This paper proposes a novel yet intuitive method for the calibration of the CCyB through the cycle in the euro area, including the positive neutral CCyB rate. The paper implements the Risk-to-Buffer framework by Couaillier and Scalone (2024) in both a DSGE and macro time series setting and proposes a calibration of the PN CCyB aimed to reduce the macroeconomic amplification of shocks occurring in an environment where risks are neither subdued nor elevated. The suggested positive neutral CCyB rates for the euro area are consistent across methodologies and robust to alternative specifications, ranging between 1% and 1.5%. The results also highlight the role of different shocks and sources of cyclical systemic risk for the calibration of the CCyB through the cycle. The flexibility of the method regarding the modeling tools, the selection of specific levels of risks as well as the choice of state variables and of exogenous shocks make it particularly suitable to be tailored to national specificities and policymakers' preferences.

Keywords: Financial stability, macroprudential policy, capital requirements, countercyclical capital buffer.

JEL Codes: C32, E51, E58, G01.

Non-Technical Summary

In the aftermath of the COVID-19 pandemic, an increasing number of jurisdictions adopted a more proactive approach to the use of the CCyB and set a positive rate for the buffer in the early phases of the financial cycle, when cyclical systemic risk is not elevated. The implemented target positive neutral (PN) CCyB across euro area countries rates range from 0.5% and 2%, reflecting policymakers' preferences, country-specific characteristics, but also the different calibration methods used. While the experience and international guidance on the calibration of the CCyB to address cyclical systemic risk is well-established, methods to inform the calibration of the target PN CCyB rate are relatively scarce.

Against this background, this paper proposes a novel method to calibrate the PN CCyB rate for the euro area based on the Risk-to-Buffer approach developed by (Couaillier and Scalone (2024)). The method we propose is grounded in state-of-the-art techniques and is technically rigorous, while also being intuitive and easy to implement. The main idea underlying the Risk-to-Buffer approach is that higher risk leads to a greater amplification of adverse shocks, leading to more severe macroeconomic outcomes and higher banking sector losses. Hence, different levels of cyclical systemic risks will correspond to different calibrations of the CCyB rate. The calibration of the CCyB using the Risk-to-Buffer approach involves two steps. First, a macroeconomic model is used to generate risk-dependent scenarios, namely the impact on GDP of set of adverse shocks, obtained for different systemic risk intensities. While the same set of shocks is used in each scenario, higher risk leads to a greater amplification of adverse shocks, leading to more severe macroeconomic outcomes and greater losses for the banking sector. In the second step, the losses associated to the different scenarios are mapped to the capital requirements needed to cover them. Specifically, we specify a mapping rule such that the CCyB is calibrated to absorb losses occurring under adverse scenarios corresponding to different levels of risk. Consistent with the use of the PN CCyB in an environment where cyclical systemic risk are neither subdued nor elevated, the PN CCyB rate is calibrated to address median cyclical systemic risk, while the CCyB rate at the peak of the cycle is calibrated to tackle elevated cyclical systemic risk. A further advantage of the method is that it is sufficiently flexible to allow policymakers to select the preferred reference risk level. We implement the Risk-to-Buffer approach and obtain suggested calibrations for the PN CCyB rate in both a structural (DSGE) and an empirical (macro time series) modeling framework.

We find that, first, taking the median systemic risk level as the relevant reference, the calibrated PN CCyB rates are consistent across the two approaches. Specifically, both the structural and the baseline time series approach (using the ECB's domestic systemic risk indicator as state variable) suggest PN CCyB rates of 1.25% and 1.3% respectively. Overall, considering a broad set of cyclical systemic risk variables to define the risk states, the suggested PN CCyB rates range from 1% to 1.5%. While for the calibration of the PN CCyB rate, we are agnostic about the specific source of shocks and apply all at the same time, the results are robust also across different shocks.

A second interesting finding from the empirical approach relates to the relationship between the degree of nonlinear amplification generated by different shocks or different risk variables in determining the relative importance of the PN CCyB in the overall CCyB calibration. We find that shocks associated to the materialization of domestic financial imbalances such as credit shocks tend to be strongly amplified, warranting a relatively lower importance of the PN CCyB in the overall CCyB calibration and a higher importance of using the CCyB to address emerging cyclical systemic risks. This is consistent with the original objective of the CCyB to increase bank resilience when domestic financial imbalances (notably excessive credit growth) build up. Instead, shocks affecting the real side of the economy (e.g. output and inflation shocks), which are mostly unrelated to the materialization of domestic imbalances but rather result from factors exogenous to the financial cycle, call for a relatively more important role of the PN CCyB in the overall CCyB calibration. This is consistent with one of the objectives of the PN CCyB to increase resilience against shocks that may occur at any phase of the cycle, such as, for example, health emergencies, geopolitical events or natural disasters. Our results are robust to the use of different cyclical systemic risk variables. Third, we find that the relative contribution of the different shocks to the calibration of the PN CCyB is overall stable across state variables.

The results of this paper illustrate the potential usefulness of the proposed methodology to guide the calibration of the CCyB. In particular, the flexibility of the method regarding the specific levels of risks as well as the choice of state variables and exogenous shocks make it particularly suitable to be tailored to national specificities and policymakers' preferences.

1 Introduction

The Countercyclical Capital Buffer (CCyB) was introduced as part of the Basel III framework in 2010, serving as a key macroprudential tool to strengthen the banking sector's resilience and reduce credit procyclicality. The CCyB is intended to be built up during the expansion phase of the financial cycle, when credit is expanding quickly and financial vulnerabilities are rising, and to be released during downturns to help banks absorb losses and maintain credit flow to the economy. However, only a handful of euro area countries had activated the CCyB prior to the COVID-19 pandemic, due to the limited evidence of broad cyclical systemic risks. Hence, when the COVID-19 pandemic hit, national macroprudential authorities had little capital available to be released to provide relief to the banking sector. This experience highlighted the desirability to hold releasable capital buffers, as shocks with potentially disruptive consequences may materialize in any phase of the financial cycle. Therefore, in the aftermath of the COVID-19 pandemic, an increasing number of jurisdictions adopted a more proactive approach to the use of the CCyB and set a positive rate for the buffer in the early phases of the financial cycle, when cyclical systemic risk is not elevated. To date, 20 countries worldwide (Australia, Czech Republic, Denmark, Cyprus, Estonia, Greece, Hong Kong, Hungary, Ireland, Latvia, Lithuania, Netherlands, Norway, Poland, Portugal, Slovenia, South Africa, Spain, Sweden and the United Kingdom) have adopted such a strategy. With the exception of Denmark and Norway, national authorities have set a target rate for the CCyB they aim to have in place in an environment of neither elevated nor subdued cyclical systemic risk, commonly referred to as "positive neutral" CCyB (henceforth, PN CCyB) rate. The implemented target PN CCyB across euro area countries rates range from 0.5% and 2%, reflecting policymakers' preferences, country-specific characteristics, but also the different calibration methods used.[1]

While the experience and international guidance on the calibration of the CCyB to address cyclical systemic risk is well-established (see for example Basel Committee (2010); Detken. et al. (2014); European Systemic Risk Board (2014/1)), methods to inform the calibration of the target PN CCyB rate are relatively scarce (see Section 2). While expert judgment is an important element in driving policy decisions, model-based analyses are also crucial in informing such decisions by providing a structured framework for analyzing complex economic, financial, and systemic dynamics. Rigorous and technically sound models help policymakers assess potential

[1] See Basel Committee (2024) and ECB/ESRB (2025) for an overview of the experience thus far with the implementation of a PN CCyB approach.

outcomes, test different scenarios, and make data-driven decisions, ultimately enhancing the effectiveness of economic policies. Against this background, this paper proposes a novel method to calibrate the PN CCyB rate for the euro area based on the Risk-to-Buffer approach developed by (Couaillier and Scalone (2024)). The method we propose is grounded in state-of-the-art techniques and is technically rigorous, while also being intuitive and easy to implement. The main idea underlying the Risk-to-Buffer approach is that higher risk leads to a greater amplification of adverse shocks, leading to more severe macroeconomic outcomes and higher banking sector losses. Hence different levels of cyclical systemic risks will correspond to different calibrations of the CCyB rate. The calibration of the CCyB using the Risk-to-Buffer approach involves two steps. First, a macroeconomic model is used to generate risk-dependent scenarios, namely the impact on GDP of set of adverse shocks, obtained for different systemic risk intensities. While the same set of shocks is used in each scenario, higher risk leads to a greater amplification of adverse shocks, leading to more severe macroeconomic outcomes and greater losses for the banking sector. In the second step, the losses associated to the different scenarios are mapped to the capital requirements needed to cover them. Specifically, we specify a mapping rule such that the CCyB is calibrated to absorb losses occurring under adverse scenarios corresponding to different levels of risk. Consistent with the use of the PN CCyB in an environment of neither elevated nor subdued cyclical systemic risk, the PN CCyB rate is calibrated to address median cyclical systemic risk, while the CCyB rate at the peak of the cycle is calibrated to tackle elevated cyclical systemic risk. A further advantage of the method is that it is sufficiently flexible to allow policymakers to select the preferred reference risk level. This approach can complement others that emphasize cost-benefit considerations in the calibration of capital buffers, by providing a risk-based calibration grounded in the amplification of macroeconomic shocks under different systemic risk environments.[2]

We implement the Risk-to-Buffer approach to calibrate the PN CCyB rate in both a structural and an empirical modeling framework. In the structural approach (Section 3), the 3D DSGE model by Mendicino et al. (2020) is used to generate the risk-dependent scenarios in response to a set of shocks and, subsequently, to calibrate the CCyB. The 3D model is a micro-founded DSGE model with financial frictions where households, entrepreneurs and banks may default on their liabilities. Banks have to comply with the capital requirements set by the macroprudential authority, requiring banks to hold capital in relation to the size of their loan portfolio. In the

[2]For a cost-benefit analysis using the same DSGE framework, see Herrera et al. (2024)

model, high bank vulnerability (i.e. a higher probability of default) amplifies the propagation of financial shocks, leading to more severe macroeconomic outcomes (i.e. GDP decline). This feature of the model allows to generate scenarios whose severity is related to different risk levels. Increasing capital requirements can partially mitigate negative risk amplifications, by reducing banks excessive leverage and the fraction of banks defaulting. This feature of the model is used to link each risk scenario with the capital requirement (capital requirement mapping). Operationally, we define three risk scenarios by calibrating the bank risk parameter in the model so that bank default probability in the steady state equals observed percentiles of the Expected Default Frequency (EDF) for the Euro Area median bank estimated by Moody's.[3] The choice of which level of risk to cover ultimately reflects the preferences of the policymaker. In this application, we illustrate the methodology using low, medium, and high risk scenarios corresponding to the 5th, 95th, and 90th percentiles of the euro area's historical EDF distribution, respectively, but the framework is flexible and can be adapted to alternative percentiles based on policy objectives. To generate the scenarios, we focus on financial shocks, which produce the most pronounced non-linear effects. We simulate a financial shock leading to a decline in GDP of -1.5% under the median risk and use this shock size throughout the exercise. The PN CCyB rate is then determined so that the resulting required capital is sufficient to reduce the simulated GDP losses under median risk to the level observed in the low-risk case. In addition, the CCyB rate to address heightened risk is determined such that the resulting required capital is sufficient to bring the simulated GDP losses under high risk to the same level observed in the low-risk case.

In the empirical approach (see Section 4) the risk-dependent scenarios are generated using a Multivariate Smooth Transition Local projection model, estimated on a set of macroeconomic and financial variables. Consistent with De Nora et al. (2025), the composite domestic Systemic Risk Indicator (d-SRI) developed by Lang and Forletta (2019) is used as a state variable to describe the state of the economy in the baseline calibration. We identify a set of real and financial structural shocks via structural identification and simulate the model to generate the risk-dependent scenarios. Specifically, all shocks are used to generate the scenarios considered, such that the scenarios used in this approach do not depend on a specific narrative. To map the

[3] The EDF is used to calibrate different degrees of bank fragility. These scenarios are intended to inform the calibration of capital needs across risk environments, not to define a real-time rule for the build-up or release of the buffer. The design of operational policy rules for the dynamic adjustment of the CCyB is outside the scope of this paper and is left for future research.

risk-dependent scenario to capital requirements, we assume that, in the high-risk scenario, the CCyB rate is set at 2.5%.[4] Assuming a linear relationship between GDP and bank losses (and hence with capital requirements)[5], the PN CCyB requirement is computed as the ratio between the average impact on GDP obtained under the median risk scenario and the one obtained under the high risk scenario.[6,7] The empirical approach allows us to test the robustness of the calibration considering different measures of cyclical systemic risk used in the literature, such as debt service ratios (Drehmann and Juselius (2013)), credit to GDP ratios and the Basel credit-to-GDP gap (Drehmann et al. (2011)) as well as the individual indicators included in the composite d-SRI Lang et al. (2019).

Finally, we exploit the flexibility of the empirical approach to perform an alternative exercise, where only non-financial shocks are considered to generate the scenarios. This aims to consider only shocks stemming from extreme real events such as health emergencies as well as natural disasters, wars and shocks arising from climate change, political events or technological disruptions that may happen at any stage of the financial cycle, against which a PN CCyB rate may provide additional resilience.

There are several advantages of using both a structural and an empirical approach. First, the two approaches are complementary, ensuring a more robust calibration of the PN CCyB rate. On the one hand, in the structural approach, both the scenario design and the capital requirement mapping are framed within the same structural macroeconomic model, allowing for a micro-founded and theoretically sound calibration strategy. On the other hand, the empirical approach allows to extract information from actual data, and to consider a larger set of potential risk measures. Second, in the empirical model different shocks can be used to generate risk-

[4] This value serves as a policy-relevant benchmark: it corresponds to the maximum rate subject to mandatory reciprocity under the EU Capital Requirements Directive (CRD IV), and is in line with observed buffer settings in several jurisdictions (e.g. Sweden, Norway, UK) during periods of elevated risk. Moreover, 2.5% is broadly consistent with the structural model results, providing a useful anchor for comparative purposes. Importantly, this choice does not imply a mechanical dependence between the empirical and structural models. Rather, it allows us to maintain comparability of PN CCyB levels across approaches.

[5] The assumption of a linear relationship between GDP losses and capital requirements follows Couaillier and Scalone (2024) and is in line with standard practice in macroprudential stress testing frameworks. While this mapping is a simplification and the underlying relationship may in reality exhibit some non-linearity, it provides a transparent and tractable way to implement the calibration. Exploring more complex, possibly non-linear mappings between macroeconomic dynamics and capital needs is a natural extension for future research.

[6] Similarly to the calibration based on the structural model, the choice of the median risk here is illustrative. The methodology is flexible and allows the calibration of the PN CCyB to be tailored to alternative levels of risk, depending on policymakers' preferences or specific policy objectives.

[7] This approach is alternative to the one presented in the original application in Couaillier and Scalone (2024), where the Risk to Buffer integrates the non-linear macroeconomic model with a Stress test model, linking the macroeconomic scenarios to banks' capital shortfall under stressed conditions.

dependent scenarios. This allows to test the robustness of the CCyB calibration to different shocks and explore how they affect the calibration of the PN CCyB. Finally, the information derived from one approach can be used as input for the calibration exercise performed with the other approach. In our case, we benchmark the capital requirement level corresponding to the high-risk scenario in the empirical approach to that resulting from the structural model approach.[8]

We find that, first, taking the median systemic risk level as the relevant reference, the calibrated PN CCyB rates are consistent across the two approaches. Specifically, both the structural and the baseline time series approach (using the d-SRI as state variable) suggest PN CCyB rates of 1.25% and 1.3% respectively. Overall, considering a broad set of cyclical systemic risk variables to define the risk states, the suggested PN CCyB rates range from 1% to 1.5%. While, for the calibration of the PN CCyB rate, we are agnostic about the specific source of shocks and apply all at the same time, the results are robust across different shocks and also across different state variables. In this regard, a second interesting finding relates to the relationship between the degree of nonlinear amplification generated by different shocks or different risk variables in determining the relative importance of the PN CCyB in the overall CCyB calibration. We find that shocks associated to the materialization of domestic financial imbalances such as credit shocks tend to be strongly amplified, warranting a relatively lower importance of the PN CCyB in the overall CCyB calibration and a higher importance of using the CCyB to address emerging cyclical systemic risks. This is consistent with the original objective of the CCyB to increase bank resilience when domestic financial imbalances (notably excessive credit growth) build up. Instead, shocks affecting the real side of the economy (e.g. output and inflation shocks), which are mostly unrelated to the materialization of domestic imbalances but rather result from factors exogenous to the financial cycle, call for a relatively more important role of the PN CCyB in the overall CCyB calibration. This is consistent with one of the objectives of the PN CCyB to increase resilience against shocks that may occur at any phase of the cycle, such as, for example, health emergencies, geopolitical events or natural disasters. Similar conclusions hold when considering different cyclical systemic risk variables. For example, we find that the Debt Service Ratio results in a greater amplification of shocks on economic activity, leading to a relatively relatively lower importance of the PN CCyB in the overall CCyB calibration

[8]This setting, together with the assumption that the link between the macro dynamics and the capital shortfall is linear, allows to avoid using the Stress test model, used in the original Risk-to-Buffer approach (Couaillier and Scalone (2024)).

and a higher importance of using the CCyB to address emerging cyclical systemic risks. This result suggests that economies characterized by a high debt service burden tend to suffer more from disruptions in the residential real estate sector, calling for a higher CCyB rate to address these vulnerabilities. Conversely, the openness of the economy (current account balance) does not significantly amplify the considered shocks. Hence, rather than requiring the activation of a relatively higher CCyB to address risks related to trade openness, the results suggests that economies with such characteristics would benefit from introducing a PN CCyB approach. Overall, we find that the relative contribution of the different shocks to the calibration of the PN CCyB is overall stable across state variables.

2 Related literature

This paper relates to the literature on the calibration of the CCyB which, thus far, has mostly focused on developing approaches for the calibration of the CCyB in the upswing of the cycle. DSGE model approaches usually calibrate the CCyB by either maximizing social welfare or minimizing an ad hoc credit volatility function (see for example Clerc et al. (2015)). These models have also been used to derive optimal calibration rules, exploring different indicators to guide the build-up of the CCyB. 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. Herrera et al. (2025) suggest that optimal response of the CCyB depends on the initial level of capitalization. Bologna and Galardo (2024) propose a calibration based on the evolution of risk indicators. Mendicino et al. (2020) show that capital requirements can offset the negative amplification effects related to higher risks. Other papers use stress test approaches to simulate adverse scenarios and compute the corresponding capital shortfall, which is then used to calibrate the CCyB rate (Bennani et al. (2017); Budnik et al. (2019); Couaillier and Scalone (2024); Dees et al. (2017); Van Oordt (2023)). Finally, empirical approaches using panel, 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); Passinhas and Pereira (2023)).

The literature on the calibration of the PN CCyB rate is still scarce, with methodologies having been developed mostly by the national authorities having introduced a framework for its setting (see Basel Committee (2024) and Appendix B in ECB/ESRB (2025)). These include, for instance, analyses of historical losses, stress test models, assessments of the impact of buffer releases during the pandemic and expert judgment. In Ireland, the calibration of the 1.5% target rate for the PN CCyB rate is informed by a macroprudential stress testing framework, used to simulate an adverse but not overly severe scenario, consistent with an environment of neither elevated nor subdued risk (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 used to construct 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 sets the 1% target rate for the CCyB in normal times based on historical losses incurred by the banking sector during average economic downturns (Lietuvos Bankas, 2017). In the United Kingdom, the calibration of the PN CCyB in the United Kingdom is based on a series of different approaches: stress tests, historical losses and academic literature (Bank of England, 2023). In the Netherlands, set at 2% target PN CCyB rate is primarily calibrated to be proportional to the peak accumulated losses of Dutch banks in previous crises (De Haan and Kakes (2020)). Recent study proposed approaches for the calibration of the PN CCyB rate for the euro area. De Nora et al. (2025) rely on a quantile panel regression model with local projections using data on 318 euro area banks from 2005 to 2019 to calibrate the target PN CCyB rate. The latter aims to cover bank losses arising from adverse developments that are not linked to the materialisation of cyclical systemic risks, and/or may be related to unidentified risks. The CCyB rate in the upturn of the cycle, when systemic risk is elevated, is calibrated to cover bank losses due to cyclical systemic risks. Their approach suggests PN CCyB rates ranging from 1.1% to 1.8%, depending on the policymaker's preferences regarding the severity of losses it aims to cover. Finally, Muñoz and Smets (2025) rely on a calibrated DSGE model for the euro area to study the optimal setting of the CCyB over the cycle, including the PN CCyB rate. In their model, the PN CCyB is modeled as a structural, steady state component, while the calibration rule relevant for the setting of the

CCyB to address emerging system risks depends on the evolution of a set of indicators. The calibrated optimal PN CCyB rate is determined as a component of the optimal structural capital requirements that is symmetric in size to the calibrated maximum optimal cyclical capital requirement. Their results suggest PN CCyB rates for the euro area ranging from 1.8% and 2.5%.

Our paper is most closely related to De Nora et al. (2025) and Muñoz and Smets (2025). Our approach is complementary to the Losses-to-Buffer approach by De Nora et al. (2025) in two dimensions. First, by relying on two macroeconomic modeling approaches and on macroeconomic, rather than bank-level, data. Second, while the Losses-to-Buffer approach aims to capture the unexpected nature of losses covered by the positive neutral CCyB rate, the Risk-to-Buffer approach calibrates the rate to cover potential losses occurring when cyclical systemic risks are not elevated. Notwithstanding these differences, the two approaches yield broadly consistent results in terms of suggested PN CCyB rates. Compared to Muñoz and Smets (2025) and consistent with the experience with the implementation of a PN CCyB approach so far, our framework maintains a clear link between cyclical systemic risk and the calibration of the PN CCyB. Rather than interpreting the PN CCyB as a structural capital requirement, our approach calibrates the target rate to reduce the amplification of shocks occurring under a median risk scenario, consistent with the setting of the PN CCyB in an environment where cyclical systemic risk is neither subdued nor elevated. At the same time, the two approaches can be seen as complementary: while Muñoz and Smets (2025) rely on a cost-benefit framework to derive optimal steady-state capital levels, our analysis focuses on the risk amplification channel to calibrate buffers in a median-risk environment.

3 A structural approach

In this calibration exercise, we apply the Risk-to-Buffer approach within the 3D DSGE model framework to calibrate the PN CCyB rate. We first provide a brief description of the 3D DSGE model, followed by an overview of the data and approach used to calibrate different levels of systemic risk. Next, we present impulse response functions to financial shocks, conditional on the level of risk, highlighting its relevance for the amplification of shocks. Finally, we calibrate the PN CCyB rate and the CCyB to address elevated systemic risk (CCyB$_{max}$) to mitigate the amplification effects in a median and high risk scenario, respectively.

3.1 Model

The 3D model is a micro-founded DSGE model with financial frictions, where borrowing households, entrepreneurs, and banks can default on their liabilities (Mendicino, Nikolov, Scalone, & Supera, mimeo; Mendicino et al. (2020)). Borrowing households finance their house purchases with bank loans and default on their mortgage loans when the collateral value falls below their outstanding debt obligations. Entrepreneurs invest in capital, financing these purchases with entrepreneurial wealth and bank loans, and default when the return on their investment is lower than the contractual debt obligations. The financial system in this model consists of two types of independent banks: those specializing in lending to households and those focusing on lending to entrepreneurs. Both types raise equity from shareholders and accept deposits from saving households to fund their loan portfolios. Banks default when their net worth becomes negative, creating deadweight losses for the economy. These defaults are positively correlated with i) banks' leverage and ii) bank risks. Higher levels of risk (leverage) imply higher PDs for banks. Banks must comply with risk-weighted capital requirements set by the macroprudential authority, which oblige them to hold capital in proportion to the size and composition of their loan portfolios. In line with Basel III, a risk weight of 0.5 is applied to mortgage loans. Capital requirements can mitigate defaults by reducing bank leverage, and thus, the amplification of cyclical risk levels can be counteracted by increasing capital buffers to lower bank leverage. This mechanism is explained in the following section in more detail.
The model is calibrated for the euro area following Mendicino et al. (2020) with structural parameters set to match key macroeconomic and macro-financial indicators characteristic of this region.

Banks default decision

Since the calibration of the buffer relies on the model feature that higher risk levels correspond to higher probabilities of default, we briefly outline the banks' default mechanism.[9] The model features two types of specialized banks, each lending either to households or to entrepreneurs. As the problems faced by both types are symmetric, the following setup applies to both. Each bank issues equity (EQ_t) to shareholders and debt (D_t) to patient households, offering a gross nominal interest rate $R^{d,nom}t$. These funds are then used to extend loans to borrowers (B_t). The

[9] For a more detailed description of the model, see Mendicino, Nikolov, Scalone, Supera, mimeo.

return on a diversified loan portfolio yields a nominal gross return of $\omega t + 1R^{nom}t + 1$, where $\omega t + 1$ is the bank-specific idiosyncratic asset return shock. Banks operate across two periods and return their terminal net worth to shareholders if it is positive. If the terminal net worth is negative, the bank defaults. Formally, the representative banks default if,

$$\omega_{t+1} R_{t+1}^{nom} B_t < R_t^{d,nom} D_t \tag{1}$$

Thus, a low realization of idiosyncratic asset return shock increases default rates. The standard deviation of the distribution of this idiosyncratic shock can be understood as a measure of bank risk. The bank is subject to two constraints: a balance sheet one, $B_t = EQ_t + D_t$, and a regulatory one, $EQ_t \geq \phi_t B_t$, where ϕ_t is the capital requirement on the portfolio of loans. Since, in the model, capital requirements are always binding by construction[10] (the return on deposits are always lower than the cost of issuing equity and the model is solved in linear form) we can express the loans and deposits in terms of equity requirements $B_t = EQ_t/\phi_t$, $D_t = (1 - \phi_t)EQ_t/\phi_t$. Hence, we can rewrite equation 1 as follows,

$$\omega_{t+1} R_{t+1}^{nom} < R_t^{d,nom}(1 - \phi_t) \tag{2}$$

Accordingly, the bank's probability of failure is negatively related to the capital requirement, due to reduced leverage, and positively related to the realization of idiosyncratic shocks. When applying the Risk-to-Buffer approach within this model, we rely on two counteracting effects driven by risk and capital requirements of the model. On the one hand, the greater the underlying level of risk in the banking system (as captured by the idiosyncratic asset return shock), the greater the amplification of different shocks via the banking system; on the other hand, a higher capital requirement and reduced leverage can mitigate that amplification. Hence in the calibration, first, the variance of the idiosyncratic asset return shock is calibrated to capture specific systemic risk impacting positively the banks probabilities of default. Second, the capital buffer is calibrated to the level offsetting that precise level of risk.

[10] In the model, capital requirements are assumed to be always binding, meaning banks operate exactly at the regulatory minimum. While in reality banks often hold voluntary buffers above the minimum requirement, this simplifying assumption does not affect the core objective of our exercise. We focus on the calibration of the minimum legally binding capital buffer that would be required to absorb losses under a given level of systemic risk. The presence of voluntary buffers would primarily influence the actual cost or behavioral response to activating the CCyB, but not the risk coverage objective. In this sense, our results provide guidance on the level of buffer that should be set by the policymaker, regardless of banks' internal capital management strategies.

3.2 The amplification effect of risk in the 3D model

This section describes the transmission mechanism of a financial shock used for the subsequent calibration of the CCyB, and explains how different risk levels impact this transmission.

The alternative risk levels represented by the bank risk parameter are calibrated using historical data on banks' Expected Default Frequency (EDF) estimated by Moody's from January 2009 to December 2023. As the 3D DSGE model explicitly models banks' default probabilities, we define three risk scenarios by calibrating the bank risk parameter in the model so that banks' default probability in the steady state equals observed percentiles of the EDF for the median euro area bank.[11] The low, medium, and high-risk scenarios are defined such that the risk parameter matches the 5th, 50th, and 95th percentiles of the EDF distribution, respectively. The choice of these percentiles is illustrative, the methodology is sufficiently flexible to accommodate alternative policy preferences. In particular, the macroprudential authority may choose to calibrate the PN CCyB to different levels by focusing on lower (or higher) percentiles of the risk distribution. The model can readily accommodate such alternatives. To calibrate the baseline capital requirements in the model, we take the average capital ratio in the sample period (2009–2023) as representative of prevailing conditions. Therefore, when defining different levels of systemic risk based on the EDF percentiles, we implicitly assume that if such risk levels have materialized in the past, they remain plausible reference points for the future. This assumption is in line with common calibration strategies based on historical data, such as the historical loss approach, where past outcomes are used to inform buffer levels without disentangling the underlying structural drivers.[12]

Figure 1 shows the kernel density estimate of these EDFs, highlighting the percentiles considered for calibrating the risk levels. The values of these percentiles determine the level of the calibrated buffer, while the distances between them indicate the shares allocated to the PN CCyB and CCyBmax, as illustrated in the next section.

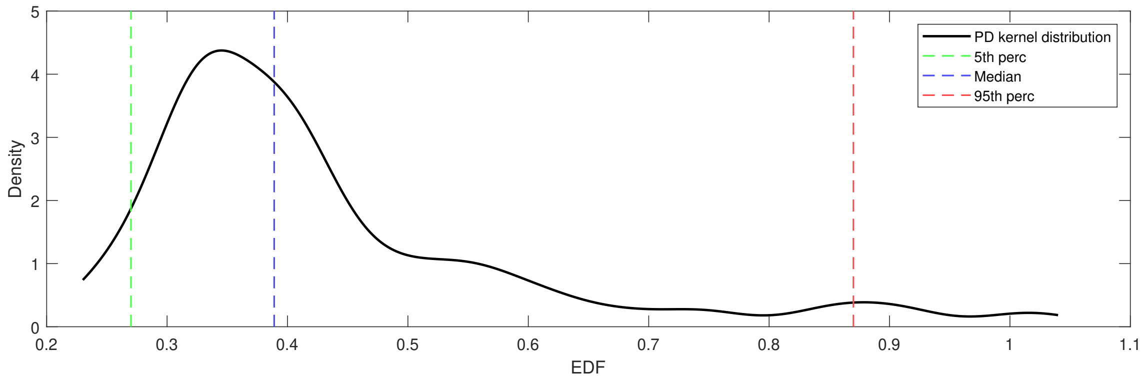
It is important to emphasize that the EDF is used in this context only to calibrate different degrees of bank fragility in order to quantify the amplification effects of exogenous shocks. These scenarios are intended to inform the calibration of capital needs across risk environments, not to define a real-time rule for the build-up or release of the buffer. As such, our use of EDF is illustrative and does not imply that capital requirements should mechanically track EDF levels

[11] The EDF of the model are annualized to make them comparable to the data counterpart.

[12] For more details on these approaches and the jurisdictions that apply them, see ECB/ESRB (2025).

over time. The design of operational policy rules for the dynamic adjustment of the CCyB is outside the scope of this paper and is left for future research.

Figure 1: Euro Area Expected Default Frequencies distribution

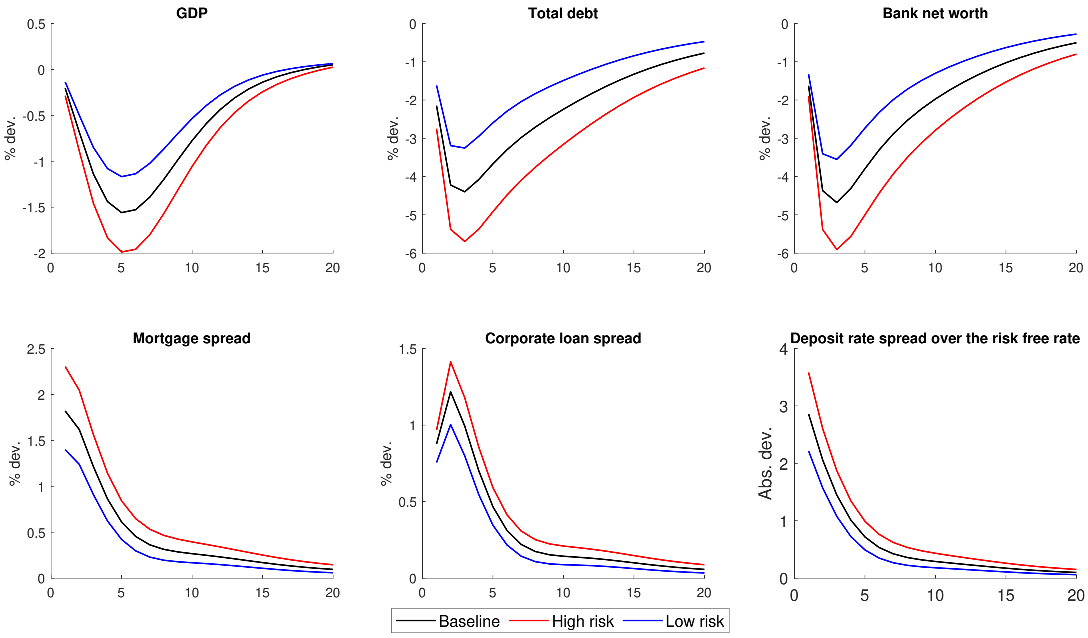


Note: The graph shows the kernel density estimate of the expected default frequencies (EDF) for the Euro area over the period from January 2009 to December 2023.

To simulate the scenarios, we consider a financial shock consisting of an exogenous change in the variance of the bank-idiosyncratic asset return shock. The shock is calibrated to yield a -1.5% GDP decline under the median risk scenario, and apply the same shock size across all risk levels. Figure 2 shows the impulse-responses of selected model variables in response to the financial shock. The blue, black and red lines represent the responses under low, medium and high risk, respectively. The bank risk shock raises the probability of bank default, which in turn increases bank funding costs and the deposit risk premium. In turn, tighter financial conditions for banks lead to a contraction in lending and an increase in borrowing costs for households and firms, pushing them closer to default. Consequently, a shock originating in the banking sector is transmitted through credit and lending rate channels, negatively impacting the real economy and causing a decline in economic activity (GDP).

As the bank risk parameter shapes the variance of the bank-idiosyncratic shock, the amplification of the shock is greater the higher the prevailing risk level, as shown by the differences across the blue, black, and red lines. When the bank risk shock hits in a fragile banking environment (red line), bank funding costs rise more sharply, amplifying the adverse transmission effects described above on credit, borrower default rates, and, ultimately, economic activity.

Figure 2: IRF to a financial shock



Note: The IRF shows the IRF to a financial shock under the three different levels of risk calibrated considering the 5th (blue), 50th (black) and 95th (red) percentiles of the EA EDF series.

3.3 The calibration of the CCyB

On the basis of the results of the previous section, we proceed with the calibration of the CCyB. For each risk scenario, we compute the capital buffer requirement that offsets the amplification of the financial shock, leading to risk-dependent calibrations of the CCyB. Consistent with the use of the PN CCyB in an environment of neither elevated nor subdued cyclical systemic risk, we calibrate the PN CCyB rate such that the resulting required capital is sufficient to offset the amplification under median risk. In other words, we compute the capital requirements necessary to reduce the simulated GDP losses under median risk to the level observed in the low-risk case:

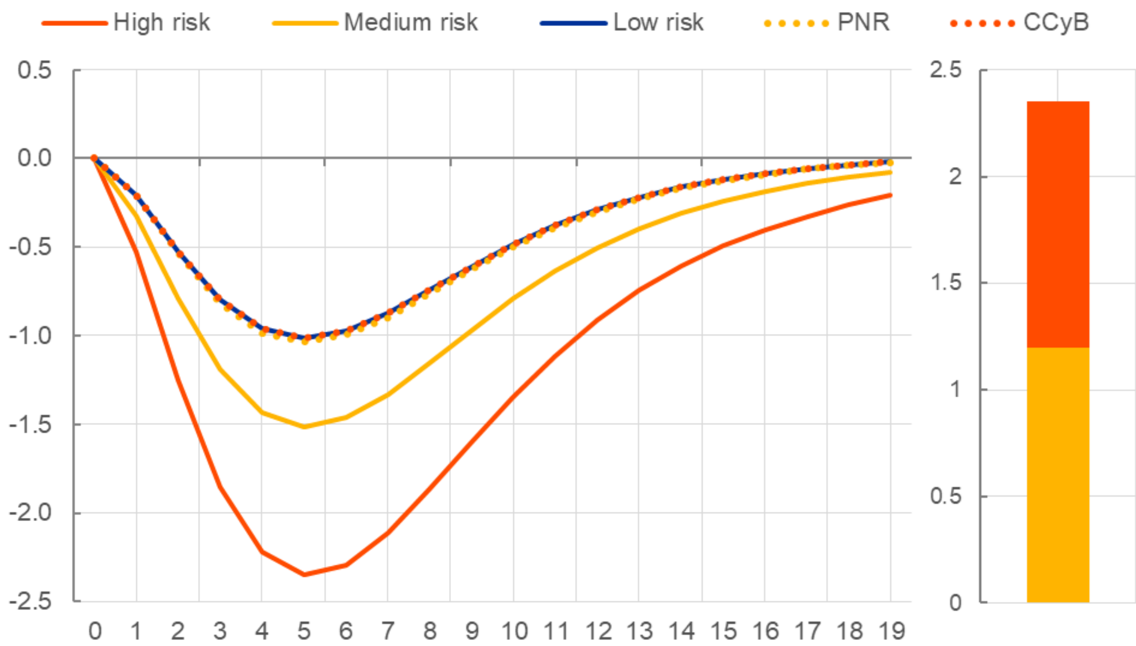
$$\text{Recession}^{\text{PNR}}_{\text{Median Risk}} = \text{Recession}_{\text{Low Risk}}$$

The CCyB rate at the peak of the cycle (when risk is elevated) is calibrated to tackle elevated cyclical systemic risk. In this case, the CCyB is calibrated such that the resulting required capital is sufficient to reduce the simulated GDP losses under high risk to the level observed in the low-risk case:

$$\text{Recession}_{\text{High Risk}}^{\text{CCyB High}} = \text{Recession}_{\text{Low Risk}} \tag{3}$$

Figure 3 shows the response of GDP to the same financial shock considered in Section 3.2 and the calibrated CCyB rates suggested by the model. The blue, yellow and red lines in the figure represent the response of output to the financial shock under low, medium, and high risk levels, respectively. The dotted lines show the GDP response under the medium (yellow dotted line) and the high (red dotted line) risk levels when the capital buffers calibrated to reduce the corresponding risk amplification are activated. The figure shows that there exists a level of capital buffer capable to offset each of the risk amplifications. Specifically, the model suggests a CCyB buffer rate at the peak of the cycle (when risk is high) around 2.3% and a PN CCyB rate of 1.25%.

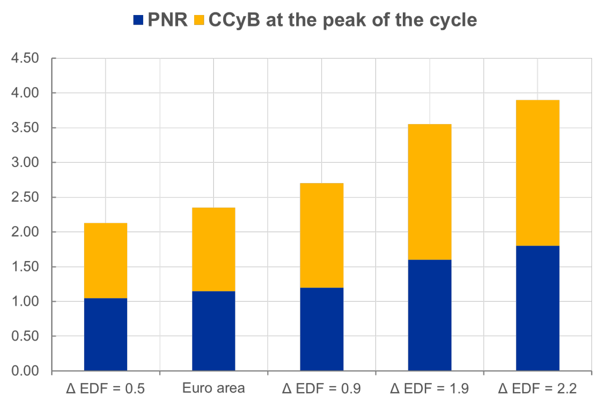
Figure 3: IRF to a financial shock under different levels of risk and capital buffers



Note: The y-axis shows output deviations from its steady-state level, while the x-axis represents quarters after the shock materializes. The blue, yellow, and red lines show the output response to the financial shock in low-, medium-, and high-risk scenarios, respectively. The dotted yellow (red) line shows the output response in the medium (high) risk scenario with the PN CCyB (CCyBmax) calibrated to offset the amplification effect.

The distribution of the EDF plays a key role in the CCyB calibration exercise, as its percentiles are used to calibrate the different levels of bank risk corresponding to different degrees of risk amplification. First, the distance between the percentiles of the EDF distribution used to calibrate the risk levels influences the size of the capital buffers required to offset the shock amplification. Specifically, if the values of the higher percentiles of the EDF distribution are very large, indicating elevated bank risk, the CCyB required under the high-risk scenario will be larger to offset the greater risk amplification. If the median EDF is relatively elevated, the resulting PN CCyB rate will also be higher, consistent with the need to neutralize the recession amplification associated with the medium-risk scenario. Second, the distance between the 50th and 95th percentiles of the EDF distribution (used to identify the medium and high-risk scenarios, respectively) is also important for determining the relative calibration of the PN CCyB in the overall CCyB. A shorter distance between the median and high-risk percentiles implies a larger PN CCyB share, as a larger buffer is needed to counteract the amplification effect on GDP at medium risk levels. Thus, the EDF distribution influences not only the magnitude of the required buffers but also determines the allocation between the PN CCyB and the CCyB at high-risk to adequately address risk amplification at different levels. To illustrate this point, figure 4 shows the PN CCyB rate and the CCyB rate at the peak of the cycle obtained when calibrating the bank risk parameter in the model to match the percentiles of the EDF distributions for a set of euro area countries characterized by different EDF volatility.

Figure 4: Calibrated capital buffers for different EDF distributions



Note: The y-axis shows the level of capital buffer, while the x-axis shows different levels of risk. The blue bar represents the calibrated PN CCyB rate, and the yellow bar represents the calibrated CCyB rate at the peak of the cycle.

4 A time series approach

In this section, we apply the Risk-to-Buffer approach in a non-linear time series framework. First, we present the non-linear econometric model used to generate the scenario and its main features in terms of data, identification, and non-linear dynamics. Second, we show how the non-linear dynamics of the model can be used to generate risk-dependent scenarios and calibrate the PN CCyB rate.

4.1 The econometric model

The model is a Multivariate, Smooth Transition, Regime Switching model (Auerbach and Gorodnichenko (2013); Tenreyro and Thwaites (2016)) estimated using the Local Projections (henceforth, LP) method by Jordà (2005).[13]

In the model, a state variable z_t determines the transition between two extreme regimes of the economy that affect the propagation of the shocks in the economy. The model is estimated for each horizon $h = 0, ..., H$. The model is a time series process with p number of lags:

$$\begin{aligned} Y_{t+h} = \; & F(z_{t-1})(\alpha_h^H + \Sigma_{\ell=1}^{p} \beta_{h,\ell}^H Y_{t-\ell}) \\ & + (1 - F(z_{t-1}))(\alpha_h^U + \Sigma_{\ell=1}^{p} \beta_{h,\ell}^U Y_{t-\ell}) \\ & + \bar{u}_{h,t}, \end{aligned} \tag{4}$$

where Y_t is the $(n, 1)$ vector of endogenous variables at time t, z_{t-1} is the scalar interaction variable at time $t-1$ and $\bar{u}_{h,t}$ is the $(n, 1)$ vector of errors at horizon h and time t. The state effect is determined by $F(z_t)$, i.e. the scalar function governing the transition between the two extreme regimes. This function normalizes the state variable z_t into a scalar included in the interval $[0, 1]$ and increases in z_t. Higher (lower) values of z_t correspond to $F(z_t)$ closer to 1 (0), determining the dynamics of the model in each state as a convex combination of the two extreme states. As standard in these types of models, the transition function is the logistic transformation of the original z_t:

$$F(z_t) = \frac{1}{1 + exp\left(-\theta\left(\frac{z_t - v}{\sigma_z}\right)\right)} \tag{5}$$

[13]The original version of the macroeconomic model is presented in Couaillier and Scalone (2024).

where θ is the smoothing parameter governing the smoothness of the transition from one state to another[14], v determines the part of the sample spent in either state[15], and σ_z is the standard deviation of the observed state variable. Both parameters are calibrated, in line with Auerbach and Gorodnichenko (2013). We set c at the historical median of the original state variable, so that the resulting state spends half of the time in both regimes. Our baseline specification uses $\theta = 3$ (in line with Tenreyro and Thwaites (2016)), but the amplifications found in the estimated model are robust to a large range of alternative calibrations. Confidence intervals are constructed as described in Couaillier and Scalone (2024).

4.2 Estimation of the macroeconomic model

In our benchmark specification, the model is estimated on aggregate euro area (EU19) data at a quarterly frequency, ranging from 2001 Q1 to 2019 Q4. The variables included are output (GDP), inflation (HICP), short-term interest rate (3-months EURIBOR), credit to the non-financial private sector, and house prices. Rates are reported in levels, whereas the other variables are expressed in percentage quarterly changes. The time series model has one lag and is estimated at a 12-quarter ahead horizon.

Consistent with De Nora et al. (2025), the benchmark state variable to capture cyclical systemic risk is the domestic Systemic Risk Indicator (d-SRI) developed by Lang et al. (2019). This is a composite risk indicator that weights different cyclical risk indicators relevant for the identification of cyclical systemic risk.[16] As in the structural approach presented in Section 3, we define different risk levels using percentiles of the logistic transformation of the aggregate d-SRI for the euro area. Specifically, the low, medium, and high cyclical systemic risk states correspond to the 1st, 50th, and 100th percentiles of the distribution of the logistic transformation of the d-SRI, respectively.

We apply a Cholesky decomposition to identify economic and financial shocks.[17] The order used in the Choleski identification is in line with Couaillier and Scalone (2024): output, inflation,

[14] The higher θ, the faster $F(z_t)$ goes toward 0 and 1, i.e. converging to dummy-regime switching.

[15] $z_t > v$ is equivalent to $F(z_t) > 0.5$. Defining v as the $p - th$ quantile of the historical time series of z_t forces $F(z_t)$ to spend $p\%$ of the time below 0.5, i.e. in the low regime.

[16] The d-SRI is composed by weighting the following indicators: the two-year change in the bank credit-to-GDP ratio, the two-year growth rate of real total credit, the two-year change in the debt-service-ratio, the three-year change in the RRE price-to-income ratio, the three-year growth rate of real equity prices, the current account-to-GDP ratio. The weights are chosen to maximize the early warning property of the composite indicator.

[17] Structural identification is not mandatory to design adverse scenarios in our application, which can also be obtained using reduced-form shocks. Nonetheless, providing a structural interpretation to the set of shocks can help to interpret the non-linear dynamics found in the model.

policy rate are ordered first, followed by credit and house prices. This implies that financial variables react on impact to macroeconomic shocks, whereas macroeconomic variables react to financial shocks with a one-quarter lag. The variance covariance matrix of the reduced-form errors $u_{1,t}$ is decomposed via Cholesky to obtain the impact matrix of the model:

$$\bar{u}_{t,1} = \Omega_{vj}\bar{\epsilon}_{t,1}$$

where $\bar{\epsilon}_{1,t}$ is the vector of structural shocks hitting the economy at time t. Each element of the $(n, 1)$ vector is a structural shock of the model, i.e. output shock, inflation shock, monetary policy shock, lending shock and housing prices shock. Via the impact matrix, each structural shock hitting the economy $\bar{\epsilon}_{1,t}$ is propagated on impact through its own impact vector on the full set of endogenous variables:

$$\varepsilon_{vi,t} = \omega_{vi}\epsilon_{i,t},$$

where ε_{vi} is the effect of shock i on variable v, ω_{vj} is the element of the impact matrix mapping the effect of the structural shock i on the variable v. The local projection coefficients b^U_{jv} and b^D_{jv} propagate over time h the impact effect of the shock i on each endogenous variable j:

$$irf_{ji,h} = \left(F(z_t)b^U_{jv} + (1 - F(z_t))\, b^D_{jv}\right)\varepsilon_{vi,t}$$

where $IRF_{ji,h}$ is the impulse response of variable j of shock i at horizon h. The state variable determines the weights of the local projections coefficients of the two extreme regimes in the propagation of the shock.

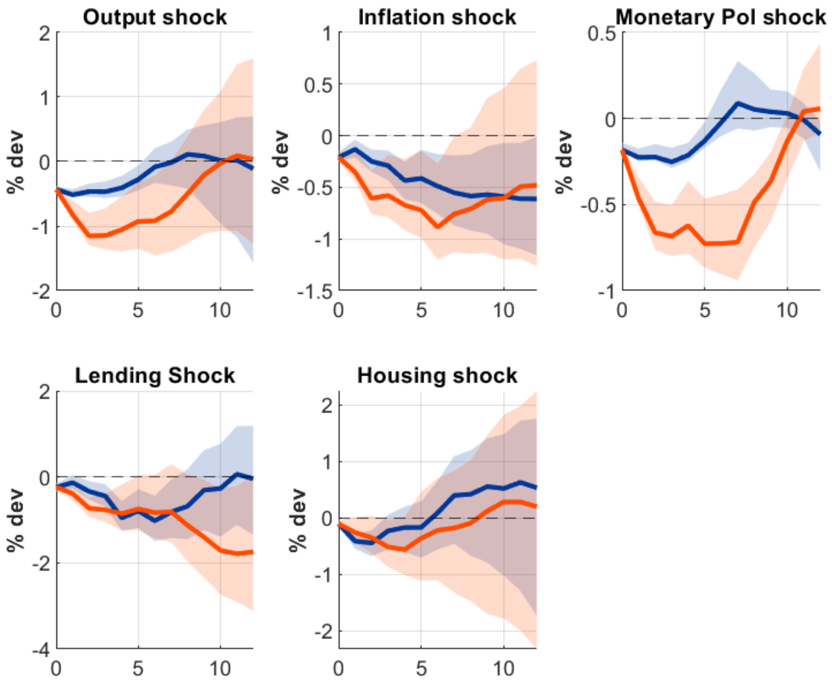
Each shock $\varepsilon_{vi,t}$ $(i = 1, ..., N)$ hits the endogenous variables v of the model $(v = 1, ..., N)$, whose variations are propagated over time through:

$$IRF_{ji,t+h} = F\left(z_t\right)\sum_{i=1}^{K} b^U_{jv,h}\varepsilon_{vi,t} + \left(1 - F\left(z_t\right)\right)\sum_{i=1}^{K} b^D_{jv,h}\varepsilon_{vi,t}$$

where $b^U_{jv,h}$ and $b^D_{jv,h}$ are the local projection coefficients linking the regressor v to the endogenous variable j, estimated for horizon h.

All the variables of the model (GDP, inflation, policy rate, total lending, housing prices) are shocked at the same time and each shock has the same size (one standard deviation of the respective variables).

Figure 5: Impulse responses of Output to the structural shocks



Note: The responses of output growth are cumulated. The red (blue) lines are the impulses when risk is high (median). Shaded areas represent the 90% confidence intervals.

Even if the degree of amplification can vary across different types of shocks, the results illustrate that, overall, higher cyclical risks amplify economic fluctuations. Figure 5 depicts the impulse-responses of GDP to the structural shocks. The peak GDP response to output and inflation shocks is about double under high risk with respect to median risk. The impact of monetary policy shocks on GDP is three times stronger when cyclical systemic risk is high than at the median level. Finally, lending shocks and housing shocks tend to be also more amplified and are more persistent when the d-SRI is high.[18] The non-linear amplification of these shocks is in line with structural models featuring a financial accelerator (Bernanke et al. (1999); Guerrieri and Iacoviello (2017); Kiyotaki and Moore (1997)). In this type of models, debt amplifies the propagation of shocks as, under high leverage, binding financial constraints increase the propagation of economic and financial shocks.

[18]These results are consistent with the ones presented in Couaillier and Scalone (2024), where a similar model is estimated by using the debt service ratio as state variable.

4.3 Calibration of the positive neutral CCyB rate

In line with the original Risk-to-Buffer approach (Couaillier and Scalone (2024)), we leverage on the non-linear dynamics of the macroeconomic model to calibrate capital requirements for different cyclical systemic risk intensities. First, we pin down the maximum CCyB requirement (CR_{Max}) as the level of capital required at the peak of the cycle, namely under maximum risk (i.e. $F(z_t) = 1$). Second, we assume a linear relationship between the macroeconomic dynamics and bank losses BL_i,[19]. This allows us to directly compute the capital requirement corresponding to the risk level considered j:

$$CR_j = CR_{Max} \frac{Macro_j}{Macro_{Max}}.$$

This approach can be used to estimate the CCyB requirement in any state i based on the ratio between the macroeconomic responses to the shocks in state i and the macroeconomic responses to the shocks under maximum risk. In our application, and consistent with the objective of the PN CCyB, first the macroeconomic responses to the shocks are obtained under the median risk ($Macro_{Median}$). Second, the PN CCyB requirement is calibrated taking the median risk level as the relevant reference risk level.[20]

In our calibration exercise, we focus on the non-linear dynamics of output. We compute the impulse responses of GDP to the five identified shocks. We report the effect on output, ordered as variable 1, of each shock i:

$$IRF_{1i} = F(z_t) \sum_{i=1}^{K} b_{1j}^U \varepsilon_{1i} + (1 - F(z_t)) \sum_{i=1}^{K} b_{1j}^D \varepsilon_{1i}$$

where ε_{ji} denotes the impact of shock i on variable j.

One possible way to derive the ratio between the macroeconomic dynamics under different risk levels is to compute the average impulse response reaction over the horizon H:

$$PNR = CR_{Max} \frac{Macro_{Median}}{Macro_{Max}} = CR_{Max} \frac{\frac{1}{H}\sum_{h=1}^{H}\left(IRF_{11,h}^{Median} + ... + IRF_{1N,h}^{Median}\right)}{\frac{1}{H}\sum_{h=1}^{H}\left(IRF_{11,h}^{Max} + ... + IRF_{1N,h}^{Max}\right)} =$$

[19] The assumption of a linear relationship between GDP losses and capital requirements follows Couaillier and Scalone (2024) and in the current application, this assumption corresponds to use a linear Stress test model

[20] As in the structural application, the choice of the the reference risk to use for the positive neutral rate can accommodate the preferences of the policy maker.

$$= CR_{Max} \frac{\frac{1}{H}\sum_{h=1}^{H}\left(\left(\sum_{j=1}^{N}\sum_{i=1}^{N} b_{1j}^{U}\epsilon_{ji}\right) F\left(z_t^{Median}\right)\right) + \left(\sum_{j=1}^{N}\sum_{i=1}^{N} b_{1j}^{D}\epsilon_{ji}\right)\left(1 - F\left(z_t^{Median}\right)\right)}{\frac{1}{H}\sum_{h=1}^{H}\left(\sum_{j=1}^{N}\sum_{i=1}^{N} b_{1j}^{U}\epsilon_{ji}\right)}. \tag{6}$$

For the sake of simplicity, we assign equal weight to each horizon, however, policymakers could assign alternative weights according to their preferences.[21]

According to the calibration equation, the more the coefficients across the two states differ, the higher the distance between $Macro_{Median}$ and $Macro_{High}$, implying a smaller calibrated PN CCyB rate. Hence, the relative importance of the different shocks affects the non-linear dynamics and, hence, the buffer calibration. When simulating the set of shocks, the impact of shock i on variable j ($\varepsilon_{ij,t}$) will determine the weights of the coefficients used to determine the impulse responses (e.g. $b_{11}^{D}, b_{11}^{U}, ..., b_{1N}^{U}, b_{1N}^{D}$). The larger (smaller) the impact of the shock on variables, leading to relatively greater difference across the medium and high risk states in terms of impact on GDP, the smaller (higher) the calibrated PN CCyB rate will be. To illustrate this, let us consider a model with only two endogenous variables where the difference between b_{11}^{D} and b_{11}^{U} is low, whereas the difference between b_{12}^{D} and b_{12}^{U} is high. Under these assumptions, increasing the relative size of the first shock will imply higher ε_{11} and a higher weight on coefficients that vary less with respect to the other coefficients. This will lead to a smaller distance between $Macro_{Median}$ and $Macro_{High}$, and therefore to a higher PN CCyB rate. Conversely, increasing the size of the second structural shock will imply a higher ε_{12} and a higher weight on the coefficients that vary more across the state. This will yield a greater difference between $Macro_{Median}$ and $Macro_{High}$ and a lower PN CCyB rate.

Conversely, the absolute size of the scenario does not affect the calibration of the PN CCyB rate. Since the maximum buffer level is exogenously fixed, scaling up the scenario would have the same effect on the numerator and on the denominator of the equation, as long as the scale coefficient is the same for all the shocks.

The following results are obtained considering shocks of equal, one standard deviation magnitude. This is in line with the main objective of the PN CCyB to build up resilience in the early phase of the financial cycle, considering cyclical and non-cyclical risks. In a second application (see Appendix A), we calibrate the PN CCyB only considering real shocks. This "Real PN CCyB" is more in line with the interpretation of the PN CCyB as a buffer covering against risks

[21] For example, decaying weights could give more importance to the short-term dynamics. Alternatively, uncertainty in the estimation could be considered by weighting the impulse responses in a way that is inversely proportional to the estimated confidence interval at each horizon.

unrelated to the evolution of the financial cycle (e.g., Covid-type shocks).

First, we fix the CCyB rate at the peak of the cycle (i.e. in the high-risk scenario) at 2.5%. This value is not intended to reflect an optimal threshold, but works as a benchmark that is consistent with the mandatory reciprocity threshold in EU regulation and is in line with observed buffer settings in several jurisdictions (e.g. Sweden, Norway, UK) during periods of elevated risk. This level conveniently aligns with our structural model results and therefore facilitates comparability across approaches. However, it does not imply a mechanical dependence of one model on the other. In this sense, the two models remain methodologically independent and serve as mutual cross-checks, while anchoring the high-risk scenario to a plausible policy-relevant capital level.

Second, all the shocks in the model are simulated. For each shock, we produce a set of one standard deviation recessionary shocks hitting the economy for four consecutive periods. The model is simulated to generate a high-risk scenario whose dynamics have a comparable magnitude to the one usually featured in the adverse scenarios of the EBA banks stress tests.[22] Since in the simulation all the shocks have the same probability, the calibration is not dependent on a specific shock selection and, hence, not related to a specific narrative.[23]

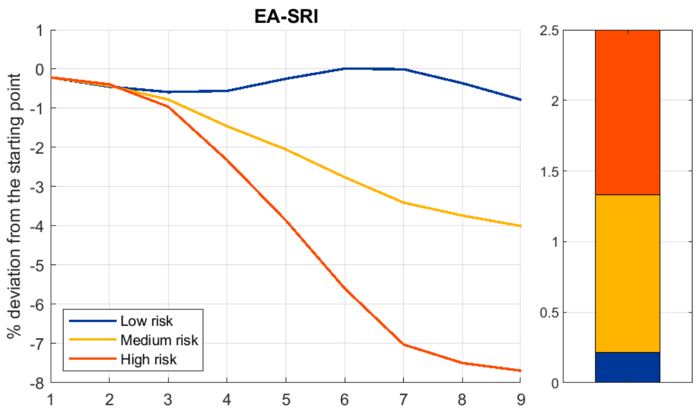
Figure 6 reports the macro dynamics obtained under three different risk levels: low risk ($F(z_t) = 0$, blue line), medium risk ($F(z_t) = 0.5$, yellow line) and high risk ($F(z_t) = 1$, red line). Under high risk, the same sequence of recessionary shocks produces a recession overall twice as large compared to the median risk case. When risks are low, the effects are substantially smaller.

Third, the obtained macro dynamics are used to compute $Macro_{Median}$ and $Macro_{Max}$, by averaging the impulse response of the first ten horizons. The computed average responses are used in Equation 6 to obtain the CCyB rate corresponding to the corresponding risk level. Taking the medium risk level as the relevant reference, this approach suggests a 1.3% PN CCyB rate.

[22] See EBA macrofinancial scenarios, for example European Banking Authority (2023).

[23] Alternatively, choosing the shocks in line with a narrative would allow for calibrating buffers with respect to more specific risks.

Figure 6: GDP dynamics for different levels of cyclical systemic risk and corresponding CCyB requirements



Note: Left-hand side: the lines report the output deviation from the starting point under the low risk (blue line), medium risk (yellow line), and high risk (red line). Right-hand side: CCyB rate levels corresponding to the low risk (blue part), median risk (yellow part) and high risk (red part).

4.4 Calibration across different state variables

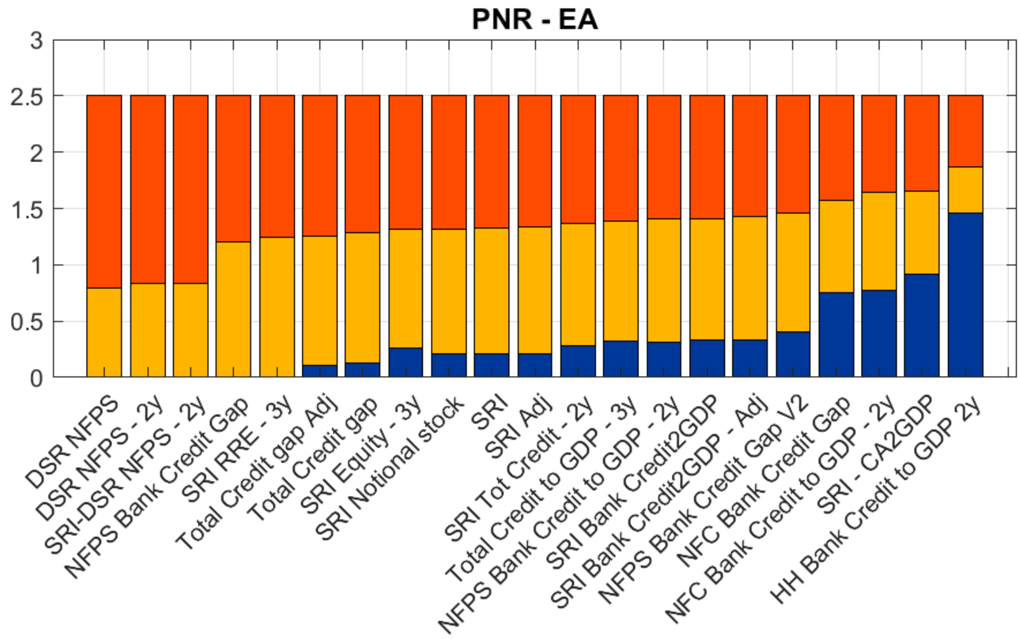
In this sub-section we show alternative PN CCyB calibration results obtained using different state variables to identify the cyclical systemic risk regimes, to assess the robustness of the one obtained in subsection 4.3. This also allows us to further explore an alternative PN CCyB calibration as the median PN CCyB rate obtained across the models using different state variables. Specifically, we considering different measures of cyclical systemic risk used in the literature due to their early warning performance in predicting banking crises These include: i) the debt service ratio (DSR, Drehmann and Juselius (2013)); ii) credit-to-GDP gaps (Drehmann et al. (2011)), both broad and sectoral (i.e. for the household sector and for firms); iii) credit-to GDP ratios, both broad and sectoral[24]; iv) the individual indicators included in the composite d-SRI Lang et al. (2019), namely the debt service ratio of the two-year change in the bank credit-to-GDP ratio, the two-year growth rate of real total credit; the two-year change in the debt-service-ratio, the three-year change in the RRE price-to-income ratio, the three-year growth rate of real equity prices and the current account-to-GDP ratio.

Figure 7 depicts the PN CCyB calibrations for the alternative state variables considered. The bulk of the PN CCyB rates range between 1% and 1.5%, with a median PN CCyB rate across the different state variables around 1.3%. Among the d-SRI components, the DSR component determines a lower PN rate (0.8%), suggesting that, when used as state variable, the DSR provides stronger amplifications of the macro dynamics with respect to the other state variables. PN CCyB rates obtained using the equity prices, total credit and bank credit components of the d-SRI range between 1.2% and 1.3%, in line with the baseline calibration. Finally, the current account component of the d-SRI delivers a higher PN CCyB level of 1.5%, in line with the fact that the current account as state variable amplifies relatively less the macroeconomic dynamics. This is consistent, for example, with the 1.5% PN CCyB rate set by the Central Bank of Ireland, that refers to the openness of the economy and the resulting vulnerability to external shock among the motivations for introducing a PN CCyB. Across the state indicators, the DSR in level is associated to the lower PN CCyB rate, while bank credit and total credit indicators, including the credit-to-GDP gap, deliver PN CCyB rates around 1.3%.

When using the DSR as state variables, the model delivers higher amplifications and, hence, a lower calibrated PN CCyB rate, due to the larger distance between the $Macro_{Median}$ and

[24]For credit we can both consider the broad credit or exclusively bank credit.

Figure 7: PN CCyB level across different state variables



Note: CCyB rates for different risk measures. Results for the low, median and high risk levels are reported in blue, yellow and red respectively. The states are order from according to the respective found PN CCyB level, from lower to higher.

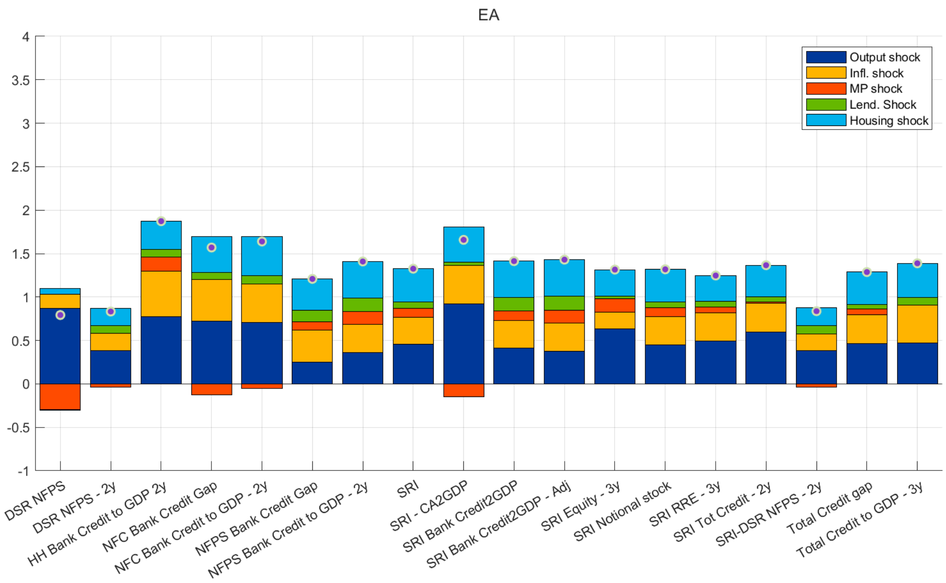
$Macro_{High}$ scenarios. This also implies that, when the indicator increases over time, the elasticity of the CCyB to the increase of the risk level will be higher. Conversely, state variables leading to a smaller amplification (such as the d-SRI) yield a higher calibrated PN CCyB rate. This also implies a lower elasticity of the calibrated CCyB rate to changes in the risk indicator when it is above the reference level.

4.5 The role of different shocks in the PN CCyB calibration

In this sub-section we study how the different shocks affect the calibration of the PN CCyB rate obtained across the state variables.

In line with the calibration mechanism presented above, shocks leading to a stronger nonlinearity in the impulse-responses, contribute less to the calibration of the PN CCyB rate, whereas the shocks whose impulse response is less amplified by the state variable will contribute more to the calibration of the PN CCyB rate. The underlying logic is that, when the state variable plays a substantial role in the amplification, the increase in shock propagation deriving from switching from the median to the high risk level will be substantial. As a result, following the mapping rule (Equation 4), the PN CCyB rate will be relatively lower, and only when the risk indicator will increase above the median level, the shocks will start to produce more negative effects on the economy, implying stronger losses for banks and faster increase in the calibrated CCyB rate. Vice-versa, the shocks featuring less amplification will imply a relatively higher PN CCyB level. In this case, switching from median to high level will determine a smaller increase in the severity of the scenario, and hence, of the losses to cover, implying a smaller elasticity of the CCyB level to the risk variation.

Figure 8: PN CCyB - Shock decomposition across state variables



Note: PN CCyB levels (red dots) across different risk measures. For each risk measure, the PN CCyB is decomposed according to the shock type of the model: Output shock (blue), Inflation shock (yellow), Monetary policy shock (red), Lending shock (green), Housing shock (light blue).

For each state variable, we quantify the PN CCyB share associated to the each model shock $k = 1, .., N$:

$$PNR\_Decomp_K = 2.5\% \frac{\frac{1}{H}\sum_{h=1}^{H} IRF_{1K,h}^{Median}}{\frac{1}{H}\sum_{h=1}^{H}\left(IRF_{11,h}^{Max} + ... + IRF_{1N,h}^{Max}\right)}$$

Figure 8 reports the results of this decomposition, showing that the relative contribution of different shocks is overall stable across the state variables. First, real shocks (i.e. output shock and inflation shock, respectively the blue and yellow bars in Figure 8) contribute to more than half of the PN CCyB across all the state variable considered. This derives from the fact that the responses to these two shocks are relatively less linear with respect to those obtained for the other shocks. Among the financial shocks, the housing shock explains an important fraction of the PN CCyB, whereas the lending shock plays a smaller role, in line with the fact that its dynamics are relatively more non-linear. These results suggest that shocks associated to the materialization of domestic financial imbalances such as credit shocks tend to be strongly amplified, warranting a relatively lower importance of the PN CCyB in the overall CCyB calibration and a higher importance of using the CCyB to address emerging cyclical systemic risks. This is consistent with the original objective of the CCyB to increase bank resilience when domestic financial imbalances (notably excessive credit growth) build up. Instead, shocks affecting the real side of the economy (e.g. output and inflation shocks), which are mostly unrelated to the materialization of domestic imbalances but rather result from factors exogenous to the financial cycle, call for a relatively more important role of the PN CCyB in the overall CCyB calibration. This is consistent with one of the objectives of the PN CCyB to increase resilience against shocks that may occur at any phase of the cycle, such as, for example, health emergencies, geopolitical events or natural disasters. In the Appendix, we show the calibration of the PN CCyB obtained using only real shocks across the different state variables. The results are overall consistent with the baseline.

Using the DSR as state variable (both in levels and in 2-year differences), housing shocks are relatively more amplified, meaning that for those state variables the housing shock is less important for the calibration of the d-SRI. This is consistent with the role of private sector debt burden in amplifying disruptions in the residential real estate sector. Finally, monetary policy shocks also contribute to a small fraction of the PN CCyB level, in line with the fact that the state-dependent effects of the monetary policy shocks are higher than for the other shocks.

5 Conclusion

Due to the increasing use of a "positive neutral" approach to the setting of the CCyB worldwide and the still relatively scarce literature on methods to calibrate the PN CCyB rate within the overall CCyB calibration, this paper presents a novel methodology based on the Risk-to-Buffer approach by Couaillier and Scalone (2024). The proposed calibration methodology is grounded in state-of-the-art techniques and is technically rigorous, while also being intuitive, easy to implement and sufficiently flexible to be tailored to individual countries and policymakers' preferences. The main objective of the methodology is to suggest calibrated rates for the PN CCyB rate and the CCyB rate at the peak of the cycle (e.g. when systemic risks are elevated) according to the severity of risk. We implement the Risk-to-Buffer approach and obtain suggested calibrations for the PN CCyB rate in both a structural (DSGE) and an empirical (macro time series) modeling framework. This risk-based approach can complement cost-benefit analyses by providing a consistent mapping between cyclical systemic risk levels and capital needs, thus enriching the set of tools available to policymakers for PN CCyB calibration.

We find that, first, taking the median systemic risk level as the relevant reference, the calibrated PN CCyB rates are consistent across the two approaches. Specifically, both the structural and the baseline time series approach (using the d-SRI as state variable) suggest PN CCyB rates of 1.25% and 1.3% respectively. Overall, considering a broad set of cyclical systemic risk variables to define the risk states, the suggested PN CCyB rates range from 1% to 1.5%. While for the calibration of the PN CCyB rate, we are agnostic about the specific source of shocks and apply all at the same time, the results are robust also across different shocks.

A second interesting finding from the empirical approach relates to the relationship between the degree of nonlinear amplification generated by different shocks or different risk variables in determining the relative importance of the PN CCyB in the overall CCyB calibration. We find that shocks associated to the materialization of domestic financial imbalances such as credit shocks tend to be strongly amplified, warranting a relatively lower importance of the PN CCyB in the overall CCyB calibration and a higher importance of using the CCyB to address emerging cyclical systemic risks. This is consistent with the original objective of the CCyB to increase bank resilience when domestic financial imbalances (notably excessive credit growth) build up. Instead, shocks affecting the real side of the economy (e.g. output and inflation shocks), which are mostly unrelated to the materialization of domestic imbalances but rather result from factors exogenous to the financial cycle, call for a relatively more important role of the PN CCyB in the overall CCyB calibration. This is consistent with one of the objectives of the PN CCyB to increase resilience against shocks that may occur at any phase of the cycle, such as, for example, health emergencies, geopolitical events or natural disasters. Similar conclusions hold when considering different cyclical systemic risk variables. For example, we find that the Debt Service Ratio results in a greater amplification of shocks on economic activity, leading to a relatively relatively lower importance of the PN CCyB in the overall CCyB calibration and a higher importance of using the CCyB to address emerging cyclical systemic risks. This result suggests that economies characterized by a high debt service burden tend to suffer more from disruptions in the residential real estate sector, calling for a higher CCyB rate to address these vulnerabilities. Conversely, the openness of the economy (current account balance) does not significantly amplify the considered shocks. Hence, rather than requiring the activation of a relatively higher CCyB to address risks related to trade openness, the results suggests that economies with such characteristics would benefit from introducing a PN CCyB approach.

Third, we find that the relative contribution of the different shocks to the calibration of the PN CCyB is overall stable across state variables.

The results of this paper illustrate the potential usefulness of the proposed methodology to guide the calibration of the CCyB. In particular, the flexibility of the method regarding the specific levels of risks as well as the choice of state variables and exogenous shocks make it particularly suitable to be tailored to national specificities and policymakers' preferences.

References

P. Aguilar, S. Hurtado, S. A. Fahr, and E. Gerba. Quest for Robust Optimal Macroprudential Policy. Banco de Espana Working Paper 1916, Banco de Espana, 2019.

Alan J Auerbach and Yuriy Gorodnichenko. Output spillovers from fiscal policy. *American Economic Review*, 103(3):141–46, 2013.

Bank of England. The financial policy committee's approach to setting the countercyclical capital buffer. Policy statement, Bank of England, 2023.

Basel Committee. Guidance for national authorities operating the countercyclical capital buffer. *BCBS Report*, 2010.

Basel Committee. Range of practices in implementing a positive neutral countercyclical capital buffer. *BCBS Report*, 2024.

Taryk Bennani, Cyril Couaillier, Antoine Devulder, Silvia Gabrieli, Julien Idier, Pierlauro Lopez, Thibaut Piquard, and Valerio Scalone. An analytical framework to calibrate macroprudential policy. Technical report, Banque de France Working Paper, 2017.

Ben S Bernanke, Mark Gertler, and Simon Gilchrist. The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics*, 1:1341–1393, 1999.

Pierluigi Bologna and Maddalena Galardo. Calibrating the countercyclical capital buffer using aurocs. *Economic Notes*, 53(1):e12230, 2024.

Katarzyna Barbara Budnik, Mirco Balatti, Giovanni Covi, Ivan Dimitrov, Johannes Groß, Ib Hansen, Michael Kleemann, Tomas Reichenbachas, Francesco Sanna, Andrei Sarychev, et al. Macroprudential stress test of the euro area banking system. Technical report, European Central Bank Working Paper, 2019.

L. Clerc, A. Derviz, C. Mendicino, S. Moyen, K. Nikolov, L. Stracca, J. Suarez, and A. Vardoulakis. Anchoring countercyclical capital buffers: The role of credit aggregates. *International Journal of Central Banking*, 2015.

Cyril Couaillier and Valerio Scalone. Risk-to buffer: setting cyclical and structural banks capital requirements through stress test. 2024.

L. De Haan and J. Kakes. European banks after the global financial crisis: peak accumulated losses, twin crises and business models. *Journal of Banking Regulation*, 21(3):197–211, 2020.

G. De Nora, A. Pereira, M. Pirovano, and F. Stammwitz. From losses to buffer – calibrating the positive neutral ccyb rate in the euro area. *mimeo*, XX(XX), 2025.

Stéphane Dees, Jérôme Henry, and Reiner Martin. Stampe: stress-test analytics for macroprudential purposes in the euro area. *Frankfurt am Main: ECB*, 2017.

C. Detken., O. Weeken, L. Alessi, D. Bonfim, M. Boucinha, C. Castro, S. Frontczak, G Giordana, J. Giese, N. Jahn, J. Kakes, B. Klaus, J. Lang, N. Puzanova, and P. Welz. Operationalising the Countercyclical Capital Buffer: Indicator Selection, Threshold Identification and Calibration Options. ESRB Occasional Paper Series 5, European Systemic Risk Board, 2014.

M. Drehmann and M. Juselius. Evaluating early warning indicators of banking crises: Satisfying policy requirements. BIS Working Papers 421, Bank for International Settlements, 2013.

M. Drehmann, C. Borio, and K. Tsatsaronis. Anchoring countercyclical capital buffers: The role of credit aggregates. *International Journal of Central Banking*, 7(4):189–240, 2011.

ECB/ESRB. Using the countercyclical capital buffer to build resilience early in the cycle. Technical report, European Systemic Risk Board and European Central Bank, 2025.

European Banking Authority. Macro-financial scenario for the 2023 eu-wide banking sector stress test, January 2023.

European Systemic Risk Board. Recommedation on guidance for setting countercyclical buffer rates. Recommendation, European Systemic Risk Board, 2014/1.

Luca Guerrieri and Matteo Iacoviello. Collateral constraints and macroeconomic asymmetries. *Journal of Monetary Economics*, 90:28–49, 2017.

Luis Herrera, Mara Pirovano, and Valerio Scalone. The importance of being positive: costs and benefits of a positive neutral rate for the countercyclical capital buffer. *Macroprudential Bulletin*, 2024.

Luis Herrera, Caterina Mendicino, Kalin Nikolov, and Valerio Scalone. Monetary policy tightening and macroprudential policies. *Mimeo*, 2025.

J. Hájek, J. Frait, and M. Plašil. he countercyclical capital buffer in the czech republic. *Financial Stability Report 2016/2017*, 2017.

Òscar Jordà. Estimation and inference of impulse responses by local projections. *American economic review*, 95 (1):161–182, 2005.

Nobuhiro Kiyotaki and John Moore. Credit cycles. *Journal of political economy*, 105(2):211–248, 1997.

Jan Hannes Lang and Marco Forletta. Bank capital-at-risk: measuring the impact of cyclical systemic risk on future bank losses. 2019.

Jan Hannes Lang and Marco Forletta. Cyclical systemic risk and downside risks to bank profitability. Working Paper Series 2405, European Central Bank, 2020.

Jan Hannes Lang, Cosimo Izzo, Stephan Fahr, and Josef Ruzicka. Anticipating the bust: a new cyclical systemic risk indicator to assess the likelihood and severity of financial crises. *ECB Occasional Paper*, (219), 2019.

Lietuvos Bankas. Countercyclical capital buffer - background material for decision. Technical report, Lietuvos Bankas, December 2017.

M. Lozej, L. Onorante, and A. Rannenberg. Countercyclical capital regulation in a small open economy dsge model. Working Paper Series 2144, European Central Bank, 2018.

Caterina Mendicino, Kalin Nikolov, Javier Suarez, and Dominik Supera. Bank capital in the short and in the long run. *Journal of Monetary Economics*, 115:64–79, 2020.

J. Morell, J. Rice, and F. Shaw. A framework for macroprudential stress testing. *Research Techincal Paper 2002/7*, 2022.

Manuel A. Muñoz and Frank Smets. The positive neutral countercyclical capital buffer. Unpublished manuscript, October 2025.

Joana Passinhas and Ana Pereira. A macroprudential look into the risk-return framework of banks' profitability. Working Paper Series 03, Banco de Portugal, 2023.

M. Plašil. The countercyclical capital buffer rate for covering the usual level of cyclical risks in the czech republic. *Thematic articles on Financial Stability*, 2019.

Silvana Tenreyro and Gregory Thwaites. Pushing on a string: Us monetary policy is less powerful in recessions. *American Economic Journal: Macroeconomics*, 8(4):43–74, 2016.

M.R.C. Van Oordt. Calibrating the Magnitude of the Countercyclical Capital Buffer Using Market-Based Stress Tests. *Journal of Money, Credit and Banking*, 55(2-3):465–501, 2023.

A Appendix: The real PN CCyB

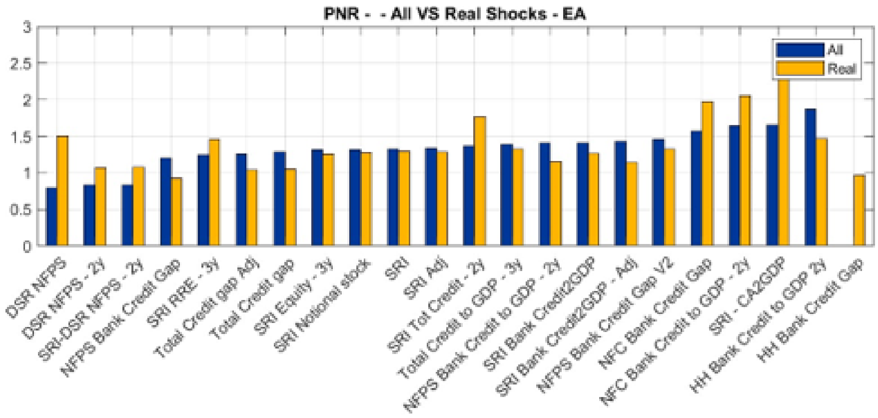
In this Appendix we present an alternative calibration of the PN CCyB, where only the real shocks (output shocks and inflation shocks are considered). Since in our model the first two shocks are considered real and the three following shocks are monetary/financial that means that the formula for the Real PN CCyB becomes the following:

$$PNR = 2.5\% \frac{Macro_{Median}}{Macro_{Max}} = 2.5\% \frac{\frac{1}{H}\sum_{h=1}^{H}\left(IRF_{11,h}^{Median} + IRF_{12,h}^{Median}\right)}{\frac{1}{H}\sum_{h=1}^{H}\left(IRF_{11,h}^{Max} + IRF_{12,h}^{Max}\right)}$$

$$= 2.5\% \frac{\frac{1}{H}\sum_{h=1}^{H}\left(\left(\sum_{j=1}^{N}\sum_{i=1}^{2} b_{1j}^{U}\epsilon_{ji}\right) F\left(z_t^{Median}\right)\right) + \left(\sum_{j=1}^{N}\sum_{i=1}^{2} b_{1j}^{D}\epsilon_{ji}\right)\left(1 - F\left(z_t^{Median}\right)\right)}{\frac{1}{H}\sum_{h=1}^{H}\left(\sum_{j=1}^{N}\sum_{i=1}^{2} b_{1j}^{U}\epsilon_{ji}\right)}.$$

As shown in Figure 9, under this alternative calibration approach, the "Real" PN CCyB level obtained by using the d-SRI as state variable is very close to the one presented above in subsection 4.3, where all the shocks of the model are used. The median Real PN CCyB across the different state variables is also around 1.3%, whereas most different state variables deliver Real PN CCyB ranging between 1% and 1.5%. When using real shocks only, the DSR and DSR transformations have smaller amplifications than in the baseline case, implying that the respective Real PN CCyB levels are relatively higher.

Figure 9: Standard and Real PN CCyB



Note: PN CCyB levels found across the different risk measures. In the standard approach, the full set of shocks is used (blue bars). In the alternative case, the PN CCyB levels are found by simulating only the output shocks and the inflation shocks (yellow bars).

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